ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

A COLLECTIVE INTELLIGENCE MODEL FOR ASSESSING COLLABORATIVE INNOVATION POWER INCLUDING RISKS

Ph.D. THESIS

Ayça ALTAY

Department of Industrial Engineering

Industrial Engineering Programme

NOVEMBER 2012

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

A COLLECTIVE INTELLIGENCE MODEL FOR ASSESSING COLLABORATIVE INNOVATION POWER INCLUDING RISKS

Ph.D. THESIS

Ayça ALTAY

(507072102)

Department of Industrial Engineering

Industrial Engineering Programme

Thesis Advisor: Assoc. Prof. Dr. Gülgün KAYAKUTLU

NOVEMBER 2012

İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

RİSK İÇEREN İŞBİRLİĞİ YENİLEŞİM GÜCÜNÜN DEĞERLENDİRMESİ İÇİN BİR ORTAK ZEKA MODELİ

DOKTORA TEZİ

Ayça ALTAY
(507072102)

Endüstri Mühendisliği Anabilim Dalı

Endüstri Mühendisliği Programı

Tez Danışmanı: Doç. Dr. Gülgün KAYAKUTLU

KASIM 2012

Ayça Altay, a **Ph.D.** student of ITU **Graduate School of Science Engineering and Technology,** student ID **507072102**, successfully defended the thesis entitled "**A COLLECTIVE INTELLIGENCE MODEL FOR ASSESSING COLLABORATIVE INNOVATION POWER INCLUDING RISKS**", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor : **Assoc. Prof. Dr. Gulgun KAYAKUTLU** ....
İstanbul Technical University

Jury Members : **Prof. Dr. Cengiz KAHRAMAN** ....
İstanbul Technical University

Prof. Dr. Gündüz Ulusoy ....
Sabancı University

Prof. Dr. Y. İlker TOPÇU ....
İstanbul Technical University

Assoc. Prof. Dr. Orhan FEYZİOĞLU ....
Galatasaray University

Date of Submission : 09 July 2012
Date of Defense : 02 November 2012

To my family…

FOREWORD

I would like to thank my advisor Associate Prof. Dr. Gulgun KAYAKUTLU for her endless encouragement and support, and her excellent supervision.

I would also like to thank to my jury, Prof. Dr. Cengiz KAHRAMAN and Prof. Dr. Gündüz ULUSOY for their valuable contribution and criticism; TÜBİTAK, ITU Rectorate and Tinçel Foundation for funding my research; my decision makers Mihrican OZTURK YUKSEL, Ayla ALTINKURT ESEN and Prof. Dr. Tufan V. KOÇ for making vital evaluations for my dissertation; Dr. Carlos ANDRÉS ROMANO and Dr. Cristobal INSA MIRALLES for their contributions during my stay in Spain; and my roommates Res. Assist. Ceren Buket KAYI and Res. Assist. Kutay TİNÇ for their support.

Finally, I would like to thank my parents and my brother who have always supported my decisions, trusted in me and always been there for me.

09.07.2012 Ayça ALTAY

(Industrial Engineer)

TABLE OF CONTENTS

ABBREVIATIONS

R&D : Research and Development
SME : Small and Medium Enterprise
PSO : Particle Swarm Optimization
GA : Genetic Algorithm
SOM : Self Organizing Maps
FCM : Fuzzy Cognitive Map
PPPSO: Predator-Prey Particle Swarm Optimization
FS : Foraging Search

LIST OF TABLES

Page

LIST OF FIGURES

A COLLECTIVE INTELLIGENCE MODEL FOR ASSESSING COLLABORATIVE INNOVATION POWER INCLUDING RISKS

SUMMARY

SMEs are known to be agile in action but fragile when faced with economic crises and in order to survive, they are urged to produce short term solutions with quick benefits. On the other hand, it is known that innovation is the key to the long-term success of companies, regardless of its size; which is a fact that most SMEs ignore. The ones that do not ignore innovation mostly outsource R&D and innovation activities since they do not have resources or cultural capabilities that are necessary for innovation. The literature offers this problem several solutions most of which contain SME collaborations. These collaborations are three-fold: with large enterprises, with universities or with other SMEs. Collaborations with large firms are considered to involve more risk that the SME is eventually absorbed by the large firm. Collaborations with universities are generally project-based short-term alliances and are mainly established upon knowledge transactions. For SMEs that require more than knowledge for innovation, a suitable collaboration option is with other SMEs.

SME collaborations in literature are regional or industry based, yet, recent studies point out that firms from different industries tend to form robust collaborations similar to industry-cluster based collaborations. Partner selection studies mainly involve favoring one company by the choice of one proper company among a group. Nevertheless, the means of construction or clustering of such innovation collaborations remain unexploited. The partner selection studies mainly omit the accordance of firms to each other, that is, synergy, while concentrating on the completion of resources.

In this dissertation, the synergy concept is analyzed with a quantitative approach. A cluster of collaborating firms are observed to be related a set of components, in which each firm represents a component, and an analogy with the Reliability Theory is constructed. The expected lifetime of an alliance is accepted as a measure of the accordance among collaborating firms and calculated using a system reliability approach. It is also pointed that in all systems (e.g. biological, physical, industrial, etc…) synergy has an exponential accelerating effect. Hence, the effect of synergy is considered as an exponential determinant of the innovation capacity of an alliance.

As accordant firms gather, their main aim is to increase the innovation capacity. Yet, innovation activities are mostly vague and radical activities that contain a great deal of risk. Hence, while increasing the innovation capacity, firms require enduring and decreasing the risk that is in the very nature of innovation.

Both synergy and innovation capacity/risk are affect and driven by a number of criteria which are either qualitative or quantitative. In order to eliminate and simplify the excessive number of criteria, obtain the related information from

companies and process it, Fuzzy Cognitive Maps (FCMs) are utilized and a fuzzy questionnaire is prepared. The centralities of the FCMs are used for the weights of the criteria and fuzzy questionnaires are conducted for retrieving company information.

For constructing the SME innovation collaboration clusters, the Foraging Search algorithm is utilized. The Foraging Search is a nature-based algorithm and imitates the Animal Food Chain in nature which contains flesh-eating, grass-eating and both flesh and grass eating animals. The algorithm is proven to be robust and effective for clustering problems which constitutes the main motivation of utilizing it.

51 SMEs from different industries are clustered in a way that provides the highest synergized innovation capacity for the weakest collaboration cluster. The optimized case has yielded to11 collaboration clusters with 2 outlier companies. Innovation capacity is calculated to be increased from 7.95% to 66.9% for each collaboration cluster. Results indicate that synergy and innovation capacity is uncorrelated, as well as synergy and risk. A very weak correlation is measured between innovation capacity and risk.

RİSK İÇEREN İŞBİRLİĞİ YENİLEŞİM GÜCÜNÜN DEĞERLENDİRMESİ İÇİN BİR ORTAK ZEKA MODELİ

ÖZET

KOBİ'ler eylemlerinde çevik, ancak kriz zamanlarında ise kırılgan olarak bilinmektedirler. Bu nedenle hayatta kalmak için kısa dönemli, hızlı sonuçlara odaklanmaktadırlar. Diğer taraftan, yenileşimin, firmaların büyüklüklerinden bağımsız olarak, uzun dönem başarısının anahtarı olduğu ve KOBİ'lerin bu gerçeği yok saydıkları bilinmektedir. KOBİ'lere bakıldığında, firmaların büyük çoğunluğunun, yenileşim ile ilgili aktiviteleri üretimlerinin ana bir parçası olarak görmediklerinden kaçındıkları görülmektedir. Yenileşim ile ilgilenen KOBİ'lerin büyük bir çoğunluğu ise yeterince kaynakları olduğundan ve kurumsal kültürlerine uygun olmadığından, yenileşim etkinliklerini dışarıya vermektedirler. Bu KOBİ'ler ise yenileşim ile ilgili etkinliklerini dışarıya verdiklerinden, yenileşim ve radikal müşteri talepleri gibi bilgileri kaybetmektedirler. Konu ile ilgili literatür bu sorun için birçok çözüm üretmektedir; bu çözümlerden biri de işbirlikleridir. Bu işbirlikleri üç çeşittir: büyük firmalarla işbirlikleri, üniversitelerle işbirlikleri ve diğer KOBİ'lerle işbirlikleri. Büyük firmalarla işbirlikleri, büyük firmanın KOBİ'yi yutması ile sonuçlanma riski barındırmaktadır. Üniversiteler ile işbirlikleri ise genellikle proje bazlı ve kısa dönemli işbirlikleridir ve bilgi aktarımına dayanır. Üniversiteler uzun vadede KOBİ'lerin bilgi kaynaklı danışmanları görevini üstlenirler ve KOBİ'lerin bilgi dışındaki kaynaklarını tamamlamakta yetersiz kalabilirler. Yenileşim için bilgiden fazla kaynağa ihtiyacı olan KOBİ'ler için en uygun işbirliği seçeneği, diğer KOBİ'ler ile işbirlikleri olarak görülmektedir.

Literatürde KOBİ işbirlikleri genellikle bölgesel veya sektörel bazdadır. Belirli bölgedeki veya belirli sektördeki KOBİ'ler için bir arada işbirlikleri düşünülmüştür. Son yıllarda ise, müşteri bazlı bir ayrıştırmaya gidilmiştir. Ancak, yeni çalışmalar farklı sektörden firmaların da sektörel bazdaki işbirlikleri kadar güçlü ve verimli işbirlikleri yapabileceğini göstermektedir. Bunun yanı sıra, bilişim teknolojilerinin gelişmesi ile işbirlikleri için coğrafi bölgelerin öneminin kalmadığı da belirtilmektedir. Bu tezin konusu olan işbirlikleri, farklı sektör veya bölgedeki ve müşteriye sahip KOBİ'lerin de verimli işbirliği kurabileceği üzerinedir.

İşbirlikleri için en büyük adım işbirliği yapılacak ortak veya ortakların seçilmesidir. Ortak seçimi çalışmaları genellikle bir firma için en uygun ortağın, bir firma grubu arasından seçilmesine yöneliktir. Çoklu firmalar için ortak seçimi ise eşleşme problemi olarak çözülmektedir. İşbirliğine girecek firma veya firmalar için sadece bir ortak bulmak literatürdeki yaygın bir uygulamadır. Ancak, işbirliği grubu veya işbirliği kümesi oluşturma üzerine olan çalışmalar henüz az sayıdadır. İşbirliklerinin birden fazla firma ile de yapılabildiği bilinmektedir. Bir yandan da, literatürdeki ortak seçimi çalışmaları ise genellikle firmaların birbirine uyumunu (sinerjiyi) ihmal ederek, gereken kaynakların tamamlanıp tamamlanmadığı üzerine

yoğunlaşmaktadırlar veya firmaların özelliklerinin birbirine uygun olup olmadığına tek yönlü olarak bakmaktadırlar.

Bu tezde, sinerji kavramı sayısal bir yaklaşım ile analiz edilmiştir. Bir işbirliği kümesi, elemanlardan oluşan bir sistem; firmalar ise bu sistemin elemanları olarak ele alınmış ve Güvenilirlik Teorisi ile bu yönde bir analoji kurulmuştur. KOBİ'lerdeki işbirlikleri optimize edilirken, aynı kümedeki işbirlikleri seri bağlı bir sisteme, farklı kümeler ise paralel bağlı bir sisteme benzetilmiştir. Aynı kümedeki bir elemanın bozulması, ilgili kümedeki bir KOBİ'nin işbirliğinden ayrılması anlamına gelmektedir. Bu nedenle aynı kümedeki elemanlardan birisi işbirliğinden ayrıldığında o işbirliği çökmektedir. Bir işbirliğinin çökmesi, o kümedeki eleman sayısına da bağlıdır. İki elemanlı bir işbirliğinde bir eleman işbirliğinden ayrıldığında otomatik olarak işbirliği bitmektedir. Ancak, daha fazla elemanlı bir işbirliğinde ise bir firmanın işbirliğinden ayrılması halinde, kalan firmalar işbirliğine devam edebilirler. Bu açıdan, seri bağlanmış sistemden farklılaşmanın yolu işbirliğindeki firma sayısını arttırmaktan geçer.

Bir işbirliğinin beklenen yaşam ömrü, firmalar arası uyumun bir ölçüsü olarak kabul edilmiş ve bu ömür, bir sistem güvenliği yaklaşımı ile ele alınmıştır. Ayrıca, sinerjinin her tip sistemde (biyolojik, fiziksel, endüstriyel, vb.) üstel ve hızlandırıcı bir etkisi olduğuna değinilmiştir. Güvenirlik teorisi ile kurulan analoji ile sinerjinin üstel etkisi birleştirilerek bir işbirliğinin beklenen yaşam ömrü, o elemanların en zayıf halkası ile ilişkilendirilerek matematiksel olarak hesaplanmıştır. Böylece, sinerjinin etkisi, bir işbirliğindeki yenileşim kapasitesini etkileyen ayrı bir etmen olarak değerlendirilmiştir.

Sadece sinerji yaratmak bir firmanın nihai amacı değildir. Sinerjik bir işbirliği oluşturabilen uyumlu firmaların bir araya gelmesindeki amaç ise yenileşim kapasitelerini arttırmaktır. Yenileşim etkinlikleri radikal olduklarından ve belirsizlik içeriklerinden, yüksek derecede risklidirler. Bu nedenle, firmaların yenileşim kapasitesini arttırırken, yenileşimin özünde olan riski de yöneterek azaltmaları gerekmektedir.

Sinerji ve yenileşim kapasitesi/risk kavramları hem sözel hem de sayısal olabilen birçok etkenden etkilenmektedirler. Çok sayıdaki etkenleri azaltmak, firmalardan bu etkenler hakkındaki bilgileri alabilmek ve işleyebilmek için Bulanık Bilişsel Haritalar yönetimi kullanılmış ve Bulanık Mantık içeren bir anket uygulanmıştır. Bulanık Bilişsel Haritalar'dan elde edilen değerler etken ağırlıkları olarak kullanılmış ve anketten verileri firma bilgileri olarak alınmıştır.

KOBİ yenileşim işbirliği kümelerini kurabilmek için, Besin Arama algoritması kullanılmıştır. Besin Arama yöntemi doğa bazlı bir algoritma olup hayvanların besin zincirini (ot yiyenler, et yiyenler, hem ot hem et yiyenler) taklit etmektedir. Doğadaki besin zincirinde enerji koruma yasası gereği ot yiyenlerin sayısı hem otçul hem etçil hayvanların sayısından çoktur. Aynı şekilde, hem otçul hem etçillerin sayısı ise etçil hayvanlardan çoktur. Otçul hayvanların zincirde iki düzeyde avcısı, hem otçul hem etçil hayvanların ise bir düzeyde avcısı bulunmaktadır. Hem otçul hem etçil hayvanlar, otçullardan hızlı ancak etçillerden yavaştır. Parçacık Sürü Algoritması'ndan da yararlanılan Besin Arama Algoritmasına göre sürü elemanları üç hızını korumak ister. Bu hızlardan ilki eylemsizlikten gelen kendi hızlarıdır. Bir diğeri, elemanların en iyi değerlerini korumak istemesidir ve üçüncüsü ise sürünün en iyisine ulaşma isteğidir. Besin Arama Algoritması bunlara "avcılardan kaçma" etkenlerini de ekler. Otçullar sadece av gibi davranmaktadırlar, etçiller sadece avcı gibi davranmaktadırlar. Otçulların yavaş ve sürü halindeki hareketi algoritmada yerel aramanın, etçillerin hızlı ve tek başına hareketleri global aramanın etkin şekilde yapılmasını sağlar. Hem otçul hem etçiller ise hem av hem avcı gibi davranarak bu iki arama türü arasında dengeyi sağlar. Algoritma öncelikle doğrusal olmayan sürekli problemlerde denenmiş ve iyi sonuçlar vermiştir. Bunun üzerine bir kombinatoryal optimizasyon problemi olan kümeleme problemleri üzerinde denenmiş, verdiği sonuçların güçlü ve verimli olması sonucunda KOBİ optimize işbirliği kümelerini oluşturmak için kullanılmıştır.

Besin Arama Algoritması'nın bu kümeleme probleminde kullanılmasının başka bir nedeni de kümeleme geleneksel kümeleme problemlerine uymayışıdır. Geleneksel kümeleme problemlerinde uzaklık/yakınlık gibi ölçütler kullanılırken, bu problemde bazı ölçütlerin birbirinden uzak, bazı ölçütlerin birbirinden yakın olması gerekmektedir. Uzaklık ve yakınlık birbirine çevrilebilen işlemlerdir, ancak, bu kümeleme tipinin yeniliği bazı ölçütlerin birbirini tamamlayıcı olması gerektiğidir. Bu da uzayda ilgisiz olduğu gözlemlenebilen veri noktalarının aslında aynı küme içinde olabilmesi demektir. Bu nedenle geleneksel kümeleme yöntemleri olan K Ortalamalar, Öz Düzenleyici Haritalar, Bulanık Kümeleme gibi yöntemler kullanılamamaktadır. Bu tür kümeleme işlemleri için metasezgisellerden yararlanılması gerekmektedir. Bir kümeleme problemi için kesin olarak belirlenmiş bir en iyi algoritma olmamasına ve tamamlayıcılığa bağlı bu tür bir kümeleme problemi yeni bir problem olsa da, Besin Algoritması'nın daha önce verdiği sonuçlara güvenilerek bu problem çözülmüştür.

Optimizasyon probleminin amacı sinerjilendirilmiş yenileşim kapasitesinin riske oranının maksimize edilmesidir. Ancak her işbirliği kümesi için bu değer farklıdır. Örneğin, bir işbirliği kümesi için bu değer büyütülmek istendiğinde, başka bir işbirliği kümesi için amaç değeri küçüklenmektedir. Çalışmada, tüm işbirliği kümeleri göz önünde bulundurulduğundan işbirliği kümelerinin amaç fonksiyonu değerlerinin en küçüğünün en büyük hale getirilmesi amaçlanmıştır. Bir başka değişle, amaç fonksiyonu en güçsüz KOBİ işbirliklerini de belli bir verimlilik ve uyum düzeyine getirmeyi amaçlamaktadır. Kullanılabilecek diğer amaç fonksiyonları ortalama işbirliği gücünün en büyüklenmesi veya maksimum ortala işbirliği gücünün en büyüklenmesi olabilir.

Farklı sektörlerden 51 KOBİ, en güçsüz işbirliği kümesinin yenileşim kapasitesi enbüyüklenecek şekilde kümelenmiştir. Optimum kümelemede, 11 işbirliği kümesi oluşturulmuş; 2 firma küme dışı kalmıştır. Yenileşim kapasitesindeki artış, her bir küme için %7.95 ile %66.9 arasında hesaplanmıştır. Bunun anlamı, en kötü işbirliğinde yenileşim kapasitesinin %7.95 artacağı ve en kötü işbirliğinde ise yenileşim kapasitesinin %66.9 oranında artacağıdır. Sonuçlar, sinerji-yenileşim kapasitesi, sinerji-risk arasında korelasyon olmadığını göstermektedir. Yenileşim kapasitesi ve risk arasında ise çok zayıf korelasyon bulunmuştur. Bu korelasyon değerleri amaç fonksiyonundaki sinerji, yenileşim ve risk parametrelerinin birbirlerini kuvvetlendirecek veya sönümlendiremeyecek olmalarıdır. Bu parametreler birbirlerinden bağımsız olarak belirlenmektedirler ve bulunan amaç fonksiyonu değeri gerçekçidir.

Sonraki çalışmalar, farklı tipteki, amaca özel yenileşim aktiviteleri için optimize iş kümelerini çıkarmayı hedeflemektedir. Bunun yanı sıra, hiçbir KOBİ'nin küme dışı kalmaması gibi yeni kısıtlar probleme eklenerek farklı işbirlikleri kurulabilir. Ek olarak, yeni bir kümeleme problemi oluşturulmuştur, ancak, bu kümeleme problemi için bir doğrulama yöntemi bulunmamaktadır. Tamamlayıcılık içeren küme problemleri için bir doğrulama endeksi tanımlanması da gelecek çalışmaların kapsamı içindedir.

1. INTRODUCTION

1.1 A Brief Background of the Study

The 2008 economic crisis has hit all enterprises worldwide hardening the ongoing harsh competition among (Blomqvist et al., 2005). While every industry is affected negatively from the crisis, each country has its own industries that have once been considered as impulsive forces and are now extremely impaired (Tambunan, 2011). To face this global economic context has become difficult for all companies and in particular the Small and Medium Enterprises (SMEs), which are defined as autonomous economic enterprises employing less than 250 people with an annual turnover of less than 50 million Euros and a balance sheet total of less than 43 million Euros in Europe (Harindranath et al., 2008) and they constitute 99% of all enterprises and 60% of all employment in the EU (Nieto and Santamaria, 2006). SMEs are known to be agile in action due to their flexible and rapid-responsive nature, but once they are hit by the crisis, they are more fragile than larger enterprises (Nieto and Santamaria, 2006; Raymond and St-Pierre, 2010). SMEs are seeking rescuing solutions among the two survival choices. The majority of SMEs has preferred to focus on short-term improvements to generate quick benefits (Ahuja, 2007; Villa et al., 2009). Many of them have acted to apply the limited faster, cheaper, better logic. The SMEs that have tried to gain speed in order to "save the day" have also outsourced their R&D departments or other activities that have been considered supplementary (Henoch and Gonzalez, 2003) which has generated the loss of the knowledge and context due to the incoherence in technology, market, workforce, process and customer between the outsourcing and the outsourced enterprise (Kim, 2008; Raymond and St-Pierre, 2010). They have also lost the knowledge about "what customer wants" because of sales through distributors (Url-1, 2010).

Meanwhile, other SMEs have led themselves to alliances and this minority have been more successful in survival (Blomqvist et al., 2005). The EU have also supported collaboration both solely among SMEs and among SMEs and large enterprises

(Nieto and Santamaria, 2006), especially in the times of crises (Schütze et al., 2011) (Blomqvist et al., 2005). The major motivations of these collaborations are exploiting synergies among networks. There is the fact of networks to be more adaptive to changes than individual enterprises or institutions as well as providing a strong defense against environmental factors (Nieto and Santamaria, 2006). Until recently, these collaboration networks have been constituted of enterprises of the same geographical region, industry or sub-industry (Nieto and Santamaria, 2006; Raymond and St-Pierre, 2010; van de Vrande et al., 2009). Yet, recent studies and applications show that successful networks and collaborations can be independent of region or industry (Harindranath et al., 2008; Nieto and Santamaria, 2006).

To all types of enterprises, including SMEs, innovation related activities such as Research and Development (R&D) had been known to be a supplementary activity and was expected to use the stock of knowledge with the least risk. The economic crisis made the necessity of these activities to be comprehended as the key factor of growth and sustainability while the content has been internationalized (Gerybadze and Reger, 1999; Raymond and St-Pierre, 2010). In brief, R&D provides an innovative lead for systems. In terms of SMEs, they are known to be agile in behavior but what they lack in terms of innovation is the access for the external resources close-minded culture (Nieto and Santamaria, 2006) which they believe is only available for the large firms (Lee et al., 2010). Both for large enterprises and SMEs, the focus is on open innovation which compels extracting necessary resources and knowledge from outsiders (van de Vrande et al., 2009). The more collaboration means increase in SMEs' innovation capacity and strength. However, collaborations also involve potential risks that may invert all the positive effects which may ultimately cause losing competitive advantage or existential dependence to partners (Blomqvist et al., 2005). Hence, it is of vital importance that the collaboration is well-planned with a minimum likeliness of failure and the characteristics of SMEs and the collaboration be well-analyzed at each phase. One major problem in collaborations is the selection of partners (Swoboda et al., 2011; Villa et al., 2009) which is achieved three-fold: one-to-one matching of SMEs (Blomqvist et al., 2005), a symbiotic relation of SMEs grouped under a large enterprise (Sawers et al., 2008; Swoboda et al., 2011) and a network among SMEs. Applications of one-to-one matching of SMEs are rare due to not being robust for two reasons (Blomqvist et al., 2005): SMEs are weak in completing resources and SMEs may not be strong enough to handle all resources. Secondly, in case of conflicts between SMEs, the split of these companies is easier than a multi-company case. The SME-Large Enterprise collaborations involve a high risk of the SME being technologically embedded in the related large enterprise due to the hierarchical structure (Sawers et al., 2008). On the other hand, SME networks are less hierarchical than SME-large enterprise collaborations and more robust than one-to-one matched SMEs. However, the risks that are in the very nature of collaboration are also involved in these networks.

Innovation and R&D oriented SME collaborations have mostly been applied by networking SMEs by product, industry or geographical region just as other SME collaborations (Nieto and Santamaria, 2006). Predetermined industry or regional clusters have provided a basis for the collaborative business. On the other hand, interregional and inter-industry applications have also been observed to be successful (Henoch and Gonzalez, 2003; Okamuro, 2007). Meanwhile, the consensus is on that innovation and collaborations are always connected to risk taking and many SMEs are either scared or unwilling to take Yet, innovation without risk-taking is beyond the bounds of possibility in today's challenging world, even for SMEs (Url-1, 2010).

1.2 Innovation

1.2.1 Definition and characteristics of innovation

In literature there has not been a common ground of the term "innovation" and "innovativeness" among researchers. A variety of definitions are provided below:

"Innovation is the process of making changes, large and small, radical and incremental, to products, processes, and services that results in the introduction of something new for the organization that adds value to customers and contributes to the knowledge store of the organization" (O'Sullivan and Dooley, 2009)

Innovation is "the introduction of a new product, process, technology, system, technique, resources, or capability to the firm or its markets" (Covin and Miles, 1999).

Innovation is the “change that speeds up and improves the way we conceive, develop, produce and access new products, industrial processes and services” (European Commission, 2010)

The latest OECD definition (OECD and the European Commision, 2005) is "Innovation is the implementation of a new or significantly improved product, service, process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations".

According to these definitions, the common ground is that (i)innovation involves the change that is in products, processes, markets and the organization structure. (ii)Innovation contributes to organizational knowledge and firm’s environment as well as adding value to the customer. The term “innovation” is often confused with terms *change, invention, design* and *creativity* (O'Sullivan and Dooley, 2009). These terms are not direct definitions but concepts involved in innovation.

According to the Oslo Manual, there are 4 types of innovation (OECD and the European Commision, 2005):

a. ***Product Innovation*** is the introduction of a newly offered or significantly improved good or service. The contribution and improvement can be in "technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics".
b. ***Process Innovation*** involves new offers or significant changes in the production or delivery method.
c. ***Market Innovation*** involves new or significantly improved implementation of marketing methods. These changes can be in "product design or packaging, product placement, product promotion or pricing".
d. ***Organizational Innovation*** new or significantly improved implementation of "business practices, workplace organization or external relations" that add value to the organization.

According to Rogers (1983), the most important features of innovation are adoption and the diffusion of the adoption, which indicated the rate and speed of the adoption of the innovation. Moreover, he proposes 5 stages of innovation diffusion that are affected by 5 criteria. The stages are knowledge, persuasion, decision, implementation and confirmation and the criteria are relative advantage, compatibility, complexity, trialability, observability (Rogers, 1983; Tapaninen et al., 2009). The first three criteria are also known to represent the advantages and the disadvantages of the innovation (Tapaninen et al., 2009).

1.2.2 R&D for innovation

R&D is defined as the "Research and experimental development (R&D) comprises creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications" (OECD Glossary of Patent Terminology, 2012). Yet, it is considered as the basic and the most regarded tool for innovation so that non-R&D tools of innovation are considered as neglected tools of innovation (Hervas-Oliver et al., 2011).

In conventional point of view, R&D is never related directly to the manufacturing process, it is always considered as a supplementary activity by companies which have short-term goals and objectives (Burton et al., 2008). Yet, it is long understood that R&D is essential in order to provide sustainability and the competitive advantage in the long run (Skinner, 2007).

General characteristics of R&D projects are given below (Keizer and Halman, 2004; Matheson and Menke, 1994; Wageman, 2004):

- They are long term projects, thus involves risk in a long horizon.
- The projects have no precise objective in most cases.
- They involve a great deal of uncertainty.
- They are affected by a great number of variables.
- Scope of the projects is highly vague.
- The set of tasks may not be comprehensible and complete.
- The cost of remediation may not be fully predicted.
- The quality of the output and performance may not be well-defined.
- Task descriptions, deliverables, milestones can be fuzzy.
- The number of trials for success cannot be easily estimated.
- They are radical innovation projects rather than incremental projects

As can be observed from the characteristics of R&D, while increasing capacity, R&D also involves a great deal of risk in its nature.

1.2.3 Open innovation

Classical R&D approach encourages in-house R&D, however, in terms of open innovation, it is considered as an open system (Chesbrough et al., 2008). Open innovation is defined as " the use of inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively" (Chesbrough et al., 2008). The open innovation model differs from the classical R&D approach in a way that it assumes that firms or innovative units should benefit from external ideas and knowledge as well as its own (Mortara et al., 2009). An innovation unit can benefit from open innovation by shortened life cycles, decreased R&D costs and wider diffusion of knowledge by enabling "value creation" and "value capture"(Chesbrough et al., 2008; Vanhaverbeke, 2011).

1.2.4 Innovation and SMEs

With the global economic crisis that started to hit the world in 2008, companies that used structured R&D have passed ahead of the system itself. The system itself has become a bottleneck for technological development. It is also known that while the physical investments were slowed down and production centers are closed down, R&D investments are geared up (Url-2, 2009; Kim, 2008) despite the shortage in disposable income.

As the SMEs case, it is known majority is stuck to the conventional R&D approach which implies that R&D is a supplementary activity (Rammer et al., 2008). Since they are relatively small enterprises that prey on solely the production process, R&D is always remained in the backseat of the minds of SME managers who are generally owners act independently (Batterink et al., 2010).

Additionally, SMEs usually expect most rapid development with the least research, they are more prone to skip ‘Research’ and aim ‘Development’. What makes them right about this ideology are their limited resources and capabilities as well as the role of supplier (Bos-Brouwers, 2010; Ortega-Argilés and Voigt, 2009; Rodríguez-Pose and Refolo, 2008). As a solution to the “least research objective”, lucky SMEs outsource their R&D activities, which usually ends up losing valuable customer information (Henoch and Gonzalez, 2003). Luckier ones try to conduct the research in-house with its limited sources, achieving quite small advances (Rodríguez-Pose and Refolo, 2008). Lastly, unlucky SMEs do not have the chance to conduct any

R&D activities, even outsourced. Hence, it is plausible to claim that SMEs one-by-one have neither time nor resource that could accelerate the innovation. They are also discouraged by the diseconomies of scale and lack of expertise (Batterink et al., 2010). Having observed this fact, the aim of this research is to encourage SMEs to collaborate in a manner that increases their innovation capacities by working together with trust and concentrating on open innovation. Hence, this dissertation is designed around the synergy in collaboration.

1.3 Innovative Collaborations

1.3.1 Knowledge collaborations

The modern economy of the 21st century is driven by knowledge (Nagurney and Qiang, 2010). In project-based industries, one type of collaboration is formed by sharing and exchanging project-based knowledge and experience which are called knowledge collaborations (Dietrich et al., 2010). Knowledge collaborations can be constituted for single projects (Un et al., 2010) as well as in a multi disciplinary fashion (Nagurney and Qiang, 2010). Best knowledge collaborations are constructed with universities, research institutes, suppliers, customers and competitors and the most efficient collaborations are formed with universities (Un et al., 2010).

1.3.2 Innovation Collaborations

In knowledge collaborations, the common resource that is shared is knowledge (Nagurney and Qiang, 2010). Knowledge collaborations are named as innovation collaborations if other resources such as technological or organizational resources are shared and exchanged within collaborations in order to increase innovation capacity (Dittrich and Duysters, 2007). The levels of innovation collaborations vary from small units such as inter-departmental collaborations (Cuijpers et al., 2011), to an international level (Hendriks, 2012). The main objectives of innovation collaborations are completing the missing in-house resources, reducing risks and constraints, sharing responsibility and increasing innovation capability together with flexibility (Chou and Chou, 2011). However, it also involves plenty of risks, mainly losing proprietary knowledge (Chou and Chou, 2011). Other risks include the risks that are accompanied by the nature of innovation and collaboration such as the incompatibilities among firms, risk by involving other partners such as suppliers, etc. which will be the main subject of this dissertation.

1.4 Innovation collaborations among SMEs

It has been aforementioned that SMEs do not have resources for actualizing R&D activities. Hence, the most common solution offered for that problem is collaborating or forming R&D alliances (Narula, 2004; Okamuro, 2007). These collaborations are also encouraged by the European Union (Villa et al., 2009). Even though it is proven that these collaborations have positive effects on SMEs and industry has no effect in the success of alliances (M. Zhang and Yin, 2012), a vast percentage of these alliances have been observed to fail (Dickson et al., 2006). Torrent-Sellens et al (2006) list the causes of failure as disagreement on sharing resources, conflict due to having different cultures among partners, conflict in goals and objectives, inflexibility in alliance roles, unintentional knowledge overflows and different learning speed of partners. Chou claims that the root cause of such failures is the opportunistic behavior of partners which causes distrust among partners (Chou, 2008). On the other hand, Mulligan et al. (2005) claims the failures are caused by poor definition of objectives, poor arrangement of actions, poor resource allocations, poor feedbacks and poor inspection of performances. Most of these failure causes can be traced back and rooted to incorrect matching or grouping of partners since these causes are based on conflicts among partners, or in other terms, negative synergy among them. For a collaboration to be successful, it is of vital importance that the partners are matched or grouped in a way that maximizes the synergy among partners, while maximizing the innovation capacity and minimizing the innovation risks (Hu, 2010).

1.5 Motivation of the Study

Since it is known that innovation is crucial for all enterprises and SMEs do not have the ability or power to innovate themselves, SMEs are merely obliged to collaborate in order to increase their innovation capacities. It is the aim of this dissertation to propose an intelligent algorithm to optimize SME innovation collaboration clusters that maximizes synergized innovation capacity and minimizes the innovation risks.

1.6 The Objectives of the Study

The objectives of this dissertation are two-fold: academic and industrial.

Academic objectives include

- Constructing a mathematical model for synergy
- Producing a new meta-heuristic variation (The Foraging Search) for various types of optimization problems involving clustering problems
- Assessing innovation capacity and risk criteria derived from the literature in SMEs point of view
- Prioritization of innovation capacity, innovation risk and synergy criteria

Industrial objectives include

- Contributing SMEs to increase their innovation capacities
- Proposing innovation collaboration structure with the aim of R&D services for SMEs.

2. LITERATURE REVIEW

2.1 Innovation Collaboration in SMEs and SME Clusters

Innovation collaboration of SMEs has been a trending topic in research in recent years parallel to the EU developments and policies encouraging incentives of driving forces (Tödtling and Kaufmann, 2002). R&D activities also tend to develop in networks rather than in-house activities (Motohashi, 2008a). Studies of the last decade tend to group SME innovation collaborations in three types: collaborations with larger enterprises, collaborations with universities & other scientific foundations and collaborations among SMEs. Other minor collaboration types include collaboration with public companies and Supply Chain partners such as suppliers, sales channels and customers (Edquist et al., 2004).

Collaborations with larger companies consists of a network of SMEs focused around a large enterprise (Lazoi et al., 2011). SMEs can learn about ICT technologies by gathering around larger enterprises (Lazoi et al., 2011). It is also given in literature that larger companies expect fundamental R&D research and knowledge in their alliances with SMEs rather than its products which means pragmatic returns for SMEs in the longer run (Motohashi, 2008a). Hence, SMEs that collaborate with large corporations should be aiming "exploring new R&D themes" or "commercializing own technology seeds" (Motohashi, 2008b). For other objectives, studies claim that SME-large enterprise collaborations and networks are damaging for SMEs (Motohashi, 2008b), it is even claimed that SMEs and large enterprises should not collaborate (Gardet and Mothe, 2012). It is also advised to SMEs to respect secrecy and allow knowledge spillovers at a minimum level (Tschetschonig, 2012). The main danger for SMEs is that large enterprise may "swallow" the SME (Sawers et al., 2008). The collaboration may produce an innovation that the large benefit but the SME cannot because of its organizational structure. (Gardet and Mothe, 2012) SME-large enterprise collaborations are more reliable when the large enterprise serves as a bridge or as a trustable hub but not as a leader among SMEs (Lazoi et al., 2011).

SME-university / scientific foundation collaborations are claimed to produce faster and effective results (Un et al., 2010). The main driver for SMEs to collaborate universities is the expertise of the university in related subjects (Collier et al., 2011). In most of these collaborations, SMEs and universities work one-to-one rather than by being grouped with SMEs to one research cooperation (Collier et al., 2011; Peças and Henriques, 2006). These one-to-one collaborations mainly rise to a consulting level where “network orchestrator” or “network broker” concept arises. The network broker is generally from the university or the scientific foundation that facilitates the innovation process at each phase of the collaboration by identifying SMEs needs, bringing out the knowledge demands and searching for proper collaboration schemes for the SME(Batterink et al., 2010). Brokerage splits the collaboration in two: the identification and facilitation with the broker and the main collaboration (either with SMEs or with large enterprises) according to the needs of the SME identified by the broker. It is also possible that universities act as brokers, as a whole institute (Flores et al., 2009). For the university-SME types of collaborations above all enabler, the sole criterion that either starts or ends the collaboration is funding and this type of collaborations commonly last for short terms and brings short-term benefits (up to 12 months) (Flores et al., 2009; Peças and Henriques, 2006). Moreover, universities are helpful for providing knowledge as the missing resource of SMEs but they can barely provide other missing resources (Rodríguez-Pose and Refolo, 2008). Hence, if the SME lacks other resources alongside funding, a one-to-one university collaboration will not be enough for increasing innovation capacity of that SME. In that case, SMEs turn to other collaboration partners such as other SMEs.

The main benefits of innovation collaborations among SMEs have been explained three-fold by Teixeria et al. (2008): the reduction in and sharing of the risks and cost caused by inherent characteristics of innovation, simplifying the technological context and entrance to new markets. Another classification is made to observe that SMEs expect mostly “applied research” and “development” rather than basic research, design or marketing (Narula, 2004). Furthermore, manufacturing SMEs seek for product innovation (Matthews, 2010) and service SMEs seek for process innovation in their collaborations (Un et al., 2009). Contrarily, Zhang claims the success of an alliance is independent of the industry but dependent to the expectations of the SMEs (Zhang and Yin, 2012). According to literature, there are numerous criteria that affect the success of this type of collaboration. Dickson (Dickson et al., 2006) states that the most important criterion for SME innovation is the firm size. However, in this study, only firm size is emphasized and other criteria are ignored. Zhang (Zhang and Yin, 2012) analyses R&D based criteria and concludes that number of patents, being in a high-tech industry, R&D expenditure of the firm and rate of R&D personnel are considered as the most effective criteria in R&D alliances of SMEs. These studies do not consider collaboration related criteria for the success of networks or alliances. Hence membership structure, partner relationship, external support and rules of cost and outcome sharing can be also added to these criteria (Okamuro, 2007).

It is also of recent research that SMEs collaborate in virtual teams which are groups that work together without the boundaries of time and geographical space (Nader et al., 2008). This structure is found to be more time and cost effective than physical teams, since it eliminates costs such as travel, relocation, etc., provide productivity and flexibility (Cascio, 2000; McDonough et al., 2001; Nader et al., 2008; Nader et al., 2009; Powell et al., 2004).

Another discussion is on the industry being high technological or low technological. Cosh et al. (2005) claim that collaborations are beneficial for SMEs that operate in high technological industries whereas SMEs operating in low technological industries are proposed to benefit from incentives instead of collaborations. However, on the other hand, Teixeria (2008) advice SMEs operating in low technological industries to collaborate in order to increase their innovation abilities considering the cultural and geographical proximities as well as technological diversities. According to this study, if SMEs have close values for these criteria, innovation collaborations of SMEs in low technological industries. Yet, it is known that low technology related enterprises do not participate in R&D collaborations as much as high technology related SMEs (König, 2010).

Most of the studies related to SME innovation collaborations apply their methods on predetermined clusters or already existing collaborations. SME innovation studies include clustering upon the pre-generated groups, such as industrial sector, geography or company size. Lazoi et al. (2011) propose aerospace industry SME clusters in Italy to collaborate only with bigger companies. Braun (Braun, 2003) analyzes tourism industry and offers clusters with focus on IT Systems. Generally characteristics of SMEs are recognized and innovation precautions and advices are proposed cluster-wise (Chen and Cao, 2006). Conventionally innovation clusters are not formed in innovation network studies; most studies work on existing case stories. As Chapman et al. (Chapman et al., 2004) and Zhang and Yin (2012) states, productive and efficient collaborations do not necessarily require SMEs from the same region and / or industry. Moreover, for the SMEs those do not have a history of collaboration of innovation, it is important to assign them partners that will give the best collaboration results.

The studies given above and presented in Appendix A do not consider risks that arise from innovation determinants and the direction of synergy and possible disputes among partners, since they work on existing collaborations. The partner matching or grouping, or partner selection is the most important risk to start new collaborations. Hence, next section analyses the literature of partner selection algorithms and methods.

2.2 Partner Selection in Alliances

In the process of forming collaborations or alliances, the literature offers a wide selection of methods and applications four numerous types of collaborations as given in Appendix B. In the partner selection phase, three types of selections. The first type of partner selection in literature is named as “choosing” since for a given company, it aims to choose one or a limited number of firms to collaborate among a number of options (Cummings and Holmberg, 2012; Feng et al., 2010; Ye, 2010). The second type of selection which is very similar to “choosing” is “matching”, that is one-to-one assignment of companies given in a set (Zhang et al., 2008). The difference between “choosing” and “matching” is that in “choosing” only one firm is aimed to be assigned to a company but in “matching” all firms in a given set are aimed to be assigned to each other. Lastly, the third type of partner selection is “grouping” which is clustering of all companies in a set (Zhao et al., 2008). Partner selection models are mostly exploited in strategic alliances (Ding and Liang, 2005; Huang et al., 2010; Li and Ferreira, 2008) and virtual enterprises (Huang et al., 2011; Ip et al., 2003; Ye, 2010)As can be observed from Table 2.2, the main method for partner selection is Multi Criteria Decision Making (MCDM) methods which are mainly used mainly “choosing” type of selection. The most exploited MCDM method is TOPSIS (Li and

Ferreira, 2008; Wu et al., 2009; Ye, 2010; Ye and Li, 2009). In case of incomplete and uncertain information, MCDM models are hybridized with Fuzzy Logic (Chen et al., 2010; Ding and Liang, 2005; Feng et al., 2010; Ye, 2010). The selection criteria and criteria groups change depending on the need and type of collaboration, yet, several studies group the criteria as "task-related" and "partner-related" independent from the type of collaboration (Cummings and Holmberg, 2012; Dong and Glaister, 2006). Cumming and Holmberg (2012) also add "risk-related" as another class of criteria. Another classification is achieved as "individual" and "collaborative" criteria (Feng et al., 2010). Other classifications involve industry or collaboration type based criteria (Feng et al., 2010; Wu et al., 2009).

Using mathematical models in either exact or metaheuristic methods is another common application in literature (Fischer et al., 2004; Huang et al., 2010; Ip et al., 2003; Zhao et al., 2008). These models can have either single (Zhao et al., 2008) or multiple objectives (Hajidimitriou and Georgiou, 2002). The common main objective for alliances is set as profit maximization and cost minimization (Hajidimitriou and Georgiou, 2002; Huang et al., 2010). The most common constraint is due dates of projects or subprojects (Ip et al., 2003; Zhao et al., 2008). Other objectives depend on the type of collaborations. For virtual enterprises, various objectives are maximizing the completion of resources for each subproject (Zhao et al., 2008), maximizing the overall agreement (Huang et al., 2010), minimizing risk (Ip et al., 2003), and minimizing disutility (Fischer et al., 2004 338). For strategic collaborations, other objectives include maximizing quality and customer satisfaction (Huang et al., 2010) and for international joint ventures, maximizing financial index values is another objective (Hajidimitriou and Georgiou, 2002).

The rate of innovation collaborations in partner selection problems is very low. Hacklin et al. (Hacklin et al., 2006) applies a "choosing" study over a company in renewable energy industry using Computer Facilitated Quantitative Data Analysis method. In this method, they assigns a benchmark score and a complexity of alliance coefficient to each candidate company and these values are aggregated with a consolidation function. In this way, this method is analog to MCDM methods. Chen et al. (Chen et al., 2010) also utilize an AHP method for choosing the best partner. Baum et al. (Baum et al., 2012) propose a graph theory based clustering method among 25 SMEs.

The literature does not bring variety to methods, but they introduce numerous criteria for a successful collaboration. Bunduchi (Bunduchi, 2012) thoroughly investigates the element of trust among partners in his study. Wu et al. (Wu et al., 2009) reveal patent, market share, unique competencies in their study. Dong and Glaister (2006) offer international expansion possibilities as an important criterion. Feng et al. (2010) adds individual attributes such as technological capability, financial health, knowledge experience, etc. and alliance attributes such as resource completion and goal correspondence.

All studies apart from Huang et al. (2010), ignore the synergy phenomenon in their studies. The concept is integrated in all objectives of collaboration as a coefficient.

It is in the context of this dissertation to extract innovation and risk criteria as well as synergy criteria that have effect on collaborations. These criteria are thoroughly analyzed in the model building and application phase. The listed possible methods for solving the partner selection problem and the novelty of this study are presented below:

- Statistical Methods: These methods are applied to measure the efficiency of existing collaborations. The methods are static, and do not consider the new collaborations that can emerge.
- MCDM Methods: The problem is a multi-objective problem which has two main objectives: maximizing the innovation capacity and minimizing the risk and both objectives are affected from the same criteria. Moreover, synergy is known to have an exponential effect on systems and alliances (Tresch et al., 2006) and MCDM methods cannot reflect that effect.
- Mathematical Models: Best possible alternatives are network models, yet the exponential synergy effect is hard to be modeled. Moreover, the exponential effect of synergy would be shown in a non-linear programming model. Yet, for n firms to be grouped there are 2^n-1 collaboration schemes, which yields to a computational complexity for the model.
- Metaheuristics: For the multi-objectives of maximizing synergized innovation capacity and minimizing collaboration risk, the best method is to solve the partner selection problem by metaheuristics since they require simpler mathematical models and reduce the computational time of solution of such problems. Yet, it is a problem to select the proper metaheuristic. There are

numerous possible alternatives in literature. This partner selection problem is "clustering" type, since it groups all firms given in a set of elements. 51 SMEs are to be constructed best alliance clusters. Hence, it is needed to go over the clustering literature.

2.3 Clustering Literature

Clustering is defined as the act of grouping unlabeled data in accordance with their specific characters and similarities (Jain, 2010). It is widely used in data mining as a basic tool for the comprehension, analysis and processing of the related data objects properly (Zhang and Cao, 2011). An accurate clustering is achieved through maximizing the degree of similarity of data objects within each group while minimizing the similarities among different clusters (Jain et al., 1999). Methods and algorithms for a more robust and accurate clustering have been improved for over five decades. The studies demonstrate that there is no one best algorithm for every clustering problem and different problems may favor different methods (Jain, 2010; Lu et al., 2007).

One of the most important studies over clustering methods have been conducted by Gan et al. (Gan et al., 2007)that groups clustering methods in eight classes. These groups include hierarchical clustering methods (Espinoza et al., 2012; Schonlau, 2002), fuzzy clustering methods (Ross, 2004), center based clustering methods such as K-Means, K-Medians (Aboyni and Feil., 2000), graph based methods such as CACTUS (Ganti et al., 1999), grid based methods such as STING (Wang et al., 1997), density based methods such as DBSCAN (Ester et al., 1996) and model based methods such as Gaussian clustering (Banfield and Rafttery, 1993). The last group of clustering methods is search-based methods where various heuristic and metaheuristic algorithms are used (Gan et al., 2007). These metaheuristics include Genetic Algorithms (GA) (Jimenez et al., 2007), Ant Colony Optimization (ACO) (Wang et al., 2007), Tabu Search (TS) (Sung and Jin, 2000) and Particle Swarm Optimization (PSO) (Cui et al., 2005).

The oldest clustering method is known to be the hierarchical clustering, which uses tree-like diagrams or dendograms for extracting clusters (Leone et al., 2008). The basic advantage of the algorithm is that it does not require a predetermined number of clusters; the optimum number of clusters is determined according to the shape of the dendogram. Yet, hierarchical algorithms have a number of disadvantages that prevents them to be widely used for real world problems. The clusters obtained via Hierarchical Clustering are static and may overlap due to information loss (Omran et al., 2005). Center-based algorithms such as K-Means Algorithm overcome the disadvantages of Hierarchical Clustering, yet these algorithms require the cluster number to be determined in advance (Aboyni and Feil., 2000).

In order to eliminate the disadvantages and protect the advantages of hierarchical and center based clustering methods, search based and hybrid search based methods are produced (Omran et al., 2005). Moreover, search based algorithms also eliminate an unforeseen disadvantage of former clustering methods, that is, they handle clustering problems as optimization problems and avoid local optima (Gan et al., 2007; Omran et al., 2005).

Search based algorithms applied in clustering embrace various metaheuristics; algorithms used either directly for clustering or parameter tuning for other clustering methods. Earlier applications mainly involve Tabu Search, Simulated Annealing and / or Genetic Algorithms. Jiang et al. (Jiang et al., 1997) implement a discrete Genetic Algorithm (GA) approach for clustering chemical data and GAs are observed to overcome early convergence and parameter selection problems. Cowgill et al. (1999) prove that GAs dominate K-Means method. In the parameter tuning part of clustering, Scheunders (1997) utilize GAs to find optimum inputs for K-Means which are number of clusters and initial cluster centers.

A K-Means based Tabu Search (TS) algorithm is applied without any additional operators by Sultan (1995). The TS algorithm for clustering has been developed over years with additional operators. Sung and Jin (2000) operate a modified TS algorithm with two additional operators named packing and replacing which contribute to fast convergence on randomly created data sets. Liu et al. (Liu et al., 2008) compare the performance of TS algorithm in terms of least-square-error regarding combinations of five improvement operators and three neighborhood modes.

Simulated Annealing (SA) is another approach for clustering which is mostly used in hybrid forms with other clustering methods. One of these approaches involves Fuzzy Clustering parameters tuned by SA (Yang et al., 2005). Saha and Bandyopadhyay (2008) hybridize SA with GAs, that is crossover and mutation are embedded in the

SA algorithm. Another hybridization algorithm is achieved through Tabu Search (Osman and Christofides, 1994). All modifications and hybridizations attempt to eliminate local optima and provide a fast convergence.

With the analysis of the search based clustering methods, it is plausible to claim that in the recent years, Tabu Search, Genetic Algorithms and Simulated Annealing algorithms are being hybridized, modified or replaced with novel and more efficient algorithms. Focus is on collaborative intelligence algorithms like Ant Colony Optimization (ACO) and Particle Swarm Optimization. Ant Colony Clustering differs by defining an explicit objective function (Zhang and Cao, 2011). Moreover, Herrmann and Ultsch (2010) affirm that Ant Colony Clustering may yield to small and excessive number of clusters with a distorted topology, but produce better results than many other search based clustering algorithms with further improvements. The literature proposes various valuable applications of Ant Colony Clustering such as fault or anomaly detections (Tsang and Kwong, 2005; Xu et al., 2012), consumer segmentation (Jiang and Wang, 2011), design of manufacturing cells (Kao and Fu, 2006). Latter studies emphasize the advantages of hybrid Ant Colony Clustering methods. These hybridizations are achieved through both conventional methods such as hierarchical clustering (Azzag et al., 2007) or K-Means (Kuo et al., 2005b), or intelligent methods such as Neural Networks (Kabir et al., 2012).

Particle Swarm Optimization algorithm is the most recent search-based method that is proven to be successful in clustering. The main PSO algorithm is used in two ways. One of the methods employed transforms the PSO algorithm into a discrete form which is formulized as an optimization problem (Jarboui et al., 2007). The other case is that the main PSO algorithm, the particles represent cluster centers and those centers are updated at each iteration (Chen and Ye, 2004; Saka and Nasraoui, 2009). As in the case of Ant Colony Clustering, Particle Swarm Clustering has also been improved with modifications and hybridizations. Modifications involve embedding new operators for fast convergence or avoiding local optima (Tsai and Kao, 2011) or more radical changes in the structure of the algorithm such as Predator-Prey PSO algorithm being applied to clustering (Jang et al., 2007). Hybridizations are mainly employed with Genetic Algorithms (Kuo and Lin, 2010; Kuo et al., 2012; Paterlini and Krink, 2006) and Fuzzy Logic (Izakian and Abraham, 2011; Li, 2012).

In this study, a new PSO-based Collective Intelligence metaheuristic, the Foraging Search, is introduced, proved to be more efficient than PSO and PP_PSO algorithms and applied to the SME clustering for innovation collaboration.

2.4 Methodology - Collective Intelligence Literature

Collective Intelligence is the collective behavior of individuals for creating intelligent apparent solutions (Malone, 2006). These solutions can have a good or disastrous affects, yet the result is merely affected by the impact of the solution, hence a solution yielding an unfortunate impact can also be considered "intelligent" (Malone, 2006). Collective intelligence encapsulates a broad scientific area from psychology to engineering. It adopts both qualitative methods and concepts such as collective mental maps (Heylighen, 1999) or collective consciousness and quantitative methods such as PSO (Cui et al., 2005) or ACO (Abdallah and Emara, 2009). It also produces valuable results when integrated with other techniques such as game theory approaches (Boschetti and Brede, 2008; Brede et al., 2007; Brede and Boschetti, 2007) or other group decision making techniques that are traditionally used such as statistical analyses.

In human collaboration, collective intelligence confronts several obstacles. These obstacles can be listed as the limited capacity of human thinking and human memory, the vagueness and the noise in human interaction, the difference between perceptions of people, the ego in people leading them to play power games (Heylighen, 1999) and the errors in the information flow. Different collective intelligence forms face with different combination of those impediments. The first type of collective intelligence is reflective collective intelligence (Malone, 2006). This dialog based intelligence development is prone to fail in cases of emergence of all the obstacles mentioned above. Structural collective intelligence is relatively more systematic but it still encounters the perception differences and the vagueness of the language. Evolving collective intelligence is learning based, vastly used in academia and less prone to be tangled in obstacles. Informational flow collective intelligence suffers less from the limit of human capacity since the information channels store the data. Noetic collective intelligence assumes that unvisited parts of human brain can be visited via group thinking. Flow collective intelligence removes the power plays and claims that when individual boundaries are removed, a group can act as an individual. Statistical collective intelligence is crowd based and declares that in presence of a clearly defined goal or direction, the vast of the group will find the way. Relevational collective intelligence uses knowledge that creates solutions out of the blue. These eight forms can intersect (Malone, 2006) or be totally exclusive according to the problem dynamics. In our project, reflective collective intelligence will be used during the workshops and interviews. The intelligent assistant structure will also determine what other forms of collective intelligence we will require.

Three important properties of collective intelligence are known as 'stigmergy', 'self-organization' and 'lack of intelligence' (Heylighen, 1999). Stigmergy is a cast of indirect communication between the individuals in a group. The feedback and the communication between the group is provided by a trace spread by the individuals (Izquierdo-Torres, 2004). The trace can be static or dynamic as in the case of termite mounding and the ball in a football game (Heylighen, 1999). Self-organization denotes the eagerness in individuals for cooperating in a synergic manner (Izquierdo-Torres, 2004). Finally, lack of intelligence emphasizes on the difference between the 'global good' and the 'individual good'. When a global good score is obtained, all individuals in group may think that they are adapting good. Yet the group may contain some relatively 'bad' individuals whose impacts on the global score are compensated by the good individuals (Heylighen, 1999). Collective intelligence here should work on whether to choose between the global good, the individual good and the determined proportional mixture of both (Boschetti and Brede, 2008).

There have been several attempts to classify the techniques of Collective Intelligence starting with the efforts in the field of artificial intelligence (Rajaram, 1990). The most recent research is run by MIT Center for Collective Intelligence as part of the Handbook for Collective Intelligence project (Url-3, 2009). Early studies were mainly run by automation or robotics experts (Hassan et al., 2005; Rajaram, 1990; Sigel et al., 2002; Yoshida et al., 2000). As the supply chains and customer services gained importance, collective intelligence methods were used in decision making process and social sciences (Huang et al., 2007; Mouli et al., 2006; Wang et al., 2006). These methods have recently been used in data mining applications (Cui et al., 2005; Rasmussen et al., 2007) web based collaboration practices (Kittur et al., 2009). Hence, the taxonomic review of Collective Intelligence studies remains quite insufficient.

Current Collective Intelligence applications provide a wide-ranging focus for researchers. Yet, the novelty in Intelligence literature lies in hybrid methods removing literature classification borders (Chen et al., 2008; Marinakis et al., 2009; Zhang and Tang, 2009). Expansion of the context and hybridization of the intelligence methods infer to clustering of the literature rather than classification. In this part, over 100 Collective Intelligence studies (articles and papers) are clustered in order to fins literature gaps and intensifications using a range of methods in order to be able to compare the methods as well. The methods used are Fuzzy K-Means, Self Organizing Maps (SOM) and PSO Clustering. The clusters are validated using 6 cluster validity indices from literature.

Research in this field is globally shared by published articles and international conference presentations; both are investigated. For this study, a total of 135 articles and papers from various resources and databases are analyzed. It is observed that majority of the methods are composed of Particle Swarm Optimization and Ant Colony Optimization. Ant Colony Optimization is mostly applied to solve problems with Supply Chain Management and Project management. Most of the authors claim that simulation is also a necessary method to validate the optimum solutions found by Collective Intelligence methods. Finance and robotics problems are mostly solved using Particle Swarm Optimization. Additionally, proposal of new methods are applied to benchmark problems from other historical studies.

All difference based clustering techniques utilize Euclidean Distance metric is used which is given in Equation (2.1). Let X_i and X_j be two vectors in the space R^n and x_{mn} denote the n^{th} column of the m^{th} vector. The Euclidean distance between these two vectors is calculated as

$$d_{ij} = \left[(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \cdots + (x_{in} - x_{jn})^2\right]^{1/2} \qquad \textbf{(2.1)}$$

2.4.1 Fuzzy k-means clustering

In Crisp K-means method, any data point is either a total member of cluster or not. Contrarily, Fuzzy K-Means claims that data points have memberships to all clusters and one data point may not totally belong to a cluster. The method calculates memberships of data points in clusters. The algorithm is given below (Bezdek, 1981):

Step 1. The number of clusters, k, is defined. The parameter m' is defined. m' is known as the weighting parameter, has a range of (1,∞) and is a measure of fuzziness of the process. The partition matrix ($\widetilde{U}$) which shows the memberships of data points to clusters is initialized randomly.

Step 2. Cluster centers v_i^r are calculated using the formula below:

$$v_i^r = \frac{\sum_{c=1}^{n} {\mu_{ic}}^{m'} \cdot x_{cj}}{\sum_{c=1}^{n} {\mu_{ic}}^{m'}} \tag{2.2}$$

where i denotes the cluster, r denotes the iteration number, μ_{ic} denotes the membership of c^{th} data points i^{th} cluster and x_{cj} denotes the value of c^{th} data point at the j^{th} dimension.

Step 3. The partition matrix is updated for the r^{th} step.

$${\mu_{ic}}^{(r+1)} = \left[\sum_{j=1}^{k} \left(\frac{d_{ic}^{(r)}}{d_{jc}^{(r)}} \right)^{\frac{2}{M-1'}} \right]^{-1} \tag{2.3}$$

where d denotes the distance between the cluster center and the data point.

Step 4. Step 2-3 are repeated until values of memberships of elements converge to the clusters.

2.4.2 SOMs

Self Organizing Maps, also known as Kohonen Networks, use Neural Networks for clustering. It also provides a rather lower dimensional projection actual data while preserving the original topology. The two dimensional projection of the data make clustering easier. Self Organizing Maps also needs the number of coordinates, therefore the number of clusters a priori. The algorithm of Kohonen's Self Organizing Maps is given below (Su et al., 2002).

Step 1. The weights of the neurons (the weight vectors- $\underline{w_j}$) are initialized randomly.

Step 2. The winning neuron is found, having the below property (2.4).

$$j^* = \arg\min \left\| \underline{x(k)} - \underline{w_j} \right\| \tag{2.4}$$

where k= 1, 2,…, mxn, $\underline{x(k)}$ is the input vector and mxn is the total number of neurons which means the winning neuron is the neuron that has the vector whose Euclidean Distance of difference with the weight vector, makes the minimum angle between the x axis.

Step 3. The weights of the winning neuron and its neighborhood are adjusted with the below formula (2.5)

$$\underline{w_j}(k+1) = \underline{w_j}(k) + \eta(k)N_{j*}(k)\left(\underline{x}(k) - \underline{w}_j(k)\right) \quad \textbf{(2.5)}$$

where $\eta(k)$ is the learning rate at the k^{th} iteration, $N_{j*}(k)$ is the topological neighborhood of the winning neuron at k^{th} iteration. It can be observed that the algorithm is dependent on $\eta(k)$ (learning rate) and $N_{j*}(k)$ (neighborhood of the winning neuron).

Step 4. Steps 2-3 are repeated until the elements in clusters remain still.

Once the clusters are obtained, the results are to be tested in order to check the validity and robustness of the method.

2.4.3 PSO clustering

As a metaheuristic, PSO can be used for clustering as well as optimization. As aforementioned clustering methods, it also used a predetermined cluster number. In this algorithm, each particle represents k cluster centers, given k as the predetermined cluster number. The steps of the algorithm are provided below (Cui et al., 2005):

Step 1. Each particle is initiated representing k cluster centers, where x_{ijm} is the cluster center of the m^{th} dimension of the j^{th} cluster in i^{th} particle. It is essential that the cluster centers are uniformly assigned in the range of [0,1] since the elements are binary.

Step 2. The objective function of each particle is calculated. For this case, the objective function is determined as maximizing intercluster distances and minimizing intercluster distances, hence maximizing intercluster distances minus intercluster distances.

Step 3. The particle bests and swarm bests are determined or updated.

Step 4. The particle velocities are updated according to the formula (2.6).

$$v_{ijm} \leftarrow wv_{ijm} + c_1 r_1 \left(\frac{x_{ijm}^{pb} - x_{ijm}}{\Delta t} \right) + c_2 r_2 \left(\frac{x_{ijm}^{sb} - x_{ijm}}{\Delta t} \right) \quad i = 1, \dots, n,$$

$$j = 1, \dots, k, m = 1, \dots, k \qquad \textbf{(2.6)}$$

where v_{ijk} is the velocity of the m^{th} dimension of the j^{th} cluster in i^{th} particle, w is the inertia coefficient, c_1 is the cognitive coefficient, c_2 is the social coefficient, r_1 and $r_2$are random numbers, x^{pb} is the personal best and x^{sb} is the swarm best.

Step 5. The particle positions are updated according to the formula (2.7)

$$x_{ijm} \leftarrow x_{ijm} + v_{ijm} \qquad \textbf{(2.7)}$$

Step 6. Steps 2-5 are repeated until the elements in the swarm best remains still.

2.4.4 Cluster validity

There is no rigid formula for the optimum number of clusters for a given data set in any clustering method. Besides, robustness of the clusters is to be measured. Additionally, after clustering, a measure for method robustness is required. For both robustness measurement and finding the optimum number of cluster, numerous statistical methods have been developed. In this study, C Index, Dunn’s Validity Index , Davies-Bouldin Index, Goodman/Kruskal Index, Kendall’s Tau Index and Silhouette Index are used and evaluated.

2.4.4.1 The C index

The C Index is defined as in Equation (2.8)

$$C = \frac{d - d_{min}}{d_{max} - d_{min}} \qquad \textbf{(2.8)}$$

where d_{max} is the maximum intracluster distance and d_{min} is the minimum intercluster distance and d is the average intracluster distance. This index only requires minimum intracluster distances, meaning as small clusters as possible. However, it does not require intercluster distances. A smaller value of the C Index indicates a better clustering (Milligan and Cooper, 1985).

2.4.4.2 Davies-Bouldin index

The Davies-Bouldin Index validity index is calculated as in Equation (2.9) (Legany et al., 2006):

$$DB = \frac{1}{n} \cdot \sum_{i=1}^{n} \max_{j=1,\ldots,n;i\neq j} \left(\frac{s_i + s_j}{d_{ij}}\right) \quad \textbf{(2.9)}$$

where s_i is the average distance of i^{th} cluster elements to the cluster center, d_{ij} is the distance of cluster centers for clusters i and j. This index requires clusters as small as and as far as possible from each other, distances within cluster should be small and distances between clusters should be large, a smaller value for Davies-Bouldin Index indicates a better clustering.

2.4.4.3 Dunn's index

The Dunn's validity index is calculated as in Equation (2.10) (Bezdek and Nikhil, 1995):

$$D = \min_{1\leq i\leq n} \left\{ \min_{1\leq j\leq n} \left\{ \frac{d(c_i, c_j)}{\max_{1\leq k\leq n} \{d'(c_k)\}} \right\} \right\} \quad \textbf{(2.10)}$$

where $d(c_i, c_j)$ is the Euclidean distance between cluster i and cluster j which is measured by the distance of the two closest elements of two clusters and $d'(c_k)$ is the intra-cluster distance within cluster k, and n is the number of clusters. Most clustering techniques want to minimize intra-cluster distance and maximize intercluster distance. As a result, the larger the D value is, the better the clustering is. On the way to find the optimum number of clusters, it can be concluded that the number of clusters which yield a largest D value is the optimum number of clusters.

2.4.4.4 Goodman-Kruskal index

Goodman-Kruskal Index is based on distance comparisons of components from clusters (García-Osorio and Fyfe, 2004). Let (p, q, r, s) be four different elements that are clustered and named a quadruple. In clustering, it is essential that the elements within a cluster are close to each other and the elements in different clusters are apart. In that manner, a quadruple is assigned concordant if it satisfies one of the conditions below:

- $d(p,q) > d(r,s)$, p and q are different clusters, and r and s are in the same cluster.
- $d(p,q) < d(r,s)$, p and q are in the same cluster and r and s are in different clusters.

On the other hand, a quadruple is assigned discordant if it satisfies on of the conditions given below:

- $d(p,q) > d(r,s)$, p and q are in the same cluster, and r and s are in different clusters.
- $d(p,q) < d(r,s)$, p and q are in different cluster and r and s are in the same cluster.

All concordance and discordance conditions signify within two couples, the closer ones are allowed to be in the same cluster whereas further ones are to be in different clusters.

The Goodman-Kruskal Index calculates the concordance ratio of all possible quadruples for clustering. It is formulated as in Equation (2.11)

$$GK = \frac{Q_c - Q_D}{Q_C + Q_D} \quad \textbf{(2.11)}$$

where Q_c is the number of concordant quandruples and Q_D is the number of discordant quadruples. According to the formula, in case of many concordant quadruples and few discordant quadruples, the Goodman-Kruskal ratio increases. Hence, a large value of the index indicates a more robust clustering.

2.4.4.5 Kendall's index

Similar to the Goodman-Kruskal index, Kendall's Index also uses the quadruple rules in order to calculate cluster validity. In addition, Kendall's Index involves the fact that not all quadruples necessarily form concordance or discordance. Moreover, the majority of these quadruples may be concordant or discordant, which is also reflected in Equation (2.12)

$$K = \frac{Q_c - Q_D}{N(N-1)/2} \quad \textbf{(2.12)}$$

where N is the number of all elements, Q_c is the number of concordant quandruples and Q_D is the number of discordant quadruples (Campello and Hruschka, 2009). As in Goodman-Kruskal Index, a larger Kendall's Index indicates a more valid clustering.

2.4.4.6 Silhouette index

The Silhouette Index constructs the silhouette width for each element in each cluster, and average silhouette width for each cluster and overall average silhouette width for a total data set (García-Osorio and Fyfe, 2004). The Silhouette Width for each element is calculated as in Equation (2.13)

$$S(i) = \frac{(b(i) - a(i))}{\max\,(a(i), b(i))} \qquad \textbf{(2.13)}$$

where i is the i^{th} element, $a(i)$ is the average distance of the i^{th} element to other elements in the same cluster and $b(i)$ is the average distance of the i^{th} element to other elements in the nearest cluster. This formula gives the average Silhouette Width for each element and from each element, cluster Silhouette Width is to be calculated as the average Silhouette Widths of the elements in the same cluster. Likely, the overall Silhouette Index is the average Silhouette Widths of al clusters.

2.4.5 Focus in collective intelligence research

A total of 135 articles and papers from various resources and databases, are clustered in order to understand literature intensifications. Three research features are defined. The first feature considers the method applied in the paper; the second feature considers the industry in which the problem is implemented and the last feature involves the application field that the method is applied. For clustering the three features of research, articles are classified into categorical data. Papers including agents are classified according to the methods that are coded for agents (generally in first two methods). 10 methods, 12 industries and 11 functions are derived through 135 papers as follows.

i. Methods

1. Mathematical Models (M1): Group mind can be embedded in mathematical models in order to reach for group intelligence.

2. Multi Criteria Decision Making (M2): Group Decision Making methods are also a part of Collective Intelligence. Group thinking can be achieved through Multi Criteria Decision Making.
3. Simulation (M3): Even though simulation is not an intelligence method, parameters found with intelligence methods are in need of testing through simulation. Most papers on Collective Intelligence apply simulation for solution validation.
4. Swarm Intelligence (M4): This method stands for other mathematical methods developed for Collective Intelligence and those that are not commonly used such as Breeding Swarm Optimization.
5. Collective Intelligence (M5): This technique considers categorical methods of Intelligence such as interviews, focus groups or search conferences.
6. Particle Swarm Optimization (M6): The paper uses the basic algorithm or variations of Particle Swarm Optimization.
7. Ant Colony Optimization (M7): The paper uses the basic algorithm or variations of Ant Colony Optimization.
8. Hybrid Collective Intelligence (M8): This technique embeds other methods such as Game Theory, etc… in categorical methods of Intelligence.
9. Hybrid Particle Swarm Optimization (M9): The paper uses Particle Swarm Optimization by embedding parameters of other metaheuristics (eg. Genetic Algorithms, Neural Networks, etc…) in the PSO algorithm
10. Hybrid Ant Colony Optimization (M10): The paper uses Ant Colony Optimization by embedding parameters of other metaheuristics (eg. Genetic Algorithms, Neural Networks, etc…) in the ACO algorithm

ii. Industries

11. Automotive (I1): All aspects of automotive production such as vendor selection, production planning are considered.
12. Banking (I2): Banking issues such as portfolio selection or information authentication crediting are involved.
13. Construction (I3): Applications of construction businesses such as construction termin planning are classified in this group.
14. Energy (I4): Either renewable or fossil energy sources are planned and forecasted.

15. Environment (I5): The industry stands for environmental issues such as rural or urban planning.
16. Media (I6): The industry stands for all transactions of media, such as advertising, broadcasting.
17. Public Services (I7): Planning of public services is made such as hospitalization or firefighting issues.
18. Robotics/Electronics/Mechanics (I8): Applications of robots, electronic devices and their dynamic specifications are classified.
19. Transportation (I9): Planning of movement of goods, services and people are involved.
20. Web-IT (I10): The industry stands for web and information technologies such as Web 2.0.
21. Historical Studies (I11): Studies that obtain their data from former studies, existing libraries or other benchmark problems are classified in this section.
22. Unspecified Industry (I12): Studies that generate their own data randomly or in an imaginative way are classified in this section. Also, studies that do not specify their source of data are included here.

iii. Business Functions:

23. Finance (BF1): Investment strategies such as portfolio selection, cost minimization are involved.
24. Human Resources (BF2): Optimization of personnel numbers and job assignments to the jobs are planned.
25. Knowledge Management/Data Mining (BF3): Providing the necessary and eliminating the redundant information such as analysis of knowledge sharing is analyzed in this section.
26. Manufacturing (BF4): Both the factors that affect manufacturing such as optimization of manufacturing floor layout and the manufacturing itself such as optimization of production lines are aspects of the class.
27. Marketing (BF5): Optimization of all marketing issues such as advertising is classified here.
28. Product Development (BF6): Design of a new product, especially its physical attributes, is involved in this section.
29. Project Management (BF7): Scheduling and planning of the projects such as project crashing, scheduling are involved in this section.

30. Research and Development (BF8): Design of new systems apart from sole products, such as evaluation of new technologies is involved.
31. Risk Management (BF9): Studies on minimizing risk and maximizing return such as eliminating faults in industries are classified.
32. Supply Chain Management/Inventory (BF10): Analysis of logistical movements such as optimization in facility layout or travelling salesman problem is involved in this section.
33. Unspecified Function (BF11): Some studies use data without claiming to which business function they belong. These studies are classified in this section.

In order to calculate similarities of or distances between the papers, the categorical data should be converted into numerical data. This obligation leads to preparation of the identity matrix which is constituted of binary variables. In the identity matrix, each row represents a paper and each column represents a feature. If i^{th} paper has the j^{th} feature, then the cell in the i^{th} row and j^{th} column in the identity matrix is given the value of 1. Otherwise, the value of 0 is assigned to the related cell. The identity matrix consists of 135 rows and 33 columns. In columns, first 10 belong to the methods, second 12 belong to the industry and the last 11 belong to the application. In that way, for clustering, 135 elements with 33 features are constructed. Each row of the identity matrix has at least 3 values of 1 since each paper has its method, industry and function even if the last two are not specified.

The number of 1's in a row is not limited since a paper can use more than one method or can validate its method using various data from different industries or functions. For example, let Article X be a paper that uses both Particle Swarm Optimization and Ant Colony Optimization in order to compare these methods. Furthermore, assume that Article X tests the results through simulation. For this, Article X may use benchmark problems from historical studies for validation and then apply the validated technique on a problem in automotive industry that concerns facility layout of the manufacturing floor. Facility layout of the manufacturing floor concerns 3 business functions since it is directly applied to manufacturing, it involves the movement of inventory and it wants to minimize the cost. In this case, Article X has three methods: Particle Swarm Optimization, Ant Colony Optimization and Simulation. Likely, Article X has two industries, historical studies and automotive, and three business functions, inventory, finance and manufacturing. In the identity matrix, the value 1 should appear a total of eight times (3 methods, 2 industries and 3 functions).

As a summary, it can be concluded that if there are applications represented in multiple fields (eg. Layout) they are represented by 1 in each function touched. (eg. Manufacturing, Supply Chain) If specific algorithm is driven by combining any Collective Intelligence method with other intelligence method(s), it is classified as Hybrid Intelligence method. If two different Collective Intelligence methods are applied in research, they are both represented in features for that article. Articles that study other researches with historical and driven data are shown with representation both in Historical Studies and Theoretical Studies. The table for specifications of 135 studies are given in the Appendix C (Abdallah and Emara, 2009; Afshar et al., 2009; Aghaie and Mokhtari, 2009; Alatas and Akin, 2009; Alba et al., 2008; Albritton and McMullen, 2007; Ali and Kaelo, 2008; Alici et al., 2006; Almeder, 2009; Araujo, 2010; Arora et al., 2010; Assareh et al., 2010; Bin et al., 2009; Bontoux and Feillet, 2008; Boonyaritdachochai et al., 2010; Boschetti and Brede, 2008; M. Brede et al., 2007; M. F. Brede and Boschetti, 2007; Cai et al., 2007; Calderon et al., 2006; Camci, 2008; Chan and Swarnkar, 2006; Chang et al., 2009; Chaturvedi et al., 2009; Che and Wang, 2010; Chebouba et al., 2009; A. L. Chen et al., 2008; D. Chen and Zhao., 2009; W. Chen et al., 2010; W. Chen et al., 2006; Christmas et al., 2010; Christodolou, 2009; Coelho, 2009; Cornu, 2005; X. Cui et al., 2005; Z. Cui et al., 2008; Cura, 2009; Deng and Lin, 2011; Duan and Liao, 2010; Dye and Hsieh, 2010; Falco et al., 2007; Fuellerer et al., 2010; Gajpal and P., 2009; Gao et al., 2006; Geem, 2009; Gunes et al., 2008; Q. J. Guo et al., 2006; Guo et al., 2007; Y. W. Guo et al., 2006; Haibing et al., 2006; Han et al., 2009; Hani et al., 2007; Hassan et al., 2005; He and Wang, 2007; X. L. Huang et al., 2007; Iwasaki et al., 2006; Jia and Yang, 2007; Y. Jiang et al., 2007; Y. Jiang, Liu, C., Huang, C. ,Wu, X., 2010; Jursa, 2007; Kang et al., 2008; Kittur et al., 2009; Koshino et al., 2006; Kuan and Wong, 2010; R. J. Kuo et al., 2011; R. J. Kuo and Shih, 2007; R. J. Kuo et al., 2005a; R. J. Kuo and Yang, 2011; Lam et al., 2007; H. S. Lee et al., 2010; S. G. Li and Rong, 2009; X. Li et al., 2010; R. Liang et al., 2008; Y. C. Liang and Smith, 2004; Liao et al., 2005; W. B. Liu and Wang, 2008; Y. Liu et al., 2007; Lopez et al., 2009; Y. Marinakis and Marinaki, 2008; Y. Marinakis and Marinaki, 2010; Y. Marinakis et al., 2008;

Meneses et al., 2009; Mohammed et al., 2007; Moisa and Ngulube, 2005; Montalvo et al., 2006; Mouli et al., 2006; Muhammad-Moradi et al., 2009; Niknam and Firouzi, 2009; Obermair et al., 2006; Olofsson, 2006; Onut et al., 2007; Rameshkumar et al., 2005; Rasmussen et al., 2007; Rezazadeh et al., 2009; Rodriguez and Reggia, 2004; Salman et al., 2002; Samanta and Nataraj, 2009; Seckiner and Kurt, 2008; D. Y. Sha and Hsu, 2008; Sharma et al., 2011; L. Sheremetov and Rocha-Mier, 2004; L. Sheremetov et al., 2005; Shi and Eberhart, 1998; Siahkali and Vakilian, 2009; Sigel et al., 2002; Silva et al., 2008; Silva et al., 2009; Sousa et al., 2004; Sun, 2009; Tasgetiren and Liang, 2003; Toksari, 2007; Tripathi et al., 2007; C. Y. Tsai and Yeh, 2008; Tuyls et al., 2005; Ugur and Aydin, 2009; VenayagamoorthyGrant et al., 2007; VenayagamoorthySmith et al., 2007; H. S. Wang et al., 2010; J. Wang and Wang, 2008; W. Wang et al., 2006; Watcharasitthiwat and Wardkein, 2009; C. H. Wu et al., 2008; F. Xu et al., 2007; I. T. Yang, 2006a, 2006b; J. Yang et al., 2008; P. Y. Yin and Wang, 2006; Yoshida et al., 2000; Yuan and Wang, 2005; Zeng et al., 2007; D. Zhang et al., 2007; J. R. Zhang et al., 2007; X. Zhang and Tang, 2009; F. Q. Zhao et al., 2006; Ziari, 2010).

Once the identity matrix is prepared, execution of the mathematical clustering methods can be started. Totally, 15 variations of 2 different clustering techniques aforementioned in the Clustering Literature are applied. These variations are listed in Table 2.1.

The applications are achieved with Microsoft Excel and Matlab 7.0. The results of the execution involve the cluster numbers (if they are not previously defined), cluster sizes and the list of papers that are assigned to each cluster. The identity matrix is fed into each subprogram to receive the clustering results for a default number of iterations defined per method (eg.60 fuzzy k-means, 100000 for SOM). Having the cluster genes, cluster characters should be defined. To define the cluster character, the following is proposed:

a) The feature that exists %75 or more in a cluster is defined as cluster specific character (dominant character).

b) The feature that exists 51-74.99% in a cluster can be discussed to be a cluster character (recessive character).

c) The feature that exists less than 50% in a cluster is not at all a cluster character.

Table 2.1: Methods and variations.

Method	No of Clusters	Application
SOM	10	1x10 Mapping
		2x5 Mapping
		5x2 Mapping
		10x1 Mapping
	11	1x11 Mapping
		11x1 Mapping
	12	1x12 Mapping
		2x6 Mapping
		3x4 Mapping
		4x3 Mapping
		4x3 Mapping
		6x2 Mapping
		12x1 Mapping
Fuzzy K-Means	10	-
	11	-
	12	-
PSO	10	-
	11	-
	12	-

Knowing the cluster characters, the robustness of the clusters can be checked. It is a fact that a good clustering involves a homogenous distribution within a cluster and a heterogeneous distribution among clusters. After obtaining the clustering results, whenever clusters are not homogeneously defined, the method is executed for further iterations. Execution is finalized when number of articles included in the residual cluster is saturated. Then the robustness of clusters is checked through a mathematical and through defined criteria. The mathematical method refers to Dunn's Index which is explained in the Clustering Literature, measures the robustness and offers an intuition about optimum number of clusters. We also propose several intuitive criteria on checking the robustness of clusters. These criteria are defined below:

a. Total number of misplaced papers: After the cluster characteristics are defined, the organizations of the clusters are checked. A cluster should contain all papers that have all of its characters. For example, if the characters of Cluster A are Particle Swarm Optimization and Product Development, all papers having both of these characters and yet being placed in another cluster is a candidate for missing papers of that cluster. If a candidate paper does not satisfy as much as the number of characters in its own cluster (say, Cluster B), than it satisfies the characters of Cluster A, then this paper is a missing paper of Cluster A. The total number of missing papers is the total of the numbers of each cluster's missing papers.

b. Total number of outliers within clusters: If there exists a paper in a cluster which does not have any of the cluster characteristics, then this paper is an outlier for the cluster. The total number of outliers in clusters is the sum of all the number of outliers in each cluster.

c. The number of clusters with no specific character: According to the results of the method, some clusters have less than 3 papers. Those clusters cannot have their characters specified, they collect outliers in overall.

d. Number of recessive characters: The number of recessive characters in a clustering is a measure of the heterogeneity of a cluster. The less the number of recessive characters are the better the clustering is.

e. The percentage of clusters with no specific character: The number of clusters with no specific character was defined as a criterion. Yet, for example, 2 clusters have no specific character. The effect of number "2" is different when the method results in "3" clusters or "11" clusters overall. As a result, the percentage is added as another criterion.

f. The percentage of papers with no specific character: Using a variation of any method, assume that 1 cluster is obtained with no specific character and 10 clusters are obtained overall. This reveals that 10% of clusters have no character. Furthermore, assume that this cluster with no specific character has 23 papers in it. This makes 23/135= 17.04% of the elements without a specific character.

These criteria build the statistics of the methods that supports the decision of robustness of the clustering method which aids comparison of the variations of clustering methods.

After clustering with 15 variations, it is observed that the cluster characters occurred at a different frequency rates. Some characters appear with almost every variation, some appear only once or twice whereas some never appear. Frequencies of these characters are evaluated. Additionally, non-existent characters are also depicted in order to recognize the gap in the research.

2.4.6 Clustering results

2.4.6.1 Kohonen's SOM

4 variations for *k*=10 (1x10, 2x5, 5x2, 10x1) exist for SOMs. Learning parameter $\eta(k)$ is started from 0.90 and exponentially decreased to 0.1 through iterations. The sigma for Gaussian neighborhood is started from 20% and exponentially decreased from 1% through iterations. The papers in the clusters and cluster characters are given in Table D.1, Table D.2, Table D.3, Table D.4 of Appendix D and overall method statistics are provided in Table 2.3.

2 variations for *k*=11 (1x11, 11x1) exist for SOMs. Learning parameter $\eta(k)$ is started from 0.95 and exponentially decreased to 0.12 through iterations. The sigma for Gaussian neighborhood is started from 12% and exponentially decreased from 1% through iterations. The papers in the clusters and cluster characters are given in Table D.5, Table D.6 in Appendix D and method Statistics are provided in Table 2.5.

6 variations for *k*=12 (1x12, 2x6, 3x4, 4x3, 6x2, 12x1) exist for SOM. Learning parameter $\eta(k)$ is started from 0.90 and exponentially decreased to 0.1 through iterations. The sigma for Gaussian neighborhood is started from 12% and exponentially decreased from 1% through iterations. The papers in the clusters and cluster characters are given in Table D.7, Table D.8, Table D.9, Table D.10, Table D.11, Table D.12 in Appendix D, and method Statistics are provided in Table 2.3.

2.4.6.2 Fuzzy K-Means clustering

In the Fuzzy K-Means case, 33 dimensional cluster center is formed and fuzzy cluster membership values between [0, 1] are assigned randomly. The best results are obtained when m' = 1.01.

The papers in the clusters and cluster characters for the case where $k = 10$ are given in Table D.13 in Appendix D and method Statistics are provided in Table 2.3. The papers in the clusters and cluster characters for the case where $k = 11$ are given in Table D.14 in Appendix D and method Statistics are provided in Table 2.5. The papers in the clusters and cluster characters for the case where k = 12 are given in Table D.15 in Appendix D and method Statistics are provided in Table 2.3.

2.4.6.3 PSO clustering

The best values are obtained when the number of particles is 50, the inertia rate is 1, the cognitive coefficient is 2.5 and the social coefficient is 1.5. The results of the case where k = 10 as presented both in Table D.16 in Appendix D and Table 2.3.The papers in the clusters and cluster characters are given in Appendix C.16 and method Statistics are provided in Table 2.3. The results of the case where k = 11 as presented both in Table D.17 in Appendix D and Table 2.4.The papers in the clusters and cluster characters are given in Table D.17 and method Statistics are provided in Table 2.4. The papers in the clusters and cluster characters for the case k = 12 are given in Table D.18 in Appendix D and method Statistics are provided in Table 2.5.

2.4.7 Results and discussions

Literature review demonstrated the most common topics examined in Collective Intelligence research to be Project Management, Supply Chain Management, Finance, Robotics/Electronics/Mechanics and Product Development (Table 2.4). These topics can be considered as literature intensification points. Topics such as energy or environment are newly examined issues and other topics such as public services are barely touched by authors. Another outcome is that hybrid methods appear as a developing area which has not been yet well-exploited.

Nonexistent cluster characters denote the barely touched fields (literature gaps) of Collective Intelligence which is given below.

Non-existent characters are

- Swarm Intelligence
- Mathematical Modeling
- Multi Criteria Decision Making
- Automotive
- Construction
- Media
- Transportation
- Human Resources

- Knowledge Management/Data Mining
- Marketing
- Research and Development

To evaluate methods, 18 combinations of 3 methods are reviewed. Additionally, 6 cluster validity indices from literature are calculated for each variation. 6 other indices are proposed. The results are provided in Table 2.5.

10 out of 18 combinations, Dunn's Index have led to the same value due to using maximum and minimum distances instead of average values. Yet, proposed criteria have drastically different values for the same Dunn's Index.

Applying a multivariate correlation analysis, it is not proven that, in the 5% significance level, Dunn's Index and the proposed criteria are correlated.

Same multivariate correlation analysis applied to Davies-Bouldin Index, it is proven that the first two of the proposed criteria (number of missing papers and outliers in clusters) are correlated with the Davies-Bouldin Index values. Yet, the correlations with both criteria are not very strong. The correlation coefficient with the number of missing papers is 0.58 and with outliers in the clusters is 0.52.

According to Dunn's Index and Davies-Bouldin Index, the best method for clustering is Fuzzy K Means (Table 2.6). On the other hand, two indices conflict on the optimum cluster size. According to Dunn's Index, 10 is the optimum cluster size whereas according to Davies-Bouldin Index, the optimum cluster size is 12.

It is also observed that as cluster sizes become equal, method disappears as the cluster character. Instead, industry or business function appears to be the cluster character. As the cluster size gets larger(i.e. involving more than 30 papers), commonly used methods (i.e. Particle Swarm Optimization, Ant Colony Optimization) or business functions that methods are commonly applied (i.e. Supply Chain Management) appear as the cluster character. As the cluster size gets smaller (i.e. involving less than 7-8 papers), more specific (rather less commonly used) details of the papers arise as the cluster character. Additionally, some articles have characters that belong to more than one cluster. In this case, the distance to the cluster determines the membership to the clusters or in general case, the number of

Table 2.2: Literature intensifications of Collective Intelligence.

Character	Dominant	Recessive	Total
Particle Swarm Optimization	54	12	66
Ant Colony Optimization	46	4	50
Unspecified Industry	36	8	44
Project Management	25	14	39
Historical Studies	15	22	37
Supply Chain Management / Inventory	19	7	26
Hybrid Particle Swarm Optimization	11	12	23
Product Development	13	6	19
Robotics/Electronics/Mechanics	11	5	16
Finance	11	5	16
Banking	11	2	13
Unspecified Business Function	3	8	11
Simulation	2	4	6
Energy	1	5	6
Collective Intelligence	2	3	5
Hybrid Ant Colony Optimization	1	3	4
Environment	2	0	2
Web-IT	1	1	2
Risk Management	1	1	2
Hybrid Collective Intelligence	1	0	1
Public Services	0	1	1
Manufacturing	0	1	1
Mathematical Models	0	0	0
Multi Criteria Decision Making	0	0	0
Swarm Intelligence	0	0	0
Automotive	0	0	0
Construction	0	0	0
Media	0	0	0
Transportation	0	0	0
Human Resources	0	0	0
Knowledge Management / Data Mining	0	0	0
Marketing	0	0	0
Research and Development	0	0	0

Table 2.3: The results of Collective Intelligence clustering.

Method	CI	DBI	DI	GKI	KTI	SI	1	2	3	4	5
Fuzzy 10	0.359	1.896	0.353	0.7110	0.4764	0.9119	14	3	0	4	0
Fuzzy 11	0.386	1.875	0.333	0.7596	0.4764	0.8721	19	12	1	8	9.09
Fuzzy 12	0.434	1.713	0.333	0.8444	0.4954	0.8725	8	1	0	12	0
SOM 1x10	0.404	2.495	0.333	0.5215	0.4955	0.6000	49	8	0	13	0
SOM 2x5	0.379	1.976	0.316	0.7584	0.5445	0.8854	2	6	0	6	0
SOM 5x2	0.352	2.242	0.316	0.7240	0.4704	0.8948	7	7	0	7	0
SOM 10x1	0.376	2.216	0.316	0.7212	0.4780	0.8812	43	6	0	8	0
SOM 1x11	0.427	1.922	0.316	0.8032	0.5189	0.8486	3	1	0	8	0
SOM 11x1	0.389	2.337	0.316	0.7551	0.4964	0.8491	6	12	1	3	9.09
SOM 1x12	0.409	1.982	0.316	0.8214	0.4814	0.8636	1	2	0	3	0
SOM 2x6	0.403	1.918	0.316	0.7871	0.4882	0.8505	11	2	0	4	0
SOM 3x4	0.430	2.209	0.333	0.7835	0.4714	0.8265	19	10	1	8	8.33
PSO 10	0.341	2.020	0.316	0.5030	0.4438	0.7864	43	8	0	4	0
PSO 11	0.404	2.095	0.333	0.6153	0.4862	0.7042	48	4	0	7	0
PSO 12	0.346	1.898	0.333	0.6535	0.4745	0.7923	33	5	0	7	0

common characters is a factor that affects membership. If a paper has 2 common characters with one cluster and 3 with another, the paper is not necessarily but more likely to be involved in the second cluster in order to minimize the distance to the cluster center.

Table 2.4: Correlation among indices.

Index	CI	DBI	DI	GKI	KTI	SI	1	2	3	4	5	6
CI	1.0000	-0.0659	0.0164	0.5389	0.2264	-0.0791	-0.3073	-0.2226	0.1454	0.3662	0.1324	0.0643
DBI	-0.0659	1.0000	-0.1439	-0.4470	0.0050	-0.5145	0.3779	0.5370	0.2346	0.1355	0.2296	0.1390
DI	0.0164	-0.1439	1.0000	-0.1570	-0.0532	-0.1903	0.2055	-0.0416	0.1113	0.2846	0.1044	0.1066
GKI	0.5389	-0.4470	-0.1570	1.0000	0.1874	0.7358	-0.8398	-0.2624	0.1707	-0.1092	0.1682	0.1515
KTI	0.2264	0.0050	-0.0532	0.1874	1.0000	-0.0383	-0.2516	-0.2479	0.0017	0.1722	0.0071	0.0118
SI	-0.0791	-0.5145	-0.1903	0.7358	-0.0383	1.0000	-0.7131	-0.1274	0.0837	-0.4342	0.0875	0.1096
1	-0.3073	0.3779	0.2055	-0.8398	-0.2516	-0.7131	1.0000	0.2021	-0.0999	0.3018	-0.1032	-0.0958
2	-0.2226	0.5370	-0.0416	-0.2624	-0.2479	-0.1274	0.2021	1.0000	0.7421	-0.0157	0.7466	0.7402
3	0.1454	0.2346	0.1113	0.1707	0.0017	0.0837	-0.0999	0.7421	1.0000	-0.0754	0.9990	0.9582
4	0.3662	0.1355	0.2846	-0.1092	0.1722	-0.4342	0.3018	-0.0157	-0.0754	1.0000	-0.0834	-0.0724
5	0.1324	0.2296	0.1044	0.1682	0.0071	0.0875	-0.1032	0.7466	0.9990	-0.0834	1.0000	0.9683
CI	1.0000	-0.0659	0.0164	0.5389	0.2264	-0.0791	-0.3073	-0.2226	0.1454	0.3662	0.1324	1.000

3. SYNERGY MODELING AND INDEX

This section involves modeling of synergy in collaborations. First, the criteria that affect synergy are depicted by literature survey. Since the number of criteria has been too many for the model, which would lead to a computational complexity, the criteria are prioritized and eliminated using Fuzzy Cognitive Maps (FCMs).

In order to be able to optimize the collaboration, these criteria have to be quantified. This quantification is achieved in two stages: The values for the criteria of each SME are obtained by the questionnaires in linguistic variables. These variables are processed and defuzzified. The second part is achieved through an analogical approach among biological synergetic systems, collaborations and reliability theory. This approach is modeled in a way to provide synergy coefficients and synergy indices.

The first part of this section introduces factors that affect synergy in alliances. The second part introduces FCMs and the third part explains the application of FCMs for the synergy criteria. In the fourth part, the linguistic variables and the fuzzy questionnaire is explained. In the fifth part, the analogy of synergy, collaboration and reliability theory is explained and synergy coefficient and index is introduced.

3.1 Factors that Affect Synergy

3.1.1 Organizational and tangible Factors

3.1.1.1 Education level of the research team

Hurley (1995) claims that education level of the members of the collaboration team affect the progress in technical innovation in collaborations. A higher degree of education denotes a higher level of synergy. Sveiby and Simmons (2002)also claim that educated people tend to collaborate more than uneducated people.

3.1.1.2 Country

Rai et. al. (1996) discusses that difficulties and misunderstandings are more likely to arise within an organization if collaborators are from different countries because of the cultural differences. On the other hand, not all countries have the same level of conflict among each other. Thus, for an international collaboration status, countries should be classified.

3.1.1.3 Performance culture

Cheung (2006) implies that project performance measure culture has an effect on alliance debates. Combining or integrated two very different performance measure cultures is an issue in alliances, whereas if cultures are similar, it is more manageable to integrate (Olk and Ariño, 2003).

3.1.1.4 Governmental subsidies

Rai et. al. (1996) argues that governmental incentives positively affect alliances. Other political based encouragements such as the EU encouragement are also included in this type of subsidies (Nieto and Santamaria, 2006).

3.1.1.5 Financial condition

Financial condition is revealed as a very important factor in alliances discussed in various number of studies (S. H. Chen et al., 2008; J. F. Ding, 2009; Twardy, 2009){Ramaseshan, 1998 #422} . It can be summarized as "the more the financial power and the better the financial condition of the collaboration is, the synergy is improved".

3.1.1.6 Legal culture and structure

Twardy (2009) states that rules, regulations and legal form of a partner has a 25% importance on the success of the alliance. A more structured legal approach is a barrier to corruption in firms and thus, in alliances.

3.1.1.7 Organizational structure

Twardy (2009) states that the governance model of a company has more than 25% importance on the success of an alliance. The best condition for synergy is to balance the freedom and control in a firm with collaboration (Theodoulides, 2005).

3.1.1.8 The clarity of visions, goals and objectives

Margoluis (2008) states that visions, goals and objectives should be common or at least shared between the partners. This statement is to be analyzed under alliance strategies. Besides, in order to share a vision, a goal or an objective, they must be clear and well-understood by the collaboration team members (Gomes-Cassares, 2003).

3.1.1.9 Type of leadership

The type of leadership stands for the decision making structure of an organization (Margoluis, 2008) It differs from organizational structure since organizational structure indicates the participation in decisions whereas type of leadership indicates the implementation of decisions.

3.1.1.10 Past cooperation experience

According to Chen et al. (2008) past cooperation experience affects the efficiency of an alliance. Bad experiences lead to unwillingness towards collaboration whereas good experiences yield to eagerness. The property is calculated company by company since it is an organizational and tangible property.

3.1.2 Organizational and intangible criteria

3.1.2.1 Commitment capabilities to alliance

Ramaseshan and Loo (1998) proves that as openness and devotion of companies increase, the efficiency of the alliance increases. It has been found to decrease the turnover rate and increase the lifetime and the accordance of an alliance.

3.1.2.2 Inter-organizational communication

"Inter-organizational communication is defined as formal as well as informal sharing of meaningful information between firms" (Ramaseshan and Loo, 1998). In alliances, it is possible that both human and the machine problems may arise.

3.1.2.3 Values and company culture

Twardy (2009) denotes that companies should deal with each other's culture during alliance building phase. On the other hand, Rai et. al. (Rai et al., 1996) claims that these differences may occur even among the companies within the same country. Company culture also includes the decision making mechanism which is analyzed under the "Organizational Structure" and "Type of leadership" topics". It is also claimed that in alliances different cultures should build a common ground for the sake of alliance (Sutherland et al., 2006).

3.1.2.4 Production and organization flexibility

Margoluis (2008) claims that companies in an alliance should be flexible especially while collaborating towards uncertain outcomes. This flexibility can be in either the variety or production quantity of products (Mlynarek, 2011).

3.1.2.5 Administrative capacity

Administrative capacity is defined as "the capacity of the organization to manage grants, reporting procedures and administrative tasks" (Margoluis, 2008). It is defined by the self-evaluation of the company in the following four areas: Management, Programming, Monitoring, Evaluation.

3.1.2.6 Company's pace

Company's pace denotes whether the company is able to adapt changes in a slow or fast manner (Linder et al., 2004). It is possible to assign benchmark points for this criterion such as industry average, rivals or business partners.

3.1.2.7 Attitude towards alliance

Attitude towards alliance denotes whether the company is willing and ready for alliance (Linder et al., 2004). As the eagerness of the company increases, the probability of synergy increases.

3.1.2.8 Brand / firm reputation

According to Ding (2009), having a good reputation in the target geographical scope is one of the most important criteria in alliances. A good reputation may increase the eagerness to collaborate.

3.1.3 Alliance and tangible factors

3.1.3.1 Scope of the alliance

Eden (2007) discusses that a restricted alliance scope negatively affects the efficiency of the alliance. However, the worse is claimed as conflicting scope ideas among the firms in alliance.

3.1.3.2 The compatibility of visions, goals and objectives

Except for the clarity of visions, goals and objectives, they also have to be compatible within the companies in alliance (Gomes-Cassares, 2003; Margoluis, 2008). Conflicting or irrelevant objectives may decrease the lifetime of alliances as in the scope criterion.

3.1.3.3 Structure of the alliance (clarity of roles)

Margoluis (2008) discusses that for an alliance in order to be effective, individuals and companies should know their tasks in a complete manner. Moreover, in order to avoid further predicaments, roles should be clearly defined in the beginning phase of the alliance.

3.1.3.4 Division of labor

Division of labor refers to the number of decision maker and implementer companies in an alliance (Margoluis, 2008). Boundaries of interference in terms of work should be clearly identified by the alliance, since the labor should be divided justly as stated in the previous criterion.

3.1.3.5 Dysfunctional conflict

Dysfunctional conflict is defined as disputes that cannot be agreed on (Ramaseshan and Loo, 1998). Unlike dysfunctional conflict, functional conflicts are disputes that can be agreed on. Ramaseshan and Loo proves that excessive number of dysfunctional conflicts can negatively affect the efficiency of an alliance.

3.1.3.6 Funding balance

Linder et. al. (2004) and Twardy (2009) state that expectations from the alliance have a big impact of the implementation of alliance. The decision of the funding regime should be clarified before the constitution of the alliance and firms should not be avoiding to contribute.

3.1.3.7 Reward and compensation systems

Rai et. al. (1996) implies that applications in human resources, especially reward and compensation systems, have a big impact on a collaboration's working capacity. Moreover, he argues that difference in such systems may arise even in the same countries.

Different types of compensations may include base pay, commission, overtime pay, bonuses, profit sharing, stock options, ravel / meal / housing and other benefits such as dental, insurance, medical, vacation, leaves, retirement, taxes.

Although being a company property, in an alliance the accordance of these properties determine the strength. Thus, reward and compensation systems will be considered.

3.1.3.8 Organizational resources

Margoluis (2008) states that organizational resources are to be completed for a good collaboration. Organizational resources to be provided are listed as skilled personnel, trade contacts, machinery, efficient procedures and capital (Rose et al., 2010). Although these are provided company by company in an alliance, the completion of these resources depends on the alliance. Thus, this property is an alliance property.

3.1.3.9 Geographical scope

Ding (2009) states that a wider geographical scope indicates a better alliance. Yet, in this study, working with SMEs limit the borders of geographical scope as a target scope.

3.1.3.10 Technological capabilities

Chen et. al. (2008) state that technological capabilities of companies within alliance should be complementary. Yet, they do not provide a list of technological resources to be met. Data gathered from the literature provide various resources for different industries. However, in this study we provide basic elements that are valid to all industries

- Computers

- Communication equipment
- Automated data processing
- Database Management Systems
- Management Information Systems
- Related information, equipment, goods and services

3.1.4 Alliance and intangible factors

3.1.4.1 Communication, coordination and information sharing systems

Communication is defined as the ability to interact and share information in an apparent manner (Margoluis, 2008) and it is one of the alliance efficiency affecting criteria according to Ding (2009).

3.1.4.2 Coordination between sales and marketing

According to Ding (2009), coordination between Sales and Marketing is an important criterion that positively affects the efficiency of alliances and it is best if the two business functions are united in a unit in alliances.

3.1.4.3 Interorganizational trust

Ramaseshan and Loo (1998) proves that interorganizational trust positively affects the alliance. It has also been claimed as one of the most effective criteria for the existence of collaborations (Gardet and Mothe, 2012).

3.2 Fuzzy Cognitive Maps (FCMs)

Cognitive maps are tools used for analysis of inter-element relations within a system. Cognitive maps are composed of variables and relationships within variables (Hasiloglu and Cinar, 2008). Each variable is linked with each other with either a positive relationship which denotes a direct proportion or a negative relationship which denotes an inverse proportion. Cognitive mapping starts with defining the relationships between variables with arrows drawn from the affecting variable to the affected variable. The next step in cognitive map is the construction of the pairwise comparison matrix. Rows and columns of the pairwise comparison matrix are constructed by the variables and uses binary notation. For example, if the i^{th} variable positively affects the j^{th} variable, then i^{th} row and j^{th} column of the matrix is 1. If the relationship is negative, then the ith row and jth column of the matrix is -1 and lastly if there is no relationship, the i^{th} row and j^{th} column of the matrix is 0. Finally, it is assumed that any variable does not affect itself, therefore the diagonal of the pairwise comparison matrix is 0 (Selcuk Burak Hasiloglu, 2009)

There are three properties of variables: indegree, outdegree and centrality. Indegree of a variable is the sum of the related column of the matrix, that is, the sum of variables that affect the related variable. Outdegree of a variable is the sum of related row of the matrix, that is, the sum of variables that are affected by the related variable. Lastly, centrality is the sum of indegree and outdegree. This value is 0 for every variable in the basic cognitive maps which encourages the use of fuzzy cognitive maps.

Fuzzy cognitive maps differ from basic cognitive maps. Unlike basic cognitive maps, fuzzy cognitive maps measure the relation in the interval of [-1, 1] which means the relationships among two variables does not necessarily have to be at the same degree. Therefore, centrality of a variable may not be 0 and centrality becomes a measure of dominance.

The pairwise comparison matrix has two properties: index density and the hierarchy index. The index density (*D*) implies the density of relationships within a system. Whereas, the hierarchy index (*h*) implies the democracy within the variables. If h = 0, then the map is fully democratic and if h = 1, then the map is fully hierarchical (Hasiloglu, 2009; Hasiloglu and Cinar, 2008).

Formulae for all properties for a given pairwise comparison matrix E.

$$E = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{m1} & c_{m2} & \cdots & c_{mn} \end{bmatrix} \quad \textbf{(3.1)}$$

$$od_i = \sum_{i=0}^{N} c_{ij} \quad i = 1,2, \dots., N \quad \textbf{(3.2)}$$

$$id_i = \sum_{i=0}^{N} c_{ji} \quad i = 1,2, \dots., N \quad \textbf{(3.3)}$$

$$c_i = od_i + id_i \quad \textbf{(3.4)}$$

$$D = \frac{C}{N^2} \quad \textbf{(3.5)}$$

$$h = \frac{12\sigma_{od}^2}{N^2 - 1} \quad \textbf{(3.6)}$$

where

od_i: the outdegree of the i^{th} variable

id_i: the indegree of the i^{th} variable

c_i: the centrality of the i^{th} variable

D: the index density of the pairwise comparison matrix

C: the number of connections between variables

N: the number of variables

σ_{od}^2: the variance of the outdegrees

given that $\forall c_{ij} \in [-1,1]$.

3.3 The Prioritization and Elimination of Synergy Factors

3.3.1 FCM for synergy factors

Once the criteria are defined, a fuzzy cognitive map of criteria can be deriven in order to determine weights of these criteria. For building the fuzzy cognitive map, the pairwise comparison of the criteria is made to observe the possibility and degree of relations within them. The fuzzy cognitive matrix is a 33x33 matrix and the degrees of relations are determined by an industry expert. For a criterion given in a row, the industry expert is first asked if the given criterion affects a criterion in the related column. If the row criterion affects the column criterion, then the industry expert is asked to determine the degree of the effect in words of 10 degrees from -5 to +5 where the numbers correspond the phrases given below:

-5: affects strongly in a negative way

-4: affects moderately-strongly in a negative way

-3: affects moderately in a negative way

-2: affects weakly-moderately in a negative way

-1: affects weakly in a negative way

+1: affects weakly in a positive way

+2: affects weakly-moderately in a positive way

+3: affects moderately in a positive way

+4: affects moderately-strongly in a positive way

+5: affects strongly in a positive way

The number 0 presents “no relation at all”, and it is not placed within the scale presented above, since the first question asked to the industry expert determines if the number is 0 will be used or the second question determining the relation degree is to be asked. The scale given above is used for the second question.

The fuzzification of the scale given above is made by normalizing the numbers by dividing each cell of the 32x32 matrix dividing by 5. So the strong positive effect is presented by 1 and the strong positive effect is presented by -1. 3 decision makers have completed the questionnaire: 1 industry expert, 1 academician and 1 strategy consultant. The united fuzzy cognitive matrix obtained is given in Appendix E.

According to the united fuzzy cognitive matrix for synergy, the final centralities and weights of the criteria are given in Table 3.1 and Table 3.2.

Analyzing the groups, it can be seen that organizational and intangible factors affect synergy the most, which is followed by alliance related and intangible factors, alliance related and tangible factors and organizational and tangible factors (Table 3.2)

As in the innovation / risk criteria case, although the aim is to use a minimum number of factors with maximum importance value, finding a strict cutting point is difficult with importance values that close to each other. In this manner, among the 32 criteria, 22 of them with a total importance of slightly less than 80% is selected. As a result, the most important criteria to be asked in the fuzzy questionnaire are structure of alliances, inter-organizational trust and dysfunctional conflict the least important criteria are country, governmental subsidies and geographical scope.

3.4 The Fuzzy Synergy Questionnaire

After the application of FCMs to the synergy criteria and the elimination of the less important 10 criteria, the Fuzzy Synergy Questionnaire is prepared and presented in Appendix F. The remaining criteria and their linguistic variables are determined in order to be able to quantify the synergy data.

Table 3.1: Centralities and weights of synergy criteria.

Criterion	Criterion Name	Centrality (Weight)	Cumulative Weight
F22	Structure of alliances (Clarity of roles)	0,0493	0,0493
F32	Inter-organizational trust	0,0482	0,0975
F24	Dysfunctional conflict	0,0455	0,1430
F14	Values and company culture	0,0433	0,1863
F30	Communication/coordination / information sharing systems	0,0422	0,2285
F12	Commitment capabilities to alliances	0,0404	0,2689
F13	Inter-organizational communication	0,0395	0,3084
F20	Scope of the alliance	0,0390	0,3474
F25	Funding balance	0,0387	0,3861
F18	Attitude towards alliance	0,0380	0,4241
F21	The compatibility of visions, goals and objectives	0,0380	0,4620
F27	Organizational resources	0,0362	0,4982
F7	Organizational structure	0,0333	0,5316
F17	Company’s pace	0,0330	0,5646
F16	Administrative capacity	0,0318	0,5963
F19	Brand / Firm reputation	0,0308	0,6272
F5	Financial condition	0,0294	0,6566
F9	Type of leadership	0,0291	0,6857
F3	Performance culture	0,0277	0,7134
F26	Reward and compensation systems	0,0269	0,7404
F29	Technological capabilities	0,0269	0,7673
F8	The clarity of vision, goals and objectives	0,0264	0,7937
F1	Education level of the research team	0,0239	0,8176
F15	Production flexibility	0,0231	0,8407
F10	Resources for R&D	0,0224	0,8631
F6	Legal culture and structure	0,0218	0,8849
F23	Division of labor	0,0218	0,9066
F11	Past cooperation experience	0,0216	0,9282
F31	Coordination between sales and marketing	0,0194	0,9476
F28	Geographical scope	0,0186	0,9662
F4	Governmental subsidies	0,0179	0,9841
F2	Country	0,0159	1,0000

Table 3.2: Weights of the selected synergy criteria

Criterion	Criterion Name	Weight of Selected Criteria
F22	Structure of alliances (Clarity of roles)	0,0621
F32	Inter-organizational trust	0,0607
F24	Dysfunctional conflict	0,0573
F14	Values and company culture	0,0546
F30	Communication, coordination and information sharing systems	0,0532
F12	Commitment capabilities to alliances	0,0509
F13	Inter-organizational communication	0,0498
F20	Scope of the alliance	0,0491
F25	Funding balance	0,0487
F18	Attitude towards alliance	0,0478
F21	The compatibility of visions, goals and objectives	0,0478
F27	Organizational resources	0,0456
F7	Organizational structure	0,0420
F17	Company's pace	0,0416
F16	Administrative capacity	0,0400
F19	Brand / Firm reputation	0,0389
F5	Financial condition	0,0370
F9	Type of leadership	0,0367
F3	Performance culture	0,0350
F26	Reward and compensation systems	0,0339
F29	Technological capabilities	0,0339
F8	The clarity of vision, goals and objectives	0,0333

Table 3.3: Weights of criteria classes of synergy.

Factors	**Average weight of a factor**
Organizational/Intangible	0.0343
Alliance /Intangible	0.0328
Alliance /Tangible	0.0327
Organizational/ Tangible	0.0240

3.4.1 Structure of alliances (clarity of roles)

This criterion is a tangible alliance criterion which states that the roles of firms in alliances should be clarified by the time of collaboration formation. Being an alliance criterion makes it to be measured in the existence of collaboration since it changes from collaboration to collaboration. In order to be able to measure the criteria, the linguistic variables are presented in scenarios that would reflect the firms' opinion. The main three linguistic levels for the questionnaire are determined as in 14th question of the questionnaire Appendix F. The three main levels are:

- The roles cannot be determined in the beginning of the collaboration, they can be determined as the projects emerge through the collaboration. (Option 1)
- I consider that the roles will be clear enough when the collaboration is unique, we do not necessarily have to draw an example. (Option 2)
- I consider that the roles will be clear enough if we draw from the previous success stories. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix F.

3.4.2 Inter-organizational trust

This criterion is a tangible alliance criterion which states that the more the companies in collaboration trust in each other, the more synergy the alliance has. As in the "clarity of roles" case, this is also an alliance attribute, which means it changes from collaboration to collaboration. In order to be able to measure the criteria, the denoted linguistic variables are presented in scenarios that would reflect the firms' opinion. Since the firms do not know each other, they cannot be asked how much they trust each other. Instead, it can be asked that how much they trust the alliance and how

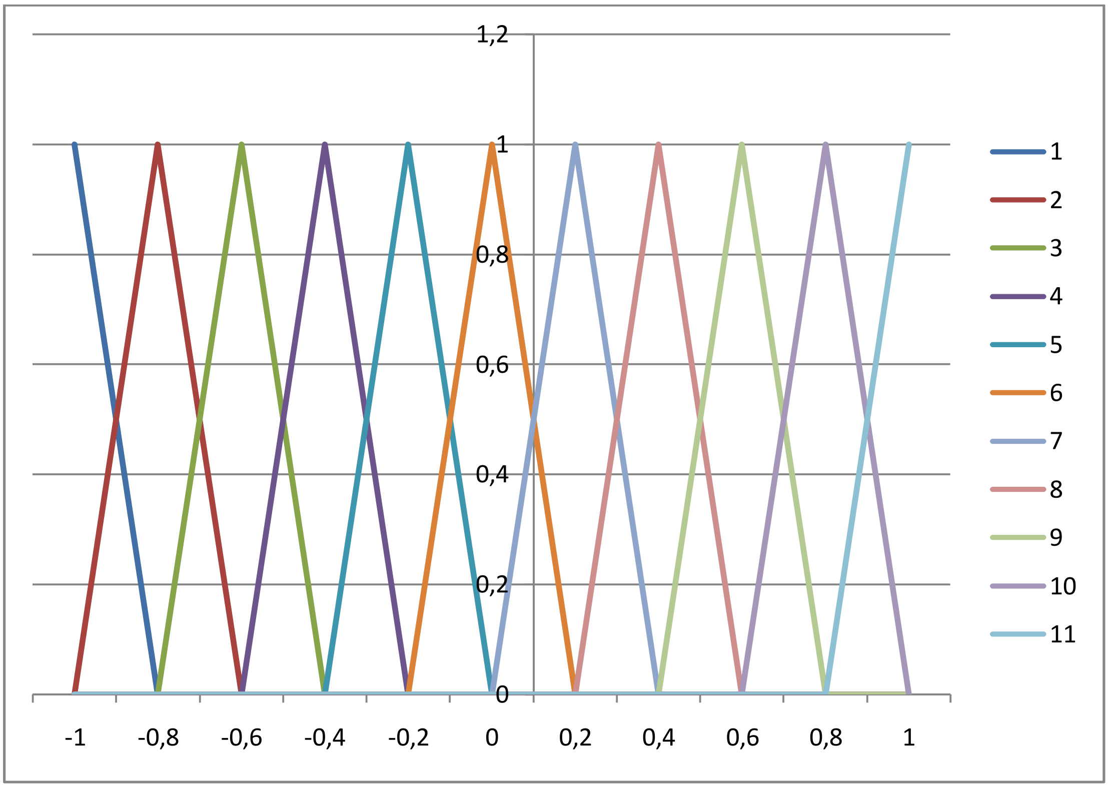

Figure 3.1: Fuzzy numbers for 11-point Likert scale.

much they are willing or open to share as in the 8th question of the questionnaire in Appendix F. The three main levels are:

- We want to participate in collaborations but we do not have the experience (Option 1)
- We can contribute to alliances but our resources are limited. (Option 2)
- We are ready for collaborations that do not interrupt our daily processes (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2 and Line 11 represents Option 3.

3.4.3 Dysfunctional conflict

This criterion is an intangible alliance criterion which states that the more the companies are disable to create a common ground too often, the synergy is negatively affected. As an alliance attribute, in order to be able to measure the criteria, the linguistic variables are presented in scenarios that would reflect the firms' opinion. The main three linguistic levels for the questionnaire are determined as in 10th question of the questionnaire Appendix F. The three main levels are:

- We want to participate in collaborations but we do not have the experience (Option 1)
- Partners should focus on solving their own problems and should not interfere with other companies. (Option 2)
- There should be no conflict if each company achieves what it is responsible for (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2 and Line 11 represents Option 3.

3.4.4 Values and company culture

This criterion is an intangible organizational criterion which states in order to create synergy; the firms should be willing to create a common ground for the sake of the alliance. The firms should be as adaptive to each other as possible. The firm's choice for the criterion is asked in the 11th question of the questionnaire in Appendix F.

The three main levels are:

- We prefer partners that can adapt to our culture. (Option 1)
- Our firm culture is strict but we can provide a flexible working team. (Option 2)
- We are willing to create a common ground, our employees and business are flexible enough (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2 and Line 11 represents Option 3.

3.4.5 Communication, coordination and information sharing systems

This criterion is an intangible alliance criterion which states in order to create synergy, the technical and cultural problems among firms should be reduced as possible. It is also safe to claim that technical problems are easier to be managed than cultural problems. The main three linguistic levels for the questionnaire are determined as in question 15 of Appendix F. The three main levels are:

- It is possible to encounter structural problems due to cultural conflict among partners. (Option 1)
- It is possible to encounter structural problems due to technical problems among partners. (Option 2)
- If all other firms will be able to construct a functional communication, coordination and information sharing system, there will not be any problems on our side. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix F.

3.4.6 Inter-organizational communication

As an intangible and organizational criterion, this is measured using the 3rd question of the questionnaire given in Appendix F. This criterion states that in order to create synergy, the firms should be as open to communication as possible. The three main levels are determined to be:

- Our firm is not open for communicating other firms. (Option 1)
- Our firm is neither open nor closed for communicating other firms. (Option 2)
- Our firm is open for communicating other firms. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with a five-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.2. Line 1 represents Option 1, line 3 represents Option 2, Line 5 represents Option 3 and the other lines represent the options presented in the related question given in Appendix F.

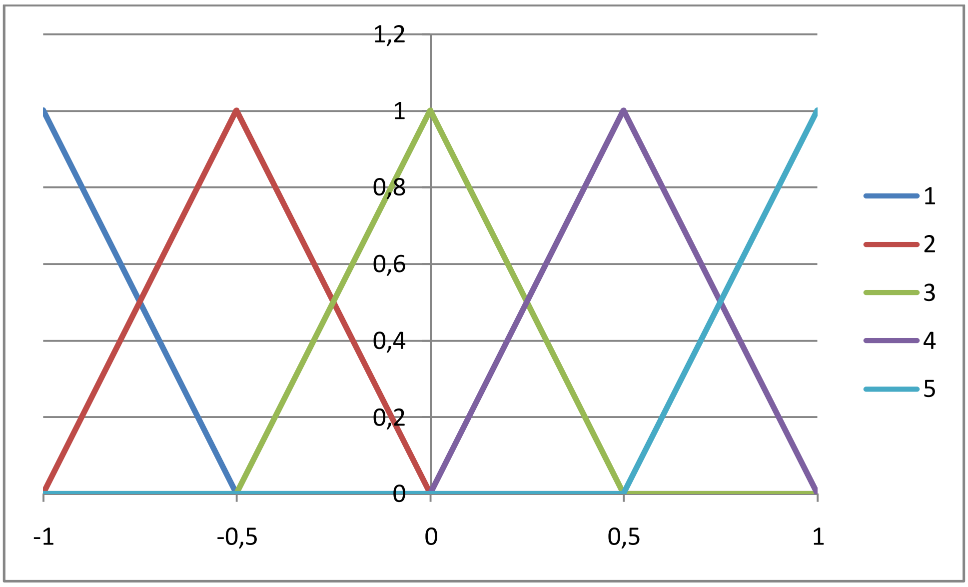

Figure 3.2: Fuzzy numbers for 5-point Likert scale.

3.4.7 Scope of the alliance

This criterion is a tangible and organizational criterion and is measured using the 9th question in the questionnaire which states long-term collaborations tend to contribute to synergy more. The three main levels are:

- Our business is not appropriate for collaborations. (Option 1)
- Our business is more appropriate for short-term collaborations. (Option 2)
- Our business is more appropriate for long-term collaborations. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix F.

3.4.8 Funding balance

This criterion is a tangible alliance criterion which states in order to create synergy, the funding should be balanced among firms and should not be piled on one or some of the firms in the alliance. It is also safe to claim that technical problems are easier to be managed than cultural problems. The main three linguistic levels for the questionnaire are determined as in the 13th question of Appendix F. The three main levels are:

- The allocation of the funding scheme should be made according to the firms' financial condition. The strongest firm should undertake the investments (Option 1)
- Some companies should undertake the long-term investments and other should undertake the short-term investments. (Option 2)
- Each firm should invest in projects related to itself. For common projects, shares should be defined in agreements. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix F.

3.4.9 Attitude towards alliance

As an intangible and organizational criterion, this is measured using the 2nd question of the questionnaire given in Appendix F. This criterion states that in order to create synergy, the firms should be willing to collaborate as much as possible. The three main levels are determined as

- We do not need collaborations. (Option 1)
- We do not want neither participate in nor stay away from collaborations. (Option 2)
- We strongly want to participate in a collaboration.(Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with a five-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.2. Line 1 represents Option 1, line 3 represents Option 2, Line 5 represents Option 3 and the other lines represent the options presented in the related question given in Appendix F.

3.4.10 The compatibility of visions, goals and objectives

This criterion is a tangible, alliance attribute and as other alliance criteria, and the compatibility changes from collaboration to collaboration. In order to measure this criterion, the firms' opinions are asked as an open question. Since this is an innovation collaboration, the firms are asked their objectives and visions in innovation as in the 4th question of the questionnaire in Appendix F.

However, it is needed to quantify the measure these oral and linguistic expressions in order to be able to embed the question in the model. For that, an empiric Text Clustering method is applied. The defining words of visions and objectives are extracted which lead to 31 words as listed below:

- Product
- Service
- Innovation
- Technology
- Development
- Change
- Perfection
- Adaptation
- Growth
- Quality
- Market
- Dealers
- Becoming a brand
- Conscious
- Fun
- Sincerity
- Agents
- Cheap
- Design
- European Union
- Industry
- Sales amount
- Competition
- Speed
- Employee
- Pioneer

- Natural
- Global
- Vision
- Insurance

Using these 31 words as dimensions, the Euclidean Distances of firms to each other are calculated as achieved in the Literature Review of Collective Intelligence section. Then, these lengths are normalized between -1 and 1, -1 being the farthest and 1 being the nearest. Nearer firms are considered as more compatible, whereas farther firms are considered as less compatible. The character matrix is presented in Appendix F.

3.4.11 Organizational resources

This criterion is a tangible, alliance attribute and as other alliance criteria, and the compatibility changes from collaboration to collaboration. It is known that in alliances, resources should be complementary. These resources are listed as:

- Skilled personnel
- Trade contacts
- Machinery
- Efficient procedures
- Capital

In the first part of the 22nd question of the questionnaire in Appendix F, in the first part of the question, the firms are asked at what degree they have had these 5 resources and at the alliance level the fuzzy values for these values are united to observe at what degree the alliance has had these resources. In this question, a seven-point Likert Scale which has the fuzzy numbers as shown in Figure 3.3 is used.

The main linguistic levels for the question are

- We cannot provide any. (Option 1)
- We can provide our share. (Option 2)
- We can provide all for the alliance. (Option 3)

In the figure 3.3., line 1 represents Option 1, line 4 represents Option 2, Line 7 represents Option 3 and the other lines represent the options presented in the

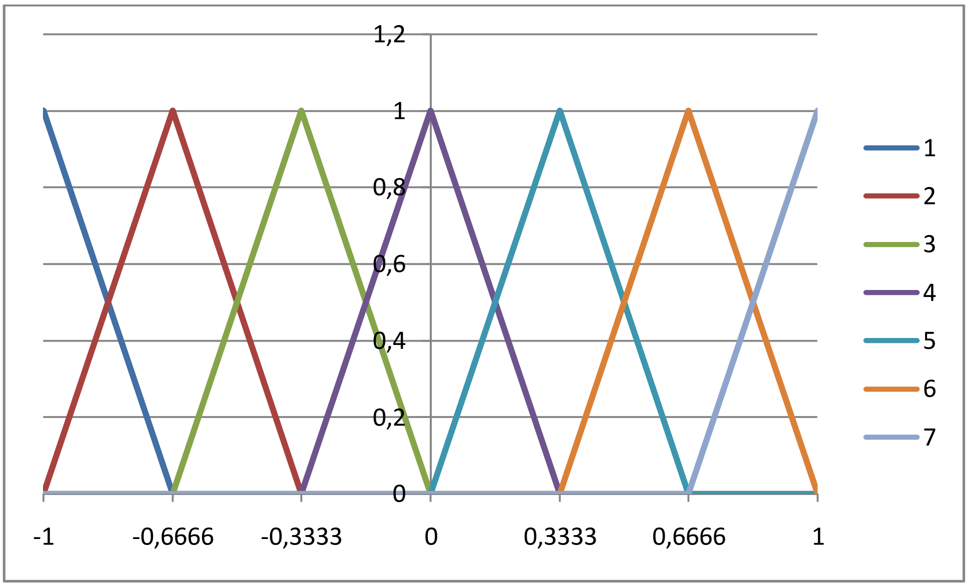

Figure 3.3: Fuzzy numbers for 7-point Likert scale.

related question given in Appendix F.

3.4.12 Organizational structure

This criterion is a tangible and organizational criterion and is measured using the 5th question of the questionnaire in Appendix F. The criterion states that for a better collaboration, the hierarchy and the democracy in the firms. The three main levels are:

- Our structure is totally hierarchical. (Option 1)
- In our structure, democracy and hierarchy is balanced. (Option 2)
- Our structure is totally democratic. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value. Here, the most desired option is not one of the ends but the one in the center. Hence, the fuzzy numbers are given as in Figure 3.4.

3.4.13 Company's pace

This is a tangible, organizational criterion which states that companies should be as agile as possible for a better collaboration. Industry average is selected as a benchmark point for the agility and the 6th question of the questionnaire in Appendix F is asked with an eleven-point type Likert scale with fuzzy numbers as given in Figure 3.4

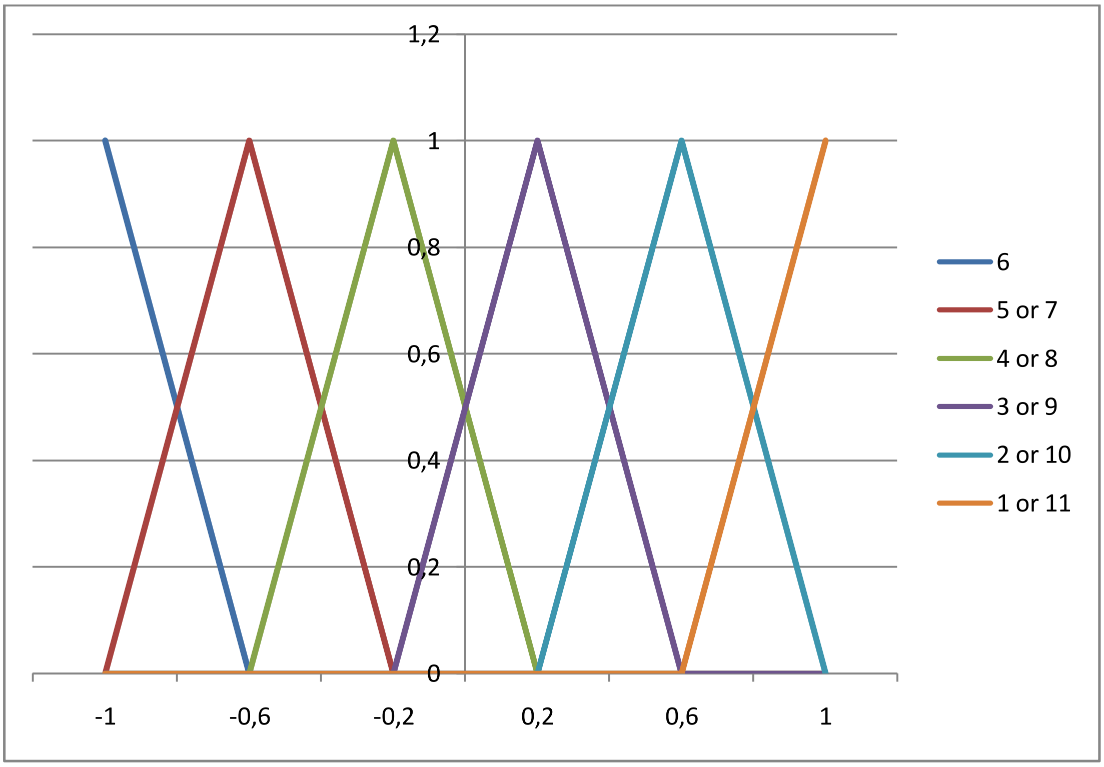

Figure 3.4: Fuzzy numbers for 11-point Likert Scale with the most desired option in the center.

The main linguistic levels are

- We are slower than the industry average. (Option 1)
- We move at an industry average speed. (Option 2)
- We are faster than the industry average. (Option 3)

3.4.14 Administrative capacity

This is an intangible, organizational criterion which states that management of the companies should be effective as possible for a better collaboration. This is measured through the 20th question of the questionnaire in Appendix F. The question measures the effectiveness of administration in three dimensions: company, department and employee. The answers of each dimension are asked with a seven-point Likert Scale with three main levels of:

- I completely disagree that the effectiveness increases. (Option 1)
- I neither agree nor disagree that the effectiveness increases. (Option 2)
- I completely agree that the effectiveness increases. (Option 3)

For the criterion value, the union of three dimensions is calculated.

3.4.15 Brand / firm reputation

This is an intangible, organizational criterion which states that the firm should be known in the market as much as for a better collaboration. This is measured through the 21st question of the questionnaire in Appendix F. The three main levels are:

- Our reputation is limited like all other firms in the industry. (Option 1)
- Our industry does not involve any information about firm reputation. (Option 2)
- We are a well-accepted firm with a good reputation. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1.

3.4.16 Financial condition

This is a tangible, organizational criterion which states that management of a good financial state of companies positively affects the collaboration. This is measured through the 7th question of the questionnaire in Appendix F with four choices of which more than one can be selected. The options are:

- We have gone to public offerings. (Option 1)
- Shareholders finance the company. (Option 2)
- We own more than one firm. (Option 3)
- Other (Choice 4)

The fuzzy number equivalents of the options are presented in Figure 3.5 Since, Option 4 is not selected by any of the SMEs, it is not assigned a fuzzy number.

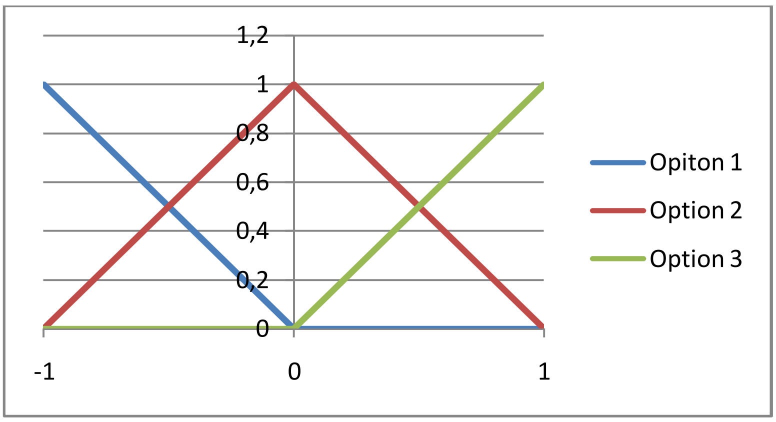

Figure 3.5: Fuzzy numbers for Financial Condition criterion.

3.4.17 Type of leadership

This is a tangible, organizational criterion which states that the decision making structure of a company should let initiatives which is asked in the 19th question of the questionnaire given in Appendix F. The three main levels are:

- Decisions are made and implemented by one person/committee. (Option 1)
- Decisions are made on a common ground but implementation is made by a person / committee. (Option 2)
- All employees are delegated to decide in case of emergencies. (Option 3)

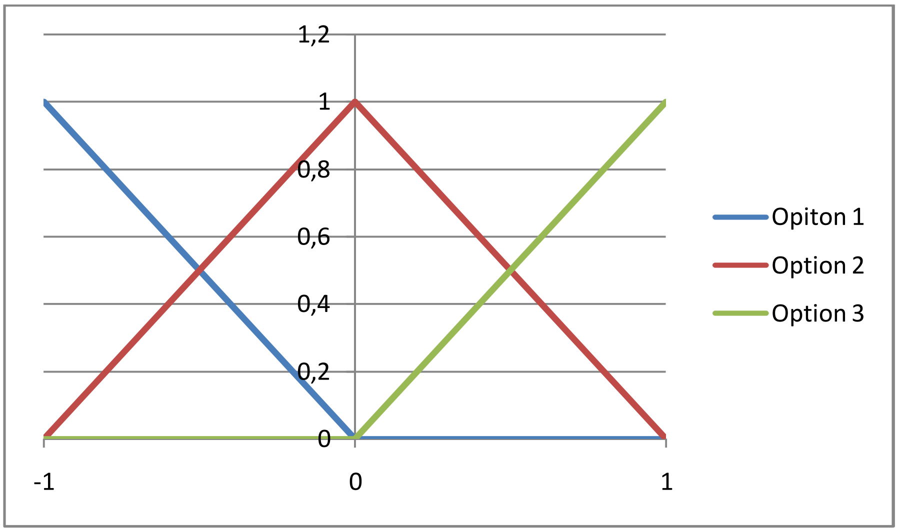

Figure 3.6: Fuzzy numbers for 3-point Likert Scale.

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1.

3.4.18 Performance culture

Performance culture stands for the performance measure system of the firm which is a tangible, organizational criterion. . This is measured through the 16th question of the questionnaire in Appendix F with four choices of which more than one can be selected. The options are:

- We measure outputs such as profit, amount of products, etc... (Option 1)
- We measure effort such as working hours, etc... (Option 2)
- We do not measure performance. (Option 3)
- Other (Choice 4)

The fuzzy number equivalents of the options are presented in Figure 3.6. Since, Option 4 is not selected by any of the SMEs, it is not assigned a fuzzy number.

3.4.19 Reward and compensation systems

Reward and Compensation Systems stand for the performance evaluation system of the firm which is a tangible, organizational criterion. . This is measured through the17th question of the questionnaire in Appendix F with four choices of which more than one can be selected. The options are:

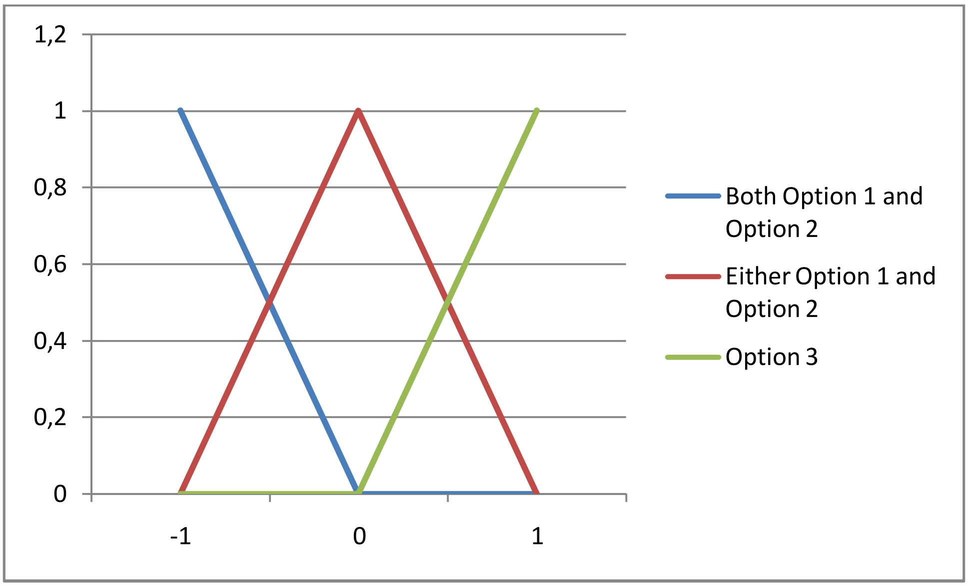

Figure 3.7: Fuzzy numbers for Performance Culture and Reward and Compensation Systems criteria.

- We utilize prize systems (Option 1)
- We utilize compensation systems (Option 2)
- We do not utilize any performance evaluation system. (Option 3)
- Other (Choice 4)

The fuzzy number equivalents of the options are presented in Figure 3.7. Since, Option 4 is not selected by any of the SMEs, it is not assigned a fuzzy number.

3.4.20 Technological capabilities

This criterion is a tangible, alliance attribute and as other alliance criteria, and the compatibility changes from collaboration to collaboration. It is known that in alliances, resources should be complementary. These resources are listed as:

- Computers

- Communication equipment
- Automated data processing
- Database Management Systems
- Management Information Systems
- Related information, equipment, goods and services

In the first part of the 22nd question of the questionnaire in Appendx G, the firms are asked at what degree they have had these 5 resources. In the second part of the same question at what degree the alliance has had these resources is asked . At the alliance level the fuzzy values for these values are united to observe level of these resources using a seven-point Likert Scale which has the fuzzy numbers as shown in Figure 3.3 is used.

The main linguistic levels for the question are

- We cannot provide any. (Option 1)
- We can provide our share. (Option 2)
- We can provide all for the alliance. (Option 3)

In the figure 3.3., line 1 represents Option 1, line 4 represents Option 2, Line 7 represents Option 3 and the other lines represent the options presented in the related question given in Appendx G.

3.4.21 The clarity of visions, goals and objectives

This is an intangible, organizational criterion which states that visions, goals and objectives that should be clearly stated or written and well-accepted by the employees. This is measured through the 18th question of the questionnaire in Appendix F. The question measures the effectiveness of administration in three dimensions given below:

- Written visions, goals and objectives reflect the reality and are well accepted by the employees
- Written visions, goals and objectives are well accepted by most the employees
- Visions, goals and objectives tend to change according to the industry and market conditions.

Here, the first expression is the desired condition having the fuzzy value [1 1 0], and the third expression is the unwanted condition having the fuzzy value [0 -1 -1]. The second expression is between these two-endpoints, having the fuzzy value [-1 0 1]. Hence for taking the union of the dimensions, the third dimension is reversed as explained below:

The answers of each dimension are asked with a seven-point Likert Scale with three main levels for which the fuzzy numbers are given in Figure 3.3:

- I completely disagree that the effectiveness increases. (Option 1)
- I neither agree nor disagree that the effectiveness increases. (Option 2)
- I completely agree that the effectiveness increases. (Option 3)

The value for this criterion by multiplying fuzzy numbers (expression's fuzzy value multiplied by firm's answer to that expression), then the union of all fuzzy numbers are taken.

3.5 The Calculation of the Synergy Coefficient

3.5.1 Conversion of organizational values to alliance values

The two main groups of the 22 selected criteria given above is either organizational criteria or alliance criteria. From this distinction, an alliance synergy score needs to be calculated. An alliance is formed by a number of firms, each of which has its scores for all organizational criteria that are composed of fuzzy numbers. For converting these criteria scores of all firms into one alliance score, the union of these fuzzy scores is taken for each criterion.

For example, consider that an alliance consists of 3 firms. For the criterion, "Type of leadership", assume that the answers of the three firms are respectively, 8, 5 and 6 out of 11-points of Likert-Scales. Hence, their scores in fuzzy numbers are [0.2 0.4 0.6], [-0.4 -0.2 0] and [-0.2 0 0.2] which are given in Figure 3.8.

For the alliance, the union of these scores is taken, as in Figure 3.9. For obtaining one alliance score out of the fuzzy value; the fuzzy value is defuzzified using the centroid method which is the gravity center of the graph, the point -0.045. Hence, the organizational values are converted into one alliance value.

3.5.2 Calculation of the synergy coefficient of an alliance

Since organizational values are converted into alliance values, it is easier to obtain alliance values from alliance criteria. According to the fuzzy questionnaire structure, all alliance criteria have one triangular fuzzy number assigned to them. Alliance scores are just obtained by defuzzifying them using the centroid method.

Once all scores are obtained, weighted sum of the criteria values are calculated. The weights are taken from Table 3.1 which contains the results of the FCM. Hence, the FCM results also provide the weights of the criteria.

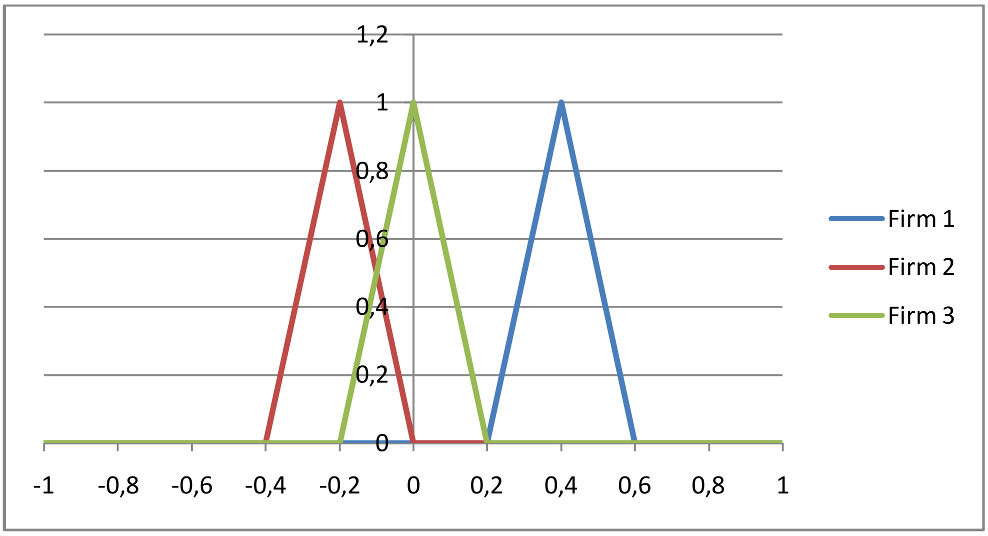

Figure 3.8: Example of 3 firms for the organizational criterion "Type of Leadership".

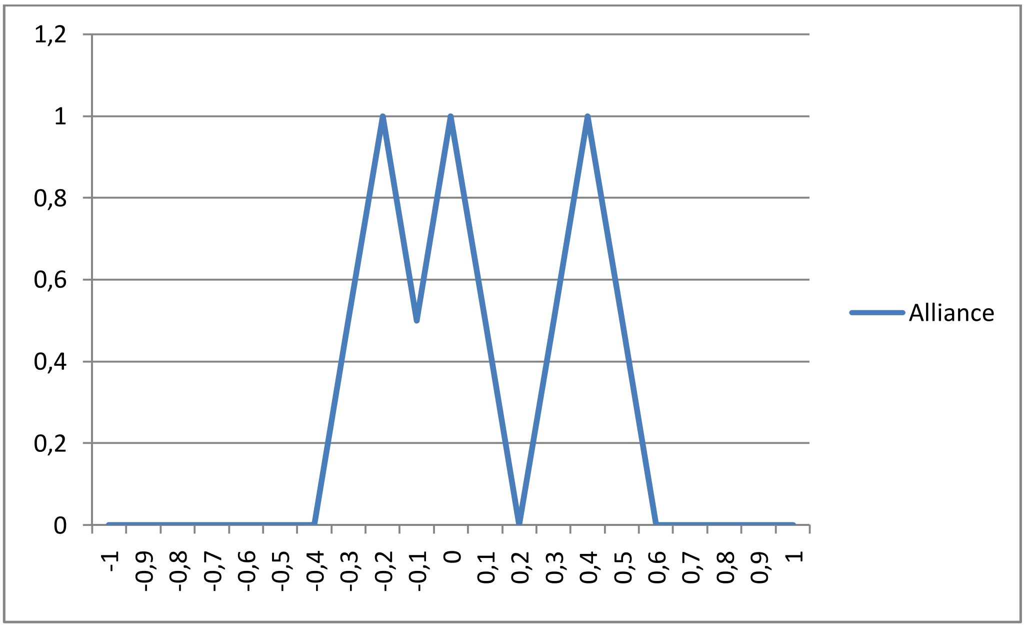

Figure 3.9: Fuzzy value of the alliance in the example.

The weights are obtained from the FCM, whereas the values are obtained from the questionnaire. As a simpler example, assume that 5 criteria are used for evaluation with weights and values given in Table 3.4.

The synergy coefficient is calculated as the weighted sum of the criteria values and the weights which gives the synergy coefficient as 0.164.

Table 3.4: A simple example for the synergy coefficient.

Criteria	Weight	Value
1	0.3	-0.2
2	0.2	0.45
3	0.2	0.97
4	0.15	0.4
5	0.15	-0.8

3.6 The Synergy Index

3.6.1 The Weibull distribution

Weibull distribution is widely used in estimating the expected lifetime or the strength of a system in reliability theory Wiley Series in Probability and Statistics (Nelson, 2004). It uses theory of constraints or "the weakest link" for estimation (S. Ross, 2006).

The density function and the cumulative function for Weibull distribution is as follows (Ross, 2006):

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-v}{\alpha}\right)^{\beta-1} \exp\left\{-\left(\frac{x-v}{\alpha}\right)^{\beta}\right\} \quad \textbf{(3.7)}$$

$$F(x) = 1 - \exp\left\{-\left(\frac{x-v}{\alpha}\right)^{\beta}\right\} \quad \textbf{(3.8)}$$

where α, β and v are Weibull parameters and $x > v$. v is generally taken in the interval $0 < v < \infty$ since the lifetimes of systems are greater than 0.

The expected value of the Weibull distribution is $E[X]=\propto\cdot\Gamma\ (1+1/\beta)$.

$$E[X] = \propto\cdot\,\Gamma\left(1+\frac{1}{\beta}\right) \quad \textbf{(3.9)}$$

3.6.2 The analogy between the weibull distribution and synergy

Synergy is well-known to be the concept of generating a greater sum than the sum of individuals. Yet, with the presence of synergy, the questions of "how greater than the sum?" and "how do the individuals affect the sum?" also arise.

Simple logic suggests that the better accordance within the alliance, the greater the synergy is. As a result, synergy is positively related with the accordance.

The analogy between the Weibull distribution and synergy lies in accordance, since the synergy represents the expected lifetime of an alliance. Synergy factors in accordance resemble robust system elements and robust system elements make the system live longer which brings us to Theory of Constraints. Hence, the Weibull distribution will assist in calculating the synergy, analogous to expected lifetime of the alliance or in other words "reliability", given the robustness of system elements, analogous to good combination of synergy factors.

Despite all best fit characters, there is one healthy assumption to be made in order to use Weibull distribution for calculating synergy, that is, for one company case, there is no synergy to be calculated. This assumption also holds in practice, one company cannot generate a synergic alliance by itself!

3.6.3 The parameters of Weibull distribution

For an alliance, we are given the number of companies and the merged value for synergy factors for each SME cluster. On the other hand, we have Weibull parameters α, β and v. The analogy between the alliance lifetime and synergy suggests that $v \geq 0$. Hence, v can be considered 0 since the synergy is analogous to the lifetime of a system. Making this assumption, the formula becomes

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} \exp\left\{-\left(\frac{x}{\alpha}\right)^{\beta}\right\} \quad \textbf{(3.10)}$$

In the formula β is the shape parameter and α is the rate parameter. If $\beta = 1$, the Weibull distribution becomes the Exponential distribution.

Moreover, considering the knowledge that in physical and biological systems, synergy is modeled with an accelerating effect, which resembles the shape of exponential distribution (Tresch et al., 2006).

It is mentioned before that the synergy will not be calculated for one company case. However, this case is necessary in order to prove the appropriateness of Weibull distribution function. In the Weibull distribution, assume that the shape parameter β denotes the number of firms in a collaboration cluster. For one company case, $\beta = 1$, the distribution becomes the Exponential distribution which resembles a system with 1 parts. For $\beta = 2$, the distribution becomes the Weibull distribution and so on. For $\beta = n$, this is analogous to a system with n parts. Hence, distribution of synergy is modeled as the reliability of a system of n parts. Therefore, it is safe to accept β as the number of companies in the collaboration cluster.

When it comes to parameter α, in the reliability analogy, it denotes the strength of elements which is equivalent to the merged synergy coefficient that will be calculated using synergy factors.

As a result, the synergy index in a collaboration cluster, with properties of number of companies and merged synergy coefficient is reflected as the reliability of a system with n parts and a robustness index.

3.6.4 The synergy index

After modeling synergy as the reliability, it is necessary to estimate the synergy index. In this study, the synergy index is seen as the expected life of an alliance hence the expected lifetime of a system. If the synergy factors are merged in a negative way, that is, if the companies are discordant, the lifetime, thus, the synergy index is negative and vice versa.

The formula for calculating the synergy index becomes

$$\mathfrak{s} = \alpha \cdot \Gamma\left(1 + \frac{1}{\beta}\right) \qquad \textbf{(3.11)}$$

where s: the synergy index

α: the merged synergy coefficient

β: number of companies

The synergy index will be used in calculating the maximization of (innovation/risk) index. It is known that in collaborations the innovation can be greater than the sum of the individual if the accordance within them is great and the innovation can be less than the individuals itself if the accordance is unsatisfactory.

3.6.5 The sensitivity analysis to Weibull distribution

The synergy index calculated by the Weibull distribution is sensitive to the number of firms in alliance. For example, assume that there are 2 cooperation clusters, one of them involving 2 companies, the other involving 3. Furthermore assume that the merged synergy coefficients of both clusters are the same and equal to 0.7. Calculating the synergy indices using Weibull distribution favors 3-company-alliance better than 2-company-alliance. This can be considered as a parallel system. It is always safer to increase the number of parallel elements.

In the figure below, the sensitivity to number of firms in alliance for $\alpha = 0.7$ is shown

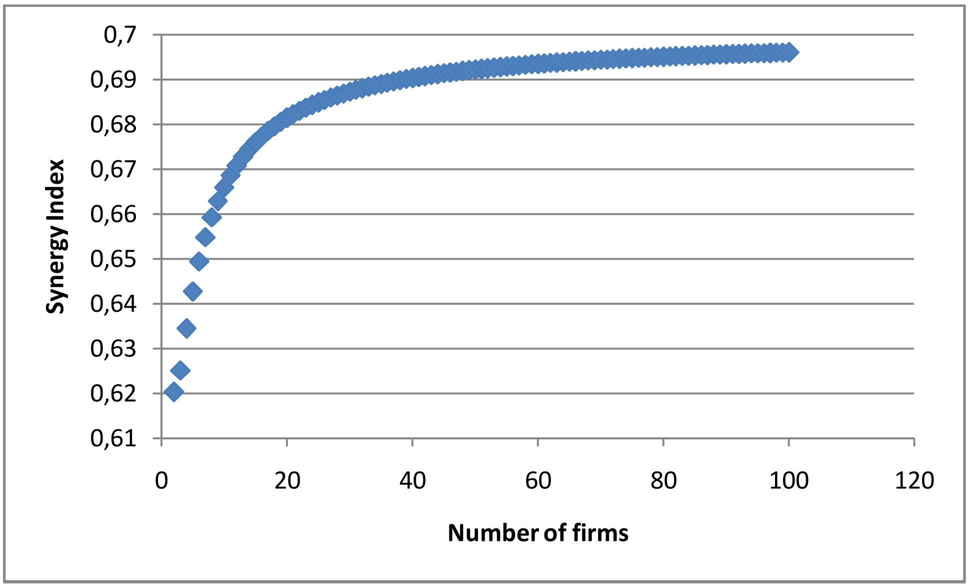

Figure 3.10: Sensitivity of synergy index to the number of firms.

4. INNOVATION AND RISK MODELING

This section involves modeling of innovation capacity and innovation risks in innovation collaborations. First, the criteria that affect innovation and risk are extracted out of literature. Since the number of criteria has been too many for the model, which would lead to a computational complexity, the criteria are prioritized and eliminated using a FCM approach.

The first part of this section introduces factors that affect innovation capacity in alliances. These criteria also affect the risk of innovation in their nature, hence, it is also explained how these criteria affect the innovation risk. The second part explains the application of FCMs for the innovation capacity and risk criteria. In the third part, the linguistic variables and the fuzzy questionnaire is explained. In the fourth part, the calculation of the innovation and risk indices is explained.

4.1 Criteria that Affect Innovation and Risk in SMEs

In this part, most criteria are derived through literature review and some criteria are proposed. 48 criteria that affect innovation in SMEs are grouped under 12 criteria groups which are listed as:

1. Industry
    a. Number of firms in the industry (F1)
    b. High tech or low tech? (High tech) (F2)
    c. Inclining or declining in the area? (Inclining) (F3)
    d. Collaborative, cooperative? (Competitive) (F4)
    e. Speed of change (F5)
2. Enterprise Demographics
    a. Facility location (F6)
    b. Age of the firm (F7)
    c. Facility size (F8) [2]
    d. Workforce size (F9)
3. Financial Features

a. Financial resources (F10)
b. Annual profit (F11)
c. Annual productivity (F12)
d. Venturing activities (F13)
e. Capital structure (F14)

4. Organizational Culture
    a. Shareholder structure (F15)
    b. Leadership level (F16)
    c. The learning organization of the firm (F17)
    d. Resource allocation policy (F18)
    e. Competitive relations (F19)
    5. Customer relations
    a. Is the customer an industrial one or the end customer? (Having an industrial customer) (F20)
    b. Level of education of the customer (F21)
    c. Income level of the customer (F22)
    d. Level of collaboration with customers (F23)
    e. Customers' contribution to innovation (F24)
6. Sales Channels
    a. Structure of the sales channels (mediary, direct sales, vb…) (Having an intermediary sales partner) (F25)
    b. Reaction to change (Having a traditional sales channel) (F26)
    c. Activity enforcement by sales channels (F27)
    d. Demand fluctuations and changes (F28)
    e. Sales channels' contribution to innovation (F29)
7. Suppliers
    a. Number of suppliers (F30)
    b. Activity enforcement by suppliers (F31)
    c. Suppliers' contribution to innovation (F32)
8. Employee relations
    a. The rate of white collar employees. (F33)
    b. (Having prize based personnel system (F34)
    c. Number of qualified workers (F35)
    d. Per employee efficiency – labor productivity (F36)

   e. Turnover rate (F37)
9. Intellectual properties
   a. Number of licenses that firm has obtained (F38)
   b. Number of patents that firm has applied for (F39)
   c. Number of patents that the firm has obtained (F40)
10. Innovation and R&D policy
   a. Open innovation – closed innovation (Closed innovation) (F41)
   b. R&D structure (lab, department, outsourced, none? (F42)
   c. In what area does the organization consider itself innovative, is it innovative at all? (F43)
   d. Paradigm shifts in the history of the firm (F44)
11. Government Regulations
   a. Tax Policies (F45)
   b. Governmental encourage and guarantee (F46)
12. Relations with Institutions and Universities (F47)
   a. Relations with universities (F47)
   b. Relations with other institutes (F48)

4.1.1 Industry Related Criteria

4.1.1.1 Number of firms in the industry

Even though earlier studies indicate that R&D activities and innovation are invariant to the number of firms in the industry (Sah and Stiglitz, 1986), a latter study states that it is effective in innovation (Kim and Pennings, 2009). As the number of firms in the industry increase, the competition among them indirectly increases, hence firms tend to get innovative to stay ahead of the competition. This case increases the innovation capacity, and as the number of R&D activities increase, the risk increases as it is in the very nature of R&D. Hence, for this criterion, innovation capacity and risk is directly proportional to the increase in the number of the firms.

4.1.1.2 Being in a high technological industry

It is known that high technological industries are more prone to innovation activities, they even can be pioneers (Blonigen and Taylor, 2000; Cruz, 2006). Hence, as the industry uses more technology, innovation activities are accelerated. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.1.3 Industry trend

The industry being inclining or declining in the geographical scope may affect the innovation activities of the firm. If the industry is declining in the area, many firms may withdraw from the industry. Remaining firms tend to continue with their prolonged businesses. Early innovators in the industry can benefit from innovation, but once the declining starts, it is harder to innovate (Dewar, 1988). Firms may eliminate their innovative activities.

As the industry inclines in the area, more firms join the industry and innovative activities may become necessary to survive and as in the previous cases, as innovative activities are increased, the risk also increase.

4.1.1.4 Being in a collaborative / competitive industry

If the industry is collaborative, open innovation activities take place in the industry. Since knowledge and other resources for innovation is shared, innovation is accelerated yielding to an increased innovation capacity. However, in the case of innovation risk, it is quite the contrary. Since innovation activities are based on better knowledge and is collaborated, the risk caused by innovation activities is reduced (van de Vrande et al., 2009).

In case of competitive industries, firms need innovative activities to stay ahead of the competition. However, this time the risk is not shared, and knowledge is not verified, hence, the risk is also increased.

In case of industries having firms oblivious to each other, firms tend to save the day or at best, compete only with themselves. Hence, innovation activities are not increased. Innovation capacities do not tend to be increased, and since innovation activities are not increased, innovation risk also stays at a low level.

4.1.1.5 Speed of change

As in high technological industries, the industries that change rapidly, e.g. ICT, encourages the firms in innovation activities. Fast changes promote changes in firms, fostering innovation (Aiginger, 2000). This causes innovation activities to be accelerated. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.2 Enterprise Demographics Related Criteria

4.1.2.1 Facility location

Being located in an industrial area, rather than a rural area, may encourage innovation activities as the industrial areas have as the majority of the skilled employees, specifically, the R&D personnel. Likewise, since the R&D personnel are in industrial areas, knowledge may assemble in industrial areas, the R&D risk may be lower in these regions.

4.1.2.2 Age of the firm

In terms of SMEs, the firm age studies may diverge. Szirmai et al. (2011) state that firm age and innovation relationship is curvilinear. Beyond a certain age, firms become less innovative. On the other hand, Balasubramanian and Lee (2008) analyze firm age and innovation, and contrary to their expectation, they claim that older firms tend to innovate more. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.2.3 Facility size

Facility size stands for the region that the facility spreads. Larger companies may find more space for their R&D and innovation activities. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.2.4 Workforce size

Micro, small and medium enterprises are the three types of workforce size in SMEs. de Jong et al. (2003) analyze and conclude that in SMEs, as the workforce size grows, innovation activities are fostered. A study by van de Vrande et al. (2009) also confirms this result. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.3 Financial features related criteria

4.1.3.1 Financial resources

van de Vrande et al. (2009) states that as firms rely more on capital rather than loans, they feel more independent of saving-the-day activities and become more inclined to take risks that will provide growth and competitive advantage. Hence, they accelerate innovation activities. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.3.2 Annual profit

Englander et al. (1988) states that the increase in profit has the same effect with the capital of the firms. As the profit increases, the firms become inclined to invest more in R&D and innovation. Hence, as the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.3.3 Annual productivity

Englander et al. (1988) state that positive changes in the productivity have a vital effect on R&D, since a reduction is signified as a reduced "invention potential". This reduction would cause a slow-down in innovative activities. In addition, increased productivity has the opposite effect. Productivity is both an innovation driver (Nishimura et al., 2005) and a conclusion of innovation (Hall et al., 2009). Hence, as the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.3.4 Venturing activities

Fruehan et al. (1997) states that venturing is an indicator of risk and initiative taking. Venturing activities are known trigger and encourage entrepreneurial and risky activities such as innovation. As the number of innovation activities increases, innovation capacity and innovation risk also increase with a direct proportion.

4.1.3.5 Capital structure

As in the financial resources case, if capital relies more on equity, they feel more independent of saving-the-day activities and become more inclined to take risks that will provide growth and competitive advantage. Hence, they accelerate innovation activities. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.4 Organizational culture

4.1.4.1 Shareholder structure

A firms feels more secure and encouraged to innovation with strong shareholders. The more the shareholder depends on debt, saving-the-day activities become more mandatory for the firm. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.4.2 Leadership level

As in the synergy case, the governance model of a company has more than 25% importance on the success of an alliance. The best conditions for the innovation are that the freedom and control inside a firm should be balanced as well as in collaboration (Theodoulides, 2005). However, in the case of innovation risk, since the innovation is led in a balanced way by employees who can take initiative, they will act faster to seize opportunities; hence, the innovation risk is reduced.

4.1.4.3 The learning organization character of the firm

Beck defines learning organizations as an organization that “facilitates learning and personal development of all its employees, whilst continually transforming itself” (Beck, 1990). It is possible that technical and cultural obstacles prevent being a learning organization. If a firm is close to being a learning organization, then it requires constant change which runs parallel to innovation activities. . Hence, being a learning organization increases the innovation capacity. In the innovation risk case, the higher the consciousness is, that being a learning organization, reduces the risks.

4.1.4.4 Resource allocation policy

Klingebiel and Rammer (2011) claim that resource allocation policy of a firm effects innovation performance and capacity. It is important in resource allocation that basic allocation decisions and contingency mechanisms work correctly. Well-planned and precise resource allocation ensures that innovation activities will not be missed; there will be resources allocation to innovation. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.4.5 Competitive relations among the firm

Competitive relations stand for competition among workers within the firms. Competition among employees encourages employees' desire to come up with new concepts or solutions for the firm (Duygulu et al., 2008). This triggers the increase in innovation capability. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.5 Customer relations related criteria

4.1.5.1 Type of customer

Types of customers can be listed as residential, smaller commercial, larger commercial, smaller industrial, larger industrial. It is argued that larger commercial, larger industrial and residential customers can be more demanding than small commercial and small industrial customers. Hence, with this type of customers, firms can be enforced to changes in products, services or processes. Hence, innovation becomes enforced by the customer regarding the type, which increases the innovation capabilities. Since, the innovation is demanded or pulled by customers; it is less risky than pushing innovation towards them.

4.1.5.2 Education level of the customer

In the synergy part, it has been claimed that educated individuals tend to collaborate more. Educated individuals also demand more new concepts than uneducated individuals. Hence, with educated customers, innovation may be an enforcement to the company that contributes to the innovation capacity. Since, the innovation is demanded or pulled by customers; it is less risky than pushing innovation towards them.

4.1.5.3 Income level of the customer

It is affirmed that innovator consumers are mostly individuals with higher incomes and occupational statuses rather than late adopters or non-innovators (Bakkabulindi, 2011). The effect of income level can be the same as the education level of the customer. Innovator customers with high incomes demand flexibility and variety in products, services or processes. Hence, innovation can be triggered and enforced by customers. . Since, the innovation is demanded or pulled by customers; it is less risky than pushing innovation towards them.

4.1.5.4 Level of collaboration with customer

Collaboration with customers is a major market information resource for innovation (Batterink et al., 2006; Kruitbosch, 2010) even though the content of the collaboration is not innovation. Hence, these kinds of collaboration indirectly speed up innovation activities. Since, the innovation is demanded or pulled by customers; it is less risky than pushing innovation towards them.

4.1.5.5 Level of customers' contribution to innovation

It is long recognized that customers' contribution to innovation is even more significant and effective when they cooperate within innovation communities. This criterion differs from the previous criterion that this criterion involves collaboration of innovation whereas the previous criterion refers to other type of collaborations. Hence, this kind of collaboration directly speeds up innovation activities. Since, the innovation is demanded or pulled by customers; it is less risky than pushing innovation towards them.

4.1.6 Sales channels related criteria

4.1.6.1 Structure of the sales channels

The existence of intermediaries rather than direct sales channels yield to the loss of customers' knowledge through the sales channels since it eliminates encountering customers. Hence, with more implementation of intermediary channels, more knowledge is lost which slows down innovation activities, hence, decreases innovation capacity. Since, the knowledge is lost; any innovation activity is more risky being based on observations rather than actual information.

4.1.6.2 Reaction to change

Traditional sales channels such as agents, despite making face-to-face sales to customer, are more resistant to change. In this manner, nontraditional or digital sales channels are advantageous in two ways. These channels are not resistant to change as traditional channels and they can gather and process information about customers more precisely. The other advantage of digital channels is that since they are much less costly than traditional sales channels, the opportunity profit can be allocated to innovation activities (Merisavo, 2008). Hence, utilization of digital sales channels may invite innovation activities. Since the innovation that is triggered by digital sales channels is knowledge-based, it is less risky.

4.1.6.3 Activity enforcement by sales channels

Sales channels get information about customers directly and without collaborating, and dependent on the fragility of the customer demand, they may have to reflect that to the company at instant. These enforcements contribute to the innovation capacity with a less risk since it is based on the knowledge of the end customer.

4.1.6.4 Demand fluctuations and changes

As demands fluctuate highly, the firms may become obliged to apply innovative solutions to damp the fluctuation which may increase their innovative capacities. In a environment full of such uncertainties, the risk will no doubt be high.

4.1.6.5 Level of sales channels' contribution to innovation

According to Hernandez-Espallardo et al. (2012) states that any types of collaborations with sales channels enables the access to knowledge and motivates them to explore ideas which helps to increase the innovation capacity with less risk.

4.1.7 Criteria related with suppliers

4.1.7.1 Number of suppliers

As the number of suppliers increase, the dependence to suppliers and the limitations on quantities of some organizational resources can be eliminated. Moreover, a great number of suppliers may encourage the competition with suppliers which may result in suppliers working for the benefit of the company. Hence, as the number of suppliers' increase, the innovation capacity may increase. Since suppliers are also sources of external information for companies, these activities may involve less risk (Fossas-Olalla et al., 2010).

4.1.7.2 Activity enforcement by suppliers

Suppliers can also be the suppliers of rivals and may obtain information from competitors. They can change their processes and products according to the specific needs or majority of customers. Hence, these changes may enforce changes and innovation in the core firm. The innovation activity is based on external information; it helps to increase innovation capacity with less risk.

4.1.7.3 Level of suppliers' contribution to innovation

Fossas-Olalla et al. (2010) states that the higher level of collaboration increases the innovation activities and the innovation capacities of the firms, since they are also sources of external information for them. Hence, collaborations with suppliers is based on external information, it helps to increase innovation capacity with less risk.

4.1.8 Employee relations criteria

4.1.8.1 The rate of white collar employees

Pierpaolo et al.(Parrota et al., 2011) state that as the number and rate of white collar employees are higher in a company, company gets more innovative, since information and ideas usually emerge from this type of employees. This case increases the innovation capacity, and as the number of R&D activities increase, the risk increases as it is in the very nature of R&D. Hence, for this criterion, innovation capacity and risk is directly proportional to the increase in the number of the firms.

4.1.8.2 Performance evaluation system

For innovation, failure is as important as success (Newmark, 2002) since because it offers insight into what factors may inhibit innovation. Hence in order to encourage R&D personnel, reward systems are more appropriate to increase the innovation capacity. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.8.3 Number of qualified workers

Innovation relies on qualified employees that can develop and work with new knowledge to integrate it in systems (Liu, 2010). Hence, in order to increase innovation capacity, greater rates or numbers of qualifies workers are needed. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.8.4 Labor productivity

Fruehan et al. (1997) and Peeters and Pottelsberghe (2004) state that labor productivity and innovation are recursive, that is, labor productivity positively affects innovation activities, which, in turn, affects labor productivity. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.8.5 Turnover rate

High turnover rate of R&D personnel causes slowdown of innovation adoption and tardiness in innovation activities (Litian and Qingrui, 2009). Employees leaving the company also take the knowledge from the company. As innovation capability decreases for the higher values of turnover rate, the risk also increases with the loss of information.

4.1.9 Intellectual properties

4.1.9.1 Number of licenses that the firm has obtained

Number of licenses that a firm obtains has a high correlation with a firm's innovation capacity (Wayne, 2010). These two factors are both causes and results of each other. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.9.2 Number of patents that the firm has obtained

Number of patents that a firm obtains has a high correlation with a firm's innovation capacity (Hunt, 2006). As in the licenses case, these concepts are both causes and results of each other. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.9.3 Number of patents that the firm has applied for

Number of patents that a firm has applied for has a high correlation with a firm's previous case innovation capacity as in the. As in the licenses case, these concepts are both causes and results of each other. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.10 Innovation and R&D policy

4.1.10.1 Open innovation ability

The main aim of open innovation is to balance the lack of capacity in terms of knowledge (van de Vrande et al., 2009). Hence, it is given that open innovation increases innovation capability. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.10.2 R&D structure

Most SMEs apply four types of R&D structures in their firms. Most SMEs do not have an innovational or an R&D activity, which decreases their innovation capacities, but since they do not have any R&D activities, they also avoid the risk of innovation itself.

Some SMEs have an R&D department, which increases innovation capacity, while increasing the risk that comes with innovation activities.

A number of SMEs outsource R&D, which helps to increase R&D at an extent, but losing the customer information to outsiders becomes a risk (Batterink et al., 2010).

The minority of SMEs run R&D laboratories which are also centers for open innovation. This type of SMEs works on “high gain, high risk” innovation activities (Rammer et al., 2008).

4.1.10.3 Innovation level of the firm

If a company has been innovative, it can be said with no doubt that it has a higher potential for innovation and has good experience in that area. Since, these experiences also yield knowledge in the risks of innovation activities, the company will be ready to handle these risks, as well. Hence, the risk is inversely proportional with the innovation level of the firm.

4.1.10.4 Paradigm shifts in the history of the firm

The number of paradigm shifts in the firm reflects the number of radical changes that the firm has gone through. The more the firm has gone through radical changes and has adapted itself, the more it is ready for innovation. Hence, the number of shifts increases the innovation capability. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion.

4.1.11 Government regulations

4.1.11.1 Tax policies

Atkinson et al. (2011) claim that tax policies that support R&D is an important driver for innovation. Hence, supportive policies contribute to the increase the innovation capacity. As the number of innovation activities increase, innovation capacity and innovation risk also increase with a direct proportion

4.1.11.2 Governmental encouragement and guarantee

As in the taxes case, governmental encouragement to specific industries, regions, projects or networks, is an important R&D driver which increases the innovation capacity but decreases the risk.

4.1.12 Relations with institutes and universities

4.1.12.1 Relations with universities

As aforementioned, collaborations with universities are a major type of innovation alliance for firms. Universities act as an innovation broker, which identify, analyze and specify the innovational needs and capabilities. Hence, relations with universities act as a contributor to innovation capacity. Since, the innovation is achieved with the knowledge and expertise of universities, it is less risky.

4.1.12.2 Relations with other institutes

Like universities, scientific foundations and research institutions act as innovation enablers with less risk.

4.2 The Prioritization and Elimination of Innovation and Risk Factors

For prioritization and elimination of elimination and risk factors, FCMs are utilized as aforementioned in Section 3.2., 3 decision makers have completed the questionnaire: 1 industry expert, 1 academician and 1 strategy consultant. The fuzzy cognitive matrices and the united fuzzy cognitive matrix obtained are given in Appendix H.

According to the united fuzzy cognitive matrix for innovation and risk, the final centralities and weights of the criteria are given in Table 3.1.

Table 4.1: Centralities and weights of innovation and risk criteria.

Criterion	Criterion Name	Centrality (Weight)	Cumulative Weight
F18	Resource Allocation Policy	0.0420	0.042
F41	Open Innovation Ability	0.0389	0.081
F42	R&D Structure	0.0388	0.119
F43	Innovation Level of the Firm	0.0356	0.155
F17	Learning Organization Character of the Firm	0.0331	0.188
F48	Relations with Institutions	0.0302	0.218
F35	Number of qualified workers	0.0299	0.248
F12	Annual Productivity	0.0294	0.278
F11	Annual Profit	0.0291	0.307
F47	Relations with Universities	0.0289	0.336
F10	Financial recourses	0.0288	0.365
F5	Speed of change in industry	0.0284	0.393
F19	Competitive relations among the firm	0.0280	0.421
F36	Per employee efficiency – Labor productivity	0.0279	0.449
F23	Level of collaborations with the customer	0.0275	0.477
F24	Level of customers' contribution to innovation	0.0273	0.504
F4	Collaborative/Cooperative industry	0.0270	0.531
F3	Industry being inclining in the area	0.0251	0.556
F15	Shareholder structure	0.0248	0.581
F40	Number of patents that the firm has applied for	0.0236	0.605
F37	Turnover rate	0.0235	0.628
F9	Workforce size	0.0232	0.652

Table 4.1(continued): Centralities and weights of innovation and risk criteria.

Criterion	Criterion Name	Centrality (Weight)	Cumulative Weight
F39	Number of patents that the firm has obtained	0.0231	0.675
F26	Sales channels' reaction to change	0.0227	0.697
F33	The rate of white collar employees	0.0216	0.719
F32	Level of suppliers' contribution to innovation	0.0207	0.740
F29	Level of sales channels' contribution to innovation	0.0204	0.760
F2	Being in a high technological industry	0.0203	0.781
F14	Capital structure	0.0198	0.800
F7	Age of the firm	0.0196	0.820
F16	Leadership level of the firm	0.0196	0.840
F25	Structure of the sales channels	0.0194	0.859
F38	Number of licenses that the firm has obtained	0.0189	0.878
F13	Venturing activities	0.0188	0.897
F1	Number of firms in the industry	0.0183	0.915
F6	Facility location	0.0169	0.932
F20	Customer type	0.0145	0.947
F30	Number of suppliers	0.0137	0.961
F44	Paradigm shifts in the history of the firm	0.0133	0.974
F27	Activity enforcement by sales channels	0.0128	0.987
F8	Facility size	0.0125	1,000

According to the decision makers, there is not a big importance difference between factors, which has led the selection of the point for criteria elimination to be vague. Although the aim is to use a minimum number of factors with maximum importance value, finding a strict cutting point is difficult with importance values that close to each other. In this manner, among the 48 criteria, 32 of them with a cumulative importance of 80% are selected. As a result, the most important criteria to be asked in the fuzzy questionnaire are Resource Allocation Policy and the least important criterion is Facility Size. The chosen criteria and their weights obtained from the FCM is given in Table 4.2.

Table 4.3 shows the three weights of criteria groups in an increasing order.

4.3 The Fuzzy Innovation and Risk Questionnaire

After the application of FCMs to the innovation and risk criteria and the elimination of the less important 16 criteria, the Fuzzy Innovation and Risk Questionnaire is prepared which are presented in Appendix H. The remaining criteria and their linguistic variables are determined in order to be able to quantify the innovation and risk data. Tangible and measurable factors are also evaluated by experts instead of using the general ledger figures in order to have stability in terms of units in order to be able to compare with the intangibles.

Table 4.2: The final weights of the selected criteria.

Criterion	Criterion Name	Final Weight of the Criterion
F18	Resource Allocation Policy	0.0489
F41	Open Innovation Ability	0.0454
F42	R&D Structure	0.0451
F43	Innovation Level of the Firm	0.0415
F17	Learning Organization Character of the Firm	0.0386
F48	Relations with Institutions	0.0352
F35	Number of qualified workers	0.0349
F12	Annual Productivity	0.0342
F11	Annual Profit	0.0339
F47	Relations with Universities	0.0337
F10	Financial recourses	0.0335
F5	Speed of change in industry	0.0331
F19	Competitive relations among the firm	0.0327
F36	Per employee efficiency – Labor productivity	0.0325
F23	Level of collaborations with the customer	0.0321
F24	Level of customers' contribution to innovation	0.0318

Table 4.2 (continued): The final weights of the selected criteria.

Criterion	Criterion Name	Final Weight of the Criterion
F4	Collaborative/Cooperative industry	0.0314
F3	Industry being inclining in the area	0.0292
F15	Shareholder structure	0.0289
F40	Number of patents that the firm has applied for	0.0275
F37	Turnover rate	0.0274
F9	Workforce size	0.0271
F39	Number of patents that the firm has obtained	0.0270
F26	Sales channels' reaction to change	0.0264
F33	The rate of white collar employees	0.0252
F32	Level of suppliers' contribution to innovation	0.0242
F29	Level of sales channels' contribution to innovation	0.0237
F2	Being in a high technological industry	0.0236
F14	Capital structure	0.0231
F7	Age of the firm	0.0228
F16	Leadership level of the firm	0.0228
F25	Structure of the sales channels	0.0226

A Likert-type scale is used for measuring the values, yet, this scale has different number of options depending on the type of the question. These scales have been determined by the previous interviews with the SMEs.

4.3.1 Resource allocation policy

The resource allocation policies of the firms are analyzed in two-basis: basic resource allocation and contingent resource allocation. The first part of the 20th question of the questionnaire in Appendix I is asked to retrieve information on the basic resource allocation policies of the firms and the second part of the same question is asked to retrieve information on the basic contingency allocation policies. The questions are asked with an eleven-point type Likert scale with fuzzy numbers as given in Figure 3.1. The main linguistic levels for the first part of the question are

- In our industry, the resources are limited. Hence, we try to save the day by allocation of resources to the urgent businesses (Option 1)
- We conduct our budget plans for each quarter and six months. Yet, we may have to change our plans due to urgent daily needs (Option 2)

Table 4.3: Average weights of criteria groups.

Criteria Group	Average Weight
Innovation and R&D Policy	0.0294
Organizational Structure	0.0274
Relations with Other Constitutions	0.0270
Financial Features	0.0234
Industry Dynamics	0.0222
Employee Relations	0.0209
Intellectual Properties	0.0204
Customer Relations	0.0172
Enterprise Demographics	0.0168
Sales Channels	0.0163
Supplier Channels	0.0140
Government Regulations	0.0090
Innovation and R&D Policy	0.0294

- We conduct our budget plans for each quarter and six months. Other than ignorable deviations, we try to follow our plans. (Option 3)

The main linguistic levels for the second part of the question are

- After the basic expenses, unexpected payments are made when an urgent situation arises (Option 1)
- After expenses are controlled and checked, we plan for extra resources for unexpected expenses (Option 2)
- All payments are planned in advance. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.2 Open innovation ability

The open innovation ability question will give information for the willingness to share innovation abilities in collaboration.. This ability is measured through the 18th question of the questionnaire in Appendix I with four choices of which more than one can be selected. The options are:

- We are ready for collaborations that will improve market share and revenues (Option 1)
- We have research for new products / processes but we do not share the information with outsiders (Option 2)
- We do not have any innovation activities. (Option 3)
- Other (Choice 4)

The fuzzy number equivalents of the options are presented in Figure 3.7. Since, Option 4 is not selected by any of the SMEs; it is not assigned a fuzzy number.

It has been aforementioned that risk is directly proportional with the innovation for this criterion.

4.3.3 R&D structure

The R&D structure of the firm is measured through the 15th and 16th question of the questionnaire in Appendix I. The 15th question is a Yes/No question. The firm representative is asked if the firm conducts any R&D activities or not. If the answer is no, he is asked to skip the next question which retrieves information on the R&D activities of the firm. If the answer is yes, they are asked to answer the nest (16th) question with the options

- We have an R&D laboratory (Option 1)
- We have an R&D department / unit (Option 2)

- We have outsourced our R&D activities, we work with another firm for R&D. (Option 3)
- Other (Option 4)

None of the firms selected the "Other" option (Option 4); hence this option is not assigned a fuzzy number and left out of evaluations. The fuzzy numbers for this criterion in terms of innovation capacity is given below in Figure 4.1.

In terms of risks of this criterion, it was aforementioned that, when no R&D activities are conducted, it yields to no increase (or even decrease) in innovation capacity, with no risk. On the other hand, when R&D activities are conducted in a laboratory, the gain in terms of innovation capacity is highest and the risk is also high due to the very nature of R&D activities. As a third option, in-house R&D is conducted in departments, units or by several personnel, that increases the innovation capacity. Yet, the increase is not as high as the laboratory option, and the risk is lower due to the extension of the minor and slower R&D activities. As for the last option, outsourcing the R&D increases the innovation capacity, not contributing as high as a laboratory; since, outsourcing R&D yields to losing customer innovation, which in turn also yields high risk. The fuzzy numbers for risk is given in Figure 4.2.

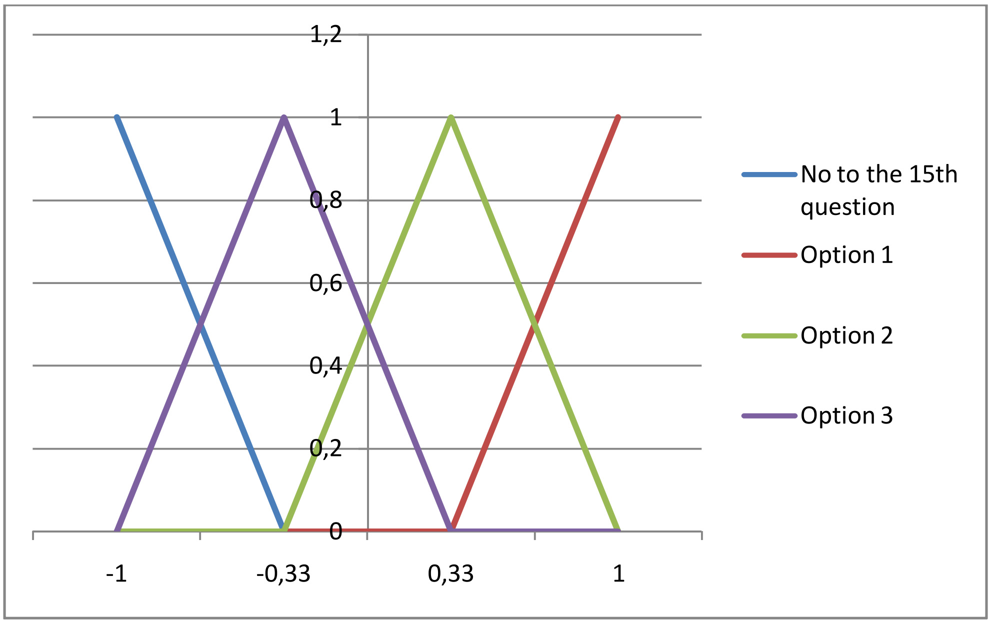

Figure 4.1: Fuzzy numbers for R&D Structure criterion in terms of innovation capacity.

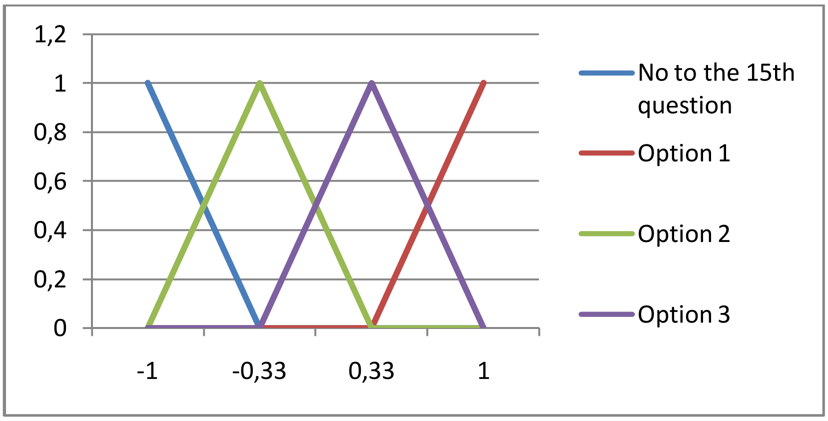

Figure 4.2: Fuzzy numbers for R&D Structure criterion in terms of risk.

4.3.4 Innovation level of the firm

In this criterion, innovation level of the firms is attempted to be retrieved through benchmarking with the industry average. The information is retrieved through the 26th question of the questionnaire in Appendix I with an eleven-point Likert-scale in comparison with the industry average in terms of coming up with new products or processes. In terms of innovation capacity, the three main levels are

- We are slower than the industry average (Option 1)
- We are at the same pace as the industry average (Option 2)
- We are faster than the industry average. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

When it comes to the risks of the criterion, since innovation is based on knowledge and a high level of innovation indicates a high management of information and knowledge, the inverse of the fuzzy values are taken in order to calculate the risk.

4.3.5 Learning organization character of the firm

As clarified before, being closer to a learning organization increases the innovation capacity of the firm which is directly proportional to the innovation risk. Two disablers of being a learning organization have been defined as limited technical resources and firm culture and the main characteristic of a learning organization have been defined as constant change led by knowledge and learning. For this criterion, firm information is attempted to be retrieved by measuring the impact of technological and cultural obstacles in the firm as presented in the 19th question of the questionnaire in Appendix I. In this question, the decision-makers are asked to evaluate four subquestions which were given as

- The emergence and sharing of new ideas are encouraged in our firm. (Option 1)
- Our firm culture is not suitable for the emergence and sharing of new ideas (Option 2)
- Our technological resources are suitable for the emergence and sharing of new ideas (Option 3)
- If improvements are made both in our firm culture and technological resources, our firm can encourage the emergence and sharing of new ideas (Option 4).

The fuzzy values of the options are given in Figure 4.3.

The firm representatives are asked to evaluate all 4 subquestions over a seven-point Likert Scale method.

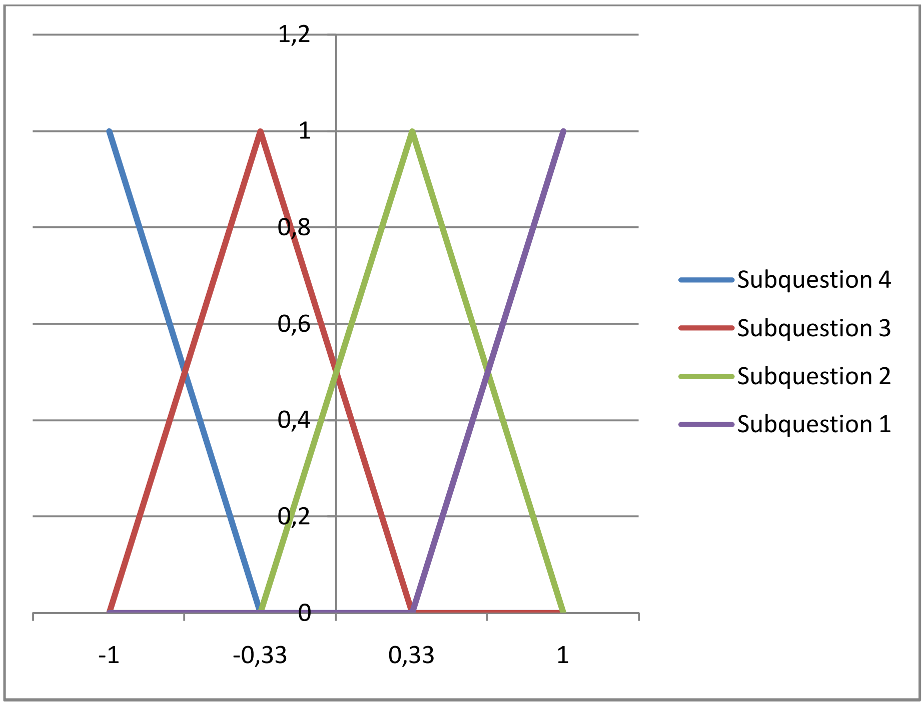

Figure 4.3: Fuzzy numbers for learning organization character of the firm criterion in terms of innovation capacity.

Since each subquestion is evaluated, the evaluation values (over 7) are taken as the weights of the subquesitons. Then, fuzzy values of all the subquestions are multiplied by their weights and the obtained fuzzy numbers are merged (unionized). For example, assume that Firm A has answered as 7, 6, 6 and 5 respectively. The fuzzy numbers for subquestions (given in Figure 4.3) are [0.33 1 1], [-0.33 0.33 1],[-1 -0.33 0.33] and [-1 -1 -0.33] which have weights 7, 6, 6 and 5. The union of the weighted fuzzy numbers is given in Figure 4.4.

As for the risk value of the firm, the risk has been aforementioned to be inversely proportional to the innovation capacity value, hence, the inverse of the fuzzy values are taken.

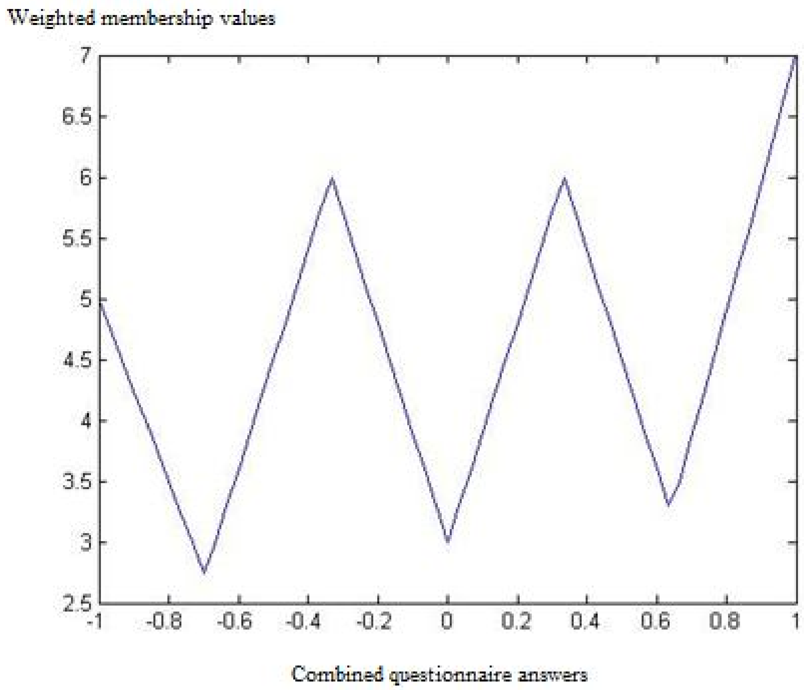

Figure 4.4: Union of fuzzy numbers for one firm for the criterion learning organization character of the firm.

4.3.6 Relations with other institutes

In this criterion, the frequency of the relations of the firm with scientific foundations and institutes are measured. The information is retrieved through the 21st question of the questionnaire in Appendix I with an eleven-point Likert-scale. In terms of innovation capacity, the three main levels are

- We rarely collaborate and do research with such institutions (Option 1)
- We sometimes collaborate and do research with such institutions (Option 2)

- We frequently collaborate and do research with such institutions (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

When it comes to the risks of the criterion, it was aforementioned that risk is inversely proportional with the innovation for this criterion. Hence, the inverse of the fuzzy values are taken in order to calculate the risk.

4.3.7 Number of qualified workers

For this criterion, the evaluation of the workers or employees is made through benchmarking with the industry average. The information is retrieved through the 27th question of the questionnaire in Appendix I with an eleven-point Likert-scale. In terms of innovation capacity, the three main levels are

- Our employees are much less qualified than the industry average (Option 1)
- Our employees are as qualified as the industry average (Option 2)
- Our employees are much more qualified than the industry average (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

When it comes to the risks of the criterion, it was aforementioned that risk is directly proportional with the innovation for this criterion. Hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.8 Annual productivity

Annual productivity is mentioned to increase innovation capacity. The evaluation of productivity is made through benchmarking with the industry. The information is retrieved through the 28th question of the questionnaire in Appendix I with an eleven-point Likert-scale. In terms of innovation capacity, the three main levels are

- We are less productive than the industry average (Option 1)
- We are as productive as the industry average (Option 2)
- We are more productive than the industry average (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

When it comes to the risks of the criterion, it was aforementioned that risk is directly proportional with the innovation for this criterion. Hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.9 Annual profit

Annual profit is mentioned to increase innovation capacity. The evaluation of annual profit is made through benchmarking with the industry. The information is retrieved through the 29th question of the questionnaire in Appendix I with an eleven-point Likert-scale. In terms of innovation capacity, the three main levels are

- We are less profitable than the industry average (Option 1)
- We are as profitable as the industry average (Option 2)
- We are more profitable than the industry average (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

When it comes to the risks of the criterion, it was aforementioned that risk is directly proportional with the innovation for this criterion. Hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.10 Relations with universities

In this criterion, the frequency of the relations of the firm with scientific foundations and institutes are measured. The information is retrieved through the 22nd question of the questionnaire in Appendix I with an eleven-point Likert-scale. In terms of innovation capacity, the three main levels are

- We rarely collaborate and do research with universities (Option 1)
- We sometimes collaborate and do research with universities (Option 2)
- We frequently collaborate and do research with universities (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix H.

When it comes to the risks of the criterion, it was aforementioned that risk is inversely proportional with the innovation for this criterion. Hence, be inversely proportional to the innovation capacity value, hence, the inverse of the fuzzy values are taken in order to calculate the risk.

4.3.11 Financial resources

The financial resources of the firm are measured in two parts as given in the first part of the 5th question in the questionnaire given in Appendix I. In the first part, the credit and capital ratio of the firms is attempted to be retrieved using an eleven-point Likert-scale. In terms of innovation capacity, the three main levels are

- We use credits to finance our businesses (Option 1)
- We both use credits and capital to finance our businesses (Option 2)
- We only use capitals funded by our shareholders to finance our businesses Option 3)

The decision maker can be indecisive between two choices; this indecision denotes the degree of the capital or credits that is used. As a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I. As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity;

hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.12 Speed of change in the industry

It has been aforementioned that higher speed of change in the industry encourages the innovation. The speed of change in the industry of the responding firms is measured through the 13th question of the questionnaire in Appendix I. The three main levels are

- Our industry does not change. (Option 1)
- Our industry is a slow-changing one. (Option 2)
- Our industry is a fast-changing one. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.13 Competitive relations among the firm

The competition among workers increases the innovation capacity. In order to evaluate the firms' competition among employees, the 23rd question of the questionnaire in Appendix I is designed. The three main levels are

- In our firm culture, competition among workers is considered to be disturbing, for that reason, competition among workers is discouraged. (Option 1)
- In our firm, it is more important that the daily operations are finished completely and accurately than the competition among workers. (Option 2)
- We utilize different performance measures, prize and compensation systems to encourage competition among workers. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.14 Labor productivity

Labor productivity is known to increase innovation capacity. This criterion is evaluated through 24th question of the questionnaire in Appendix I. The three main levels are

- Less than 30% of the employees are working with high efficiency. (Option 1)
- Half of the employees are working with high efficiency. (Option 2)
- More than 30% of the employees are working with high efficiency (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.15 Level of collaboration with customers

The preferred channels of interaction with customers is used as the measure for the level of collaboration and considered in the 9th question of the questionnaire in

Appendix I. There are four choices of response and more than response can be selected. The options are:

- We have a call center. (Option 1)
- We have an employee whose job is customer affairs. (Option 2)
- We obtain customer information through intermediaries or sales channels. (Option 3)
- Other (Choice 4)

Option 4 is not selected by any of the SMEs, it is not assigned a fuzzy number. Since it is possible to choose more than one option, the fuzzy numbers for this criterion is given in Figure 4.5.

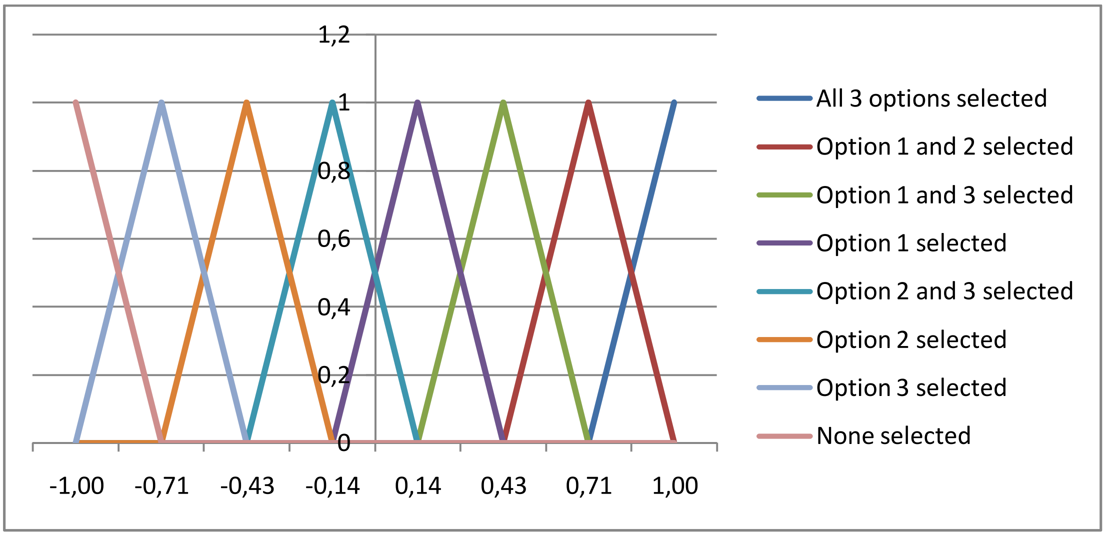

Figure 4.5: Fuzzy numbers for level of collaboration with customers in terms of innovation capacity.

When it comes to the risks of the criterion, it was aforementioned that risk is inversely proportional with the innovation for this criterion. Hence, the inverse of the fuzzy values are taken in order to calculate the risk.

4.3.16 Level of customers' contribution to innovation

It has been aforementioned that level of customers' contribution to innovation increases the innovation capacity. This contribution is measured through dynamics of customer demands and activity enforcements in three conflicting subquestions as presented in the 25th question of the questionnaire in Appendix I. In this question, the decision-makers are asked to evaluate four subquestions which were given as

- New products / services / processes can be modified according to customer demands and these arrangements are accepted as the cause of surviving (Option 1)
- Changes in products / processes / services are hard to be achieved; customers rarely / hardly demand these changes. (Option 2)
- Changes in products / processes/ services cannot be achieved at all since customer demands are standard. (Option 3)

The fuzzy values of the options are given in Figure 4.3.

The firm representatives are asked to evaluate all 3 subquestions over a seven-point Likert Scale method. Since each subquestion is evaluated, the evaluation values (over 7) are taken as the weights of the subquesitons as achieved in the criterion "Learning Organization Character of the Firm".

When it comes to the risks of the criterion, it was aforementioned that risk is inversely proportional with the innovation for this criterion. Hence, be inversely proportional to the innovation capacity value, hence, the inverse of the fuzzy values are taken in order to calculate the risk.

4.3.17 Being in a collaborative / competitive industry

As aforementioned, in terms of innovation capacity, collaborative industries produce the best results, followed by competitive industries. Lastly, in industries where firms are oblivious to each other are the last in terms of innovation capacity. To measure the innovation capacity brought by this criterion, the 14th question of the questionnaire in Appendix I is asked. The fuzzy values for the options of the questions are presented in Figure 3.1. The three main levels are

- The firms in the industry are oblivious to each other. (Option 1)
- The firms in the industry are competitive with each other. (Option 2)
- The firms in the industry are collaborative to each other. (Option 3)

In terms of risk, industries where firms are oblivious to each other have the least risk, followed by collaborative industries, which, in turn followed by, competitive industries. The risk case has neither direct nor inverse proportion with innovation options given in the related question. As the answer changes from Option 1 to Option 2, the risk increases rapidly, since the highest risk arises from Option 1 to Option 2, since the lowest risk belongs to industries in which firms are oblivious to each other and the highest risk belongs to the industries in which the firms are competitive with each other. As the answer changes from Option 2 to Option 3, the risk decreases more slowly than the increase between Option 1 and Option 2, since, the risk is highest in competitive industries but not the lowest in collaborative industries. The fuzzy numbers with respect to the options related to risk are given in Figure 4.6.

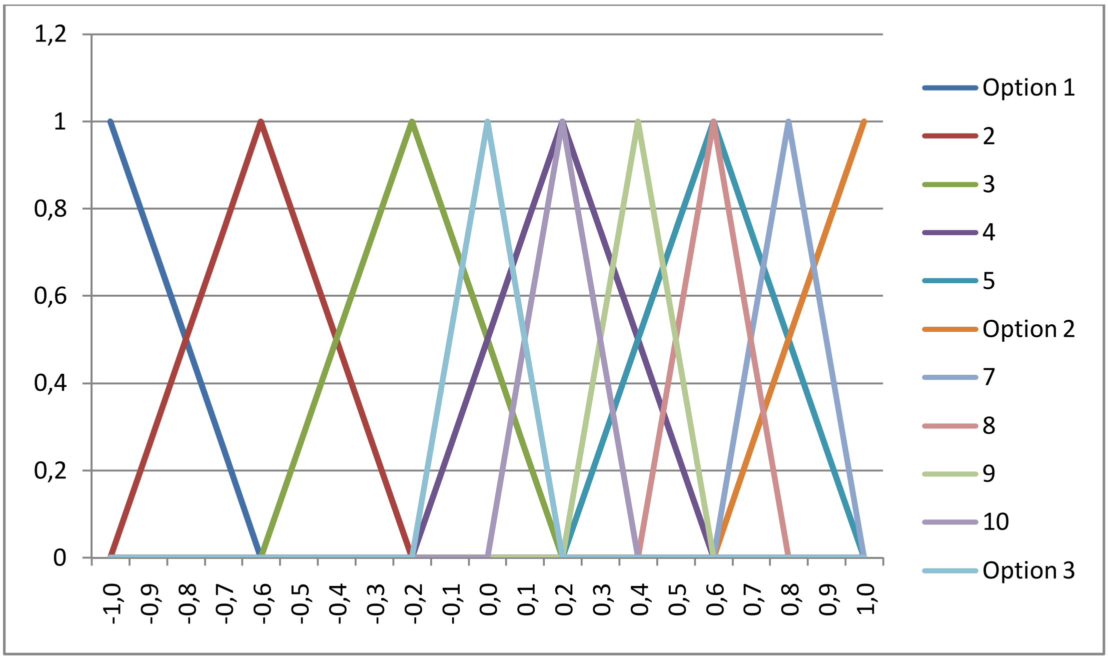

Figure 4.6: Fuzzy numbers for industry specifications in terms of risk.

4.3.18 Industry trend

If the industry is inclining in the chosen field, the innovation activities are triggered and innovation capacity increases together with innovation risks. Industry trend is asked in the 12th question of the questionnaire given in Appendix I. The three main levels are

- The demand is decreasing in the region that we operate. (Option 1)
- The demand is likely to be the same in the future. (Option 2)
- The demand is increasing in the region that we operate. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents

Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

The risk is directly proportional to the innovation capacity.

4.3.19 Shareholder structure

A firms feels more secure and encouraged to innovation with strong shareholders. Firms' structure of share holders is asked in the 6th question of the questionnaire given in Appendix I. The three main levels are

- We are open to public offerings. (Option 1)
- We rely on stock certificates. (Option 2)
- We rely on government bonds. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.20 The number of patents that the firm has applied for

Both innovation capacity and innovation risks are observed to be directly proportional to the number of patents that the firm has applied for. This number is retrieved through the 8th question of the questionnaire in Appendix I. The question only has three options:

- None. (Option 1)
- One. (Option 2)
- More than one. (Option 3)

The fuzzy numbers assigned to these options are presented in Figure 3.5. As for the risk value of the firm, the risk has been aforementioned to be inversely proportional to the innovation capacity value, hence, the inverse of the fuzzy values are taken.

4.3.21 Turnover rate

Innovation capacity is negatively affected by the turnover rate. The turnover rates of the firms are asked in the 17th question of the questionnaire given in Appendix I. The three main levels are

- Most employees leave their jobs after a short time after their orientations. (Option 1)
- The turnover rate is at the industry average level. (Option 2)
- Most of our employees have been working here for a long time. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk value of the firm, the risk has been aforementioned to be inversely proportional to the innovation capacity value, hence, the inverse of the fuzzy values are taken.

4.3.22 Workforce size

Innovation capacity and risk have been aforementioned to be directly proportional to the workforce size. This information is retrieved through the 1st question of the questionnaire in Appendix I. The question only has three options:

- Micro. (Option 1)
- Small. (Option 2)
- Medium. (Option 3)

The fuzzy numbers assigned to these options are presented in Figure 3.5. As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.23 The number of patents that the firm has obtained

Both innovation capacity and innovation risks are observed to be directly proportional to the number of the patents that the firm has obtained. This number is retrieved through the 7th question of the questionnaire in Appendix I. The question only has three options for the question how many patents are received in one year:

- None. (Option 1)
- One. (Option 2)
- More than one. (Option 3)

The fuzzy numbers assigned to these options are presented in Figure 3.5. As for the risk value of the firm, the risk has been aforementioned to be inversely proportional to the innovation capacity value, hence, the inverse of the fuzzy values are taken.

4.3.24 Sales channels' reaction to change

Digital sales channels trigger innovation more than traditional sales channels. The sales channels character is defined through the 11th question of the questionnaire in Appendix I. The question asks the ratio of digital sales channels to traditional channels for the firm. The fuzzy numbers are determined according to the percentage of digital sales channels. In Figure 4.7, the indicators of lines denote the percentage of sales channels and the lines denote the fuzzy numbers.

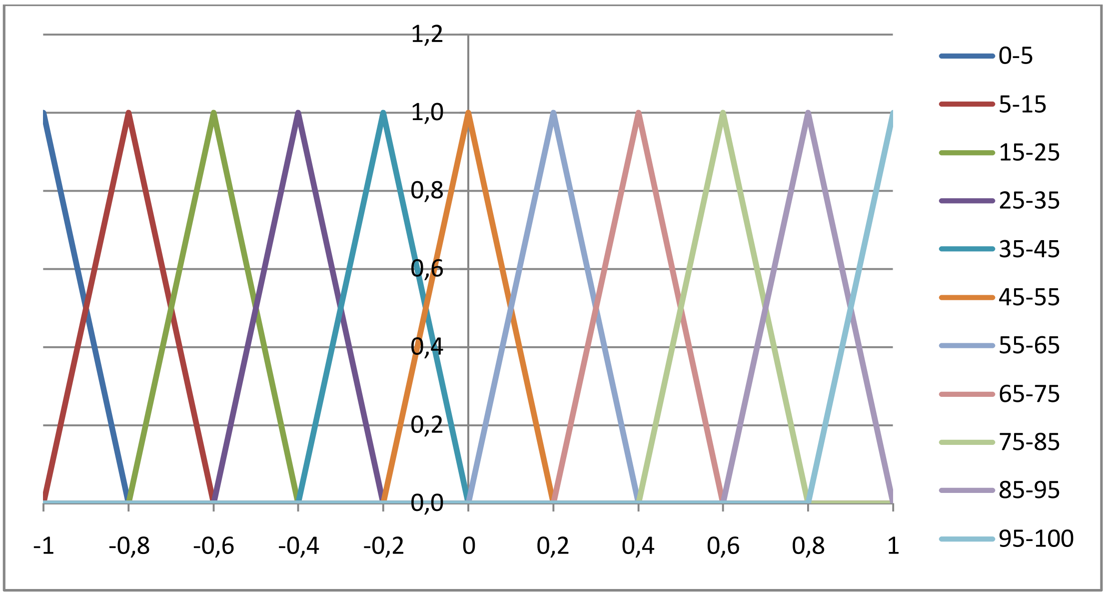

Figure 4.7: Fuzzy numbers for percentage of digital sales channels in terms of innovation capacity.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.25 The rate of white collar employees

Higher rate of white collar employees provide a high innovation capacity with high risk. The rate of white collar employees is asked through the 2nd question of the questionnaire of Appendix I. The three main levels are

- The rate of white collar employees is less than 30%. (Option 1)
- The rate of white collar employees is around 50% more or less.. (Option 2)
- The rate of white collar employees is more than 70%.. (Option 3)

The decision maker can be indecisive between the two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.26 Level of suppliers' contribution to innovation

It has been aforementioned that level of suppliers' contribution to innovation increases the innovation capacity. This contribution is measured through the 30th question of the questionnaire in Appendix I. The three main levels are

- Suppliers do not participate our researches for innovation (Option 1)
- Suppliers provide ideas that can be innovative for us. (Option 2)
- We have innovation projects that we implement together with the suppliers (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

The fuzzy numbers assigned to these options are presented in Figure 3.5. As for the risk value of the firm, the risk has been aforementioned to be inversely proportional to the innovation capacity value.

4.3.27 Level of sales channels' contribution to innovation

It has been aforementioned that level of sales channels' contribution to innovation increases the innovation capacity. This contribution is measured through the 31st question of the questionnaire in Appendix I. The three main levels are

- Sales channels do not attend our researches in innovation (Option 1)
- Sales channels provide ideas that can be innovative for us. (Option 2)
- We have innovation projects that we implement together with sales channels (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

The fuzzy numbers assigned to these options are presented in Figure 3.5. As for the risk value of the firm, the risk has been aforementioned to be inversely proportional to the innovation capacity value, hence, the inverse of the fuzzy values are taken.

4.3.28 Being part of a high technological industry

Being part of a high technological industry increases the innovation capacity as well as the innovation risk. The industry information of the firms is retrieved through the 4th question of the questionnaire in Appendix I.

- Our products do not require high technology / Our products are handmade. (Option 1)
- High technology is used in manufacturing processes. (Option 2)
- We operate in an industry that require high technology at each stage. (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.29 Capital structure

The capital structure was asked in the second part of 5th question and the ratio of borrowed funds to capital funded by shareholders is attempted to be measured. The two main levels are

- We are totally funded by borrowed funds (Option 1)
- We are totally funded by capital provided by shareholders (Option 2)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 11 represents Option 2 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.30 Age of the firm

Beyond a certain age, the firms tend to be less innovative. The ages of the firms are retrieved through 3rd question. This contribution is measured through the 30th question of the questionnaire in Appendix I. The three main levels are

- We are a long standing firm in the industry. (Option 1)
- We are at an age that is almost the industry average. (Option 2)
- We are a new firm (Option 3)

The decision maker can be indecisive between two choices, as a result, this question is asked with an eleven-point Likert-Scale, each point representing a triangular fuzzy value which is shown in Figure 3.1. Line 1 represents Option 1, line 6 represents Option 2, Line 11 represents Option 3 and the other lines represent the options presented in the related question given in Appendix I.

As for the risk of the criterion, it has been aforementioned that the risk is directly proportional to the innovation capacity; hence, the risk values are taken as equivalent to the innovation capacity value for this criterion.

4.3.31 Leadership level of the firm

The specifications are similar to the synergy criterion "Type of Leadership". The information for this criterion is taken from the synergy questionnaire which is specified in Section 3.4.18, which asks the same question under a different criterion name. Hence, the innovation capacity is the synergy created.

The fuzzy numbers assigned to these options are presented in Figure 3.5. As for the risk value of the firm, the risk has been aforementioned to be inversely proportional to the innovation capacity value, hence, the inverse of the fuzzy values are taken.

4.3.32 Structure of the sales channels

It was aforementioned that direct sales encourage innovation more than intermediaries and this character is measured using the 10th question of the questionnaire in Appendix H, with four choices of which more than one can be selected. The options are:

- We sell our products / services by intermediaries. (Option 1)
- We sell our products / services to one industrial enterprise. (Option 2)
- We sell our products / services directly to the end customer. (Option 3)
- Other (Choice 4)

Since, Option 4 is not selected by any of the SMEs; it is not assigned a fuzzy number. Since it is possible to choose more than one option, the fuzzy numbers for this criterion is given in Figure 4.5.

When it comes to the risks of the criterion, it was aforementioned that risk is inversely proportional with the innovation for this criterion. Hence, be inversely proportional to the innovation capacity value, hence, the inverse of the fuzzy values are taken in order to calculate the risk.

4.4 The Innovation Capacity and Risk Indices

The main motive of the collaboration for innovation is to gain more contribution to innovation power than the increase of risk caused. Therefore, if the ratio of innovation capacity to risk is greater than 1, than the collaboration is worth forming.

Unlike the synergy criteria, which is either organizational or alliance related, all 32 innovation and risk criteria presented in the previous section are organizational. However, in order to measure the innovation capacity and risk values these factors are to be calculated for each collaboration clusters, in other words, for each alliance. In order to compute the alliance of each criterion, the union of the values of all firms in collaboration is taken as previously mentioned in Section 3.5.1. For each criterion, the union of each firm's value is taken and defuzzified in order to obtain the criterion value. This process is done for both innovation capacity and risk. In this way, the criteria values of innovation capacity and risk for each collaboration cluster is obtained.

The innovation index measures the innovation capacity of an alliance. This value is obtained by the weighted average of the innovation criteria values of alliances as previously mentioned in Section 3.5.2. As in the synergy case, the range of the innovation capacity index is [-1, 1].

The risk index measures the risk caused by innovation activities of the alliance. As similar to the innovation capacity index, the risk index is calculated as the weighted average of the innovation criteria values of alliances as previously mentioned in Section 3.5.2. As in the innovation capacity and synergy indices, the range of the risk is index is [-1,1].

5. METHODOLOGY – THE FORAGING SEARCH

5.1 The Foundations

5.1.1 PSO Algorithm

Particle Swarm Optimization (PSO) is a population based optimization technique invented by Kennedy and Eberhart in 1995 influenced by the social behaviour of fish schooling and bird flocking 1. It simulates the "collective behaviour" of animals, which socio-cognitively share information among the swarms (Hassan et al., 2005).

Animals in nature, urge into swarms for different objectives: finding food, escaping predators, etc. These swarms, also called boids (a special name for bird swarms), have three vital principles for their collaborative movements: "collision avoidance – separation", "velocity matching – alignment" and "flock centering – cohesion" (Dutot et al., 2010; Lungu and Sofron, 2011). Collision avoidance refers to not crashing with nearby elements of the swarm, whereas velocity matching refers to adapt velocities according to the velocities of neighboring elements. The flock centering is a result of velocity matching. Since each flock-mate tends to adapt his velocity according to his neighbors, the flock tends to stay close to each other. Generalizing it to the whole swarm, they tend to stay close to a neighborhood centre. Apart from these three principles, environmental principles such as obstacle avoidance and following a desired path are also valid (Veenhuis and Köppen, 2006).

Imitating the aforementioned principles, the Particle Swarm Optimization field has gained interest because of its applicability, simplicity, and efficiency. The algorithm is proven to be robust and effective in various types of problems from single objective to combinatorial (Léon-Javier et al., 2009).

In the PSO algorithm, each solution is presented with a particle, that is, an element of the swarm. The swarm consists of a number of particles, in other words, a population of solutions (Engelbrecht, 2003). The particles move through the search space at a random degree of freedom limited by the parameters of each other (Ciuprina et al., 2002). The moving particles have two properties, position and velocity, which are updated at every iteration of the algorithm (Castro and Tsuzuki, 2007). Each particle is intelligent in a way that it keeps the memory of best position of himself and the neighborhood, which introduces the neighborhood concept. In the ultimate condition, generally the neighborhood denotes the whole swarm (Léon-Javier et al., 2009).

Let p_i be the position of the i^{th} particle in the swarm which consists of N particles, and let each particle have n dimensions defined over a maximization objective function f. The steps of the algorithm is given below (Engelbrecht, 2006):

Step 1. Particle velocities and positions of each particle are initiated such that

$$x_{i,j} = x_{min} + r(x_{max} - x_{min}), \quad i = 1, \dots, N, j = 1, \dots, n \tag{5.1}$$

$$v_{i,j} = \alpha \frac{x_{min} + r(x_{max} - x_{min})}{\Delta t} \quad i = 1, \dots, N, \; j = 1, \dots, n \tag{5.2}$$

where x denotes the position, v denotes the velocity and α is constant in the range [0,1].

Step 2. The objective value of each particle is calculated as $f(x_i)$

Step 3. The best position for each particle and the global best position for the swarm is updated. For a problem

$$\text{If } f(x_i) < f\left(x_i^{pb}\right) \text{ then } x_i^{pb} \leftarrow x_i \tag{5.3}$$

$$\text{If } f(x_i) < f\left(x_i^{sb}\right) \text{ then } x_i^{sb} \leftarrow x_i \tag{5.4}$$

where pb denotes the particle best and sb denotes the swarm best.

Step 4. Particle velocity and particle position are updated, that is, the new velocities and positions are calculated for each particle.

$$v_{i,j} \leftarrow wv_{i,j} + c_1 r_1 \left(\frac{x_{i,j}^{pb} - x_{i,j}}{\Delta t}\right) + c_2 r_2 \left(\frac{x_{i,j}^{sb} - x_{i,j}}{\Delta t}\right), i = 1, \dots, N; \; j = 1, \dots, n \tag{5.5}$$

$$x_{i,j} \leftarrow x_{i,j} + v_{i,j}\Delta t \qquad i = 1, \dots, N \qquad j = 1, \dots, n \tag{5.6}$$

where w is the inertia rate between [0,1], and r_1 and r_2 are random numbers between [0,1]. In the velocity update formula, $v_{i,j}$ is the inertia term where the particle attempts to save its own velocity, $c_1 r_1 \left(\frac{x_{i,j}^{pb} - x_{i,j}}{\Delta t}\right)$ is the cognitive term where the particle attempts to reach at least its best position, and $c_2 r_2 \left(\frac{x_{i,j}^{sb} - x_{i,j}}{\Delta t}\right)$ is the social term where the particle attempts to keep up with the best position of the swarm.

Step 5. Step 2 is returned to until a termination criterion is satisfied. Various termination criteria include iteration number, convergence of the result, convergence of error in results, etc.

Particle Swarm Optimization algorithm provides a number of parameters to be tuned. The effects of these parameters are presented below:

The inertia coefficient - w

The inertia coefficient adapts Newton's first law of motion, that is, "if there are no forces acting on a particle the velocity will stay the same" (Mikki and Kishk, 2007). If w=0, then the velocity update formula is called selfless (Castro and Tsuzuki, 2007). A higher value of the inertia parameter indicated a higher self-confidence in the particle and a lower value indicates a high trust in personal memory and the swarm. Furthermore, a higher self-confidence signifies a better exploitation and a higher self-distrust signifies a better exploration in terms of the algorithm (Liou and Hsieh, 2009). The inertia parameter is also omitted in the earlier studies, that is, w=1 (Talbi, 2011).

Over time, various variants of the inertia parameter have been developed. These variants involve the following (Nickabadi et al., 2011):

- Constant and random inertia: The inertia parameter is selected randomly before the utilization of the algorithm, and is not changed through the iterations.
- Time varying inertia: The inertia parameter is changed through iterations. The value of the parameter is assigned a high value in the earlier phases of iterations to provide exploration and decreased through iterations to provide better exploitation. The decrease can be achieved linearly and nonlinearly.
- Adaptive inertia: The instant solution of the algorithm is monitored and inertia is adjusted according to the quality of the solution.

The cognitive coefficient – c_1

The cognitive term is an indicator of the affinity of the particle to its own success. A high cognitive coefficient yields the particle to a cyclic trajectory around its best. If c_1=0, the formula becomes memoryless in terms of cognition (Thangaraj et al., 2011).

The social component – c_2

The social term is an indicator of the affinity of the particle to the success of the whole swarm. A high social coefficient implies a greater degree of affinity. Moreover, the trajectory of the particle is defined as a resultant of both the cognitive and the social component. This resultant attempts to balance exploration and exploitation only at particle level.

5.1.2 Advanced PSO algorithms

Improvements in metaheuristics are focused to provide more robust solutions as well as to avoid local optima. It is also known that even though existing algorithms are fast and efficiently convergent, it is always possible to attain algorithms with a better efficiency and robustness. Hence, since its foundation Particle Swarm Optimization algorithm is both hybridized with other metaheuristic operators and improved with modifications. The hybridizations of various metaheuristics and modifications considered as evolutionary in the context of Particle Swarm Optimization are provided below.

5.1.2.1 Hybridizations of the algorithm

Hybridizations of other metaheuristics involve another aim apart from modified algorithms, that is, hybrid algorithms aim balancing exploration and exploitation which are conflicting objectives. Exploration ensures that all search space is covered during the utilization of the algorithm, whereas, exploitation ensures that all neighborhoods of good solutions are thoroughly analyzed. Furthermore, hybridizations are achieved using two means: utilizing the algorithms one after another or embedding the operators of one metaheuristic to the other. Both means are applied for PSO algorithm and it is most hybridized with Genetic Algorithm in order to capture the advantages and eliminate the disadvantages of both algorithms (Thangaraj et al., 2011). Gnamabal et al. (2011) utilize an elitist reproduction following the determination of particle best and swarm best procedure to ensure that the algorithm produces better solutions per iteration. Similarly, Shunmugalatta and Slochanal (2008) and El-Dib et al. (2006)use the reproduction operator and update velocity at a parental level. Guo et al. (2006) and Wu (2010) embed mutation operator to the PSO algorithm. Both crossover and mutation operators are embedded in the PSO algorithm by Lian et al (2006). All aforementioned studies provide an instance for embedded hybridization whereas Yin et al. (Yin et al., 2007) utilizes algorithms one after another where PSO is utilized the first and Hill Climbing is applied according to the results of the first algorithm.

Other hybridizations involve embedding Ant Colony Optimization sequentially (Shelokar et al., 2007) or Local Search Algorithm as a part of the PSO Algorithm (Haibing et al., 2006; Shiau, 2011). Hybridizations are also achieved with exact algorithms. Kayhan et al. (Kayhan et al., 2010) utilize a sequential hybrid PSO algorithm with Solver where Solver obtains its inputs from the PSO algorithm. Different metaheuristic hybridizations involve Tabu Search (Zhang et al., 2009), Simulated Annealing (Wang and Li, 2004), Fuzzy Pareto Optimal PSO (Niknam and Firouzi, 2009), GRASP (Y. Marinakis and Marinaki, 2010) and problem-specific heuristics (Lin et al., 2010; Sha and Hsu, 2006).

5.1.2.2 The PPPSO Algorithm

As the PSO algorithm has evolved into more complicated algorithms in order to provide efficient results and effective iterations, the algorithms remained devoted to the motion of nature. One of these algorithms is Predator-Prey PSO algorithms which is a competitive PSO approach (Engelbrecht, 2006).

Three problems faced with the classical PSO are exploration overwhelming the exploitation, being blocked by the local optima and the early convergence. The hunting scheme of nature is simulated by the introduction of a second swarm (Xian-Cheng, 2006) in order to overcome the three difficulties. If a prey swarm meets a predator swarm, they diffuse just to regroup again after the predator is gone. Diffusion provides a better exploration whereas regrouping provides a better exploitation. The steps of the Predator-Prey PSO algorithm are as follows:

Step 1. Particle velocities and positions of each particle of each swarm are initiated as given in Equations (5.1) and (5.2).

Step 2. The objective function values for each particle of both swarms are calculated.

Step 3. Particle bests, that is, x_{ij}^{pb} , are found four each particle of each swarm.

Step 4. Swarm bests, that is, x_{ij}^{sb} are found for each swarm.

Step 5. The overall best value is updated.

Step 6. Velocities are updated separately according to swarms.

For the prey swarm, the velocity update formula is determined by a uniform random number *rn* between 0 and 1. If $rn<pf$, Equation (5.7) is applied for each particle and dimension.

$$v_{i,j} \leftarrow wv_{i,j} + c_1 r_1 \left(\frac{x_{i,j}^{pb} - x_{i,j}}{\Delta t} \right) + c_2 r_2 \left(\frac{x_{i,j}^{sb} - x_{i,j}}{\Delta t} \right) + c_3 r_3 \frac{D(d)}{\Delta t} \quad \textbf{(5.7)}$$

where d is the Euclidean distance to the nearest and $D(.)$ is an exponential function of the related distance, that is, $D(\text{d})=\alpha\text{e-}^{\beta d}$.

If $rn \geq pf$, Equation **(5.3)** is applied for each particle and dimension

The velocity update formula for the predator swarm in case that rn≥pf is

For predator swarm, the velocity update formula is as in Equation (5.8):

$$v_{i,j} \leftarrow \frac{r(x_{i,j}^{sb} - x_{i,j})}{\Delta t} \quad \textbf{(5.8)}$$

where r is uniformly distributed between 0 and maximum velocity v_{max}, $x_{i,j}^{sb}$ is the swarm best of the prey swarm. It must be noticed that the predator swarm do not use best position of its own swarm but the best position prey swarm, since the predator is attracted by the prey.

Step 7. The positions are updated as in Equation (5.6)

Step 8. Step 2-7 are revisited if any finishing criterion is not reached.

The Predator-Prey PSO algorithm provides additional parameters to be tuned.

Fear probability – ***pf***

If the fear probability is assigned 0 for all prey particles, then the particles treat as an ordinary swarm given in Part 2. A higher *pf* value provides a better exploration, whereas a lower *pf* value provides a better exploitation. Hence, this parameter is assigned a high value in the beginning of the algorithm to encourage exploration and is decreased through iterations for better exploitation (Engelbrecht, 2006).

Prey coefficient – c_3

If the prey coefficient is assigned much greater than the cognitive coefficient – c_1 and the social coefficient – c_2, the prey group is expected to diverge and not to regroup which results in random search for the prey particles.

Distance coefficients – α and β

The coefficient a has the same effect as the fear probability and should be decreased over time. On the other hand, β has the counter effect of α and should be increased over time.

5.1.2.3 Biological foundations of the Foraging Search

In the food chain, animals form three groups: herbivores, omnivores and carnivores. Herbivores are animals that eat plants, carnivores are animals that eat other animals and finally omnivores are animals that eat both animals and plants. In nature, herbivores are primary consumers that are below in the food pyramid. Omnivores are in secondary consumers the middle in the food pyramid and feed on both plants and specific herbivores. Lastly, carnivores are tertiary consumers and at the top of the food pyramid and feed on specific herbivores and omnivores. This makes herbivores the final hunts, the carnivores the final hunters, and omnivores both hunters and hunts as given in Figure 5.1.

In nature, according to the transformation of energy, for a specific food chain, the number of herbivores is greater than omnivores and the number of omnivores is greater than the number of carnivores. In wild environments, the herbivore-omnivore-carnivore ratio can be 10:3:1 whereas in calm environments the ratio can be 40:10:1 (Chinsamy-Turan, 2011 ; Sulton and Anderson, 2004).Omnivores are the slowest of the food chain whereas carnivores are the fastest (Lenbury et al., 1999).

5.2 The Foraging Search Algorithm

The steps of the algorithm are presented below:

Step 1. The herbivore-omnivore-carnivore ratio is determined according to the environment

- IF the environment is harsh – wild: 10:3:1

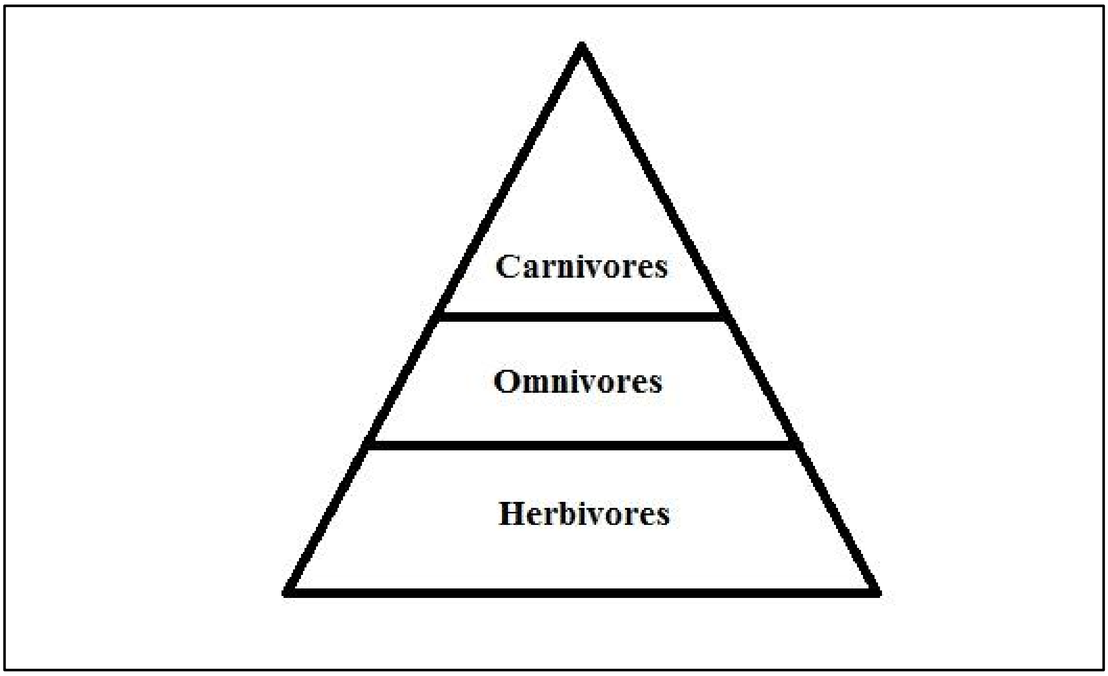

Figure 5.1: The Animal Food Chain.

- IF the environment is regular: 25:6:1
- IF the environment is calm: 40:10:1

Step 2. According to the environment swarms are initialized.

n_h: the number of herbivores

n_o: the number of omnivores

n_c: the number of carnivores

Step 3. The objective function is calculated for each particle in each swarm.

Step 4. Particle bests, that is, x_{ij}^{pb} are found four each particle of each swarm.

Step 5. Swarm bests, that isx_{ij}^{sb} found for each swarm.

Step 6. The overall best value is updated.

Step 7. The fear degrees of herbivores from omnivores (the first level hunters) and carnivores (the second level hunters) are calculated as in Equations (5.9) and (5.10)

$$p_{fho,i} = 1 - \frac{d_{fho,i}}{d_{fho}^{min}} \quad \textbf{(5.9)}$$

and

$$p_{fhc,i} = 1 - \frac{d_{fhc,i}}{d_{fhc}^{min}} \quad \textbf{(5.10)}$$

where

i=1,...,n_h

$p_{fho,i}$: fear degree from omnivores of the i^{th} herbivore (in the interval [0,1])

$p_{fhc,i}$: fear degree from carnivores of the i^{th} herbivore (in the interval [0,1])

$d_{fho,i}$: the distance of the i^{th} herbivore to the nearest omnivore

$d_{fhc,i}$: the distance of the i^{th} herbivore to the nearest canivore

d_{fho}^{min}: the minimum distance for a herbivore to fear an omnivore

d_{fhc}^{min}: the minimum distance for a herbivore to fear an carnivore

Step 8. The fear degree of omnivores from carnivores (the first level hunters) are calculated as in Equation (5.11).

$$p_{foc,i} = 1 - \frac{d_{foc,i}}{d_{foc}^{min}} \quad \textbf{(5.11)}$$

where

i = 1,…,n_o

$p_{fhc,i}$: fear degree from carnivores of the i^{th} omnivore (in the interval [0,1])

$d_{foc,i}$: the distance of the i^{th} omnivore to the nearest carnivore

d_{foc}^{min}: the minimum distance for an omnivore fear an omnivore

Step 9. For omnivores, the probability of being a hunt rather than a hunter is calculated as in Equation (5.12).

$$pp_i = \frac{dh_i}{dc_i + dh_i} \quad \textbf{(5.12)}$$

where

i=1,...,n_o

pp_i: the probability of omnivores being a hunter

dh_i: the distance of i^{th} omnivore to the nearest herbivore

do_i: the distance of i^{th} omnivore to the nearest carnivore

Step 10. The velocity update formulae are applied to each particle of each swarm, according to the swarm they belong to.

For herbivores, the velocity update formula is as in Equation (5.13)

$$v_{ij} \leftarrow \omega v_{ij} + c_1 r_{1j}\left(x_{ij}^{pb} - x_{ij}\right) + c_2 r_{2j}\left(x_{ij}^{sb} - x_{ij}\right) + p_{fho,i} c_3 r_{3j} D(d_o) + p_{fhc,i} c_4 r_{4j} D(d_c) \quad \textbf{(5.13)}$$

where

i=1,...,n_h

$v_{i,j}$: velocity of j^{th} dimension i^{th} particle of the swarm

w: the inertia coefficient

c_1 and c_2: cognitive and social coefficient

r_{1i}, r_{2i}, r_{3i}, r_{4i}: random numbers for the i^{th} particle in the interval [0,1]

x_{ij}^{pb} : the position of j^{th} dimension of personal best for the i^{th} particle of the swarm

$x_{i,j}$: the position of j^{th} dimension of the i^{th} particle of the swarm

x_j^{sb}: j^{th} dimension of the best position of the swarm

c_3: distance based coefficient of herbivores from omnivores

c_4: distance based coefficient of herbivores from carnivores

and $D(.)$ is a measure of the effect related to the distance as aforementioned before.

α and β are positive constants that define the effect of distance to velocity.

For carnivores, the velocity update formula is as given in Equation (5.14).

$$v_{i,j} \leftarrow r \cdot \left(\hat{y}_j - x_{i,j}\right) \quad \textbf{(5.14)}$$

where

i=1,...,n_c

$v_{i,j}$: velocity of j^{th} dimension of the i^{th} particle of swarm

r: random number in the interval [0,1]

$\hat{y}_j$: j^{th} dimension of the best position of the nearest hunt swarm

xi,j: the position of the j^{th} dimension of the i^{th} particle of the swarm

For omnivores, the velocity update formula is given in Equation (5.15).

$$v_{i,j} \leftarrow (1 - pp_i) \cdot \left(\omega v_{i,j} + c_1 r_{1i}\left(x_{ij}^{pb} - x_{i,j}\right) + c_2 r_{2i}\left(x_{ij}^{sb} - x_{i,j}\right) + pfoc_i c_3 r_{3i} D\left(d_{foc,i}\right)\right) + pp_i \cdot \left(r \cdot \left(\hat{y}_j - x_{i,j}\right)\right) \quad \textbf{(5.15)}$$

where

i=1,...,n_o

pp_i:: the probability of omnivores being a hunter calculated in Step 8

$v_{i,j}$: velocity of j^{th} dimension of the i^{th} particle of swarm

w: the inertia coefficient

c_1 and c_2: cognitive and social coefficient

r_{1i}, r_{2i}, r_{3i}: random numbers for the i^{th} particle in the interval [0,1]

x_{ij}^{pb} : j^{th} dimension of the personal best of the i^{th} particle of the swarm

$x_{i,j}$: the position of the j^{th} dimension of the i^{th} particle of the swarm

x_{ij}^{sb}: best position of the j^{th} dimension of the swarm

c_3: distance based coefficient of omnivores from carnivores

r: random number in the interval [0,1]

Step 11. The particle positions are updated for each particle of each swarm using Equation (5.6).

Step 12. Steps 3 and 11 are repeated until the finishing criterion is satisfied.

The newly introduced parameters are

d^{min}_{fho} **– the threshold distance of a herbivore to an omnivore**

This parameter determines the minimum closeness of an omnivore to a herbivore that the herbivore fears the omnivore.

d^{min}_{fhc} **– the threshold distance of a herbivore to a carnivore**

This parameter determines the minimum closeness of an carnivore to a herbivore that the herbivore fears the carnivore.

d^{min}_{foc} **– the threshold distance of an omnivore to a carnivore**

This parameter determines the minimum closeness of an carnivore to an omnivore that the omnivore fears the carnivore.

In the Foraging Search algorithm, the fear elements are gradual, that is, as the hunter approaches more to the hunt, the hunt fears more. In terms of the algorithm, the difference lies in the speed of exploration and exploitation. Gradual increase in these parameters provides a better balance rather than a constant value of the parameter.

5.3 The Foraging Search on Nonlinear Optimization Problems

Metaheuristic algorithms may serve as the optimization method for certain problems. There is a need for problem-specific metaheuristics as in the studies of Nearchou (Nearchou, 2004)and Tsubakinati and Evans (Tsubakitani and Evans, 1998), while, there are some metaheuristics such as the classical PSO algorithm, that can be applied in any kind of optimization problem.

Nonlinear continuous functions are considered as widely accepted benchmarking cases for new algorithms. The Foraging Search is compared with the Classical and Predator-Prey PSO algorithms according to some performance measures including the robustness of results, computer time, and number of functions utilized. At every trial, random numbers are varied in order to test the robustness and efficiency of the algorithms, which leads to different initial swarm positions and velocities for same algorithm parameters. Two benchmark problems are analyzed in this section: a two dimensional unconstrained problem and the Griewangk function of multi dimensions.

5.3.1 Two dimensional – unconstrained problem

The nonlinear, continuous, two-dimensional problem is minimizing

$$f(\vec{x}) = 100(x_2 - x_1)^2 + (1 - x_1)^2 \quad \textbf{(5.16)}$$

where $0 \leq x_1 \leq 10$ and $0 \leq x_2 \leq 10$.

The problem has a global optimum at $x_1 = 1$, $x_2 = 1$ and $f(\vec{x}) = 0$ at this optimum. For measuring success rates of algorithms, in three success levels are assigned. This assignment is considered necessary for such problems since the closeness to the number 0 is relative and arguable in mathematical terms. Success Rate 1 (SR1) is assigned as 10^{-4}, which denotes the rate out of 500 trials where the solution is equal to or smaller than 10^{-4}. The second success level, Success Rate 2 (SR2) is assigned as 10^{-7}, which denotes the rate out of 500 trials where the solution is equal to or smaller than 10^{-7}. Finally, the third success rate, Success Rate 3 (SR3) is assigned the exact solution, or 0. SR1 is determined as the standard MATLAB Package precision and also noted to be appropriate for two dimensional problems. Other success rates are determined upon the results obtained in order to reveal the distinction between different algorithm results. The results of the algorithm are provided in Table 5.1 and Figure 5.2:

Table 5.1: Results of the 2-dimensional unconstrained problem.

Performance Measure	Classical PSO	Predator – Prey PSO	The Foraging Search
Mean of 500 trials	0.1144	4.3219×10^{-6}	1.5096×10^{-8}
Standard deviation of 500 trials	0.2325	6.7716×10^{-5}	2.7201×10^{-8}
Minimum of 500 trials	1.0454×10^{-7}	4.7293×10^{-22}	0
Maximum of 500 trials	1.3707	0.0150	9.9149×10^{-8}
Mean CPU time of 500 trials (seconds)	1.5018	16.9321	12.4584
Mean number of functions	4454.51	32054.86	9515.40
SR1 (%)	17.40	99.60	100.00
SR2 (%)	00.00	84.20	100.00
SR3 (%)	00.00	00.00	57.60
Mean of 500 trials	0.1144	4.3219×10^{-6}	1.5096×10^{-8}

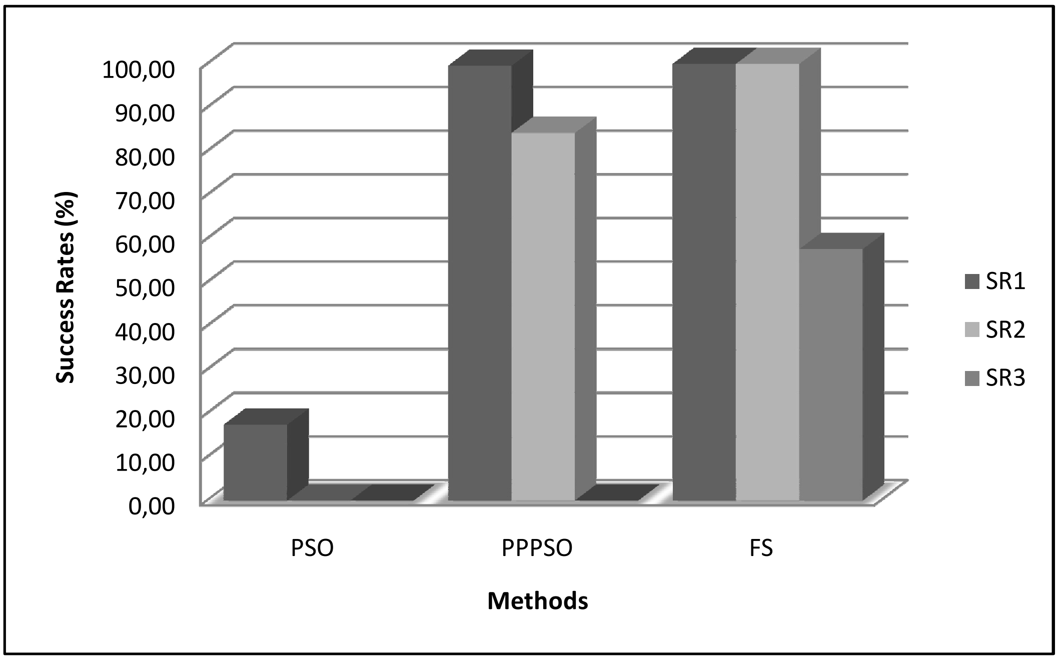

Figure 5.2: Success rates for the unconstrained problem with two variables.

Comparing the Predator Prey PSO and the Foraging Search, it is obtained that in all criteria, the Foraging Search algorithm has produced better results and dominates the Predator Prey PSO algorithm. In terms of mean number of functions, it is observed that the Predator Prey PSO algorithm uses significantly big number of functions, meaning more number of iterations, than the Foraging Search.

5.3.2 Two dimensional – constrained problem

In this section, the nonlinear, continuous, two-dimensional problem is given as

$$f(\vec{x}) = (x_1^2 - x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2 \qquad \textbf{(5.17)}$$

st

$$4.89 - x_1 - (x_2 - 2.5)^2 \geq 0 \qquad \textbf{(5.18)}$$

$$x_1^2 + (x_2 - 2.5)^2 - 4.84 \geq 0 \qquad \textbf{(5.19)}$$

where $0 \leq x_1 \leq 6$ and $0 \leq x_2 \leq 6$.

The problem has a global optimum at $x_1 = 3$, $x_2 = 2$ and $f(\vec{x}) = 0$. Considering the results obtained from the algorithms, the success levels are remained the same with the previous problem. The results are provided in Table 5.2 and the success rates are modeled in Figure 5.3.

For the constrained problem, the Foraging Search dominates other benchmark algorithms almost in every criterion. The only criterion that the Foraging Search

Table 5.2: Results of the 2-dimensional unconstrained problem.

Performance Measure	Classical PSO	Predator – Prey PSO	The Foraging Search
Mean of 500 trials	7.8546×10^{-6}	5.9888×10^{-5}	5.3660×10^{-7}
Standard deviation of 500 trials	1.5684×10^{-5}	5.9300×10^{-4}	8.8512×10^{-7}
Minimum of 500 trials	4.5214×10^{-9}	4.5500×10^{-23}	0
Maximum of 500 trials	1.7753×10^{-4}	0.0059	7.6515×10^{-6}
Mean CPU time of 500 trials (seconds)	1.8154	6.1833	2.7763
Mean number of functions	5476.00	5385.80	3327.50
SR1 (%)	99.00	99.00	100.00
SR2 (%)	04.40	09.00	39.40
SR3 (%)	00.00	00.00	14.80

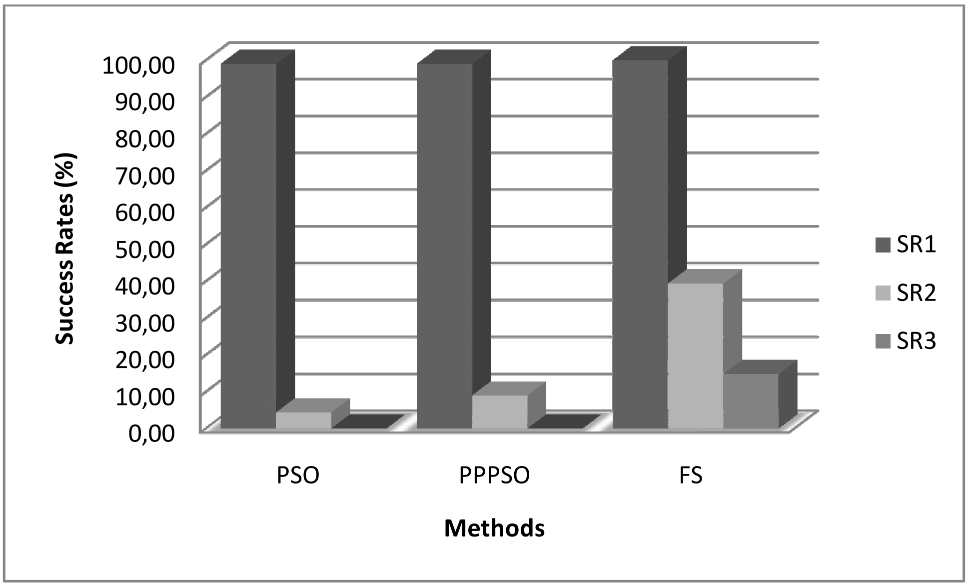

Figure 5.3: Success rates for the constrained problem with two variables.

algorithm is not dominated is computational time. However, the results of the classical PSO algorithm are not compensatory in term of trial results.

5.3.3 The Griewangk function

The Griewangk Function is generalized as

$$f_{GR}(\vec{x}) = \sum_{i=1}^{d} \frac{x_i^2}{4000} - \prod_{i=1}^{d} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \qquad \textbf{(5.20)}$$

where $-511 \le x_i \le 512$ for all i. In this study, this function is benchmarked for $d = 5$, 10, 20, 50 and 100. The function has a global minimum at $x_i = 0$ for all i and $f(\vec{x}) = 0$ at the optimum.

5.3.3.1 The case where $d = 5$

Results obtained for this or larger values of d indicate that the exact solution is not achieved by all three algorithms. However, according to the range of solutions, four success levels are attained regarding to the comparison of the algorithms. Success Rate 1 (SR1) is assigned as 10, which denotes the rate out of 500 trials where the solution is equal to or smaller than 10. The second success level, Success Rate 2 (SR2) is assigned as 5, which denotes the rate out of 500 trials where the solution is equal to or smaller than 5. Finally, the third success rate, Success Rate 3 (SR3) is assigned 1, where the rate of results are equal to or smaller than 1. The results are given in Table 5.3 and the success rates are modeled in Figure 5.4.

Table 5.3: Results of the Griewangk function for $d = 5$.

Performance Measure	Classical PSO	Predator – Prey PSO	The Foraging Search
Mean of 500 trials	21.6020	0.9303	0.9189
Standard deviation of 500 trials	35.2344	0.0132	0.0063
Minimum of 500 trials	0.0019	0.9087	0.9087
Maximum of 500 trials	320.4325	0.9823	0.9431
Mean CPU time of 500 trials (seconds)	3.9652	16.3842	22.8372
Mean number of functions	4664.32	14644.64	13653.00
SR1 (%)	51.20	100.00	100.00
SR2 (%)	34.40	100.00	100.00
SR3 (%)	11.20	100.00	100.00
Mean of 500 trials	21.6020	0.9303	0.9189

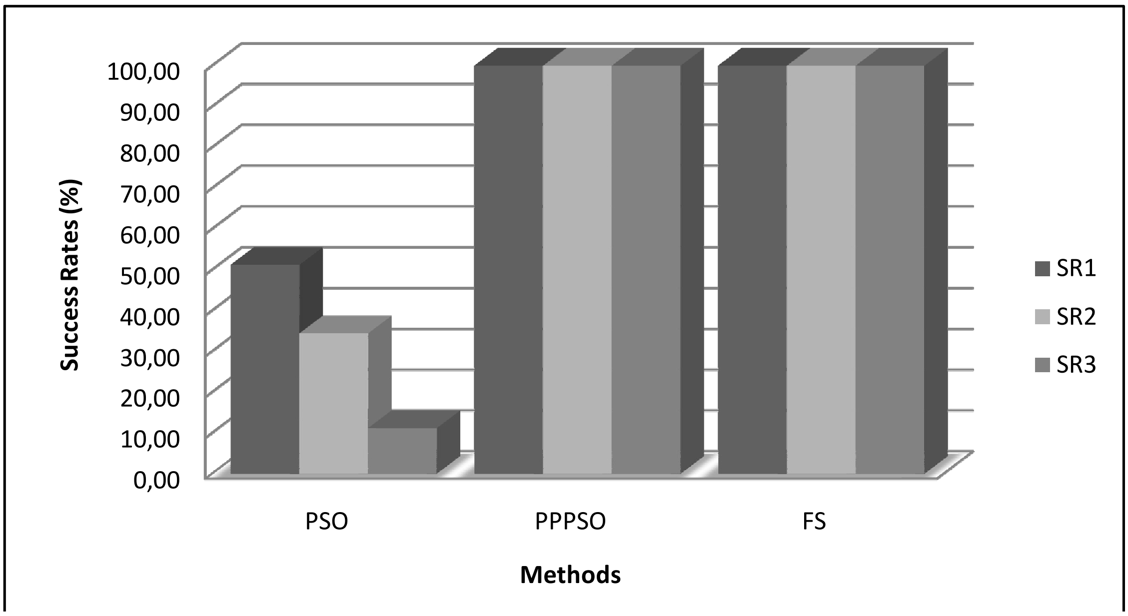

Figure 5.4: Success rates for Griewangk function with d = 5.

According to the results, the Classical PSO Algorithm has a very wide range of solutions. Out of 500 trials, 4 of them are better (smaller) than the other algorithm results. However, 96% of the results are worse than the other two algorithms and cannot be considered compensatory at a great extent.

The comparison between Predator Prey PSO and the Foraging Search results indicate that the Foraging Search produces slightly better results with less number of functions. A simple hypothesis testing under the assumptions for the true variances are not known and are not equal and the mass distributes normally, where H0 = $\mu_{PPPSO} \leq \mu_{FS}$ and H1 = $\mu_{PPPSO} > \mu_{FS}$ yields a z value of 12.26, implies that H0 hypothesis to be rejected. Hence, under given assumptions, at 99% significance level, significant evidence has been found on that Predator Prey PSO solution values are greater than the Foraging Search Solutions.

5.3.3.2 The case where *d* = 10

The exact solution is not achieved by all three algorithms. However, according to the range of solutions, four success levels are attained. Success Rate 1 (SR1) is assigned as 3, which denotes the rate out of 500 trials where the solution is equal to or smaller than 3. The second success level, Success Rate 2 (SR2) is assigned as 2, which denotes the rate out of 500 trials where the solution is equal to or smaller than 1. Finally, the third success rate, Success Rate 3 (SR3) is assigned 1, where the rate of results are equal to or smaller than 1. The results are presented in Table 5.4 and the success rates are presented in Figure 5.5.

Table 5.4: Results of the Griewangk function for d = 10.

Performance Measure	Classical PSO	Predator – Prey PSO	The Foraging Search
Mean of 500 trials	1.0970	0.9995	0.9995
Standard deviation of 500 trials	0.2036	7.0806×10^{-5}	4.5988×10^{-6}
Minimum of 500 trials	1.0079	0.9995	0.9995
Maximum of 500 trials	3.3157	0.9995	0.9995
Mean CPU time of 500 trials (seconds)	32.4974	74.8790	119.4104
Mean number of functions	5123.30	24853.34	19212.40
SR1 (%)	99.60	100.00	100.00
SR2 (%)	99.00	100.00	100.00
SR3 (%)	00.00	100.00	100.00

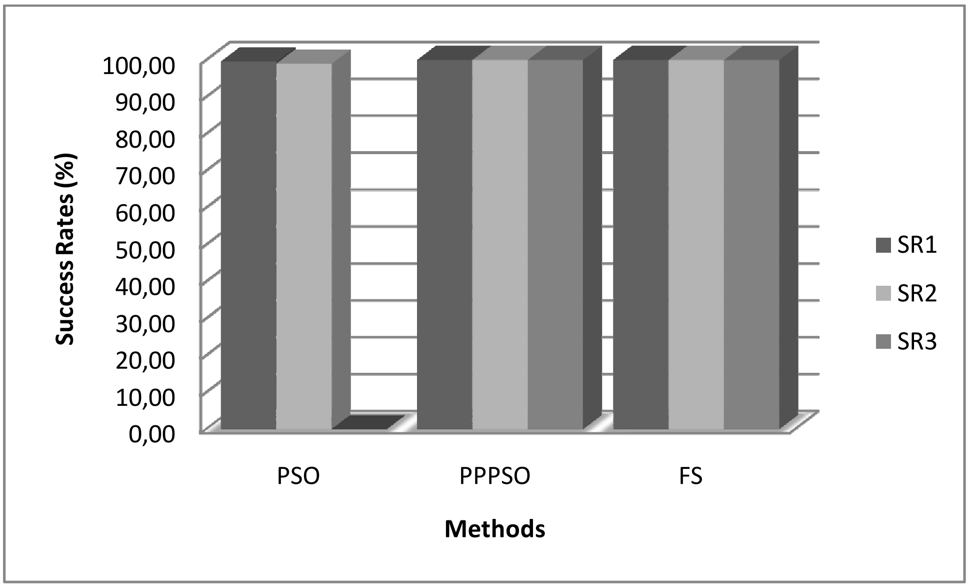

Figure 5.5: Success rates for Griewangk function with *d* = 10.

As in *d* = 5 case, the results of Classical PSO algorithm have a large variation compared to the other two algorithms, followed by a higher mean trial result. However, PPPSO and The Foraging Search have almost identical results for d =10 whereas the Foraging Search requires less number of functions, yet a higher CPU-time.

5.3.3.3 The case where *d* = 20

The exact solution is not achieved by all three algorithms. However, according to the range of solutions, four success levels are attained. Success Rate 1 (SR1) is assigned as 20, which denotes the rate out of 500 trials where the solution is equal to or smaller than 20. The second success level, Success Rate 2 (SR2) is assigned as 10, which denotes the rate out of 500 trials where the solution is smaller than equal to or 10. Finally, the third success rate, Success Rate 3 (SR3) is assigned 5, where the rate of results are equal to or smaller than 5. Finally, the last success level (SR4) is assigned 1, where the rate of results are equal to or smaller than 1. The results are presented in Table 5.5 and the success rates are presented in Figure 5.6

Table 5.5: Results of the Griewangk function for $d = 20$.

Performance Measure	Classical PSO	Predator – Prey PSO	The Foraging Search
Mean of 500 trials	3.9603	10.7054	1.0196
Standard deviation of 500 trials	2.5965	3.8943	0.0697
Minimum of 500 trials	1.8122	2.9039	1.0000
Maximum of 500 trials	27.5322	25.4187	1.3550
Mean CPU time of 500 trials (seconds)	17.9161	92.6173	100.9847
Mean number of functions	5214.00	20842.00	9210.97
SR1 (%)	99.40	97.80	100.00
SR2 (%)	97.00	47.60	100.00
SR3 (%)	82.80	04.20	100.00

.

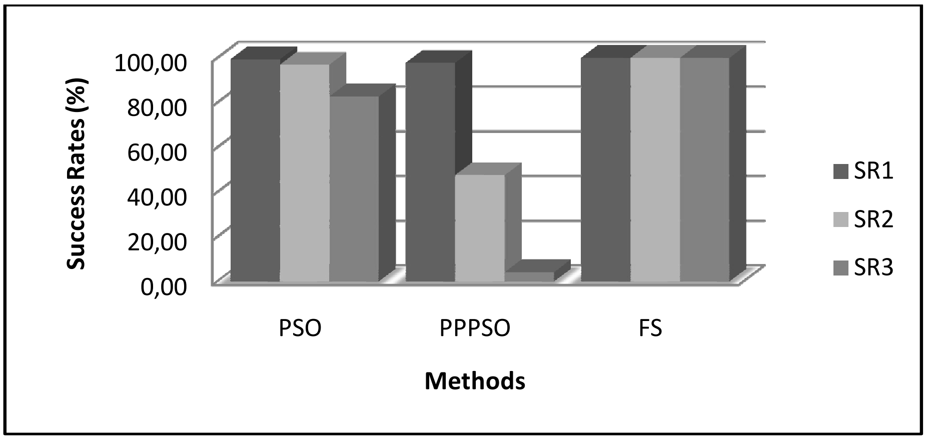

Figure 5.6: Success rates for Griewangk function with $d = 20$.

In case of $d = 20$, Classical PSO and PPPSO algorithm both have larger means and variations than the Foraging Search. Surprisingly, PPPSO results are worse than the Classical PSO algorithm in terms of all aspects: mean result of trials, time and number of function. On the other hand, the Foraging Search has produced better results in terms of trial means, minimums and maximums. However, the computational time is higher than other algorithms. Yet, the mean number of functions is smaller than of PPPSO, which indicates that the Foraging Search is a faster and more convergent algorithm in terms of number of iterations.

5.3.3.4 The case where *d* = 50

The exact solution is not achieved by all three algorithms. However, according to the range of solutions, four success levels are attained. Success Rate 1 (SR1) is assigned as 100, which denotes the rate out of 100 trials where the solution is equal to or smaller than 100. The second success level, Success Rate 2 (SR2) is assigned as 50, which denotes the rate out of 100 trials where the solution is equal to or smaller than 50. Finally, the third success rate, Success Rate 3 (SR3) is assigned 20, where the rate of results are equal to or smaller than 20. Finally, the last success level (SR4) is assigned 10, where the rate of results are equal to or smaller than 10. The results are presented in Table 5.6 and the success rates are presented in Figure 5.7.

The most intriguing result of the case d = 20, is lower mean number of functions. Both PSO and Foraging Search have achieved to converge efficiently. On the other

hand, in terms of trial results, PPPSO has produced a large varying range of results. The minimum result is 1.000 which is much smaller than the result of the other

Table 5.6: Results of the Griewangk function for $d = 50$.

Performance Measure	Classical PSO	Predator – Prey PSO	The Foraging Search
Mean of 500 trials	35.0194	60.4527	20.1454
Standard deviation of 500 trials	7.6343	84.2984	3.4620
Minimum of 500 trials	21.7161	1.0000	13.4593
Maximum of 500 trials	57.316	226.4399	27.3599
Mean CPU time of 500 trials (seconds)	9.3926	222.8563	51.8788
Mean number of functions	681.00	26251.40	2843.00
SR1 (%)	100.00	66.00	100.00
SR2 (%)	95.00	66.00	100.00
SR3 (%)	00.00	66.00	56.00
SR4 (%)	00.00	66.00	00.00

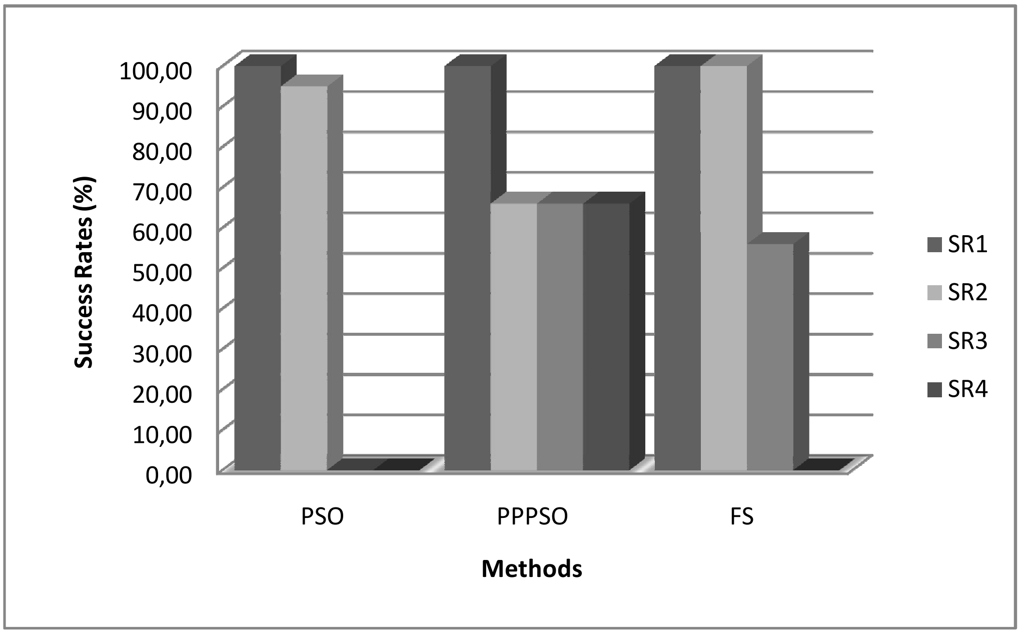

Figure 5.7: Success rates for Griewangk function with d = 50.

algorithms, but, the maximum and the mean of trial results with large variations are not compensatory by the minimum result. The best results are provided the Foraging Search, with a penalty in computation time which is also favored compared to PPPSO. Again, the mean number of functions, indirectly indicating necessary number of iterations for convergence, the Particle Prey PSO utilizes much more iterations than the Foraging Search.

5.3.3.5 The case where *d* = 100

The exact solution is not achieved by all three algorithms. However, according to the range of solutions, four success levels are attained. Success Rate 1 (SR1) is assigned as 100, which denotes the rate out of 100 trials where the solution is equal to or smaller than 100. The second success level, Success Rate 2 (SR2) is assigned the rate out of 100 trials, where the solution is equal to or smaller than 80%. Finally, the third success rate, Success Rate 3 (SR3) is assigned 60, where the rate of results are equal to or smaller than 60. Finally, the last success level (SR4) is assigned 50, where the rate of results are equal to or smaller than 50. The results are presented in Table 5.7 and the success rates are presented in Figure 5.8.

Table 5.7: Results of the Griewangk function for d = 100.

Performance Measure	Classical PSO	Predator – Prey PSO	The Foraging Search
Mean of 500 trials	106.7919	68.9474	63.0681
Standard deviation of 500 trials	13.9043	9.3685	8.6069
Minimum of 500 trials	79.9879	48.7990	48.1292
Maximum of 500 trials	140.8094	88.7055	84.0837
Mean CPU time of 500 trials (seconds)	12.0473	158.5205	95.9338
Mean number of functions	681.00	9835.6	2843.00
SR1 (%)	37.00	100.00	100.00
SR2 (%)	01.00	84.00	93.00
SR3 (%)	00.00	18.00	34.00
SR4 (%)	00.00	02.00	02.00

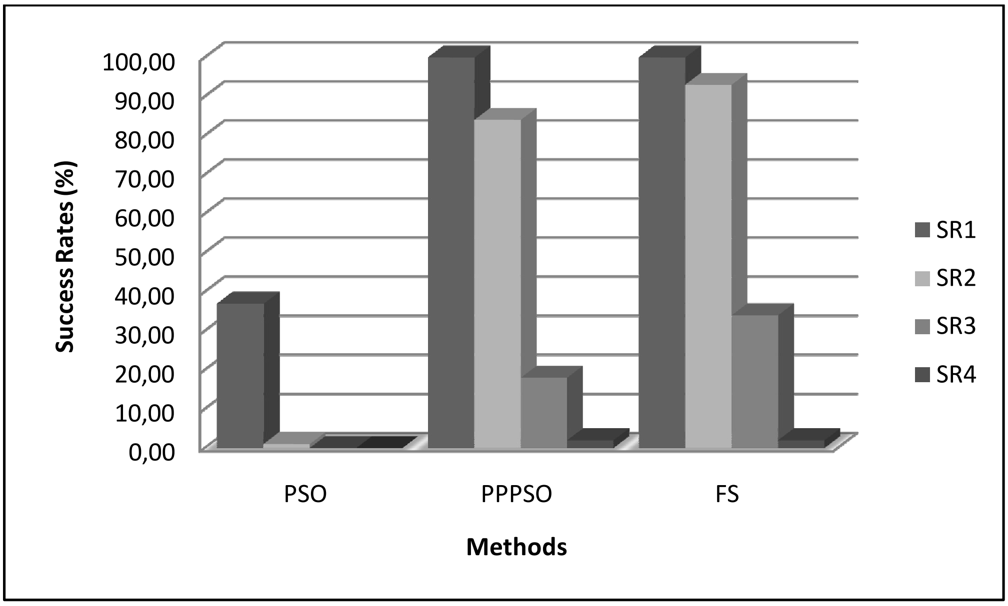

Figure 5.8: Success rates for Griewangk function with $d = 100$.

For the case d = 100, the classical PSO algorithm has produced less successful result compared to the other two algorithms. On the other hand, in terms of computational time and mean number of functions, the least successful outcomes belong to Predator Prey PSO algorithm. According to the trial results and success rates, for case d = 100, the most successful and efficiently convergent algorithm is the Foraging Search.

5.4 The Foraging Search on Clustering Problems

5.4.1 The clustering algorithm

As in the K-Means algorithm or other Search Based Algorithms, the Foraging Search requires a predetermined number of clusters. Each particle in the Foraging Search Clustering algorithm is represented by $k*d$ cluster centers where k is the number of clusters and d is the number of dimensions of the data points to be clustered. Likely, the velocity and speed updates are applied in order to locate optimum cluster centers. The steps of the Foraging Search algorithm for clustering are given below:

Step 1. The environment is defined as either calm or regular or wild.

Step 2. The herbivore:omnivore:carnivore (n_h:n_o:n_c) ratio is determined as aforementioned in Step 2 of the Foraging Search Algorithm.

Step 3. Each particle is randomly initiated for each swarm, each particle is assigned *random* $k*d$ cluster centers where k is the number of clusters and d is the dimension of data points. The particles are denoted by x_{ijm}, that is the m^{th} dimension of the j^{th}

cluster of the i^{th} particle where $i = 1, \ldots n_h \vee n_o \vee n_c$, $j = 1, \ldots, k$, $m = 1, \ldots, d$. The only constraint of clustering is that each data point should be assigned to a cluster. This constraint is achieved organically by the structure of the particles, leaving the algorithm without constraints.

Step 4. Data points are assigned to clusters using a distance metric (e.g. Euclidean distance, Mahalanobis distance, etc...).

Step 5. The quality of the clustering is measured by an objective function. The aim of clustering is building small clusters as far as possible from each other. Consequently, the objective function may involve within cluster distances, among cluster distances or a combination of both measures.

Step 6. The best objective value and position for all particles, or particle bests, are determined for each particle in each swarm.

Step 7. The best objective value and position, or swarm bests are determined for each swarm.

Step 8. The best objective value and position of all swarms, or the global best is determined.

Step 9. The fear coefficients for herbivores are calculated as aforementioned in the Equations **(5.9)** and **(5.10)**.

Step 10. The fear coefficients for omnivores are calculated as aforementioned in the Equation **(5.11).**

Step 11. The probability of being a hunt for omnivores is calculated as aforementioned in the Equation **(5.12).**

Step 12. The velocities (v_{ijk}) of each particle are updated according to their swarms using Equations **(5.13)**, **(5.14)** and **(5.15)**.

Step 13. The particle positions for each particle in each swarm are updated using Equation **(5.16)**.

Step 14. Steps 5-13 are revisited until the finishing criterion is satisfied.

5.4.2 Benchmark with other algorithms

5.4.2.1 Specifications of datasets

In this section, the Foraging Search algorithm is benchmarked with the first classical PSO Clustering algorithm applied by Chen and Ye (2004) and Predator -Prey PSO clustering applied by Jang et al. (2007). PSO Clustering, Predator -Prey PSO and Foraging Search algorithms require an objective function for clustering data points such as intra-cluster or inter-cluster distances. The main objective of clustering is grouping similar data, which signifies that within-cluster centers should be minimized while among-cluster distances should be maximized (Aboyni and Feil., 2000).

Three clustering problems that are used for benchmarking in this study are obtained through the database of UCI Machine Learning Repository.

The algorithms are applied to datasets with relatively small, medium and large number of data points in order to test and observe the performances of algorithms for all sized problems. The first dataset contains relatively small number of data points with relatively large number of attributes. The second dataset contains medium number of data with relatively low number of attributes. Lastly, the third data set contains relatively large amount of data with relatively medium amount of attributes.

The first clustering problem dataset represents the movements in Brazilian Sign Language and is suggested for clustering. The dataset contains 45 data points both integer and real valued with respect to 90 attributes. The resource of the dataset is claimed to be received from Dias et al. (2009).

The second clustering problem dataset represents the sources and specification faults in an urban waste water treatment plant and is suggested for clustering. The dataset contains a total of 527 both integer and real values with respect to 38 attributes. The resource of the data set is claimed to be obtained from Bejar and Cortés (1993).

The third clustering dataset contains data of 1990 Census of the US and is suggested for clustering. The dataset contains a total of 2523 integer and real values with respect to 63 attributes. The resource of the data set is claimed to be obtained from Chen et al. (2001).

The data in the datasets are cleaned, normalized and noises were eliminated before being fed into the three clustering algorithms. In this way, the data are prepared for clustering.

5.4.2.2 Application results

As aforementioned, the aim of clustering is to construct small clusters with a long distance in between. Thus, the performance of the clustering is measured using the 8 criteria described below:

1. Average within cluster distance(av_within)
2. Maximum within cluster distance (max_within)
3. Average inter-cluster distance using cluster centers (av_interc)
4. Minimum inter-cluster distance using cluster centers (min_interc)
5. Average inter-cluster distance using all data points (av_intere)
6. Minimum inter-cluster distance using all data points (min_intere)
7. Average number of functions used by the algorithm (no_func)
8. Cpu-time of the implementation of the algorithm (cputime)

Average within cluster distance, maximum within cluster distance, average number of functions used by the algorithm and cpu-time of the implementation of the algorithm are cost measures, that is, the lower values are better. On the other hand, average inter-cluster distance using cluster centers, minimum inter-cluster distance using cluster centers, average inter-cluster distance using all data points and Minimum inter-cluster distance using all data points criteria are benefit measures, that is, the higher values are better.

Table 5.8: Results of the algorithm for the first clustering dataset.

Method	Optimum number of clusters	Av_ within	Max_ within	Av_ interc	Min_ interc	Av_ intere	Min_ intere	No_ func	cputime
PSO	6	2.273	**4.905**	4.303	1.236	**4.977**	0.329	6400	**16.534**
PPPSO	5	3.084	6.698	2.826	**1.495**	4.292	0.357	420	96.100
FS	7	**2.174**	6.631	**4.490**	1.359	4.702	**0.731**	**166**	26.109

Each of the algorithms are run 40 times with different parameter combinations and best results are extracted. Total swarm sizes are held almost equal, since swarm sizes have a negative effect on number of functions and cpu time attributes. The results for the first, second and third datasets with the optimum number of clusters are given

Table 5.9: Results of the algorithm for the second clustering dataset.

Method	Optimum number of clusters	Av_ within	Max_ within	Av_ interc	Min_ interc	Av_ intere	Min_ intere	No_ func	cputime
PSO	27	0.667	**2.669**	0.744	**0.221**	1.003	**0.326**	210	36.279
PPPSO	29	0.538	2.742	0.930	0.163	1.003	0.292	420	378.28
FS	24	**0.494**	2.742	**1.07**	0.180	**1.036**	0.275	**588**	**29.671**

Table 5.10: Results of the algorithm for the third clustering dataset.

Method	Optimum number of clusters	Av_ within	Max_ within	Av_ interc	Min_ interc	Av_ intere	Min_ intere	No_ func	cputime
PSO	203	1.264	**4.025**	3.047	**0.879**	2.707	0.009	2100	2365.80
PPPSO	202	1.101	3.815	**3.091**	0.794	2.880	**0.201**	4200	7756.81
FS	209	**1.073**	3.885	3.047	0.853	**3.079**	0.140	**1344**	**1922.04**

respectively in Tables 5.8, 5.9 and 5.10. The best values for each performance measure are denoted with bold numbers.

In terms of almost all performance measures, Predator-Prey Particle Swarm Optimization provides the worst values of the clustering problems. The majority of the best results are generated by the Foraging Search Algorithm. The proposed algorithm also produced the next best results whenever it has not produced the best results. The classical Particle Swarm Optimization algorithm has also produced successful results and is a close second to the Foraging Search Algorithm.

6. MODELING OF THE PROBLEM

The modeling of the problem involves the synergy, innovation capacity and risk indices, whose ranges are [-1, 1]. All of these indices are cluster-wise, they change from one collaboration cluster to another. Both synergy and innovation/risk criteria have been immense in number with a high computational expensiveness. However, the FCMs have not eliminated most of the criteria yet, have provided a small amount of contribution for the computations. In this section, the objective function for the model is constructed and explained.

6.1 The Utilization of the Synergy Index

The synergy index has been derived with an analogy to the reliability theory. It is a well known fact that synergy has an exponential effect on biological and physical systems (Barreiros et al., 2008; Owusu-Mensha et al., 2011; Sadilek et al., 2012). In industrial systems, this effect has been merely analyzed in literature (Charles, 2006; Katz, 1984; Sekerka et al., 2005). This phenomenon is utilized as the exponential effect of the synergy in the SME collaboration model, which is formulated as $e^{\mathfrak{s}}$ where $\mathfrak{s}$ is the synergy index. Since the range of the synergy index is [-1, 1], the range of the synergy effect becomes $[e^{-1}, e]$. Furthermore, the analogy states that the SMEs within a cluster act as a series system, that is, if one SME fails the collaboration has to be reconstructed in order to make it work. On the other hand, inter cluster system can be considered as a parallel system, that is, all clusters work independent of each other.

The case of no collaboration where none of the firms collaborate with each other, can be considered as a collaboration clusters where one firm exists in each cluster, which gives a synergy index of 0. Hence, the effect of synergy becomes $e^0 = 1$ for each firm, which means the strength of each firm equals to its own strength. Hence, it is plausible that for any innovation or other types of collaborations to be favorable, the synergy among a collaboration cluster should be equal to or greater than 1, since the aim of the collaborating is creating positive synergy among partners.

6.2 The Utilization of the Innovation Capacity and Risk Indices

The aim of innovation collaborations is maximizing the innovation capacity among firms while minimizing the innovation risk. Maximizing the innovation capacity, which is denoted by $\mathfrak{i}$ and minimizing the risk which is denoted by ρ, can be modeled as maximizing the ratio of innovation capacity index to the risk index ($\mathfrak{i}/\rho$). If the risk of the collaboration is greater than its contribution, then the collaboration is not worth forming, hence for a collaboration to be favorable, this ratio should be equal to or greater than 1. One obstacle in calculating this ratio is the ranges of the indices, which are [-1,1]. The most favored case is when the innovation capacity index is highly positive and the risk index is highly negative, which yields to a negative solution. Innovation and risk indices stem from the same characteristics; hence, it is inconvenient to split these two indices into a multi-objective form.

In order to overcome this problem, the ranges of the innovation capacity and risk indices are normalized using linear normalization, and the range is decreased to [0,1] for both indices, in a way that preserves ordinal preference ratio among collaborations. For example, collaboration is regarded as favorable if the innovation index is 0.7 and the risk index is -0.6. Yet, in this case the $\mathfrak{i}/\rho$ = 0.7/-0.6 = -0.167. In order to avoid this misinterpretation, the numbers are normalized to the range of [0,1] by first adding 1 and next dividing by 2. Hence, the innovation capacity, that is 0.7, is normalized as (0.7+1) / 2 = 0.85, and the risk index, that is -0.6, is normalized as (-0.6+1) / 2 = 0.2. Hence, the $\mathfrak{i}/\rho$ ratio becomes 0.85/0.2 = 4.25.

It has been aforementioned that the collaboration is not worth forming, hence for a collaboration to be favorable, $\mathfrak{i}/\rho$ ratio should be equal to or greater than 1 and maximized. $\mathfrak{i}/\rho$ ratio always has a positive value since both the nominator and the denominator is always positive.

6.3 The Objective Function

6.3.1 The synergized innovation capacity with risk

Given that for a collaboration to be favorable, both $e^{\mathfrak{s}}$ and $\mathfrak{i}/\rho$ should be equal to or greater than one. Moreover, these values are both positive. Hence, it is plausible that for a collaboration to be favorable $e^{\mathfrak{s}} \cdot \mathfrak{i}/\rho$ should be equal to or greater than 1. The term denoted by $e^{\mathfrak{s}} \cdot \mathfrak{i}$ is called synergized innovation capacity and refers to the increased innovation capacity rate contributed by the synergy of the collaboration. The effect of synergy in innovation capacity can be analyzed three-fold:

- Where $i/\rho < 1$(the case where the collaboration should not be made)
- Where $i/\rho = 1$ (the case where collaboration does not make a difference)
- Where $i/\rho > 1$ (the case where the collaboration should be made)

6.3.1.1 The case Where $i/\rho < 1$

In cases where the maximum innovation capacity that can be obtained is less than the risk involved in collaboration, the collaboration is not worth operating. On the other hand, the exponential synergy index multiplier has an increasing effect on the i/ρ ratio. In that case, synergy may have a positive effect on the increasing the innovation capacity. It also may help overcoming the collaboration risks. Nonetheless, the decision of collaboration depends how much the ratio is less than 1. For example, if $i = 0.49$ and $\rho = 0.51$ then the i/ρ ratio is 0.96 and even a small synergy effect would trigger the collaboration between two firms. Yet, if $i = 0.1$ and $\rho = 1$, then the $i/\rho = 0.1$ and even with the strongest synergy affect, there is no probability for a good collaboration. The two scenarios can be seen Figure 6.1:

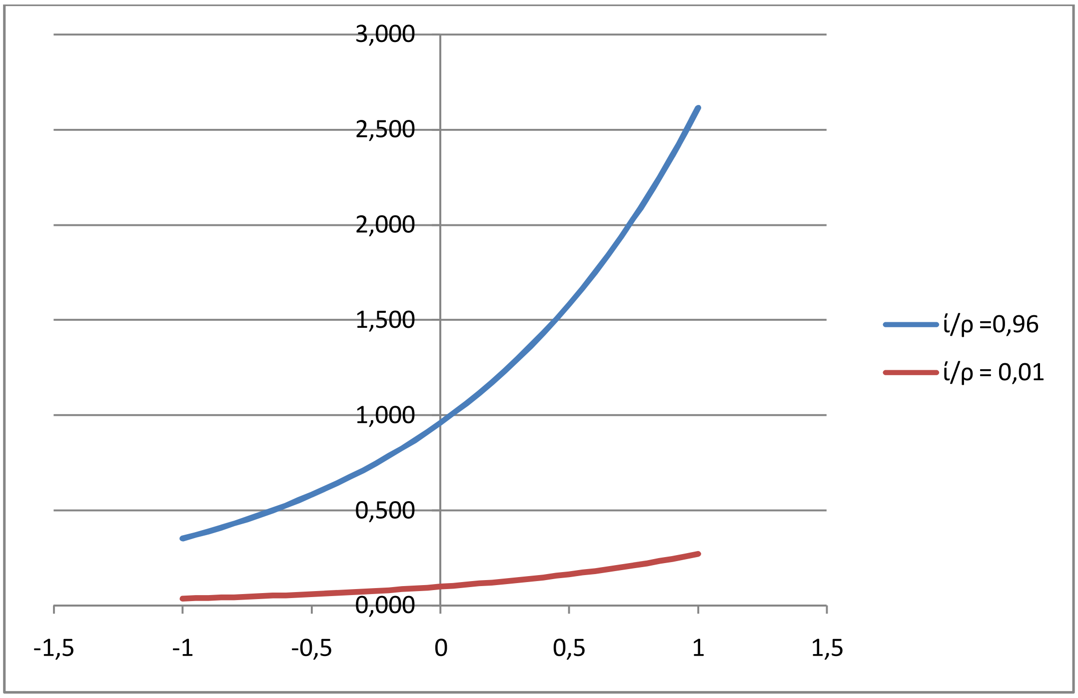

Figure 6.1: The synergy effect where $i/\rho < 1$.

6.3.1.2 The case Where *í/ρ* = 1,

In cases where maximum innovation capacity that can be obtained has the same level of risk involved in collaboration, the decision solely depends on the synergy among the firms in collaboration. If the synergy between the firms is negative, then there is a high probability that innovation capacity objective will not be achieved. On the other hand, if synergy among these firms is positive then the innovation capacity objective will be achieved with a high probability.

In cases where the maximum innovation capacity that can be obtained is less than the risk involved in collaboration, the collaboration is worth operating. However, if there

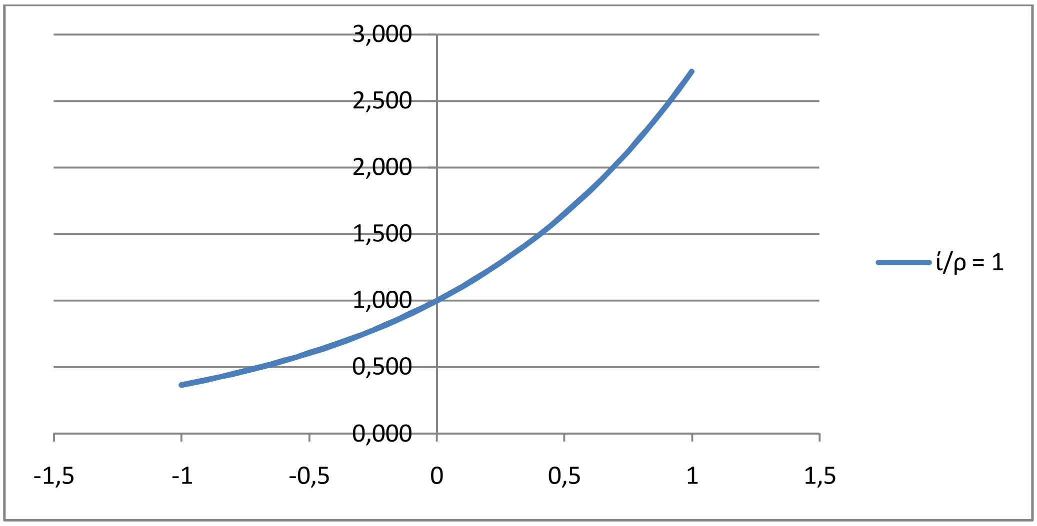

Figure 6.2: The synergy effect where *í/ρ* = 1.

6.3.1.3 The case Where *í/ρ* > 1

exists a negative synergy among collaboration, then the gain from collaboration could be diverted and the collaboration becomes no longer to be operated. Besides, the decision of collaboration depends how much the ratio is more than 1. For example, if $í = 0.51$ and $\rho = 0.49$, then $í/\rho = 1.04$ and a small negative synergy effect is likely to demolish the collaboration. Yet, if $í = 1$ and $\rho = 0.1$, hence $í/\rho = 10$, then any negative synergy among collaborating firms would never cause a decision change. As can be seen from Figure 6.3, a minor negative synergy effect could change the collaboration decision. With this objective function, if the *í/ρ* ratio is greater than *e*, the collaboration decision does not change according to the synergy index.

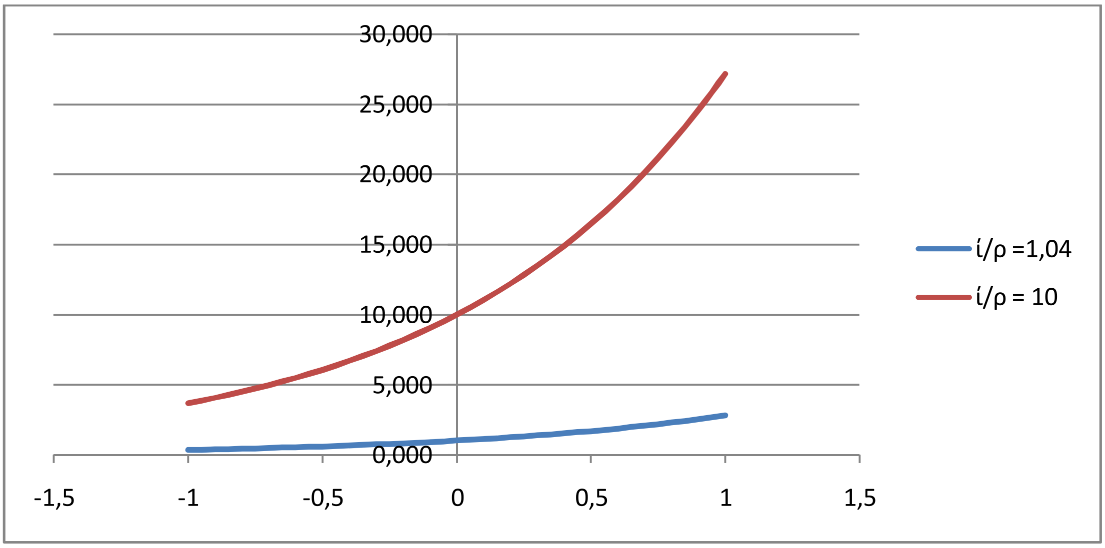

Figure 6.3: The synergy effect where $i/\rho > 1$.

6.3.2 The overall objective function

The synergized innovation capacity index and the risk index are the two components of the overall objective function which are calculated for each collaboration cluster. Yet, the aim of this dissertation is to optimize all collaboration clusters, that is, maximizing the synergized innovation capacity and minimizing the risk. In that manner, collaboration should be favorable for all collaboration clusters, which signifies that for all collaboration clusters the $e^{s} \cdot i/\rho$ should be equal to or greater than 1. If for any collaboration cluster, $e^{s} \cdot i/\rho$ is less than 1, then the collaboration is not stable and all firms act by themselves for innovation. This yields that the minimum of all $e^{s} \cdot i/\rho$ should be at least 1 for a collaboration to be stable and favorable. In addition, $e^{s} \cdot i/\rho$ value should be maximized. Given these, the objective function is

$$\max \quad \left(\min_{c} e^{s_c} \cdot i_c/\rho_c\right) \qquad \textbf{(6.1)}$$

where $c = 1, \ldots, k$ and k is the number of clusters. If the minimum of all $e^{s} \cdot i/\rho$ values are greater than 1, then all collaboration clusters are stable and all collaborations are favorable.

Since a cluster ,denoted by the index c above, is a set of firms, the mathematical model of the problem should involve sets and elements of the sets which are firms. The decision of the mathematical model is to assign firms to clusters (sets) which yield to decision variables

$$x_{b,c} = \begin{cases} 1 & if\ firm\ b\ is\ an\ element\ of\ cluster\ c \\ 0 & otherwise \end{cases} \quad \textbf{(6.2)}$$

It can easily be observed that cluster (set) values are dependent of the elements involved in itself. Hence, rewriting the objective function in **(6.1)**, **(6.3)** is obtained:

$$\max_{X} \quad \left(\min_{c(X)} e^{\text{s}_{c(X)}} \cdot \text{i}_{\text{c(X)}} / \rho_{c(X)} \right) \quad \textbf{(6.3)}$$

As a constraint, each firm should belong to a cluster, which is shown in Equation **(6.4)**.

$$\sum_{c=1}^{k} x_{b,c} = 1 \qquad \text{for all } b, \qquad b = 1, \ldots., n_f \quad \textbf{(6.4)}$$

where n_f is the number of firms.

The minimum $e^{\text{s}} \cdot \text{i}/\rho$ value is required to be maximized in order to provide more robust collaboration that provides a more synergized innovation capacity with less risk even for the weakest collaboration cluster. Different objective functions for different aims can also be produced using these indices such as maximizing the innovation capacity of the strongest collaboration. However, maximizing the innovation capacity of the strongest collaboration yields to ignoring the collaboration efficiencies of relatively weak clusters, which, in turn yields to collapse of the collaborations of weaker SMEs. Such an objective would favor the strong and disfavor the weak SMEs.

7. APPLICATION AND RESULTS

7.1 An Analysis of the Companies

For the application of the synergized innovation model with risk, the synergy and the innovation capacity questionnaires were delivered to 51 SMEs from different industries in Thrace region. 11.8% of the firms are medium-sized, whereas 21.6% are small-sized and 66.6% are micro firms. The industries of the firms are presented in Figure 7.1 with their percentages.

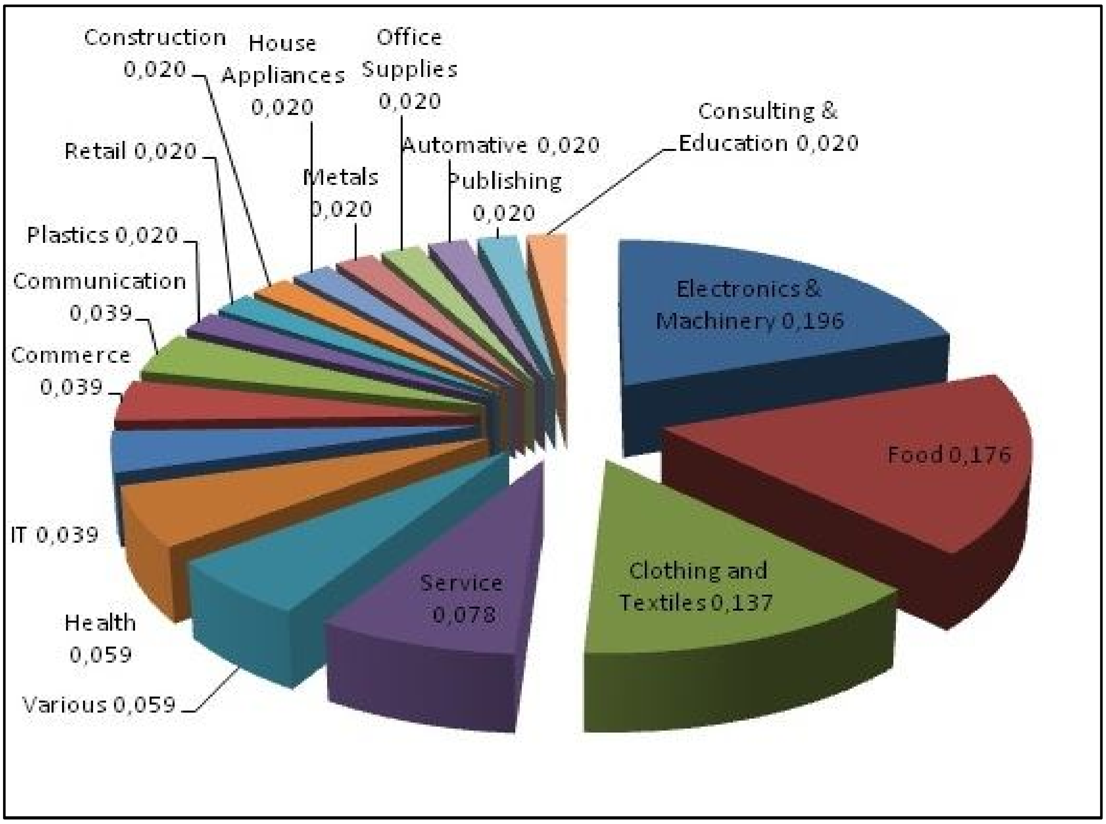

Figure 7.1: The industries of participating firms.

The questionnaires are applied to employees that are knowledgeable at the organizational activities and character of the firm. Yet, these employees should be able to evaluate the top management, since the questionnaire requires objective judgment of top management characters such as hierarchy among the firm or administrative capacity. However, in the case of micro firms, some of which do not have knowledgeable staff apart from the top managers, the questions are directed to one of the top managers. The age of the respondents vary from 24 to 56 with a mean of 35. 72.6% of the respondents are men, whereas 27.4% of the respondents are women. Table 7.1 denotes the number and the percentage of the positions of respondents in their firms.

Table 7.1: The number and percentage of the positions of respondents.

Position	Frequency	Percentage
Technical Staff	7	13.7
Expert / Engineer	12	23.5
Department Manager / Senior Manager	17	34.4
Top Manager	15	29.4
Total	51	100.0

7.2 Application of the Foraging Search for SME Clustering

7.2.1 Inapplicability of traditional clustering approaches

Traditional clustering approaches such as Hierarchical Clustering, K-Means Clustering use distance or correlation metrics for clustering data points. The SME clustering problem structure, on the contrary, is based on the adaptation of the firms provided by the merge or the union of fuzzy numbers which are achieved with different means depending on the criterion. These fuzzy numbers either are complementary or have a boosting effect with each other. Hence, two firms that have data points far from each other can make a robust cluster for collaboration, which disables the utilization of distance-based clustering methods for this problem.

7.2.2 Preference over Exact Optimization Methods

The objective function of the model as given in (6.3), is a nonlinear function due to the exponential effect of synergy. Moreover, the synergy, innovation capacity and risk functions are not differentiable. Hence, the problem is a nonsmooth, nonlinear integer programming problem which is computationally expensive to solve. The selection of Search Based Clustering Methods over exact optimization methods comes from providing a near optimal solution in a short time span.

7.2.3 Application of search-based clustering approaches

Literature proposes numerous Search Based Clustering approaches for clustering problems. The general results of this clustering algorithms propose that Genetic Algorithms maximize intercluster distances and minimize within-cluster distances better and faster than Simulated Annealing (I. Saha and Mukhopadhyay, 2008), and Particle Swarm Optimization maximize intercluster distances and minimize within-cluster distances better and faster than Genetic Algorithm (Abraham et al., 2007). In the 5^{th} section, it has been shown that the Foraging Search tends to outrank the Particle Swarm Optimization and Predator-Prey Particle Swarm Optimization algorithms. Hence, the SME innovation collaboration clustering problem is solved using the Foraging Search algorithm.

As a drawback of clustering methods that use predetermined number of clusters, the optimum number of clusters that will yield to the best value is unknown. In order to determine the optimum number of clusters, a range of number of clusters have to be tested.

7.2.4 Application and results of the foraging search clustering to SMEs

51 firms that filled out the questionnaire were involved in the clustering process, after random checks and controls were established. These controls were achieved by calling firm representatives and asking them random questions from the questionnaires in order to verify the data.

As aforementioned, since the optimum number of clusters is not known beforehand, a range of values for number of clusters are tested for clustering SMEs. In order to avoid overcrowded clusters, the range of values is started with 5 clusters, which assigns 10 firms to a cluster at average. The range is ended at 26, because more number of clusters would yield to noncooperation of firms, since most clusters would involve one firm, which is the equivalent of not forming collaboration clusters.

While calculating the best objective function, there may emerge outliers, which are firms that cannot collaborate with any other firms. These firms are denoted by clusters that contain only the related firm. If one or more of the optimized innovation collaboration clusters only one firm, these clusters contain the outlier firms that cannot be clustered in the optimal case. The objective value of such clusters are assigned N/A (none available), since for one firm, synergy and collaboration concepts are not valid.

The algorithm is run for 50 times for each number of clusters and the best values of each number of clusters are considered as the optimum allocation of SMEs to clusters that is known and calculated for that number of clusters. Figure 7.2 and Table 7.2 presents the best objective values relative to the number of clusters. The best value for the objective function is obtained with 13 clusters with an objective function value of 1.0795.

Table 7.2: Best objective function values of clusters.

Number of Clusters	Best Objective Value Obtained
5	1.0403
6	1.0106
7	1.0613
8	0.9464
9	1.0302
10	0.9684
11	1.0430
12	0.9789
13	1.0795
14	0.9317
15	1.0029
16	1.0238
17	1.0008
18	0.9909
19	0.9554
20	1.0170
21	0.9410
22	0.9708
23	0.9758
24	0.9494
25	0.9719
26	0.9838

The objective value denotes the synergized innovation capacity of the weakest cluster. In this case, the solution can be interpreted as the firms in the weakest collaboration cluster have increased their innovation capacities by 7.95% with collaboration. The risk included synergized innovation capacities of the firms with 13 clusters are given in Table 7.3.

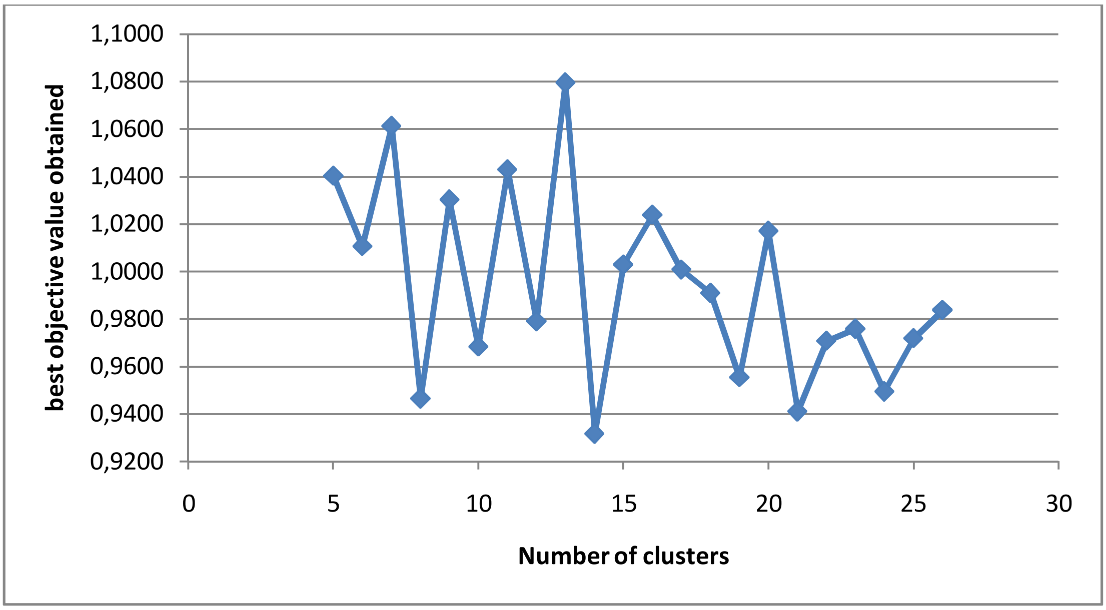

Figure 7.2: Best objective function values of clusters.

Table 7.3: The risk included synergized innovation value of clusters.

Cluster	Risk Included Synergized Innovation Value
1	1.6691
2	1.5943
3	1.3844
4	N/A
5	1.2003
6	1.2847
7	1.1465
8	1.1170
9	1.5179
10	N/A
11	1.0995
12	1.1893
13	1.0794

Within 13 clusters, it can easily be observed that 2 of these clusters contain outlier firms, and the optimum collaboration clusters involve 49 firms that are clustered within 11 collaboration clusters. The firms that the clusters contain are presented in Table 7.4.

Table 7.4: The number of firms that the clusters contain.

Cluster	Number of Firms
1	3
2	2
3	6
4	1
5	3
6	3
7	9
8	5
9	5
10	1
11	2
12	8
13	3

Controlling the firms in clusters, it is observed that they are from different industries, but they have complementary resources and are accordant to each other. As can be seen from Table 7.3, the maximum contribution of collaboration to innovation capacity is achieved in Cluster 1 with an increase of 66.91%. The average contribution of collaboration to the innovation capacity is calculated as 28%.

It can also be observed from Figure 7.2 that the change in the objective function is unpredictable and have high jumps between different numbers of clusters. These leaps are due to the unconventional structure of the clustering. The clustering is not based on similarity or dissimilarity; hence, the clustering can favor two seemingly irrelevant data points in the same clusters. Adding or subtracting one cluster from this scheme may cause these data points to split or merge with other seemingly irrelevant data points. This structure causes the objective function value vary rapidly for different number of clusters.

7.3 Correlations among Indices

The objective function given in formula **(6.3)** contains the multiplicative effect of the synergy, innovation capacity and risk indices. If any of these indices are correlated with each other, the indices would have a damping or stimulating effect on each other. For example, if the innovation capacity and risk indices were positively correlated with each other, than an increase in innovation capacity would also yield an increase in risk, which would commute each other; since the innovation index is in the nominator and the risk index is in the denominator of the objective function. Hence, it is important to measure the correlation among the indices in order to observe the interaction among indices. However, the innovation capacity and risk indices are derived from the same criteria, which the case makes it expectable that these two indices have a significant correlation with each other.

It has been aforementioned that, in order to find the optimum number of clusters for the SME innovation collaboration problem, a range of values has been tested as number of clusters. Among number of clusters between 5 and 26, 13 has yielded to the best objective function value. It has provided 11 collaboration clusters and 2 outlier firms. All clusters have their synergy, innovation capacity and risk indices, yet, measuring the correlation among indices using solely these 11 clusters does not provide enough data to generalize the results.

In order to obtain more data, all clusters that are obtained according to the number of clusters from 5 to 26 are used for evaluating the correlation among indices. Outlier firms, that is, clusters that contain only one firm, are omitted from the evaluation of correlations.

The hypotheses for the tests are given as

$H_0: \rho = 0$

$H_1: \rho \neq 0$

where ρ is the correlation coefficient between two data sets. It is known that ρ has a degree of freedom of $n-2$ for the t distribution. According to the computations that are derived from 318 such clusters, the correlation between the synergy index and the innovation capacity index is -0.08502. The correlation between the synergy index and the risk index is calculated as -0.00598. Finally, the correlation between the innovation capacity and risk index is calculated as -0.2406. The strengths of the correlations are 0.0072, 0.00003 and 0.057, respectively.

In order to observe the significance of the correlations, t-test is applied to the data points using the null hypothesis that the correlation between the two given indices is 0. The formula for measuring the significance is given as in (7.1)

$$t = r\sqrt{\frac{n-2}{1-r^2}} \tag{7.1}$$

where n is the number of data points and r is the correlation value.

Applying the formula to the correlation between the synergy index and the innovation capacity index, the t value is obtained as -1.517. Likely, for the synergy index and the risk index, the t value is calculated as -0.10631 and for the innovation capacity and risk index, the t value is calculated as -4.4065. At a 10% significance level (with a t value of 1.645), for the correlations between the synergy index and the innovation capacity index and between the synergy index and the risk index, evidence has not been found that the correlation between these indices is different than 0. On the other hand, as expected, for correlation between the innovation capacity and risk index, evidence has been found that the correlation between these indices is different than 0. This correlation is significant, yet, appears to be very weak. It is considered as acceptable, since the two indices are measured using the same criteria.

Figure 7.3 shows the scatter diagram of the data pairs of the synergy index and the innovation capacity index, whereas Figure 7.4 shows the scatter diagram of the data pairs of the synergy index and the risk index. Additionally, Figure 7.5 presents the scatter diagram of the data pairs of the innovation capacity index and the risk index.

It can be concluded that the indices do not have a stimulating or damping effect to each other; each index is responsible solely for what is represents.

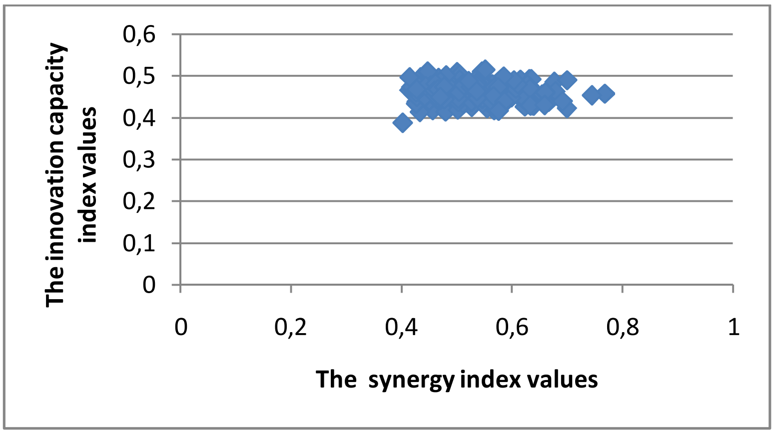

Figure 7.5: The synergy index values vs. the innovation capacity index values.

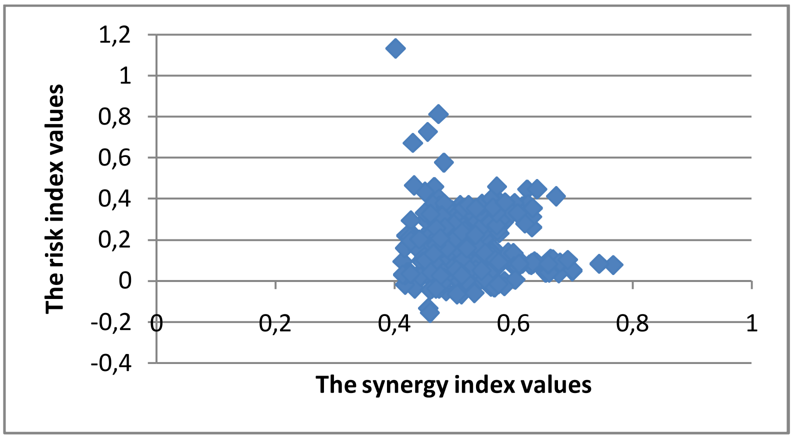

Figure 7.6: The synergy index values vs. the risk index values.

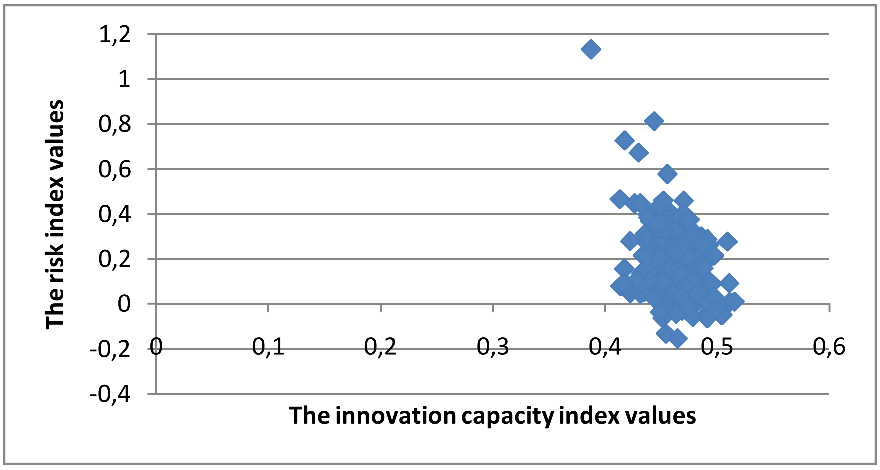

Figure 7.7: The innovation capacity index values vs. the risk index values.

8. CONCLUSIONS

To face the global economic context the companies and in particular the SMEs, which are defined as autonomous economic enterprises employing less than 250 people with an annual turnover of less than 50 million Euros and a balance sheet total of less than 43 million Euros, have to take risks to be competitive. In order to sustain in that competition, SMEs, one by one, do not have the resources or capabilities for innovation. A solution for gaining the resources and the cultural capability is to collaborate with other SMEs. However, collaboration is risky that arise from two main causes: the risk of innovation activities and the risk of collaboration itself.

The risk caused by the collaborations if the firms are accordant with each other. On the contrary, if the firms are accordant with each other, the risk is converted to an opportunity and a contribution to innovation capacity. This accordance, named synergy, is affected by a number of factors, which are either organizational or alliance based. Organizational factors are drivers that are specific to one firm and alliance based factors are drivers that are specific to the alliance, or a group of firms. In order to measure the accordance among firms and measure the contribution of the synergy among firms is to be quantified. This quantification and information retrieval from firms are achieved through FCMs and fuzzy questionnaire. An analogy with the Reliability Theory is constructed to relate the expected lifetime of the reliability systems and the expected lifetime of clusters.

Likely, there are a number of criteria that affect innovation and risk in collaborations. As in the synergy case, for elimination and quantification of the excessive number of criteria, FCMs and fuzzy questionnaires are applied. It is emphasized that synergy has an exponential effect on collaborations of all types with examples from different collaborations or merges from biology and physics to businesses.

In the fuzzy quantification models of synergy, innovation capacity and risk, it can be observed that all options of the questionnaire are complied of triangular fuzzy numbers that are symmetric, equidistant from each other and have the same effect (the same triangular area as shown in the graph) with other fuzzy numbers. This is a point where the related literature does not propose a proper quantification method, especially involving qualitative and abstract criteria. The proposed approach is the main assumption of this dissertation and would act as such initiation and further studies may include different fuzzy numbers with different structures.

Once the quantification of the synergy, innovation capacity and risk criteria is achieved, a clustering method becomes essential for optimizing collaboration clusters. However, the clustering cannot be achieved by traditional means, since it is not based on distance or proximity. This study offers an unconventional clustering behavior which is based on accordance. According to this clustering scheme, two firms with very different characteristics, denoted by two seemingly far data points in the space, could simply be in the same cluster in the optimized case, which is unexpected from traditional clustering methods. Moreover, the objective function contains the exponential power of a function which is not a differentiable function. This involvement makes the problem hard to solve with exact optimization techniques which would also be much more computationally expensive than metaheuristic methods. Hence, it becomes essential that SMEs are clustered using a proper metaheuristic method. The metaheuristics literature states that the PSO algorithm is one of the state-of-the-art methods for solving optimization problems as well as clustering. Over time, the PSO algorithm has evolved into many modifications and hybridizations for better exploration and exploitation. In this dissertation, the Foraging Search method, which is based on PSO, is proposed and tested. The method is shown to be more robust than the classical PSO algorithm and its successor the Predator-Prey PSO algorithm. Since the algorithm is proven to be trustworthy for benchmark problems, it has been applied to the SME clustering problem which has yielded to 11 collaboration clusters and 2 outlier firms. The objective function has involved maximizing the synergized innovation capacity for even the weakest collaboration cluster. Other objective functions may involve maximizing the maximum or average synergized innovation capacity obtained. Moreover, further studies can offer a constraint that ensures all firms are clustered and no outlier firms are left which may result in a decrease in the objective function value.

In terms of innovation and risk, a method for involving synergy has been offered and SMEs have been attempted to be placed in their suitable collaboration clusters. The optimized result also clusters many firms from different industries; hence further studies may involve the analysis of implementations of such collaborations considering their possible advantages and disadvantages. Another essential point is that the proposed model offers a static approach, that is, once the collaborations are built, they cannot be changed unless the aim of the collaboration is achieved. However, further studies may include the dynamic structure of collaborations, which may consider the changing conditions and trends of the collaborations and offer abolishment of the existing clusters and construction of new clusters if and when necessary.

Another further study emerges through different innovation needs of SMEs. In the introduction part, it has been aforementioned that manufacturing SMEs are in more need of product innovations; whereas service industries are in need of process innovations. Handling these different views of innovation, could introduce new constraints to the model that is dealt with the Foraging Search algorithm. Furthermore, the introduction of new constraints should be handled with penalty values in the objective function.

REFERENCES

Abdallah, H., & Emara, H. M. (2009). Ant colony optimization algorithm for solving project management problems. *Expert Systems with Applications, 36*(6), 10004-10015.

Aboyni, J., & Feil., B. (2000). *Cluster Analysis For Data Mining and System Identification*. Berlin: Birkhauser Verlag.

Abraham, A., Das, S., & Konar, A. (2007). Kernel based automatic clustering using modified particle swarm optimization algorithm. The GECCO '07: Proceedings of the 9th annual conference on Genetic and evolutionary computation.

Afshar, A., Sharifi, F., & Jalali, M. R. (2009). Non-dominated archiving multi-colony ant algorithm for multi-objective optimization. Application to multi-purpose reservoir operation. *Engineering Optimization, 41*(4), 313-325.

Aghaie, A., & Mokhtari, H. (2009). Ant colony optimization algorithm for stochastic project crashing problem in PERT networks using MC simulation. *The International Journal of Advanced Manufacturing Technology, 45*(11-12), 1051-1067.

Ahuja, V. (2007). *IT Enhanced Communication Protocols for Building Project Management By Small and Medium Enterprises In The Indian Construction Industry.* Unpublished Doctor of Philosophy, Queensland University of Technology, Queensland.

Aiginger, K. (2000). *Speed of Change*: European Commission, Enterprise Directorate-General.

Alatas, B., & Akin, E. (2009). Multi-objective rule mining using a chaotic particle swarm optimization algorithm. *Knowledge-Based Systems, 22*(6), 455-460.

Alba, E., Leguizamon, G., & Ordonez, G. (2008). Parallel ant algorithms for the minimum tardy task problem. Actas del CACIC X.

Albritton, M. D., & McMullen, P. R. (2007). Optimal product design using a colony of virtual ants. *European Journal of Operational Research, 176*(1), 498-520.

Ali, M. M., & Kaelo, P. (2008). Improved particle swarm algorithms for global optimization. *Applied Mathematics and Computation, 196*(2), 578-593.

Alici, G., Jagielski, R., Sekercioglu, Y. A., & Shirinzadeh, B. (2006). Prediction of geometric errors of robot manipulators with particle swarm optimization method. *Robotics and Autonomous Systems, 54*(12), 956-966.

Almeder, C. (2009). A hybrid optimization approach for multi-level capacitated lot-sizing problems. *European Journal of Operational Research, 200*(2), 599-606.

Araujo, R. d. A. (2010). Swarm-based translation-invariant morphological prediction method for financial time series forecasting. *Information Sciences, **180***(24), 4784-4805.

Arora, V., Chan, F. T. S., & Tiwari, M. K. (2010). An integrated approach for logistic and vendor managed inventory in supply chain. *Expert Systems with Applications, **37***(1), 39-44.

Assareh, E., Behrang, M. A., Assari, M. R., & Ghanbarzadeh, A. (2010). PSO (particle swarm optimization) and GA(genetic algorithms) techniques on demand estimation of oil in Iran. *Energy, **35***, 5223-5229.

Atkinson, R. D., Ezel, S. J., Andes, S. M., Stewart, L. A., Chang, S. G., & Sunami, A. (2011). *Innovation, Trade, and Technology Policies in Asia Pacific Economies: A Scorecard*: The Information Technology and Information Foundation.

Azzag, H., Venturini, G., Oliver, A., & Guinot, C. (2007). A hierarchical ant based clustering algorithm and its use in three real-world applications. *European Journal of Operational Research, **179***(3), 906-622.

Bakkabulindi, F. E. (2011). Individual characteristics as correlates of use of ICT in Makerere University *International Journal of Computing and ICT Research, **5***(2), 37-45.

Balasubramanian, N., & Lee, L. (2008). Firm age and innovaiton. *Industrial and Corporate Change, **17***(5), 1019-1047.

Banfield, J. D., & Rafttery, A. E. (1993). Model based gaussian and non-gaussian clustering. *Biometrics, **49***(3), 803-821.

Barreiros, L., Fernandes, A., Silva Ferreira, A. C., Pereira, H., Bastos, M. M. S. M., Manaia, C. M., et al. (2008). New insights into a bacterial metabolic and detoxifying association responsible for the mineralization of the thiocarbamate herbicide molinate. *Microbiology, **154***(4), 1038-1046.

Batterink, M. H., Wubben, E. F. M., Klerkx, L., & Omta, S. W. F. (2010). Orchestrating innovation networks: the case of innovation brokers in the agri-food sector. *Entrepreneurship and Regional Development, **22***(1), 47-76.

Batterink, M. H., Wubben, E. F. M., & Omta, S. W. F. (2006). Factors explaining the innovative output of firms in the Dutch agrifood industry. The 7th International Conference on Management in Agrifood Chains and Networks Ede, Netherlands.

Baum, J. A. C., Cowan, R., & Jonard, N. (2012). *Prescriptions for network strategy: Does evidence of network effects in cross-section support them?,* : United Nations University, Maastricht Economic and social Research and training centre on Innovation and Technology.

Beck, M. (1990). Learning organizations - how to create them. *International Journal of Manpower, **11***(5), 27-33.

Bejar, J., Cortés, U., & Poch, M. (1993). *LINNEO+: A classification methodology for ill-structured domains*: Universidad Politécnica de Cataluña.

Bezdek, J. C. (1981). *Pattern Recognition with Fuzzy Objective Function Algorithms*: Kluwer Academic Publishers.

Bezdek, J. C., & Nikhil, P. R. (1995). Cluster validation with generalized Dunn's indices. The 2nd New Zealand Two-Stream International Conference on Artificial Neural Networks and Expert Systems.

Bin, Y., Zhong-Zhen, Y., & Baozhen, Y. (2009). An improved ant colony optimization for vehicle routing problem. *European Journal of Operational Research, **196***(1), 171-176.

Blomqvist, E., Levashova, T., Öhgren, A., Sandkuhl, K., Smirnov, A., & Tarassov, V. (2005). Configuration of Dynamic SME Supply Chains Based on Ontologies, Holonic and Multi-Agent Systems for Manufacturing. In V. Marík, R. William Brennan & M. Pechoucek (Eds.), Springer Berlin / Heidelberg, 246-256.

Blonigen, B. A., & Taylor, C. T. (2000). R&D intensity and acquisitions in high-technology industries: evidence from the US electronic and electrical equipment industries. *The Journal of Industrial Economics, **48***(1), 47-70.

Bontoux, B., & Feillet, D. (2008). Ant colony optimization for the traveling purchaser problem. *Computers and Operations Research, **35***(2), 628-637.

Boonyaritdachochai, P., Boonchuay, C., & Ongsakul, W. (2010). Optimal congestion management in an electricity market using particle swarm optimization with time varying acceleration coefficients. *Computers and Mathematics with Applications, **60***, 1068-1077.

Bos-Brouwers, H. E. J. (2010). Corporate sustainability and innovation in SMEs: evidence of themes and activities in practice. *Business Strategy and the Environment, **19***(7), 417-435.

Boschetti, F., & Brede, M. (2008). An information-based adaptive strategy for resource exploitation in competitive scenarios. *Technological Forecasting and Social Change, **76***(4), 525-532.

Braun, P. (2003 September 28- October 1). SME networks: clustering for regional innovation purposes. The 16th Annual Conference of Small Enterprise Association of Australia & New Zealand, Ballarat, Victoria, Australia

Brede, M., Boschetti, F., & McDonald, D. (2007). Strategies for resource exploitation. *Ecological Complexity, **5***(1), 22-29.

Brede, M. F., & Boschetti, M. D. (2007). Managing renewable resources via collective intelligence. The ModSim07.

Bunduchi, R. (2012). Trust, partner selection and innovation outcome in collaborative new product development. *Production Planning & Control*, 1-13.

Burton, R. M., Eriksen, B. H., Hkonsson, D. D., Knudsen, T., & Snow, C. C. (2008). *Designing Organizations: 21st Century Approaches (Information and Organization Design Series)*: Springer Publishing Company, Incorporated

Cai, J., Ma, X., Li, L., Yang, Y., Peng, H., & Wang, X. (2007). Chaotic ant swarm optimization to economic dispatch. *Electric Power Systems Research, **77***(10), 1373-1380.

Calderon, T. G., Chandra, A., & Cheh, J. J. (2006). Modeling an intelligent continuous authentication system to protect financial information resources. *International Journal of Accounting Information Systems, 7*(2), 91-109.

Camci, F. (2008). Comparison of genetic and binary particle swarm optimization algorithms on system maintenance scheduling using prognostics information. *Engineering Optimization, **41***(2), 119-136.

Campello, R. J. G. B., & Hruschka, E. R. (2009). On comparing two sequences of numbers and its applications to clustering analysis. *Information Sciences, **179***, 1025-1039.

Cascio, W. F. (2000). Managing a virtual workplace. *The Academy of Management Executive, **14***(3), 81-90.

Castro, E. G., & Tsuzuki, M. S. G. (Eds.). (2007). *Simulation Optimization Using Swarm Intelligence as Tool for Cooperation Strategy Design in 3D Predator-Prey Game*: In Tech.

Chan, F. T. S., & Swarnkar, R. (2006). Ant colony optimization approach to a fuzzy goal programming model for a machine tool selection and operation allocation problem in an FMS. *Robotics and Computer-Integrated Manufacturing, **22***(4), 353-362.

Chang, R. S., Chang, J. S., & Lin, P. S. (2009). An ant algorithm for balanced job scheduling in grids. *Future Generation Computer Systems, **25***(1), 20-27.

Chapman, K., MacKinnon, D., & Cumbers, A. (2004). Adjustment or renewal in regional clusters? A study of diversification amongst SMEs in the Aberdeen oil complex. *Transactions of the Institute of British Geographers, **29***(3), 382-396.

Charles, J. R. (2006). *Couplepreneurs: Prosperity Through Partnership*: Wheatmark Publishing.

Chaturvedi, K. T., Pandit, M., & Srivastava, L. (2009). Particle swarm optimization with crazy particles for nonconvex economic dispatch. *Applied Soft Computing, **9***(3), 962-969.

Che, Z. H., & Wang, H. S. (2010). A hybrid approach for supplier cluster analysis. *Computers and Mathematics with Applications, **59***, 745-763.

Chebouba, A., Yalaoui, F., Smati, A., Amadeo, L., Younsi, K., & Tairi, A. (2009). Optimization of natural gas pipeline transportation using ant colony optimization. *Computers and Operations Research, **36***(6), 1916-1923.

Chen, A. L., Yang, G. K., & Wu, Z. M. (2008). Production scheduling optimization algorithm for the hot rolling processes. *International Journal of Production Research, **46***(7), 1955-1973.

Chen, C.-Y., & Ye, F. (2004), March 21-23). Particle swarm optimization algorithm and its application to clustering analysis. The 2004 IEEE lntemationai Conference on Networking Sensing Control, Taiwi. Taiwan.

Chen, D., & Zhao., C. X. (2009). Particle swarm optimization with adaptive population size and its application. *Applied Soft Computing, **9***(1), 39-48.

Chen, S. H., Lee, H. T., & Wu, Y. F. (2008). Applying ANP approach to partner selection for strategic alliance. *Management Decision, **46***(3), 449-465.

Chen, S. H., Wang, P. W., Chen, C. M., & Lee, H. T. (2010). An analytic hierarchy process approach with linguistic variables for selection of an R&D strategic alliance partner. *Computers & Industrial Engineering, **58***(2), 278-287.

Chen, W., Shi, Y., Teng, H., Lan, X., & Hu, L. (2010). An efficient hybrid algorithm for resource constraint project scheduling. *Information Sciences, **180,*** (1031-1039).

Chen, W., Zhang, R. T., Cai, Y. M., & Xu, F. S. (2006). Particle swarm optimization for constrained portfolio selection problems. The 2006 International Conference on In Machine Learning and Cybernetics.

Chen, X., & Cao, L. (2006). *SME Clusters in China: One Way build up Innovation Capacities*: Tech Report.

Chen, Z., Gehrke, J., & Korn, F. (2001). Query Optimization In Compressed Database Systems. The SIGMOD Conference.

Chesbrough, H., Vanhaverbeke, W., & West, J. (Eds.). (2008). *Open Innovation: Researching a New Paradigm*: Oxford University Press, USA.

Cheung, Y. K. F. (2006). *A Study of Determinants of Effectiveness in Relational Contracting.* Unpublished Master Thesis, Queensland University of Technology, Brisbane, Australia.

Chinsamy-Turan, A. (Ed.). (2011). *Forerunner of Mammals*: Indiana University Press.

Chou, A. Y. (2008). The role of knowledge sharing and trust in new product development outsourcing. *International Journal of Information Systems and Change Management, **3***(4), 301-313.

Chou, D. C., & Chou, A. Y. (2011). Innovation outsourcing: risks and quality issues. *Computer Standards & Interfaces, **33***(3), 350-356.

Christmas, J., Keedwell, E., Frayling, T., & Perry, J. R. B. (2010). Ant colony optimization to identify genetic variant association with type-2 diabetes. *Information Sciences, **181***(9), 1609-1622.

Christodolou, S. (2009). Construction imitating ants: resource-unconstrained scheduling with artificial ants. *Automation in Construction, **18***(3), 285-293.

Ciuprina, G., Ioan, D., & Monteanu, I. (2002). Use of intelligent-particle swarm optimization in electromagnetics. *IEEE Transactions on Magnetics, **38***(2), 1037-1040.

Clifton, N., Keast, R., Pickernell, D., & Senior, M. (2010). Network structure, knowledge governance, and firm performance: evidence from innovation networks and SMEs in the UK. *Growth and Change, **41***(3), 337-373.

Coelho, L. S. (2009). An efficient particle swarm approach for mixed integer programming in reliability redundancy optimization application. *Reliability Engineering and System Safety, **94***, 830-837.

Collier, A., Gray, B. J., & Ahn, M. J. (2011). Enablers and barriers to university and high technology SME partnerships. *Small Enterprise Research, **18***(1), 2-17.

Cornu, B. (2005). Collective intelligence and capacity building in a networked society collective intelligence and capacity building. The IFIP International Federation for Information Processing.

Cosh, A., Fu, X., & Hughes, A. (2005). *Management Characteristics, Collaboration and Innovative Efficiency: Evidence From UK Survey Data*. Cambridge: Centre for Business Research, University of Cambridge.

Covin, J., & Miles, M. (1999). Corporate entrepreneurship and the pursuit of competitive advantage. *Entrepreneurship: Theory & Practice, **23***(3).

Cowgill, M. C., Harvey, R. J., & Watson, L. T. (1999). A genetic algorithm approach to cluster analysis. *Computers & Mathematics with Applications, **37***(7), 99-108.

Cruz, C. (2006). determinants of the innovation sourcing strategy. The EIASM Workshop on International Strategy and Cross-Cultural Management, Toulouse, France.

Cui, X., Potok, T. E., & Palathingal, P. (2005). Document clustering using particle swarm optimization. IEEE Swarm Intelligence Symposium, The Westin.

Cui, Z., Zeng, J., & Sun, G. (2008). A fast particle swarm optimization. *International Journal of Innovative Computing, Information and Control, **2***(6), 1365-1380.

Cuijpers, M., Guenter, H., & Hussinger, K. (2011). Costs and benefits of inter-departmental innovation collaboration. *Research Policy, **40***(4), 565-575.

Cummings, J. L., & Holmberg, S. R. (2012). Best-fit alliance partners: the use of critical success factors in a comprehensive partner selection process. *Long Range Planning, **45***(2–3), 136-159.

Cura, T. (2009). Particle swarm optimization approach to portfolio selection. *Nonlinear Analysis: Real World Applications, **10***(4), 2396-2406.

de Jong, J., O'Shaughnessy, O., & Vermeulen, P. (2003). *Innovation in SMEs: An Empirical Investigation of the Input-Throughput-Output-Performance Model*: EIM Business and Policy Research.

Deng, G. F., & Lin, W. T. (2011). Ant colony optimization-based algorithm for airline crew scheduling problem. *Expert Systems with Applications, **38***, 5787-5793.

Dewar, M. E. (1988). Adopting new manufacturing technology: can it help declining manufacturing industries? *Economic Development Quarterly*, ***3***, 276-286.

Dias, D. B., Madeo, R. C. B., Rocha, T. B., Scaro, H. H., & Peres, S. M. (2009). Hand movement recognition for brazilian sign language: a study using distance-based neural networks. The 2009 International Joint Conference on Neural Networks, Atlanta, GA, USA.

Dickson, P. H., Weaver, K. M., & Hoy, F. (2006). Opportunism in the R&D alliances of SMES: The roles of the institutional environment and SME size. *Journal of Business Venturing, **21***(4), 487-513.

Dietrich, P., Eskerod, P., Dalcher, D., & Sandhawalia, B. (2010). The dynamics of collaboration in multipartner projects. *Project Management Journal, **41***(4), 59-78.

Ding, J.-F., & Liang, G.-S. (2005). Using fuzzy MCDM to select partners of strategic alliances for liner shipping. *Information Sciences, **173***(1–3), 197-225.

Ding, J. F. (2009). Partner selection of strategic alliance for a liner shipping company using extent analysis method of fuzzy AHP. *Journal of Marine Science and Technology, **17***(2), 97-105.

Dittrich, K., & Duysters, G. (2007). Networking as a means to strategy change: the case of open innovation in mobile telephony. *Journal of Product Innovation Management, **24***(6), 510-521.

Dong, L., & Glaister, K. W. (2006). Motives and partner selection criteria in international strategic alliances: Perspectives of Chinese firms. *International Business Review, **15***(6), 577-600.

Duan, Q., & Liao, T. W. (2010). Improved ant colony optimization algorithms for determining project critical paths. *Automation in Construction, **19***, 676-693.

Dutot, A., Olivier, D., & Savin, G. (2010). Collaboration and competition in boids simulation with predation. The Emergent Properties in Natural and Artificial Complex Systems, EPNACS 2010, September 15-16, Lisbon, Portugal.

Duygulu, E., Kök, R., & Ozdemir, A. (2008). Factors influencing innovation in SMEs in Turkey: an interregional comparison. The 31st Institute for Small Business & Entrepreneurship Conference, Belfast, N. Ireland.

Dye, C. Y., & Hsieh, T. P. (2010). A particle swarm optimization for solving joint pricing and lot sizing problem with fluctuation demand and unit purchase cost. *Computers and Mathematics with Applications, **60***(7), 1895-1907.

Eden, L. (2007). *Friends, Acquaintances or Stranger? Partner Selection in R&D Alliances*: Texas A&M University.

Edquist, C., Doloreux, D., & Hommen, L. (2004). Nordic regional innovation systems: an analysis of the region of east Gothia, Sweden. *Canadian Journal of Regional Science, **27***(4), 431-457.

El-Dib, A. A., Youssef, H. K. M., El-Metwally, M. M., & Osman, Z. (2006). Maximum loadability of power systems using hybrid particle swarm optimization. *Electric Power System Research, **76***, 485-492.

Engelbrecht, A. P. (2003). *Computational Intelligence: An Intrıduction*: Wiley Publishing.

Engelbrecht, A. P. (2006). *Fundamentals of Computational Swarm Intellgence*: Wiley Publishing.

Englander, S. A., Evenson, R., & Hanazaki, M. (1988). R&D, Innovation and the total factor productivity slowdown. *OECD Economic Studies, **11***(1), 7-42.

Espinoza, F. A., Oliver, J. M., Wilson, B. S., & Steinberg, S. L. (2012). Using hierarchical clustering and dendrograms to quantify the clustering of membrane proteins. *Bull Math Biology, **74***(1), 190-211.

Ester, M., Kriegel, H. P., Jörg, S., H.S., & Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. The Proceedings of 2nd International Conference on Knowledge Discovery and Data Mining(KDD-96).

Falco, I. D., Cioppa, A. D., & E., T. (2007). Facing classification problems with particle swarm optimization. *Applied Soft Computing, 7*(3), 652-658.

Feng, B., Fan, Z.-P., & Ma, J. (2010). A method for partner selection of codevelopment alliances using individual and collaborative utilities. *International Journal of Production Economics, **124***(1), 159-170.

Fischer, M., Jähn, H., & Teich, T. (2004). Optimizing the selection of partners in production networks. *Robotics and Computer-Integrated Manufacturing, **20***(6), 593-601.

Flores, M., Boër, C., Huber, C., Pluss, A., Schoch, R., & Pouly, M. (2009). Universities as key enablers to develop new collaborative environments for innovation: successful experiences from Switzerland and India. [Article]. *International Journal of Production Research, **47***(17), 4935-4953.

Fossas-Olalla, M., Lopez-Sanchez, J. I., & Minguela-Rata, B. (2010). Cooperation with suppliers as a source of innovation. *African Journal of Business Management, **4***(16), 3491-3499.

Fruehan, R. J., Cheij, D. A., & Vislosky, D. M. (1997). *Factors Influencing Innovation and Competitiveness in the Steel Industry*: Carnegie Mellon University.

Fuellerer, G., Doerner, K. F., Hartl, R. F., & Iori, M. (2010). Metaheuristics for vehicle routing problems with three-dimensional loading constraints. *European Journal of Operational Research, **201***(3), 751-759.

Gajpal, Y., & P., A. (2009). Ant colony system(ACS) for vehicle routing problem with simultaneous delivery and pickup. *Computers and Operations Research, **36***(12), 3215-3223.

Gan, G., Ma, C., & Wu, J. (2007). *Data Clustering: Theory, Algorithms, and Applications (ASA-SIAM Series on Statistics and Applied Probability)*: SIAM, Society for Industrial and Applied Mathematics.

Ganti, V., Gehrke, J., & Ramakrishnan, R. (1999). CACTUS—clustering categorical data using summaries. The In Proceedings of the fifth ACM SIGKDD international conference on Knowledge discovery and data mining (KDD '99), ACM, New York, NY, USA,.

Gao, L., Zhou, C., & Zan, K. (2006). Particle swarm optimization for simultaneous optimization of design and machining tolerances. The 6th International Conference, SEAL 2006.

García-Osorio, C., & Fyfe, C. (2004). Comparing exploratory projection pursuit artificial neural networks. The 3rd International Workshop on Practical Applications of Agents and Multiagent Systems, IWPAAMS 2004.

Gardet, E., & Mothe, C. (2012). SME dependence and coordination in innovation networks. *Journal of Small Business and Enterprise Development, **19***(2), 263-280.

Geem, Z. W. (2009). Particle-swarm harmony search for water network design. *Engineering Optimization, **41***(4), 297-311.

Gerybadze, A., & Reger, G. (1999). Globalization of R&D: recent changes in the management of innovation in transnational corporations. *Research Policy, **28***(2–3), 251-274.

Gnamabal, K., Marimuthu, N. S., & Babulal, C. K. (2011). Three-phase power flow analysis in sequence component frame using hybrid particle swarm optimization. *Applied Soft Computing, **11***, 1727-1734.

Gomes-Cassares, B. (2003). *Alliance Strategy: Fundamentals for Success*: Management Roundtable Workshop.

Gunes, F., Ozkaya, U., & Demirel, S. (2008). Particle swarm intelligence applied to determination of the feasible design target for a low-noise amplifier. *Microwave and Optical Technology Letters, **51***(5), 1214-1218.

Guo, Q. J., Yu, H. B., & Xu, A. D. (2006). A hybrid PSO-GD based intelligent method for machine diagnosis. *Digital Signal Processing, **16***(4), 402-418.

Guo, W., Chen, G., Feng, X., & Yu, L. (2007). Solving multi-criteria minimum spanning tree problem with discrete particle swarm optimization. The Third International Conference on Natural Computation., August 24-27, Haikou, China.

Guo, Y. W., Mileham, A. R., Owen, G. W., & Li, W. D. (2006). Operation sequencing optimization using a particle swarm optimization approach. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, **220***(12), 1945-1958.

Hacklin, F., Marxt, C., & Fahrni, F. (2006). Strategic venture partner selection for collaborative innovation in production systems: A decision support system-based approach. *International Journal of Production Economics, **104***(1), 100-112.

Haibing, G., Chi, Z., & Liang, G. (2006). Particle swarm optimization based algorithm for economic load dispatch. The International Symposium on Intelligence Computation & Applications (ISICA 2005).

Hajidimitriou, Y. A., & Georgiou, A. C. (2002). A goal programming model for partner selection decisions in international joint ventures. *European Journal of Operational Research, **138***(3), 649-662.

Hall, B., Lotti, F., & Mairesse, J. (2009). Innovation and productivity in SMEs: empirical evidence for Italy. *Small Business Economics, **33***(1), 13-33.

Han, Y., Tang, J., Kaku, I., & Mu, L. (2009). Solving uncapacitated multilevel lot-sizing problems using a particle swarm optimization with flexible inertial weight. *Computers and Mathematics with Applications, **57***(11-12), 1748-1755.

Hani, Y., Amodeo, L., Yalaoui, F., & Chen, H. (2007). Ant colony optimization for solving an industrial layout problem. *European Journal of Operational Research, **183***(2), 633-642.

Harindranath, G., Dyerson, R., & Barnes, D. (2008). ICT in small firms: factors affecting the adoption and use of ICT in Southeast England SMEs. The the 16th European Conference on Information Systems, ECIS 2008, Galway, Ireland.

Hasiloglu, S. B. (2009). Evaluation of the product with cognitive mapping method, one of the elements of internet marketing mix. *Journal of Applied Sciences, 9*(14), 2606-2612.

Hasiloglu, S. B., & Cinar, R. (2008). Evaluating direct marketing practices on the internet via the fuzzy cognitive mapping method. *International Journal of Business and Management, 3*(12), 31-38.

Hassan, R., Cohanim, B., de Weck, O., & Venter, G. (2005). A comparison of particle swarm optimization and the genetic algorithm. The 46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference (2005), April 18-21, Austin, Texas, USA.

He, Q., & Wang, L. (2007). An effective co-evolutionary particle swarm optimization for constrained engineering design problems. *Engineering Applications of Artificial Intelligence, 20*, 89-99.

Hendriks, K. (2012). *Innovation Policy: Efficiency of the current policy mix for Dutch SMEs consisting of national and European measures.* Tilburg University, Tilburg.

Henoch, B., & Gonzalez, E. (2003) From venture to capital. *Frontiers of E-Business Research*. Tampere: Finland e-Business Research Center.

Hernandez-Espallardo, M., Molina-Castillo, F.-J., & Rodriguez-Orejuela, A. (2012). Learning processes, their impact on innovation performance and the moderating role of radicalness. *European Journal of Innovation Management, 15*(1), 77-98.

Herrmann, L., & Ultsch, A. (2010). Strengths and weaknesses of ant colony clustering, advances in data analysis, data handling and business intelligence. In A. Fink, B. Lausen, W. Seidel & A. Ultsch (Eds.), Springer Berlin Heidelberg, 147-156.

Hervas-Oliver, J.-L., Albors Garrigos, J., & Gil-Pechuan, I. (2011). Making sense of innovation by R&D and non-R&D innovators in low technology contexts: A forgotten lesson for policymakers. *Technovation, 31*(9), 427-446.

Heylighen, F. (1999). Collective intelligence and its implementation on the web: algorithms to develop a collective mental map. *Comput. Math. Organ. Theory, 5*(3), 253-280.

Hu, H. (2010, 30-31 May 2010). The innovative ability upgrade of Shanghai medium and small-sized enterprises on the basis of independent innovation alliance. The Networking and Digital Society (ICNDS), 2010 2nd International Conference on.

Huang, B., Gao, C., & Chen, L. (2011). Partner selection in a virtual enterprise under uncertain information about candidates. *Expert Systems with Applications, 38*(9), 11305-11310.

Huang, J. J., Chen, C. Y., Liu, H. H., & Tzeng, G. H. (2010). A multiobjective programming model for partner selection-perspectives of objective synergies and resource allocations. *Expert Systems with Applications, 37*(5), 3530-3536.

Huang, X. L., Sun, N., Liu, W., & Wie, J. X. (2007). Research on particle swarm optimization and its industrial application. The ICNC 2007. Third International Conference on Natural Computation.

Hunt, R. M. (2006). *When do more patents reduce R&D?* : Federal Reserve Bank of Philadelphia.

Hurley, R. F. (1995). Group culture and its effect on innovative productivity. *Journal of Engineering and Technology Management, **12***(1–2), 57-75.

Ip, W. H., Huang, M., Yung, K. L., & Wang, D. (2003). Genetic algorithm solution for a risk-based partner selection problem in a virtual enterprise. *Computers & Operations Research, **30***(2), 213-231.

Iwasaki, N., Yasuda, K., & Ueno, G. (2006). Dynamic parameter tuning of particle swarm optimization. *IEEE Transactions on Electrical and Electronic Engineering, **1***(4), 353-363.

Izakian, H., & Abraham, A. (2011). Fuzzy C-means and fuzzy swarm for fuzzy clustering problem. *Expert Systems with Applications, **38***(3), 1835-1838.

Izquierdo-Torres, E. (2004). *Collective Intelligence in Multi-Agent Robotics: Stigmergy, Self-Organization and Evolution*: University of Sussex.

Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters, **31***(8), 651-666.

Jain, A. K., Murty, M. N., & Flyn, P. J. (1999). Data clustering: a review. *ACM Computing Survey, **31***(3), 264-323.

Jang, W.-S., Kang, H.-I., Lee, B.-H., Kim, K. I., Shin, D.-I., & Kim, S.-C. (2007). Optimized fuzzy clustering by predator prey particle swarm optimization. IEEE Congress on the Evolutionary Computation, 2007. CEC 2007, September 25-28, Singapore.

Jarboui, B., Cheikh, M., Siarry, P., & Rebai, A. (2007). Combinatorial particle swarm optimization (CPSO) for partitional clustering problem. *Applied Mathematics and Computation, **192***(2), 337-345.

Jia, Z., & Yang, X. (2007). The research on applying particle swarm optimization into human resources allocation optimization. The The Sixth Wuhan International Conference on E-Business, May 26-27, Wuhan, China.

Jiang, J. H., Wang, J. H., Chu, X., & Yu, R. Q. (1997). Clustering data using a modifed integer genetic algorithm (IGA). *Analytica Chimica Acta, **354***, 263-274.

Jiang, Q. W., & Wang, J. (2011). Applied research of ant colony clustering algorithms in healthcare consumer segments, Education and Management. In M. Zhou (Ed.), (Vol. 210, pp. 335-342): Springer Berlin Heidelberg.

Jiang, Y., Hu, T., ChongChao, H., & Wu, X. (2007). An improved particle swarm optimization algorithm. *Applied Mathematics and Computation, **193***(1), 231-239.

Jiang, Y., Liu, C., Huang, C. ,Wu, X. (2010). Improved particle swarm algorithm for hydrological parameter optimization. *Applied Mathematics and Computation, **217***, 3207-3215.

Jimenez, J. F., Cuevas, F. J., & Carpio, J. M. (2007). Genetic algorithms applied to clustering problem and data mining. The Proceedings of the 7th WSEAS International Conference on Simulation, Modelling and Optimization.

Jørgensen, F., & Ulhøi, J. P. (2010). Enhancing innovation capacity in SMEs through early network relationships. *Creativity and Innovation Management, **19***(4), 397-404.

Jursa, R. (2007). Variable Selection for wind power prediction using particle swarm optimization, 9th Annual Conference on Genetic and Evolutionary Computation, July 7-11, New York, NY, USA.

Kabir, M. M., Shahjahan, M., & Murase, K. (2012). A new hybrid ant colony optimization algorithm for feature selection. *Expert Systems with Applications, **39***(3), 3747-3763.

Kang, Q., Wang, L., & Wu, Q. D. (2008). A novel ecological particle swarm optimization algorithm and its population dynamics analysis. *Applied Mathematics and Computation, **205***(1), 61-72.

Kao, Y., & Fu, S. C. (2006). An ant-based clustering algorithm for manufacturing cell design. *The International Journal of Advanced Manufacturing Technology, **28***(11), 1182-1189.

Katz, R. (1984). Expanding the community's healing resources. *Empowerment and Synergy, **3***(2), 201-206.

Kayhan, A. H., Ceylan, H., Ayvaz, M. T., & Gurarslan, G. (2010). PSOLVER: A new hybrid particle swarm optimization algorithm for solving continuous optimization problems. *Expert Systems with Applicaitons, **37***, 6798-6808.

Keizer, A. J., & Halman, I. M. J. (2004). Diagnosing risk in radical innovation projects. *Research-Technology Management, **50***(5), 30-36.

Kim, H. E., & Pennings, J. M. (2009). Innovation and strategic renewal in mature markets: a study og the tennis racket industry. *Organization Science, **20***(2), 368-383.

Kim, S. H. (2008). An empirical analysis of growth of korean firms after the asian crisis: with a focus of technology. the Asia-Pacific Productivity Conference, July 17-19, Taipei, Taiwan.

Kittur, A., Lee, B., & Krant, R. E. (2009). Coordination in collective intelligence: the role of team structure and task independence. The CHI 2009 (Conference on Human Factors in Computing Systems).

Klingebiel, R., & Rammer, C. (2011). *Resource Allocation Flexibility for Innovation Performance: The Effects of Breadth, Uncertainty, and Selectiveness*: ZEW - Centre for European Economic Research Discussion.

Konsti-Laakso, S., Pihkala, T., & Kraus, S. (2012). Facilitating SME innovation capability through business networking. *Creativity and Innovation Management, **21***(1), 93-105.

Koshino, M., Murata, H., & Kimura, H. (2006). Improved particle swarm optimization and application to portfolio selection. *Electronics and Communications in Japan (Part III: Fundamental Electronic Science), **90***(3), 13-25.

König, M. D. (2010). *Dynamic R&D Networks: The Efficiency and Evolution of Interfirm Collaboration Networks.* ETH Zurich, Zurich.

Kruitbosch, E. (2010). *Customer Collaboration in New Product Development: The Moderating Impact of Internal R&D Efforts.* University of Twente, Twente.

Kuan, K., & Wong, K. Y. (2010). Applying ant system for solving unequal area facility layout problems. *European Journal of Operations Research, **202***, 730-734.

Kuo, R. J., Chao, C. M., & Chiu, Y. T. (2011). Application of particle swarm optimization to association rule mining. *Applied Soft Computing, **11***, 326-336.

Kuo, R. J., & Lin, L. M. (2010). Application of a hybrid of genetic algorithm and particle swarm optimization algorithm for order clustering. *Decision Support Systems, **49***(4), 451-462.

Kuo, R. J., & Shih, C. W. (2007). Association rule mining through the ant colony system for national health insurance research database in Taiwan. *Computers and Mathematics with Applications, **54***, 1303-1318.

Kuo, R. J., Syu, Y. J., Chen, Z. Y., & Tien, F. C. (2012). Integration of particle swarm optimization and genetic algorithm for dynamic clustering. *Information Sciences, **195***(0), 124-140.

Kuo, R. J., Wang, H. S., Hu, T.-L., & Chou, S. H. (2005a). Application of ant k-means on clustering analysis. *Computers & Mathematics with Applications, **50***(10–12), 1709-1724.

Kuo, R. J., Wang, H. S., Hu, T. L., & Chou, S. H. (2005b). Application of ant k-means on clustering analysis. *Computers and Mathematics with Applications, **50***(10-12), 1709-1724.

Kuo, R. J., & Yang, C. Y. (2011). Simulation optimization using particle swarm optimization algorithm to assembly line design. *Applied Soft Computing, **11***, 605-613.

Lam, K. C., Ning, X., & Ng, T. (2007). The application of the ant colony optimization algorithm to the construction site layout planning problem. *Construction Management & Economics, **25***(4), 359-374.

Lazoi, M., Ceci, F., Corallo, A., & Secundo, G. (2011). Collaboration in an aerospace SMEs cluster: innovation and ICT dynamics. *International Journal of Innovation and Technology Management (IJITM), **8***(3), 393-414.

Lee, H. S., Tseng, H. H., Zheng, M. C., & Li, P. Y. (2010). Decision support for the maintenance management of green areas. *Expert Systems with Applications, **37***, 4479-4487.

Lee, S., Park, G., Yoon, B., & Park, J. (2010). Open innovation in SMEs-an intermediated network model. *Research Policy, **39***(2), 290-300.

Legany, C., Juhasz, S., & Babos, A. (2006). Cluster validity measurement techniques. The AIKED'06 Proceedings of the 5th WSEAS International Conference on Artificial Intelligence, Knowledge Engineering and Data Bases.

Lenbury, S., Rattanamongkonkul, S., Tumravsin, N., & Amornsamankul, S. (1999). Predator-prey interaction coupled by parasitic infection: limit cycles and chaotic behavior. *Mathematical & Computer Modeling, **30***, 131-146.

Léon-Javier, A., Cruz-Cortez, N., Morenao-Armendariz, M. A., & Orantes-Jiménez, S. (Eds.). (2009). *Finding Minimal Addition Chains with a Particle Swarm Optimization Algorithm*.

Leone, M., Sumedha., & Weigt, M. (2008). Unsupervised and semi-supervised clustering by message passing: soft-constraint affinity propagation. *European Physical Journal B, **66***(1), 125-135.

Li, D., & Ferreira, M. P. (2008). Partner selection for international strategic alliances in emerging economies. *Scandinavian Journal of Management, **24***(4), 308-319.

Li, S. G., & Rong, Y. L. (2009). The reliable design of one-piece flow production system using fuzzy ant colony optimization. *Computers and Operations Research, **36***(5), 1656-1663.

Li, X. (2012). R&D intensity and productivity of exporting smes: empirical evidence from China. *International Journal of Learning and Intellectual Capital, **9***(1), 86-97.

Li, X., F., B. M., & Aneja, Y. P. (2010). An ant colony optimization metaheuristic for machine-part cell formation problems. *Applied Soft Computing, **10***(4), 1222-1236.

Lian, Z., Gu, X., & Jiao, B. (2006). A similar particle swarm optimization algorithm for permutation flowshop scheduling to minimize makespan. *Applied Mathematics and Computation, **175***, 773-785.

Liang, R., Luo, J., Yang, Q., & Luo, W. (2008). PSO combined with ILS for flowshop-based parallel task assignment problem. the Third International Symposium, ISICA 2008.

Liang, Y. C., & Smith, A. E. (2004). An ant colony optimization algorithm for the redundancy allocation problem (RAP). *IEEE Transactions On Reliability, **53***(3), 417-423.

Liao, C. H., Tseng, C. T., & Luarn, P. (2005). A discrete version of the particle swarm optimization for flowshop scheduling problems. *Computers and Operations Research, **34***(10), 3099-3111.

Lin, S. Y., Horng, S. J., W, K. T., Huang, D. K., Fahn, C. S., Lai, J. L., et al. (2010). An efficient bi-objective personnel assignment algorithm based on a hybrid particle swarm optimization model. *Expert Systems with Applicaitons, **37***, 7825-7830.

Linder, J. C., Perkins, S., & Dover, P. (2004). *Drug Industry Alliances: In Search of Strategy*: Accenture White Paper.

Liou, C. D., & Hsieh, Y. C. (2009). A PSO-based algorithm for two-machine no-wait flowshop scheduling with setup time. the International Conference on Business and Information, Kuala Lumpur, Malaysia.

Litian, C., & Qingrui, X. (2009). The mechanism of innovation capability leveraging via strategy in SMEs. IEEM 2009, IEEE International Conference on Industrial Engineering and Engineering Management, December 8-11, Hong Kong, China.

Liu, W.-H. (2010, January 21-23). Do Sources of knowledge transfer matter? a firm-level analysis in the PRD, China. the DRUID-DIME, Aalborg, Denmark.

Liu, W. B., & Wang, X. J. (2008). An evolutionary game based particle swarm optimization algorithm. *Journal of Computational and Applied Mathematics, **214***(1), 30-35.

Liu, Y., Qin, Z., Shi, Z., & Lu, J. (2007). Center particle swarm optimization. *Neurocomputing, **70***(4), 672-679.

Liu, Y., Yi, Z., Wu, H., Ye, M., & Chen, K. (2008). A tabu search approach for the minimum sum-of-squares clustering problem. *Information Sciences, **178***(12), 2680-2704.

Lopez, B., Munoz, V., Murillo, J., Federico, B., Salido, M. A., Abril, M., et al. (2009). Experimental analysis of optimization techniques on the road passenger transportation problem. *Engineering Applications of Artificial Intelligence, **22***, 374-388.

Lu, Y., He, X., & Zhong, S. (2007). Cross-species microarray analysis with the OSCAR system suggests an INSR->Pax6->NQO1 neuro-protective pathway in aging and Alzheimer's disease. *;Nucleic Acids Research(*105-114.

Lungu, V., & Sofron, A. (2011). Using particle swarm optimization to create particle systems. *CSMR*, In Print.

Malone, T. W. (Ed.). (2006). *What is Collective Intelligence and What Will We Do About It?* : Earth Intelligence Network.

Margoluis, C. (2008). *Healthy Relationships: Examining Alliances Within Population – Health – Environment Projects*: World Wildlife Fund.

Marinakis, Y., & Marinaki, M. (2008). A particle swarm optimization algorithm with path relinking for the location routing problem *Journal of Mathematical Modelling and Algorithms, **7***(1), 59-78.

Marinakis, Y., & Marinaki, M. (2010). A hybrid multi-swarm particle swarm optimization algorithm for the probabilistic traveling salesman problem. *Computers & Operations Research, **37***(3), 432-442.

Marinakis, Y., Marinaki, M., Doumpos, M., & Zopounidis, C. (2009). Ant colony and particle swarm optimization for financial classification problems. *Expert Systems with Applications, **36***(7), 10604-10611.

Marinakis, Y., Marinaki, M., Matsatsinis, N., Doumpos, M., & Zopounidis, C. (2008). Optimization of nearest neighbor classifiers via metaheuristic algorithms for credit risk assessment. *Journal of Global Optimization, **42***(2), 1573-1616.

Matheson, J. E., & Menke, M. M. (1994). Using decision quality principles to balance your R&D portfolio research. *Technology Management **37***(3), 38-43.

Matthews, J. (2010). Positive relationships among collaboration for innovation, past innovation abandonment and future product introduction in manufacturing SMEs. *Interdisciplinary Journal of Contemporary Research in Business, **2***(6), 106-117.

McDonough, E. F., Kahn, K. B., & Barczak, G. (2001). An investigation of the use of global, virtual and collocated new product development teams. *The Journal of Product Innovation Management, **18***(2), 110-120.

Meneses, A. A. M., Machado, M. D., & Schirru, R. (2009). Particle swarm optimization applied to the nuclear reload problem of a pressurized water reactor. *Progress in Nuclear Energy, **51***(2), 319-326.

Merisavo, M. (2008). *The Interaction between Digital Marketing Communication and Customer Loyalty: An Integrative Model and Research Propositions*. Helsinki: Helsinki School of Economics.

Mikki, S. M., & Kishk, A. A. (2007). Physical theory for particle swarm optimization. *Progress in Electromagnetics Research, **75***, 177-207.

Milligan, G. W., & Cooper, M. C. (1985). An examination of procedures for determining the number of clusters in a data set. *Psychometrika, **50***(2), 159-179.

Mlynarek, J. (2011). Engineered textiles in global economy. the Intelligent Textile and Mass Customization Conference.

Mohammed, A. W., Sahoo, N. C., & Geok, T. K. (2007). Particle swarm optimization with noising metaheuristics for solving network shortest path problem. the Malaysia International Conference on Communications and Telecommunications.

Moisa, L. N., & Ngulube, P. (2005). Managing collective intelligence of local communities for the sustainable utilisation of estuaries in the Eastern Cape, South Africa. *South African Journal for Library and Information Science, **71***(2), 175-186.

Montalvo, I., Izquierdo, J., Perez, R., & Tung, M. M. (2006). Particle swarm optimization applied to the design of water supply systems. *Computers & Mathematics with Applications, **56***(3), 769-776.

Mortara, L., Napp, J. J., Slacik, I., & Minshall, T. (2009). *How to Implement Open Innovation: Lessons from Studying Large Multinational Companies*. Cambridge: University of Cambridge.

Motohashi, K. (2008a). Fast growing strategy of SMEs by using R&D networks. the Kansas City Workshop on High Growth SMEs, Innovation & Intellectual Assets: Strategic Issues and Policies.

Motohashi, K. (2008b). Growing R&D Collaboration of Japanese firms and policy implications for reforming the national innovation system. *Asia Pacific Business Review, **14***(3), 339-361.

Mouli, C., Subbaiah, V., & Rao, M. (2006). Particle swarm optimization approach for vendors selection. *Journal Institution of Engineers India Part Pe Production Engineering Division, **87***, 3-6.

Muhammad-Moradi, S., Khaloozadeh, H., Forouzanfar, M., Torghabeh, R. P., & Forghani, N. (Eds.). (2009). *Swarm Intelligence in Portfolio Selection*. Rijeka, Croatia: InTech Education and Publishing.

Mulligan, D., O'Leary, O., & O'Sullivan, D. (2005, July 20-22). Innovation management practice in Irısh SME's. ICE (Innovate - Collaborate - Educate) 2005, Munich, Germany.

Nader, A. E., Shamsuddin, A., & Zahari, T. (2008). Virtual R&D teams for NPD in SMEs: Past, present and future trend. Asia Pacific Conference on Management of Technology and Technology Entrepreneurship.

Nader, A. E., Shamsuddin, A., & Zahari, T. (2009). Innovation and R&D activities in virtual teams. *European Journal of Scientific Research, **34***(3), 297-307.

Nader, A. E., Shamsuddin, A., & Zahari, T. J. (2008). R&D networking and value creation in SMEs. the Seventh conference of Industries and Mines R&D Centers - R&D and Network Value Creation, June 30, Tehran, Iran.

Nagurney, A., & Qiang , A. Q. (2010). A knowledge collaboration network model across disciplines. Paper Proceedings of the Third International Conference on Social Computing, Behavioral Modeling, and Prediction.

Narula, R. (2004). R&D collaboration by SMEs: new opportunities and limitations in the face of globalisation. *Technovation, **24***(2), 153-161.

Nearchou, A. C. (2004). A novel meta-heuristic approach for the flow shop scheduling problem. *Engineering Applications of Artificial Intelligence, **17***, 289-300.

Nelson, W. (2004). *Applied Life Data Analysis*. New York: Wiley-Blacwell Publishing.

Newmark, A. J. (2002). An integrated approach for policy transfer and diffusion. *Review of Policy Research, **19***(2), 153-181.

Nickabadi, A., Ebadzadeh, M. M., & Bakhahsh, S. (2011). A novel particle swarm optimization algorithm with adaptive inertia weight. *Applied Soft Computing, **11***(4), 3658-3670.

Nieto, M. J., & Santamaria, L. (2006). *Technological Collaboration: Bridging The Innovation Gap Between Small and Large Firms* (Business Economics Working Papers).

Niknam, T., & Firouzi, B. B. (2009). A Practical Algorithm For Distribution State Estimation Including *Renewable Energy Sources.* Renewable Energy, ***34***(11), 2309-2316.

Nishimura, K. G., Nakajima, T., & Kiyota, K. (2005). *Innovation Versus Diffusion: Determinants of Productivity Growth Among Japanese Firms*: CIRJE, Faculty of Economics, University of Tokyo.

O'Sullivan, D., & Dooley, L. (2009). *Applying Innovation*: Sage Publications Inc. .

Obermair, C., Ploderer, B., Reitberger, W., & Tacheligi, M. (2006). Cues in the Environment: A Design Principle for Ambient Intelligence. the CHI 2006 (Conference on Human Factors in Computing Systems).

OECD and the European Commision. (2005). Paris.

OECD Glossary of Patent Terminology. (Ed.) (2012).

Okamuro, H. (2007). Determinants of successful R&D cooperation in Japanese small businesses: The impact of organizational and contractual characteristics. *Research Policy,* ***36***(10), 1529-1544.

Olk, P., & Ariño, A. (2003). Centro Anselma Rubiralta de Globalizaciòn y Estrategia, University of Navarro.

Olofsson, M. (2006). Particle swarm optimization for antenna design. *Journal of Electromagnetic Waves and Applications,* ***22***(2-3), 207-218.

Omran, M. G. H., Engelbrecht, A. P., & Salman, A. (2005). Dynamic clustering using particle swarm optimization with application in unsupervised image classication. *Academy of Science, Engineering and Technology World,* ***9***, 199-204.

Onut, S., Tuzkaya, U. R., & Dogac, B. (2007). A particle swarm optimization algorithm for the multiple-level warehouse layout design problem. *Computers & Industrial Engineering,* ***54***(4), 783-799.

Ortega-Argilés, R., & Voigt, P. (2009). *Business R&D in SMEs*: Institute for Prospective and Technological Studies, Joint Research Centre.

Osman, I. H., & Christofides, N. (1994). Capacitated clustering problems by hybrid simulated annealing and tabu search. *International Transactions in Operational Research,* ***1***(3), 317-336.

Owusu-Mensha, E., Oduro, I., Dziedzoave, N. T., & sarfo, K. J. (2011). Improving the Qualities of Rice Grain Using Gibberellic Acid (GA3). *American Journal of Experimental Agriculture,* ***1***(4), 432-439.

Parrota, P., Pozzoli, D., & Mariola, P. (2011). *The Nexus Between Labor Diversity and Firm's Innovation*: Norface Migration.

Paterlini, S., & Krink, T. (2006). Differential evolution and particle swarm optimisation in partitional clustering. *Computational Statistics & Data Analysis,* ***50***(5), 1220-1247.

Peças, P., & Henriques, E. (2006). Best practices of collaboration between university and industrial SMEs. *Benchmarking: An International Journal,* ***13***(1), 54-67.

Peeters, C., & Pottelsberghe, B. V. (2004). *Innovation capabilities and firm labor productivity*. Brussels: Universite Libre de Bruxelles.

Powell, A., Piccoli, G., & Ives, B. (2004). Virtual teams: a review of current literature and directions for future research. *The Data Base for Advances in Information Systems,* ***35***(1), 6-36.

Rai, A., Borah, S., & Ramaprasad, A. (1996). Critical Success Factors for Strategic Alliances in the Information Technology Industry: An Empirical Study*. *Decision Sciences,* ***27***(1), 141-155.

Rajaram, N. S. (1990). Artificial Intelligence: A Technology Review. *ISA Transactions,* ***29***(19), 1-3.

Ramaseshan, B., & Loo, P. C. (1998). Factors affecting a partner's perceived effectiveness of strategic business alliance: some Singaporean evidence. *International Business Review,* *7*(4), 443-458.

Rameshkumar, K., Suresh, R. K., & Mohanasundaram, K. M. (2005). Discrete particle swarm optimization (DPSO) Algorithm for permutation flowshop scheduling to minimize makespan. the Advances in Natural Computation, First International Conference, ICNC 2005.

Rammer, C., Czarnitzki, D., & Spielkamp, A. (2008). *Innovation Success of Non-R&D-Performers: Substituting Technology by Management in SMEs*: Centre for European Economic Research.

Rasmussen, S., Mangalagiu, D., Ziock, H., Bollen, J., & Keating, G. (2007). Collective intelligence for decision support in very large stakeholder networks: the future US energy system. Artificial Life, IEEE Symposium on ALIFE '07.

Raymond, L., & St-Pierre, J. (2010). R& D as a determinant of innovation in manufacturing SMEs: An attempt at empirical clarification. *Technovation, **30***(1), 48-56.

Rezazadeh, H., Ghazaneari, M., Saidi-Mehrabad, M., & Jafar Sadiadi, S. (2009). An extended discrete particle swarm optimization algorithm for the dynamic facility layout problem. *Journal of Zhejiang University - Science A, **10***(4), 1862-1875.

Rodríguez-Pose, A., & Refolo, C. (2008). *The Link Between Clusters of SMEs and Public and University Research in Italy*: European Regional Science Association.

Rodriguez, A., & Reggia, J. A. (2004). Extending self-organizing particle systems to problem solving. *Artificial Life, **10***(4), 379-385.

Rogers, E. M. (1983). *Diffusion of Innovations*. Illinois: University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship.

Rose, R. C., Abdullah, H., & Ismad, A. I. (2010). A review on relationship between organizational resources, competitive advantage and performance. *The Journal of International Social Research, **3***(1), 488-498.

Ross, S. (2006). *A First Course in Probability*. New York: Prentice Hall.

Ross, T. (2004). *Fuzzy Logic with Engineering Applications*. New York, USA: McGraw Hill Publishing.

Sadilek, A., kautz, H., & Silenzio, V. (2012, Modeling spread of disease from social interactions. the 6th International AAAI Conference on Weblogs and Social Media, June 4-8, Trinity College, Dublin, Ireland.

Sah, R. K., & Stiglitz, J. E. (1986). *The Invariance of R&D to the Number of Fİrms in the Industry*. Cambridge: National Bureau of Economic Research.

Saha, I., & Mukhopadhyay, A. (2008). Genetic algorithm and simulated annealing based approaches to categorical data clustering. the Industrial and Information Systems, 2008. ICIIS 2008. IEEE Region 10 and the Third international Conference on., December 8-11, Tampa, FL

Saha, S., & Bandyopadhyay, S. (2008). A new multiobjective simulated annealing based clustering technique using stability and symmetry. the ICPR 2008. 19th International Conference on Pattern Recognition, December 8-11, Tampa, FL

Saka, E., & Nasraoui, O. (2009). Improvements in Flock-Based Collaborative Clustering Algorithms. Computational Intelligence. In C. L. Mumford & L. C. Jain (Eds.), (Vol. 1): Springer Berlin Heidelberg, 639-672.

Salman, A., Ahmad, I., & Al-Madani, S. (2002). Particle swarm optimization for task assignment problem. *Microprocessors and Microsystems,* ***26***(8), 308-316.

Samanta, B., & Nataraj, C. (2009). Use of particle swarm optimization for machinery fault detection. *Engineering Applications of Artificial Intelligence,* ***22***, 308-316.

Sawers, J. L., Pretorius, M. W., & Oerlemans, L. A. G. (2008). Safeguarding SMEs dynamic capabilities in technology innovative SME-large company partnerships in South Africa. *Technovation,* ***28***(4), 171-182.

Scheunders, E. (1997). A genetic c-means clustering algorithm applied to color image quantization. *Pattern Recognition,* ***30***(6), 859-866.

Schonlau, M. (2002). The clustergram: a graph for visualizing hierarchical and non-hierarchical cluster analyses. *The Stata Journal,,* ***2***(4), 391-402.

Schütze, J., Baum, H., Ganss, M., Ivanova, R., & Müller, E. (2011). Cooperation of SMEs – Empirical Evidences After the Crisis Adaptation and Value Creating Collaborative Networks. In L. Camarinha-Matos, A. Pereira-Klen & H. Afsarmanesh (Eds.), (Vol. 362, pp. 527-534): Springer Boston.

Seckiner, S. U., & Kurt, M. (2008). Ant colony optimization for the job rotation scheduling problem. *Applied Mathematics and Computation,* ***201***(1-2), 149-160.

Sekerka, L. E., Zolin, R., & Simon, C. (2005). *Rapid Transformation in a Dual Identity Defence University*. Monterey, California: Naval Postgraduate School.

Sha, D. Y., & Hsu, C. Y. (2006). A hybrid particle swarm optimization for job shop scheduling problem. *Computers & Industrial Engineering,* ***51***, 791-808.

Sha, D. Y., & Hsu, C. Y. (2008). Particle swarm optimization combined with genetic operators for job shop scheduling problem with fuzzy processing time. *Applied Mathematics and Computation,* ***205***(1), 148-158.

Sharma, V. K., Agarwal, M., & Sen, K. (2011). Design in heterogeneous multi-state series-parallel systems. *Applied Mathematics and Computation,* ***181***, 362-378.

Shelokar, O. S., Siarry, P., Jayaraman, V. K., & Kulkarni, B. D. (2007). Particle swarm and ant colony algorithms hybridized for improved continuous optimization. *Applied Mathematics and Computation,* ***188***, 129-142.

Sheremetov, L., & Rocha-Mier, L. (2004). Collective intelligence as a framework for supply chain management. the 2nd International IEEE Conference on Intelligent Systems Proceedings.

Sheremetov, L., Rocha, L., Guerra, J., & Martinez, J. (2005). Optimization algorithm for dynamic multi agent job routing. at the FIP International Federation for Information Processing.

Shi, Y., & Eberhart, R. (1998). A Modified particle swarm optimizer. the IEEE World Congress on Computational Intelligence.

Shiau, D.-F. (2011). A hybrid particle swarm optimization for a university course scheduling problem with flexible preferences. *Expert Systems with Applications, **38***(1), 235-248.

Shunmugalatha, A., & Slochanal, S. M. R. (2008). Optimum Cost of generation for maximum loadability limit of power system using hybrid particle swarm optimization. *Electrical Pwer and Energy Systems, **30***, 486-490.

Siahkali, H., & Vakilian, M. (2009). Electricity generation scheduling with large-scale wind farms using particle swarm optimization. *Electric Power Systems Research, **79***(5), 826-836.

Sigel, E., Denby, B., & Le Hegarat-Mascle, S. (2002). Application of ant colony optimization to adaptive routing in a leo telecommunications satellite network. *Annals of Telecommunications, **57***(5-6), 520-539.

Silva, C. A., Sousa, J. M. C., & Runkler, T. A. (2008). Rescheduling and Optimization of Logistic Processes Using GA and ACO. *Engineering Applications of Artificial Intelligence, **21***, 343-352.

Silva, C. A., Sousa, J. M. C., Runkler, T. A., & Sa da Costa, J. M. G. (2009). Distributed Supply Chain Management Using Ant Colony Optimization. *European Journal of Operational Research, **199***(2), 349-358.

Skinner, C. (2007). *Promoting Innovation and Commercialisation The Australian Framework.*Unpublished manuscript, Suzhou, China.

Sousa, T., Silva, A., & Neves, A. (2004). Particle Swarm based data mining algorithms for classification tasks. *Parallel Computing, **30***(5-6), 767-783.

Su, M. C., Ciu, T. K., & Chang, H. T. (2002). Improving the self-organizing feature map algorithm using an efficient initialization scheme. *Journal of Science and Engineering, **5***(1), 53-48.

Sulton, M. Q., & Anderson, E. N. (2004). *Introduction to Cultural Ecology*: Altamira Press.

Sun, T. H. (2009). Applying particle swarm optimization algorithm to roundness Measurement. *Expert Systems with Applications, **36***(2), 3428-3438.

Sung, C. S., & Jin, H. W. (2000). A tabu-search-based heuristic for clustering. *Pattern Recognition, **33***(5), 849-858.

Sutherland, M., Marcia, N., Sarbong, C., & Jeong, Y. R. N. (2006). *Global Strategy of Renault-Nissan Alliance*: Renault White Papers.

Sveiby, K. E., & Simons, R. (2002). Collaborative climate and effectiveness of knowledge work – an empirical study. *Journal of Knowledge Management, **6***(5), 420-433.

Swoboda, B., Meierer, M., Foscht, T., & Morschett, D. (2011). International SME alliances: the impact of alliance building and configurational fit on success. *Long Range Planning, **44***(4), 271-288.

Szirmai, A., Naudé, W., & Goedhuys, M. (Eds.). (2011). *Entrepreneurship, Innovation, and Economic Development*: Oxford Press.

Talbi, E. G. (2011). *Metaheuristics from Design to Implementation*. New York: Wiley Interscience.

Tambunan, T. T. H. (2011). Crisis-adjustment strategies adopted by SMEs in coping with the 2008-2009 global economic crisis: The case of Indonesia. *Asian Journal of Agriculture and Development, **8***(1), 57.

Tapaninen, A., Seppänen, M., & Mäkinen, S. (2009). Characteristics of innovation in adopting a renewable residential energy system. *Journal of Systems and Information Technology, **11***(4), 347-366.

Tasgetiren, M. F., & Liang, Y. C. (2003). Binary particle swarm optimization algorithm for lot sizing problem. *Journal of Economic & Social Research, **5***(2), 1-20.

Teixeira, A. A. C., Santos, P., & Oliveira Brochado, A. (2008). International R&D cooperation between low-tech SMEs: The role of cultural and geographical proximity. *European Planning Studies, **16***(6), 785-810.

Thangaraj, R., Pan, M., Abraham, A., & Bouvry, P. (2011). Particle swarm optimization: hybridization perspectives and experimental illustrations. *Applied Mathematics and Computation, **217***, 5208-5226.

Theodoulides, L. (2005, September 15 -17). Interorganizational networking and innovative clusters between small and medium sized companies. the International Conference on Economics and Management of Networks - EMNET 2005, Budapest, Hungary.

Toksari, M. D. (2007). Ant colony optimization approach to estimate energy demand of Turkey. *Energy Policy, **35***(8), 3984-3990.

Torrent-Sellens, J., Jiménez, A. I., & Vilaseca, J. (2006). *Integration in strategic alliances: a conceptual framework of IT use in marketing as NPD key factor*. Barcelona: Universitat Oberta de Catalunya.

Tödtling, F., & Kaufmann, A. (2002). SMEs in regional innovation systems and the role of innovation support--The case of upper Austria. *The Journal of Technology Transfer, **27***(1), 15-26.

Tresch, M. C., Cheung, V. C. K., & d'Avella, A. (2006). Matrix factorization algorithms for the identification of muscle synergies: evaluation on simulated and experimental data sets. *Journal of Neurophysiology, **95***, 2199-2212.

Tripathi, P. K., Bandopadhyay, S., & Pal, S. K. (2007). Multi-objective particle swarm optimization with time variant inertia and acceleration coefficients. *Information Sciences, **177***(22), 5033-5049.

Tsai, C.-Y., & Kao, I. W. (2011). Particle swarm optimization with selective particle regeneration for data clustering. *Expert Systems with Applications, **38***(6), 6565-6576.

Tsai, C. Y., & Yeh, S. W. (2008). A multiple objective particle swarm optimization approach for inventory classification. *International Journal of Production Economics, **114***(2), 656-666.

Tsang, W., & Kwong, S. (2005). Unsupervised Anomaly Intrusion Detection Using Ant Colony Clustering Model Soft Computing as Transdisciplinary Science and Technology. In A. Abraham, Y. Dote, T. Furuhashi, M. Köppen, A.

Ohuchi & Y. Ohsawa (Eds.), (Vol. 29, pp. 223-232): Springer Berlin / Heidelberg.

Tschetschonig, K. (2012). *How SMEs Protect Critical Knowledge in Joint Innovation Activities with External Partners*. Norderstedt, Germany: Grin Verlag.

Tsubakitani, S., & Evans, J. R. (1998). An emprical study of a new metaheuristic for the traveling salesman problem. *European Journal of Operations Research, 17*, 289-300.

Tuyls, K., Hoen, P. J. T., & Vanschoenwinkel, B. (2005). An evolutionary dynamical analysis of multi-agent learning in iterated games *Autonomous Agents and Multi-Agent Systems, 12*(1), 115-153.

Twardy, D. (2009). *Partner Selection: A Source of Alliance Success*: Eindhoven University of Technology and Zuyd University of Applied Science.

Ugur, A., & Aydin, D. (2009). An Interactive simulation and analysis software for solving TSP using ant colony optimization algorithms. *Advances in Engineering Software, 40*(5), 341-349.

Un, C., Romero-Martínez, A., & Montoro-Sánchez, Á. (2009). Determinants of R&D collaboration of service firms. *Service Business, 3*(4), 373-394.

Un, C. A., Cuervo-Cazurra, A., & Asakawa, K. (2010). R&D collaborations and product innovation. *Journal of Product Innovation Management, 27*(5), 673-689.

van de Vrande, V., de Jong, J. P. J., Vanhaverbeke, W., & de Rochemont, M. (2009). Open innovation in SMEs: Trends, motives and management challenges. *Technovation, 29*(6–7), 423-437.

Vanhaverbeke, W. (2011). The Benefits of Open Innovation in Low-Tech SMEs: The Quilts of Denmark Story. In P. Silberzahn & W. Van Dyck (Eds.), *The Balancing Act of Innovation*: Lannoo Publishers.

Vanhees, L. (2006). The effect of a biotechnology SMEs' network position on its innovative performance. The 14th Annual High Technology Small Firms Conference.

Veenhuis, C., & Köppen, M. (2006). Data Swarm Clustering. *Swarm Intelligence in Data Mining*, 221-241.

Venayagamoorthy, G. K., Grant, L. L., & Doctor, S. (2007). Collective robotic search using hybrid techniques: fuzzy logic and swarm intelligence inspired by nature. *Engineering Applications of Artificial Intelligence, 22*, 431-441.

Venayagamoorthy, G. K., Smith, S. C., & Singhal, G. (2007). Particle swarm-based optimal partitioning algorithm for combinatorial CMOS circuits. *Engineering Applications of Artificial Intelligence, 20*(2), 177-184.

Villa, A., Antonelli, D., Caroleo, B., Barad, M., Hennet, J.-C., Potinecke, T., et al. (2009). Promote Aggregation of SMEs: Suggestions and Actions : A Road Map to the Development of European SME Networks. In A. Villa & D. Antonelli (Eds.), Springer London, 61-115.

Wageman, S. W. (2004). Risk management on research and development projects the AACE International Transactions.

Wang, H. S., Che, Z. H., & Wu, C. (2010). Using analytic hierarchy process and particle swarm optimization algorithm for evaluating product plans. *Expert Systems with Applications, 37*(2), 1023-1034.

Wang, J., & Wang, D. (2008). particle swarm optimization with a leader and followers. *Progress in Natural Science, 18*(11), 1437-1443.

Wang, W., Wu, B., Yanwei, Z., & F., D. (2006). Particle swarm optimization for open vehicle routing problem. International Conference on Intelligent Computing, ICIC 2006,.

Wang, W., Yang, J., & Muntz, R. (1997). STING: A Statistical Information Grid Approach to Spatial Data Mining.

Wang, X. H., & Li, J. J. (2004, August 26-29). Hybrid particle swarm optimization with simulated annealing. the 2004 International Conference on Machine Learning and Cybernetics, Shangai, China.

Wang, Y., Zhang, W., Chen, J., Li, J., & Xiao, L. (2007). Using ant colony optimization for efficient clustering. Proc. SPIE 6794.

Watcharasitthiwat, K., & Wardkein, P. (2009). Reliability optimization of topology communication network design using an improved ant colony optimization. *Computers & Electrical Engineering, 35*(3), 730-747.

Wayne, K. T. (2010). Determinants of commercial innovation for university technology transfer. *Journal of Behavioral Studies in BUsiness, 3*(1), 1-23.

Wu, C. H., Lin, W. T., Li, C. H., Fang, I. C., & Wu, C. H. (2008). ant colony optimization on building an online delayed diagnosis detection support system for emergency department. 7th International Conference onComputational Intelligence in Economics and Finance, Kainan University, December 5-7, Taoyuan, Taiwan.

Wu, N., Mao, N., & Qian, Y. (1999). An approach to partner selection in agile manufacturing. *Journal of Intelligent Manufacturing, 10*(6), 519-529.

Wu, Q. (2010). Power Load Forecasts Based on Hybrid PSO with gaussian and adaptive mutation and Wv-SVM. *Expert Systems with Applicaitons, 37*, 194-201.

Wu, W. Y., Shih, H.-A., & Chan, H.-C. (2009). The analytic network process for partner selection criteria in strategic alliances. *Expert Systems with Applications, 36*(3, Part 1), 4646-4653.

Xian-Cheng, Z. (2006, July 13-17). Color İImage filter based on predator-prey particle swarm optimization. International Conference on Artificial Intelligence and Computational Intelligence, Las Vegas, Nevada, USA.

Xu, F., Chen, W., & Yang, L. (2007). Improved particle swarm optimization for realistic portfolio selection. Eighth ACIS International Conference on Software Engineering, Artificial Intelligence, July 30 - August 01, Networking, and Parallel/ Distributed Computing, Qingdao, China.

Xu, G., Du, H., Wang, H., & Meng, J. (2012). Study on the Application of Ant Colony Clustering in Fault Early Warning of Equipment Management Software Engineering and Knowledge Engineering: Theory and Practice. In Y. Wu (Ed.), (Vol. 114, pp. 1039-1045): Springer Berlin / Heidelberg.

Yang, I. T. (2006a). Multiobjective PSO algorithm in project staff management. the International Symposium on Automation and Robotics in Construction 2006, ISARC 2006.

Yang, I. T. (2006b). Performing complex project crashing analysis with the aid of particle swarm optimization algorithm. *International Journal of Project Management, **25***(6), 637-646.

Yang, J., Shi, X., Marchese, M., & Liang, Y. (2008). An ant colony optimization method for generalized TSP problem. *Progress in Natural Science, **18***(11), 1417-1422.

Yang, W., Rueda, L., & Acun, D. (2005). A simulated annealing approach to find the optimal parameters for fuzzy clustering microarray data. SCCC '05 Proceedings of the XXV International Conference on The Chilean Computer Science Society.

Ye, F. (2010). An extended TOPSIS method with interval-valued intuitionistic fuzzy numbers for virtual enterprise partner selection. *Expert Systems with Applications, **37***(10), 7050-7055.

Ye, F., & Li, Y.-N. (2009). Group multi-attribute decision model to partner selection in the formation of virtual enterprise under incomplete information. *Expert Systems with Applications, **36***(5), 9350-9357.

Yin, P. Y., & Wang, J. Y. (2006). Ant colony optimization for the nonlinear resource allocation problem. *Applied Mathematics and Computation, **174***(2), 1438-1453.

Yin, P. Y., Yu, S. S., & Wang, Y. T. (2007). Task allocation for maximizing the reliability of a distributed system using hybrid particle swarm optimization. *The Journal of Systems and Software, **80***, 724-735.

Yokakul, N., & Zawdie, G. (2010). Innovation network and technological capability development in the Thai SME sector: The case of the Thai dessert industry. *International Journal of Technology Management & Sustainable Development, **9***(1), 19-36.

Yoshida, H., Kawata, K., Fukuyama, Y., Takayama, S., & Nakashini, Y. (2000). A particle swarm optimization for reactive power and voltage control considering voltage security assessment. *IEEE Transactions on Power Systems, **15***(4), 1232-1239.

Yuan, Y., & Wang, D. (2005). Path selection model and algorithm for emergency logistics management. *Computers and Industrial Engineering, **56***(3), 1081-1094.

Zeng, H., Pukkala, T., Peltola, H., & Kellomaki, S. (2007). Application of ant colony optimization for the risk management of wind damage in forest planning. *Silva Fennica, **41***(2), 315-332.

Zhang, D., Guangming, X., Yu, J., & Wang, L. (2007). Adaptive task assignment for multiple mobile robots via swarm intelligence approach. *Robotics and Autonomous Systems, **55***(7), 572-588.

Zhang, G., Zhao, X., Li, P., & Gao, L. (2009). An effective hybrid particle swarm optimization algorithm for multi-objective flexible job-shop scheduling Problem. *Computers & Industrial Engineering, **56***, 1309-1318.

Zhang, J. R., Zhang, J., Lok, T. M., & Lyu, M. R. (2007). A hybrid particle swarm optimization-back-propagation algorithm for feedforward neural network training. *Applied Mathematics and Computation, **185***(2), 1026-1037.

Zhang, L., & Cao, Q. (2011). A novel ant-based clustering algorithm using the kernel method. *Information Sciences, **181***(20), 4658-4672.

Zhang, M., & Yin, X. (2012). The effect of R&D alliances on the speed of innovation: evidence from chinese SMEs. *Physics Procedia, **25***(0), 1155-1161.

Zhang, Q.-q., Gao, W.-d., Peng, M.-g., & Wang, W.-b. (2008). Partner selection strategies in cooperative wireless networks with optimal power distribution. *The Journal of China Universities of Posts and Telecommunications, **15***(3), 47-58.

Zhang, X., & Tang, L. (2009). a new hybrid ant colony optimization algorithm for the vehicle routing problem. *Pattern Recognition Letters, **30***(9), 848-855.

Zhao, F. Q., Zhang, Q. Y., & Yang, Y. H. (2006). An Improved particle swarm optimization (PSO) algorithm and fuzzy inference systems based approach to process planning and production scheduling integration in holonic manufacturing system (hms) and fuzzy inference systems. The International Conference on Machine Learning and Cybernetics.

Zhao, Q., Zhang, X., & Xiao, R. (2008). Particle swarm optimization algorithm for partner selection in virtual enterprise. *Progress in Natural Science, **18***(11), 1445-1452.

Ziari, I., Ledwich, G. Ghosh, A., Cornforth, D. and Wishart, M. (2010). Optimal allocation and sizing of capacitators to minimize the transtion line loss and improve the voltage profile. *Computers and Mathematics with Applications, **60***, 1003-1013.

Url-1 (2010). <http://europa.eu/rapid/pressReleasesAction.do?reference=MEMO/10/473> Retrieved November 12, 2009.

Url-2 (2009). <http://www.icdmuenchen.um.dk/en/servicemenu/News/FinancialCrisesAndRD.htm>, Retrieved November 12, 2009.

Url-3 (2009). <http://scripts.mit.edu/~cci/HCI/index.php?title=A_taxonomy_of_collective_intelligence > Retrieved November 12, 2009,

APPENDICES

APPENDIX A: Innovation collaboration in SMEs in literature.

APPENDIX B: Partner selection in literature.

APPENDIX C: The Collective Intelligence literature.

APPENDIX D: Literature clustering results.

APPENDIX E: The united synergy fuzzy cognitive matrix.

APPENDIX F: The fuzzy synergy questionnaire.

APPENDIX G: The characters of visions, goals and objectives.

APPENDIX H: The united innovation and risk fuzzy cognitive matrix.

APPENDIX I: The fuzzy innovation / risk questionnaire.

APPENDIX A: Innovation collaboration in SMEs in literature.

Table A.1: Innovation collaboration in SMEs in literature.

Study	Aim	Type of Clustering	Geographical Scope	Industry	Members	Method	Submethod
(Lazoi et al., 2011)	To analyze the process of R&D networks	By industry	Italy	Aerospace	With large enterprises	Statistical Methods	Survey analysis
(Clifton et al., 2010)	To measure performance of collaborations	By region	UK	Agriculture & Retail	With universities	Statistical Methods	Surveys & Regression analysis
(Gardet and Mothe, 2012)	To measure the effect of hub firms	By industry	All (local, national, international)	Various (Automobile, Retail, Sport, etc.)	555 SMEs with one hub firms (either in the collaboration or independent hubs)	Qualitative Methods	7 Case Studies
(Jørgensen and Ulhøi, 2010)	To offer an implementation process for existing collaborations	-	Local	Service (ticket selling)	With business partners (suppliers)	Qualitative methods	A case study

Table A.1(continued): Innovation collaboration in SMEs in literature.

Study	Aim	Type of Clustering	Geographical Scope	Industry	Members	Method	Submethod
(Motohashi, 2008a)	To compare the performances of types of alliances	By region	Japan	Manufacturing, Wholesale & Retail	-With large enterprises -With universities (1300 SMEs)	Statistical Methods	Case study Regression
(Motohashi, 2008b)	To compare the performances of types of alliances	By region	Japan	Manufacturing, Wholesale & Retail	-With large enterprises -With universities (1300 SMEs)	Statistical Methods	Case study Regression
(Peças and Henriques, 2006)	To offer an implementation process for existing collaborations	One-to-one	Lisbon, Portugal	Manufacturing	With universities	Systems Analysis	Flowcharts Case study
(Collier et al., 2011)	To determine success factors	One-to-one	Brisbane, Australia	Electronics	With universities	Qualitative Analysis	A case study of 5 SMEs
(Batterink et al., 2010)	To observe the effect of innovation brokers	By industry	Netherlands, Germany, France	Agrifood	With universities	Qualitative Analysis	Case Study

Table A.1(continued): Innovation collaboration in SMEs in literature.

Study	Aim	Type of Clustering	Geographical Scope	Industry	Members	Method	Submethod
(Yokakul and Zawdie, 2010)	To offer methods for promoting collaborations	By industry	Thailand	Dessert	With universities, large enterprises & business partners	Qualitative Analysis	Case Study
(Teixeira et al., 2008)	To compare success factors	-	International (EU + Switzerland + Norway + Brazil)	Various (Machinery, Agriculture, Building, Metal Production, Telecommunication)	With SMEs	Statistical Analysis	Clustering
(Okamuro, 2007)	To determine success factors	by industry	Japan	Manufacturing	Among 6300 SMEs	Statistical Methods	Case study & Surveys
(Xiaolin Li, 2012)	To determine success factors	By industry	China	Exporting	Among 186 SMEs	Statistical Methods	Case study & Surveys
(Konsti-Laakso et al., 2012)	To measure the ability to innovate	By industry	N/A	Town Planning	Among 4 SMEs with a large enterprise	Qualitative Analysis	Case Study
(Narula, 2004)	To measure collaboration performance	By industry	N/A	Electronics Hardware	Among 110 SMEs	Statistical Methods	Surveys

Table A.1(continued): Innovation collaboration in SMEs in literature.

Study	Aim	Type of Clustering	Geographical Scope	Industry	Members	Method	Submethod
(Un et al., 2009)	To determine success factors	By industry	Spain	Service	Among 12179 SMEs	Statistical Methods	Regression & Survey
(Vanhees, 2006)	To analyze the effect of positioning in alliances	By industry	Netherlands	Biotechnology	With SMEs	Statistical Methods	Regression & Survey
(Braun, 2003)	To reveal challenges in networks	By region and industry	Victoria, Australia	Tourism	With SMEs	Qualitative Analysis	Case Study

APPENDIX B: Partner selection in literature.

Table B.1: Partner selection in literature.

Study	Collaboration Type	Objective	Choosing / Matching / Grouping	Industry	Method	Submethod
(Wu et al., 1999)	Manufacturing Collaboration	To find a best match for each subproduction phases	Choosing	N/A	Integer Programming Graph Thepry	A network of tasks
(Hajidimitriou and Georgiou, 2002)	International Joint Ventures	To find the best match for the joint venture	Choosing	N/A	Goal programming	Two objectives
(Dong and Glaister, 2006)	Strategic collaboration	To determine partner selection criteria	N/A	N/A	Statistical Methods (	Surveys
(Ip et al., 2003)	Virtual enterprise	To find best matches for each project of a company	Choosing	Construction	Modified Genetic Algorithm	Non-linear model with a reduced solution space
(Fischer et al., 2004)	Virtual enterprise	To find a best match for the production process	Choosing	N/A	Ant Colony Optimization	One objective

Table B.1: Partner selection in literature.

Study	Collaboration Type	Objective	Choosing / Matching / Grouping	Industry	Method	Submethod
(Ding and Liang, 2005)	Strategic collaboration	To find the best match to increase power in the shipping industry	Choosing	Shipping	Multi Criteria Decision Making Fuzzy Logic	Weighted Average
(Hacklin et al., 2006)	Innovation Collaboration	To find best matches for a company	Choosing	Renewable Energy	Decision Support Systems	Computer Facilitated Quantitative Data Analysis
(Zhao et al., 2008)	Virtual enterprise	To find best partners for subprojects	Grouping	N/A	Modified Particle Swarm Optimization	16 Subprojects, Knapsack,
(Zhang et al., 2008)	Wireless network	To find the best partner	Matching	Telecommunication	Multi Criteria Decision Making	Trials on several arithmetic formulae
(Li and Ferreira, 2008)	Strategic collaboration	To find a best match among numerous firms	Choosing	N/A	Multi Criteria Decision Making	TOPSIS

Table B.1: Partner selection in literature.

Study	Collaboration Type	Objective	Choosing / Matching / Grouping	Industry	Method	Submethod
(Ye and Li, 2009)	Virtual enterprise	To find a best match among numerous firms	Choosing	N/A	Multi Criteria Decision Making	TOPSIS
(Wu et al., 2009)	Strategic collaboration	To find a best match among numerous firms	Choosing	LCD	Multi Criteria Decision Making	ANP
(Ye, 2010)	Virtual enterprise	To find a best match	Choosing	N/A	Multi Criteria Decision Making Fuzzy Logic	TOPSIS
(Feng et al., 2010)	Co-development alliance	To find a best match	Choosing	N/A	Multi Criteria Decision Making Fuzzy Logic	Modified AHP
(Huang et al., 2010)	Strategic collaboration	To find a best match among numerous firms	Choosing	Service	Multi Objective Programming	3 objectives, Pareto-Optimality
(Chen et al., 2010)	R&D Collaboration	To find a best match among numerous firms	Choosing	N/A	Multi Criteria Decision Making Fuzzy Logic	AHP

Table B.1: Partner selection in literature.

Study	Collaboration Type	Objective	Choosing / Matching / Grouping	Industry	Method	Submethod
(Huang et al., 2011)	Virtual enterprise	To find a best match to maximize the minimum agreement	Choosing	Manufacturing	Modified Particle Swarm Optimization Simulation	Non-linear model
(Cummings and Holmberg, 2012)	Strategic collaboration	To find the best match for a biomedical company	Choosing	Biotechnology	Multi Criteria Decision Making	Weighted Average
(Baum et al., 2012)	Innovation Collaboration	To assign companies in clusters	Grouping	N/A	Graph Theory	Clustering

APPENDIX C: The Collective Intelligence literature

Table C.1: The Collective Intelligence literature.

No	Author	Method									
		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
1	Kittur et al., 2009	0	1	0	0	0	0	0	0	0	0
2	Obermair et al., 2006	0	0	0	0	1	0	0	0	0	0
3	Moisa and Ngulube, 2005	0	0	0	0	1	0	0	0	0	0
4	Rodriguez and Reggia, 2004	0	0	0	0	1	0	0	0	0	0
5	Rasmussen et al., 2007	0	0	0	0	1	0	0	0	0	0
6	Boschetti and Brede, 2008	0	0	0	0	0	0	0	1	0	0
7	Sheremetov and Roche-mier, 2004	0	0	0	0	1	0	0	0	0	0
8	Cornu, 2005	0	0	0	0	1	0	0	0	0	0
9	Seheremetov et al., 2005	0	0	0	0	0	0	0	1	0	0
10	Tuyls et al., 2005	0	0	0	0	0	0	0	1	0	0
11	Brede et al., 2007a	0	0	0	0	0	0	0	1	0	0
12	Yang, 2006a	0	0	0	0	0	1	0	0	0	0
13	Zhang et al., 2007a	0	0	0	1	1	0	0	0	0	0
14	Albritton and McMillan, 2007	0	0	0	1	0	0	1	0	0	0
15	Alici et al., 2006	0	0	0	0	0	1	0	0	0	0
16	Calderon et al., 2006	0	0	0	1	0	0	0	0	0	0
17	Sousa et al., 2004	0	0	0	0	0	1	0	0	0	0
18	Cai et al., 2007	0	0	1	1	0	0	1	0	0	0
19	Venayagamoorthy et al., 2007	0	0	0	0	0	1	0	0	0	0
20	Gunes et al., 2008	0	0	0	0	0	1	0	0	0	0
21	Koshino et al., 2006	0	0	0	0	0	1	0	0	1	0
22	Iwasaki et al., 2006	0	0	1	0	0	1	0	0	0	0
23	Gao et al., 2006	0	0	0	0	0	1	0	0	0	0
24	Hassan et al., 2005	0	0	0	0	0	1	0	0	0	0
25	Yoshida et al., 2000	0	0	0	0	0	1	0	0	0	0
26	Montalvo et al., 2008	0	0	0	0	0	1	0	0	0	0
27	Guo et al., 2006a	0	0	1	0	0	1	0	0	0	0
28	Oloffsson, 2006	0	0	0	0	0	1	0	0	0	0
29	Chen et al., 2006	0	0	0	0	0	1	0	0	0	0
30	Xu et al., 2007	0	0	0	0	0	1	0	0	0	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Method									
		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
31	Cura, 2009	0	0	0	0	0	1	0	0	0	0
32	Muhammad-Moradi et al., 2009	0	0	1	1	0	0	0	0	0	0
33	Haibing et al., 2006	0	0	0	0	0	0	0	0	1	0
34	Wang et al., 2006	0	0	0	0	0	1	0	0	0	0
35	Yang, 2006b	0	0	0	0	0	1	0	0	0	0
36	Liang et al., 2008	0	0	0	0	0	1	0	0	0	0
37	Cui et al., 2005	0	0	0	0	0	1	0	0	0	0
38	Mouli et al., 2006	0	0	0	0	0	1	0	0	0	0
39	Sun, 2009	0	0	0	0	0	1	0	0	0	0
40	Han et al., 2009	0	0	0	0	0	1	0	0	0	0
41	Tasgetiren and Liang, 2003	0	0	0	0	0	0	0	0	1	0
42	Huang et al., 2007	0	0	0	0	0	1	0	0	0	0
43	Mohammed et al., 2007	0	0	1	0	0	0	0	0	1	0
44	Zhao et al., 2006	0	0	0	0	0	1	0	0	0	0
45	Rezazadeh et al., 2009	0	0	0	0	0	1	0	0	0	0
46	Rameshkumar et al., 2005	0	0	0	0	0	1	0	0	0	0
47	Guo et al., 2006b	0	0	0	0	0	1	0	0	0	0
48	Liao et al., 2005	0	0	0	0	0	0	0	0	1	0
49	Jia and Yang, 2007	0	0	0	0	0	1	0	0	0	0
50	Guo et al., 2007	0	0	0	0	0	0	0	0	1	0
51	Jursa, 2007	0	0	0	0	0	0	0	0	1	0
52	Marinakis et al., 2008	0	0	0	0	0	0	0	0	1	1
53	Onut et al., 2007	0	0	0	0	0	0	0	0	1	0
54	Camci, 2008	0	0	0	0	0	1	0	0	1	0
55	Chen et al., 2008	0	0	0	0	0	0	0	0	1	0
56	Gajpal and Abad, 2009	0	0	0	0	0	0	1	0	0	0
57	Silva et al., 2009	0	0	1	0	0	0	1	0	0	0
58	Abdallah and Emara, 2009	0	0	0	0	0	0	1	0	0	0
59	Bin et al., 2009	0	0	0	0	0	0	1	0	0	0
60	Zhang and Tang, 2009	0	0	0	0	0	0	0	0	0	1
61	Chebouba et al., 2009	0	0	0	0	0	0	1	0	0	0
62	Arora et al., 2010	0	0	0	0	0	0	1	0	0	0
63	Ugur and Aydin, 2009	0	0	1	0	0	0	1	0	0	0
64	Li and Rong, 2009	0	0	0	0	0	0	0	0	0	1
65	Christodolou, 2009	0	0	0	0	0	0	1	0	0	0
66	Fuellerer et al., 2010	0	0	0	0	0	0	1	0	0	0
67	Yuan and Wang, 2005	0	0	0	0	0	0	0	0	0	1
68	Watcharasitthiwat and Wardkein, 2009	0	0	1	0	0	0	1	0	0	0

Table C.1(continued): The Collective Intelligence literature.

		Method									
No	Author	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
69	Niknam and Firouzi, 2009	0	0	0	0	0	0	0	0	0	1
70	Marinakis and Marinaki, 2010	0	0	0	0	0	1	0	0	1	0
71	Almeder, 2009	1	0	0	0	0	0	1	0	0	0
72	Chang et al., 2009	0	0	0	0	0	0	1	0	0	0
73	Yang et al., 2008	0	0	0	0	0	0	1	0	0	0
74	Seckiner and Kurt, 2008	0	0	0	0	0	0	1	0	0	0
75	Marinakis and Marinaki, 2008	0	0	0	0	0	0	1	0	0	0
76	Toksari, 2007	0	0	0	0	0	0	1	0	0	0
77	Yin and Wang, 2006	0	0	1	0	0	0	1	0	0	0
78	Kuo et al., 2005	0	0	0	0	0	0	1	0	0	0
79	Aghaie and Mokhtari, 2009	0	0	1	0	0	0	1	0	0	0
80	Sigel et al., 2002	0	0	0	0	0	0	1	0	0	0
81	Wu et al., 2008	0	0	0	0	0	0	0	0	0	1
82	Hani et al., 2007	0	0	0	0	0	0	1	0	0	0
83	Liang and Smith, 2004	0	0	0	0	0	0	1	0	0	0
84	Geem, 2009	0	0	0	0	0	0	0	0	1	0
85	Afshar et al., 2009	0	0	0	0	0	0	0	0	0	1
86	Lam et al., 2007	0	0	0	0	0	0	0	0	0	1
87	Bontoux and Feillet, 2008	0	0	0	0	0	0	1	0	0	0
88	Zeng et al., 2007	0	0	0	0	0	0	1	0	0	0
89	Chan and Swarnkar, 2006	0	0	0	0	0	0	1	0	0	0
90	Alba et al., 2008	0	0	0	0	0	0	1	0	0	0
91	Brede et al., 2007b	0	0	0	0	0	0	0	1	0	0
92	Cui et al., 2008	0	0	0	0	0	1	0	0	0	0
93	Kang et al., 2008	0	0	0	0	0	1	0	0	0	0
94	Jiang et al., 2007	0	0	0	0	0	1	0	0	0	0
95	Zhang et al., 2007b	0	0	0	0	0	1	0	0	0	0
96	Liu et al., 2007	0	0	0	0	0	1	0	0	0	0
97	Shi and Eberhart, 1998	0	0	0	0	0	1	0	0	0	0
98	Tripathi et al., 2007	0	0	0	0	0	1	0	0	0	0
99	Alatas and Akin, 2009	0	0	0	0	0	1	0	0	0	0
100	Liu and Wang, 2008	0	0	0	0	0	0	0	0	1	0
101	Falco et al., 2007	0	0	0	0	0	0	0	0	1	0
102	Wang and Wang, 2008	0	0	0	0	0	1	0	0	0	0
103	Ali and Kaleo, 2008	0	0	0	0	0	1	0	0	0	0
104	Wang et al., 2010	0	0	0	0	0	0	0	0	1	0
105	Meneses et al., 2009	0	0	0	0	0	1	0	0	0	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Method									
		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
106	Chaturvedi et al., 2009	0	0	0	0	0	1	0	0	0	0
107	Salman et al., 2002	0	0	0	0	0	1	0	0	0	0
108	Tsai and Yeh, 2007	0	0	0	0	0	1	0	0	0	0
109	Siahkali and Vakilian, 2009	0	0	0	0	0	1	0	0	0	0
110	Sha and Hsu, 2008	0	0	0	0	0	1	0	0	0	0
111	Samanta and Nataraj, 2009	0	0	1	0	0	0	0	0	1	0
112	He and Wang, 2007	0	0	1	0	0	1	0	0	0	0
113	Silva et al., 2008	0	0	1	0	0	0	1	0	0	0
114	Lopez et al., 2009	0	0	0	0	0	0	1	0	0	0
115	Veneyagamoorthy et al., 2009	0	0	1	0	0	0	0	0	1	0
116	Kuo and Yang, 2011	0	0	1	0	0	1	0	0	1	0
117	Kuo et. al., 2011	0	0	1	0	0	1	0	0	0	0
118	Coelho, 2009	1	0	1	0	0	0	0	0	1	0
119	Chen and Zhao, 2009	0	0	0	0	0	1	0	0	1	0
120	Assareh et. al., 2010	0	0	0	0	0	1	0	0	0	0
121	Duan and Liao, 2010	0	0	0	0	0	0	1	0	0	0
122	Deng and Lin, 2011	0	0	0	0	0	0	1	0	0	0
123	Li et. al., 2010	0	0	0	0	0	0	0	0	0	1
124	Kuan and Wong, 2010	0	0	0	0	0	0	1	0	0	0
125	Lee et. al., 2010	0	0	0	0	0	0	1	0	0	0
126	Che and Wang, 2010	0	0	0	0	0	0	0	0	1	0
127	Dye and Hsieh, 2010	0	0	0	0	0	1	0	0	0	0
128	Boonyaritdachochai et. al., 2010	0	0	0	0	0	1	0	0	0	0
129	Ziari et al., 2010	0	0	0	0	0	1	0	0	0	0
130	Kuo and Shih, 2007	0	0	0	0	0	0	1	0	0	0
131	Jiang et al., 2010	0	0	0	0	0	1	0	0	0	0
132	Christmas et. al., 2010	0	0	0	0	0	0	1	0	0	0
133	Chen et. al., 2010	0	0	0	0	0	0	0	0	0	1
134	Sharma et. al., 2011	0	0	0	0	0	0	1	0	0	0
135	Araujo, 2010	0	0	0	0	0	0	0	0	1	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Industry											
		I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12
1	Kittur et al., 2009	0	0	0	0	0	0	0	0	0	1	0	0
2	Obermair et al., 2006	0	0	0	0	1	0	0	0	0	0	0	0
3	Moisa and Ngulube, 2005	0	0	0	0	0	0	1	0	0	0	0	0
4	Rodriguez and Reggia, 2004	0	0	0	0	0	0	0	0	0	0	0	1
5	Rasmussen et al., 2007	0	0	0	1	0	0	0	0	0	1	0	0
6	Boschetti and Brede, 2008	0	0	0	0	1	0	0	0	0	0	0	0
7	Sheremetov and Rochemier, 2004	0	0	0	0	0	0	0	0	0	0	0	1
8	Cornu, 2005	1	0	0	0	0	0	0	0	0	0	0	0
9	Seheremetov et al., 2005	0	0	0	0	0	0	0	0	0	0	0	1
10	Tuyls et al., 2005	0	0	0	0	0	0	0	0	0	0	0	1
11	Brede et al., 2007a	0	0	0	0	1	0	0	0	0	0	0	0
12	Yang, 2006a	0	0	1	0	0	0	0	0	0	0	0	0
13	Zhang et al., 2007a	0	0	0	0	0	0	0	1	0	0	0	0
14	Albritton and McMillan, 2007	0	0	0	0	0	0	0	0	0	0	0	1
15	Alici et al., 2006	0	0	0	0	0	0	0	1	0	0	0	0
16	Calderon et al., 2006	0	1	0	0	0	0	0	0	0	0	0	0
17	Sousa et al., 2004	0	0	0	0	0	0	0	0	0	0	0	1
18	Cai et al., 2007	0	0	0	1	0	0	0	0	0	0	0	0
19	Venayagamoorthy et al., 2007	0	0	0	0	0	0	0	1	0	0	0	0
20	Gunes et al., 2008	0	0	0	0	0	0	0	1	0	0	0	0
21	Koshino et al., 2006	0	1	0	0	0	0	0	0	0	0	0	0
22	Iwasaki et al., 2006	0	0	0	0	0	0	0	0	0	0	0	1
23	Gao et al., 2006	0	0	0	0	0	0	0	1	0	0	0	0
24	Hassan et al., 2005	0	0	0	0	0	0	0	1	0	0	0	0
25	Yoshida et al., 2000	0	0	0	1	0	0	0	1	0	0	0	0
26	Montalvo et al., 2008	0	0	0	1	0	0	0	0	0	0	0	0
27	Guo et al., 2006a	0	0	0	0	0	0	0	1	0	0	0	0
28	Oloffsson, 2006	0	0	0	0	0	0	0	0	0	0	0	1
29	Chen et al., 2006	0	1	0	0	0	0	0	0	0	0	0	0
30	Xu et al., 2007	0	1	0	0	0	0	0	0	0	0	0	0
31	Cura, 2009	0	1	0	0	0	0	0	0	0	0	0	0
32	Muhammad-Moradi et al., 2009	0	1	0	0	0	0	0	0	0	0	0	0
33	Haibing et al., 2006	0	0	0	1	0	0	0	0	0	0	0	0
34	Wang et al., 2006	0	0	0	0	0	0	0	0	0	0	1	0
35	Yang, 2006b	0	0	0	0	0	0	0	0	0	0	0	1
36	Liang et al., 2008	0	0	0	0	0	0	0	1	0	0	0	0
37	Cui et al., 2005	0	0	0	0	0	0	0	0	0	0	0	1
38	Mouli et al., 2006	0	0	0	0	0	0	0	0	0	0	0	0
39	Sun, 2009	0	0	0	0	0	0	0	1	0	0	0	0
40	Han et al., 2009	0	0	0	0	0	0	0	1	0	0	0	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Industry											
		I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12
41	Tasgetiren and Liang, 2003	0	0	0	0	0	0	0	0	0	0	1	0
42	Huang et al., 2007	0	0	0	0	1	0	0	0	0	0	0	0
43	Mohammed et al., 2007	0	0	0	0	0	0	0	0	0	0	0	1
44	Zhao et al., 2006	0	0	0	0	0	0	0	0	0	0	0	1
45	Rezazadeh et al., 2009	0	0	0	0	0	0	0	0	0	0	1	0
46	Rameshkumar et al., 2005	0	0	0	0	0	0	0	0	0	0	1	0
47	Guo et al., 2006b	0	0	0	0	0	0	0	0	0	0	0	1
48	Liao et al., 2005	0	0	0	0	0	0	0	0	0	0	1	0
49	Jia and Yang, 2007	0	0	0	0	0	0	0	0	0	0	0	1
50	Guo et al., 2007	0	0	0	0	0	0	0	0	0	0	0	1
51	Jursa, 2007	0	0	0	1	0	0	0	0	0	0	0	0
52	Marinakis et al., 2008	0	1	0	0	0	0	0	0	0	0	0	0
53	Onut et al., 2007	0	0	0	0	0	0	0	0	0	0	0	1
54	Camci, 2008	0	0	0	0	0	0	0	0	0	0	0	1
55	Chen et al., 2008	0	0	0	0	0	0	0	0	0	0	1	1
56	Gajpal and Abad, 2009	0	0	0	0	0	0	0	0	0	0	1	0
57	Silva et al., 2009	0	0	0	0	0	0	0	1	0	0	0	0
58	Abdallah and Emara, 2009	0	0	1	0	0	0	0	0	0	0	0	0
59	Bin et al., 2009	0	0	0	0	0	0	0	0	0	0	1	0
60	Zhang and Tang, 2009	0	0	0	0	0	0	0	0	0	0	1	0
61	Chebouba et al., 2009	0	0	0	1	0	0	0	0	0	0	0	0
62	Arora et al., 2010	0	0	0	0	0	0	0	0	0	0	0	1
63	Ugur and Aydin, 2009	0	0	0	0	0	0	0	0	0	0	0	1
64	Li and Rong, 2009	0	0	0	1	0	0	0	0	0	0	0	0
65	Christodolou, 2009	0	0	0	0	0	0	0	0	0	0	0	1
66	Fuellerer et al., 2010	0	0	0	0	0	0	0	0	0	0	1	0
67	Yuan and Wang, 2005	0	0	0	1	0	0	0	0	0	0	0	0
68	Watcharasitthiwat and Wardkein, 2009	0	0	0	0	0	0	0	0	0	0	1	0
69	Niknam and Firouzi, 2009	0	0	0	1	0	0	0	0	0	0	1	1
70	Marinakis and Marinaki, 2010	0	0	0	0	0	0	0	0	0	0	1	0
71	Almeder, 2009	0	0	0	0	0	0	0	0	0	0	1	0
72	Chang et al., 2009	0	0	0	0	0	0	0	0	0	0	1	0
73	Yang et al., 2008	0	0	0	0	0	0	0	0	0	0	1	0
74	Seckiner and Kurt, 2008	0	0	0	0	0	0	0	0	0	0	1	0
75	Marinakis and Marinaki, 2008	0	1	0	0	0	0	0	0	0	0	0	0
76	Toksari, 2007	0	0	0	0	0	0	0	0	0	0	1	0
77	Yin and Wang, 2006	0	0	0	0	0	0	0	0	0	0	0	1
78	Kuo et al., 2005	0	0	0	0	0	1	0	0	0	0	0	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Industry											
		I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12
79	Aghaie and Mokhtari, 2009	0	0	0	0	0	0	0	0	0	0	1	0
80	Sigel et al., 2002	0	0	0	0	0	0	0	1	0	0	0	0
81	Wu et al., 2008	0	0	0	0	0	0	0	0	0	0	0	1
82	Hani et al., 2007	0	0	0	0	0	0	0	0	1	0	0	0
83	Liang and Smith, 2004	0	0	0	0	0	0	0	0	0	0	1	0
84	Geem, 2009	0	0	0	1	0	0	0	0	0	0	0	0
85	Afshar et al., 2009	0	0	0	1	0	0	0	0	0	0	1	0
86	Lam et al., 2007	0	0	1	0	0	0	0	0	0	0	0	1
87	Bontoux and Feillet, 2008	0	0	0	0	0	0	0	0	0	0	1	0
88	Zeng et al., 2007	0	0	0	0	0	0	1	0	0	0	0	0
89	Chan and Swarnkar, 2006	0	0	0	0	0	0	0	0	0	0	0	1
90	Alba et al., 2008	0	0	0	0	0	0	0	0	0	0	0	1
91	Brede et al., 2007b	0	0	0	0	1	0	0	0	0	0	0	0
92	Cui et al., 2008	0	0	0	0	0	0	0	0	0	0	0	1
93	Kang et al., 2008	0	0	0	0	1	0	0	0	0	0	1	0
94	Jiang et al., 2007	0	0	0	0	0	0	0	0	0	0	1	0
95	Zhang et al., 2007b	0	0	0	0	0	0	0	0	0	0	0	1
96	Liu et al., 2007	0	0	0	0	0	0	0	0	0	0	1	0
97	Shi and Eberhart, 1998	0	0	0	0	0	0	0	0	0	0	0	1
98	Tripathi et al., 2007	0	0	0	0	0	0	0	0	0	0	1	0
99	Alatas and Akin, 2009	0	0	0	0	0	0	0	0	0	0	1	0
100	Liu and Wang, 2008	0	0	0	0	0	0	0	0	0	0	0	1
101	Falco et al., 2007	0	0	0	0	0	0	0	0	0	0	1	0
102	Wang and Wang, 2008	0	0	0	0	1	0	0	0	0	0	0	0
103	Ali and Kaleo, 2008	0	0	0	0	0	0	0	0	0	0	0	1
104	Wang et al., 2010	0	0	0	0	0	0	0	0	0	1	0	0
105	Meneses et al., 2009	0	0	0	1	0	0	0	0	0	0	1	0
106	Chaturvedi et al., 2009	0	0	0	1	0	0	0	0	0	0	1	0
107	Salman et al., 2002	0	0	0	0	0	0	0	0	0	1	0	0
108	Tsai and Yeh, 2007	0	0	0	0	0	0	0	0	0	0	0	1
109	Siahkali and Vakilian, 2009	0	0	0	1	0	0	0	0	0	0	0	0
110	Sha and Hsu, 2008	0	0	0	0	0	0	0	0	0	0	0	1
111	Samanta and Nataraj, 2009	0	0	0	0	0	0	0	1	0	0	0	0
112	He and Wang, 2007	0	0	0	0	0	0	0	0	0	0	1	0
113	Silva et al., 2008	0	0	0	0	0	0	0	1	0	0	0	0
114	Lopez et al., 2009	0	0	0	0	0	0	0	0	0	0	0	1
115	Veneyagamoorthy et al., 2009	0	0	0	0	0	0	0	1	0	0	0	0
116	Kuo and Yang, 2011	0	0	0	0	0	0	0	0	0	0	1	0
117	Kuo et. al., 2011	0	0	0	0	0	0	0	0	0	0	1	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Industry											
		I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12
118	Coelho, 2009	0	0	0	1	0	0	0	0	0	0	1	0
119	Chen and Zhao, 2009	0	0	0	0	0	0	0	0	0	0	0	1
120	Assareh et. al., 2010	0	0	0	1	1	0	0	0	0	0	0	0
121	Duan and Liao, 2010	0	0	0	0	0	0	0	0	0	0	1	0
122	Deng and Lin, 2011	0	0	0	0	0	0	0	0	1	0	0	0
123	Li et. al., 2010	0	0	0	0	0	0	0	0	0	0	0	1
124	Kuan and Wong, 2010	0	0	0	0	0	0	0	0	0	0	1	0
125	Lee et. al., 2010	0	0	0	0	1	0	0	0	0	0	0	0
126	Che and Wang, 2010	0	0	0	0	0	0	0	0	0	1	0	0
127	Dye and Hsieh, 2010	0	0	0	0	0	0	0	0	0	0	0	1
128	Boonyaritdachochai et. al., 2010	0	0	0	0	0	0	0	1	0	0	1	0
129	Ziari et al., 2010	0	0	0	0	0	0	0	1	0	0	1	0
130	Kuo and Shih, 2007	0	0	0	0	0	0	1	0	0	0	0	0
131	Jiang et al., 2010	0	0	0	0	0	0	0	0	0	0	1	0
132	Christmas et. al., 2010	0	0	0	0	0	0	1	0	0	0	0	0
133	Chen et. al., 2010	0	0	0	0	0	0	0	0	0	0	1	0
134	Sharma et. al., 2011	0	0	0	0	0	0	0	0	0	0	1	0
135	Araujo, 2010	0	1	0	0	0	0	0	0	0	0	0	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Business Functions										
		B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
1	Kittur et al., 2009	0	1	0	0	0	0	0	0	0	0	0
2	Obermair et al., 2006	0	1	0	0	0	0	0	0	0	0	0
3	Moisa and Ngulube, 2005	0	0	1	0	0	0	0	0	0	0	0
4	Rodriguez and Reggia, 2004	0	0	0	0	0	0	0	0	0	0	1
5	Rasmussen et al., 2007	0	0	1	0	0	0	0	0	0	0	0
6	Boschetti and Brede, 2008	0	0	0	0	0	0	0	0	1	0	0
7	Sheremetov and Roche-mier, 2004	0	0	0	0	0	0	0	0	0	1	0
8	Cornu, 2005	0	0	0	0	0	0	0	0	0	0	0
9	Seheremetov et al., 2005	0	0	0	0	0	0	1	0	0	0	0
10	Tuyls et al., 2005	0	0	0	0	0	0	0	0	0	0	1
11	Brede et al., 2007a	0	0	0	0	0	0	0	0	1	0	0
12	Yang, 2006a	0	0	0	0	0	0	1	0	0	0	0
13	Zhang et al., 2007a	0	0	0	0	0	0	1	0	0	0	0
14	Albritton and McMillan, 2007	0	0	0	0	0	1	0	0	0	0	0
15	Alici et al., 2006	0	0	0	0	0	1	0	0	0	0	0
16	Calderon et al., 2006	1	0	0	0	0	0	0	0	0	0	0
17	Sousa et al., 2004	0	0	0	0	0	0	1	0	0	0	0
18	Cai et al., 2007	1	0	0	0	0	0	1	0	0	0	0
19	Venayagamoorthy et al., 2007	0	0	0	0	0	0	0	1	0	0	0
20	Gunes et al., 2008	0	0	0	0	0	1	0	0	0	0	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Business Functions										
		B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
21	Koshino et al., 2006	1	0	0	0	0	0	0	0	0	0	0
22	Iwasaki et al., 2006	0	0	0	0	0	1	0	0	0	0	0
23	Gao et al., 2006	0	0	0	0	0	1	0	0	0	0	0
24	Hassan et al., 2005	0	0	0	0	0	1	0	0	0	0	0
25	Yoshida et al., 2000	1	0	0	0	0	1	0	0	0	0	0
26	Montalvo et al., 2008	1	0	0	0	0	0	1	1	0	0	0
27	Guo et al., 2006a	0	0	0	0	0	1	0	1	0	0	0
28	Oloffsson, 2006	0	0	0	0	0	1	0	0	0	0	0
29	Chen et al., 2006	1	0	0	0	0	0	0	0	0	0	0
30	Xu et al., 2007	1	0	0	0	0	0	0	0	0	0	0
31	Cura, 2009	1	0	0	0	0	0	0	0	0	0	0
32	Muhammad -Moradi et al., 2009	1	0	0	0	0	0	0	0	0	0	0
33	Haibing et al., 2006	1	0	0	0	0	0	0	0	0	0	0
34	Wang et al., 2006	0	0	0	0	0	0	0	0	0	1	0
35	Yang, 2006b	0	1	0	0	0	0	1	0	0	0	0
36	Liang et al., 2008	0	0	0	1	0	0	0	0	0	0	0
37	Cui et al., 2005	0	0	1	0	0	0	0	0	0	0	0
38	Mouli et al., 2006	0	0	0	0	0	0	0	0	0	1	0
39	Sun, 2009	0	0	0	0	0	1	0	0	0	0	0
40	Han et al., 2009	0	0	0	1	0	0	0	0	0	0	0
41	Tasgetiren and Liang, 2003	0	0	0	0	0	0	0	0	0	1	0
42	Huang et al., 2007	0	0	0	0	0	0	0	0	0	1	0
43	Mohammed et al., 2007	0	0	0	0	0	0	0	0	0	1	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Business Functions										
		B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
44	Zhao et al., 2006	0	0	0	0	0	0	1	0	0	0	0
45	Rezazadeh et al., 2009	0	0	0	1	0	0	0	0	0	1	0
46	Rameshkumar et al., 2005	0	0	0	0	0	0	1	0	0	0	0
47	Guo et al., 2006b	0	0	0	0	0	0	1	0	0	0	0
48	Liao et al., 2005	0	0	0	0	0	0	1	0	0	0	0
49	Jia and Yang, 2007	0	1	0	0	0	0	0	0	0	0	0
50	Guo et al., 2007	0	0	0	0	0	0	1	0	0	0	0
51	Jursa, 2007	0	0	0	0	0	0	0	0	0	1	0
52	Marinakis et al., 2008	1	0	0	0	0	0	0	0	0	0	0
53	Onut et al., 2007	1	0	0	1	0	0	0	0	0	0	0
54	Camci, 2008	0	0	0	0	0	1	0	0	0	0	0
55	Chen et al., 2008	0	0	0	0	0	0	1	0	0	0	0
56	Gajpal and Abad, 2009	0	0	0	0	0	0	0	0	0	1	0
57	Silva et al., 2009	0	0	0	0	0	0	0	0	0	1	0
58	Abdallah and Emara, 2009	0	0	0	0	0	0	1	0	0	0	0
59	Bin et al., 2009	0	0	0	0	0	0	0	0	0	1	0
60	Zhang and Tang, 2009	0	0	0	0	0	0	0	0	0	1	0
61	Chebouba et al., 2009	0	0	0	0	0	0	0	0	0	1	0
62	Arora et al., 2010	0	0	0	0	0	0	0	0	0	1	0
63	Ugur and Aydin, 2009	0	0	0	0	0	0	0	0	0	1	0
64	Li and Rong, 2009	0	0	0	0	0	0	1	0	0	0	0
65	Christodolou, 2009	0	0	0	0	0	0	1	0	0	0	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Business Functions										
		B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
66	Fuellerer et al., 2010	0	0	0	0	0	0	0	0	0	1	0
67	Yuan and Wang, 2005	0	0	0	0	0	0	1	0	0	0	0
68	Watcharasitthiwat and Wardkein, 2009	0	0	0	0	0	1	0	0	0	0	0
69	Niknam and Firouzi, 2009	1	0	0	0	0	1	0	0	0	0	0
70	Marinakis and Marinaki, 2010	0	0	0	0	0	0	0	0	0	1	0
71	Almeder, 2009	0	0	0	0	0	0	0	0	0	1	0
72	Chang et al., 2009	0	0	0	0	0	0	1	0	0	0	0
73	Yang et al., 2008	0	0	0	0	0	0	0	0	0	1	0
74	Seckiner and Kurt, 2008	0	0	0	0	0	0	1	0	0	0	0
75	Marinakis and Marinaki, 2008	1	0	0	0	0	0	0	0	0	0	0
76	Toksari, 2007	0	0	0	0	0	0	0	0	0	1	0
77	Yin and Wang, 2006	0	0	0	0	0	0	1	0	0	0	0
78	Kuo et al., 2005	0	0	0	0	1	0	0	0	0	0	0
79	Aghaie and Mokhtari, 2009	0	0	0	0	0	0	1	0	0	0	0
80	Sigel et al., 2002	1	0	0	0	0	0	0	0	0	0	0
81	Wu et al., 2008	0	0	0	0	0	1	0	0	0	0	0
82	Hani et al., 2007	1	0	0	1	0	0	0	0	0	1	0
83	Liang and Smith, 2004	0	0	0	0	0	1	0	0	0	0	0
84	Geem, 2009	0	0	0	0	0	0	0	0	0	1	0

Table C.1(continued): The Collective Intelligence literature.

		Business Functions										
No	Author	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
85	Afshar et al., 2009	0	0	0	0	0	0	1	0	0	0	0
86	Lam et al., 2007	1	0	0	1	0	0	0	0	0	1	0
87	Bontoux and Feillet, 2008	0	0	0	0	0	0	0	0	0	1	0
88	Zeng et al., 2007	0	0	0	0	0	0	0	0	1	0	0
89	Chan and Swarnkar, 2006	0	0	0	1	0	0	0	0	0	1	0
90	Alba et al., 2008	0	0	0	0	0	0	1	0	0	0	0
91	Brede et al., 2007b	0	0	0	0	0	0	1	0	0	0	0
92	Cui et al., 2008	0	0	0	0	0	0	0	0	0	0	1
93	Kang et al., 2008	0	0	0	0	0	0	0	0	0	0	1
94	Jiang et al., 2007	0	0	0	0	0	0	0	0	0	0	1
95	Zhang et al., 2007b	0	0	0	0	0	0	0	0	0	0	1
96	Liu et al., 2007	0	0	0	0	0	0	0	0	0	0	1
97	Shi and Eberhart, 1998	0	0	0	0	0	0	0	0	0	0	1
98	Tripathi et al., 2007	0	0	0	0	0	0	0	0	0	0	1
99	Alatas and Akin, 2009	0	0	0	0	0	0	0	0	0	0	1
100	Liu and Wang, 2008	0	0	0	0	0	0	0	0	0	0	1
101	Falco et al., 2007	0	0	0	0	0	0	1	0	0	0	0
102	Wang and Wang, 2008	0	0	0	0	0	0	0	0	0	0	1
103	Ali and Kaleo, 2008	0	0	0	0	0	0	0	0	0	0	1
104	Wang et al., 2010	0	0	0	0	0	1	0	0	0	0	0
105	Meneses et al., 2009	1	0	0	0	0	0	0	0	0	0	0

Table C.1(continued): The Collective Intelligence literature.

No	Author	Business Functions										
		B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
106	Chaturvedi et al., 2009	0	0	0	0	0	0	0	0	0	0	1
107	Salman et al., 2002	0	0	0	0	0	0	1	0	0	0	0
108	Tsai and Yeh, 2007	0	0	0	0	0	0	0	0	0	1	0
109	Siahkali and Vakilian, 2009	0	0	0	0	0	0	1	0	0	0	0
110	Sha and Hsu, 2008	0	0	0	0	0	0	1	0	0	0	0
111	Samanta and Nataraj, 2009	0	0	0	0	0	0	0	0	0	0	1
112	He and Wang, 2007	0	0	0	0	0	0	0	0	0	0	1
113	Silva et al., 2008	0	0	0	0	0	0	0	0	0	1	0
114	Lopez et al., 2009	0	0	0	0	0	0	0	0	0	1	0
115	Veneyagamoorthy et al., 2009	0	0	0	0	0	1	0	0	0	0	0
116	Kuo and Yang, 2011	0	0	0	1	0	0	0	0	0	0	0
117	Kuo et. al., 2011	0	0	1	0	0	0	0	0	0	0	0
118	Coelho, 2009	0	0	0	0	0	1	0	1	0	0	0
119	Chen and Zhao, 2009	0	0	0	0	0	0	0	0	0	0	1
120	Assareh et. al., 2010	0	0	0	0	1	0	0	0	0	0	0
121	Duan and Liao, 2010	0	0	0	0	0	0	1	0	0	0	0
122	Deng and Lin, 2011	0	0	0	1	0	0	0	0	0	0	0
123	Li et. al., 2010	0	0	0	1	0	0	0	0	0	0	0
124	Kuan and Wong, 2010	0	0	0	1	0	0	0	0	0	0	0
125	Lee et. al., 2010	0	0	0	0	0	0	1	0	0	0	0

Table C.1(continued): The Collective Intelligence literature.

		Business Functions										
No	Author	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
126	Che and Wang, 2010	0	0	0	0	0	0	0	0	0	1	0
127	Dye and Hsieh, 2010	0	0	0	0	0	0	0	0	0	1	0
128	Boonyaritdachochai et. al., 2010	0	0	0	0	1	1	0	0	0	0	0
129	Ziari et al., 2010	0	0	0	0	0	1	0	0	0	0	0
130	Kuo and Shih, 2007	0	0	1	0	0	0	0	0	0	0	0
131	Jiang et al., 2010	0	0	0	0	0	0	0	0	0	0	1
132	Christmas et. al., 2010	0	0	1	0	0	0	0	0	0	0	0
133	Chen et. al., 2010	0	0	0	0	0	0	1	0	0	0	0
134	Sharma et. al., 2011	0	0	0	0	0	0	1	0	0	0	0
135	Araujo, 2010	1	0	0	0	0	0	0	0	0	0	0

APPENDIX D: Literature clustering results.

Table D.1: Results for SOM 1x10.

Cluster	No of Elements	Studies	Character
1	20	3-6-9-11-58-62-65-75-78-80-88-89-90-114-122-123-124-125-130-132	Ant Colony Optimization
2	15	16-32-46-48-55-68-72-74-79-83-85-101-121-133-134	Historical Studies – (Project Management)
3	5	14-18-61-63-77	(Simulation) – Ant Colony Optimization – Unspecified Industry
4	3	69-104-118	(Hybrid Particle Swarm Optimization) – (Energy) – (Historical Studies) – Product Development
5	5	1-64-67-82-86	(Hybrid Ant Colony Optimization)
6	3	5-8-13	Collective Intelligence
7	3	4-10-100	Unspecified Industry – Unspecified Business Function
8	33	2-7-17-21-22-28-33-35-37-41-43-44-47-49-50-51-52-53-54-60-70-81-84-92-95-97-103-108-110-119-126-127-135	(Particle Swarm Optimization) – (Unspecified Industry)
9	35	12-15-19-20-23-24-25-26-29-30-31-34-38-39-42-56-59-66-71-73-76-87-93-94-96-98-99-102-105-106-107-120-128-129-131	Particle Swarm Optimization – (Historical Studies)
10	13	27-36-40-45-57-91-109-111-112-113-115-116-117	(Simulation) - (Particle Swarm Optimization) – (Robotics/Electronics/Mechanics)

Table D.2: Results for SOM 2x5.

Cluster	No of Elements	Studies	Character
1	9	12-26-38-42-46-102-107-109-120	Particle Swarm Optimization – (Project Management)
2	17	17-22-28-35-37-44-47-49-54-92-95-97-103-108-110-119-127	Particle Swarm Optimization – Unspecified Industry
3	10	4-7-10-50-53-69-81-86-100-123	Unspecified Industry
4	16	2-3-5-6-8-9-11-13-48-55-64-67-85-91-101-133	(Project Management)
5	11	18-58-65-72-74-77-79-90-121-125-134	Ant Colony Optimization – Project Management
6	22	115-19-20-23-24-25-27-36-39-40-93-94-96-98-99-105-106-112-117-128-129-131	Particle Swarm Optimization – (Robotics/Electronics/Mechanics) – (Historical Studies)
7	9	16-21-29-30-31-32-52-75-135	Banking – Finance
8	10	1-33-43-51-84-104-111-115-118-126	Hybrid Particle Swarm Optimization
9	6	34-41-45-60-70-116	(Particle Swarm Optimization) – (Hybrid Particle Swarm Optimization) – Historical Studies – Supply Chain Management
10	25	14-56-57-59-61-62-63-66-68-71-73-76-78-80-82-83-87-88-89-113-114-122-124-130-132	Ant Colony Optimization – Supply Chain Management

Table D.3: Results for SOM 5x2.

Cluster	No of Elements	Studies	Character
1	11	12-34-38-42-45-46-70-102-107-109-120	Particle Swarm Optimization
2	22	15-19-20-23-24-25-27-36-39-40-93-94-96-98-99-106-112-116-117-128-129-131	Particle Swarm Optimization – (Robotics/Electronics/Mechanics) – (Historical Studies)
3	17	17-22-28-35-37-44-47-49-54-92-95-97-103-108-110-119-127	Particle Swarm Optimization - Unspecified Industry
4	11	16-21-26-29-30-31-32-52-75-105-135	(Particle Swarm Optimization) – Banking – Finance
5	13	2-4-7-8-9-10-43-50-53-81-86-100-123	Unspecified Industry
6	12	1-5-6-11-33-51-84-104-111-115-118-126	(Hybrid Particle Swarm Optimization)
7	9	13-14-63-63-65-77-89-90-114	Ant Colony Optimization – Unspecified Industry
8	11	41-48-55-60-64-67-69-85-91-101-133	(Hybrid Ant Colony Optimization) – (Historical Studies) – (Project Management)
9	14	3-18-57-58-61-78-80-82-88-113-122-125-130-132	Ant Colony Optimization
10	15	56-59-66-68-71-72-73-74-76-79-83-87-121-124-134	Ant Colony Optimization – Historical Studies

Table D.4: Results for SOM 10x1.

Cluster	No of Elements	Studies	Character
1	23	15-19-20-23-24-25-27-36-39-40-93-94-96-98-99-102-106-112-116-117-128-129-131	Particle Swarm Optimization – (Robotics/Electronics/Mechanics) – (Historical Studies)
2	8	34-38-42-45-46-70-105-120	Particle Swarm Optimization – (Historical Studies) – (Supply Chain Management)
3	10	12-16-21-26-29-30-31-32-107-109	Particle Swarm Optimization – (Banking) – (Finance)
4	17	17-22-28-35-37-44-47-49-54-92-95-97-103-108-110-119-127	Particle Swarm Optimization – Unspecified Industry
5	11	4-7-10-43-50-53-69-81-86-100-123	Unspecified Industry
6	15	1-3-5-8-33-41-51-52-84-104-111-115-118-126-135	(Hybrid Particle Swarm Optimization)
7	10	2-13-18-48-55-64-67-85-101-133	Project Management
8	14	6-9-11-58-65-72-74-77-79-90-91-121-125-134	(Ant Colony Optimization) – Project Management
9	11	14-68-75-78-80-83-88-122-124-130-132	Ant Colony Optimization
10	16	56-57-59-60-61-62-63-66-71-73-76-82-87-89-113-114	Ant Colony Optimization – Supply Chain Management

Table D.5: Results for SOM 11x1.

Cluster	No of Elements	Studies	Character
1	22	56-57-59-60-61-62-63-66-71-73-75-76-78-80-82-87-88-89-113-114-130-132	Ant Colony Optimization – (Supply Chain Management)
2	5	14-68-83-122-124	Ant Colony Optimization – (Historical Studies) –(Product Development)
3	11	18-58-65-72-74-77-79-90-121-125-134	Ant Colony Optimization – Project Management
4	13	6-9-11-13-48-50-55-64-67-85-91-101-133	Project Management
5	9	16-32-33-41-51-52-84-118-135	Hybrid Particle Swarm Optimization – (Finance)
6	7	1-2-3-5-8-104-126	(Collective Intelligence) – (Web-IT)
7	10	4-7-10-43-53-69-81-86-100-123	Unspecified Industry
8	17	17-22-28-35-37-44-47-49-54-92-95-97-103-108-110-119-127	Particle Swarm Optimization – Unspecified Industry
9	9	12-21-26-29-30-31-38-107-109	Particle Swarm Optimization – (Finance)
10	18	34-42-45-46-70-93-94-96-98-99-102-105-106-112-116-117-120-131	Particle Swarm Optimization – Historical Studies
11	14	15-19-20-23-24-25-27-36-39-40-111-115-128-129	Particle Swarm Optimization – Robotics/Electronics/Mechanics – (Product Development)

Table D.6: Results for SOM 1x11.

Cluster	No of Elements	Studies	Character
1	23	15-20-23-24-27-34-36-39-40-45-70-93-94-96-98-99-106-112-116-117-128-129-131	Particle Swarm Optimization –(Historical Studies)
2	7	19-25-38-42-102-105-120	Particle Swarm Optimization
3	8	12-26-29-30-31-46-107-109	Particle Swarm Optimization – (Project Management)
4	17	17-22-28-35-37-44-47-49-54-92-95-97-103-108-110-119-127	Particle Swarm Optimization – Unspecified Industry
5	10	4-7-10-43-53-69-81-86-100-123	Unspecified Industry
6	9	1-2-3-5-8-104-111-115-126	
7	12	6-11-16-21-32-33-41-51-52-84-118-135	(Hybrid Particle Swarm Optimization)
8	11	9-13-48-50-55-64-67-85-91-101-133	Project Management
9	11	18-58-65-72-74-77-79-90-121-125-134	Ant Colony Optimization – Project Management
10	6	14-68-78-83-122-124	Ant Colony Optimization
11	21	56-57-59-60-61-62-63-66-71-73-75-76-80-82-87-88-89-113-114-130-132	Ant Colony Optimization – Supply Chain Management

Table D.7: Results for SOM 1x12.

Cluster	No of Elements	Studies	Character
1	16	56-57-59-60-61-62-63-66-71-73-76-82-87-89-113-114	Ant Colony Optimization – Supply Chain Management
2	11	14-68-75-78-80-83-88-122-124-130-132	Ant Colony Optimization
3	11	18-58-65-72-74-77-79-90-121-125-134	Ant Colony Optimization – Project Management
4	9	13-48-55-64-67-85-91-101-133	(Historical Studies) – Project Management
5	7	1-2-3-5-6-8-11	(Collective Intelligence)
6	14	16-21-32-33-41-51-52-84-104-111-115-118-126-135	Hybrid Particle Swarm Optimization
7	6	43-50-53-69-86-100	(Hybrid Particle Swarm Optimization) – Unspecified Industry
8	6	4-7-9-10-81-123	Unspecified Industry
9	17	17-22-28-35-37-44-47-49-54-92-95-97-103-108-110-119-127	Particle Swarm Optimization – Unspecified Industry
10	8	12-26-29-30-31-38-107-109	Particle Swarm Optimization
11	18	34-42-45-46-70-93-94-96-98-99-102-105-106-112-116-117-120-131	Particle Swarm Optimization – Historical Studies
12	12	15-19-20-23-24-25-27-36-39-40-128-129	Particle Swarm Optimization – Robotics/Electronics/Mechanics – Product Development

Table D.8: Results for SOM 2x6.

Cluster	No of Elements	Studies	Character
1	8	57-61-62-63-82-89-113-114	Ant Colony Optimization – (Unspecified Industry) – Supply Chain Management
2	10	14-65-77-78-80-88-90-122-130-132	Ant Colony Optimization
3	5	2-3-5-8-13	Collective Intelligence
4	12	1-33-41-43-51-70-84-04-111-115-118-126	Hybrid Particle Swarm Optimization
5	9	16-21-29-30-31-32-52-75-135	Banking – Finance
6	25	15-19-20-23-24-25-27-34-36-39-40-45-93-94-96-98-99-105-106-112-116-117-128-129-131	Particle Swarm Optimization – (Historical Studies)
7	11	56-59-60-66-68-71-73-76-83-87-124	Ant Colony Optimization – Historical Studies – (Supply Chain Management)
8	8	18-58-72-74-79-121-125-134	Ant Colony Optimization – (Historical Studies) – Project Management
9	10	6-9-11-48-64-67-85-91-101-133	Project Management
10	9	7-50-53-55-69-81-86-100-123	Unspecified Industry
11	19	4-10-17-22-28-35-37-44-47-49-54-92-95-97-103-108-110-119-127	Particle Swarm Optimization – Unspecified Industry
12	9	12-26-38-42-46-102-107-109-120	Particle Swarm Optimization – (Project Management)

Table D.9: Results for SOM 3x4.

Cluster	No of Elements	Studies	Character
1	17	17-22-28-35-37-44-47-49-54-92-95-97-103-108-110-119-127	Particle Swarm Optimization – Unspecified Industry
2	10	1-4-7-10-53-69-81-86-100-123	Unspecified Industry
3	6	3-5-8-9-50-55	
4	12	2-6-11-13-16-18-32-64-67-85-91-133	(Project Management)
5	11	12-21-26-29-30-31-38-42-107-109-120	Particle Swarm Optimization
6	5	104-111-115-116-118	Simulation – Hybrid Particle Swarm Optimization – (Product Development)
7	11	33-41-43-48-51-52-70-84-101-126-135	Hybrid Particle Swarm Optimization – (Supply Chain Management)
8	10	58-65-72-74-77-79-90-121-125-134	Ant Colony Optimization – Project Management
9	14	34-45-46-93-94-96-98-99-102-105-106-112-117-131	Particle Swarm Optimization – Historical Studies – (Unspecified Business Function)
10	12	15-19-20-23-24-25-27-36-39-40-128-129	Particle Swarm Optimization – Robotics/Electronics/Mechanics – Product Development
11	5	57-60-68-83-113	(Simulation) – Ant Colony Optimization – (Historical Studies) – (Supply Chain Management)
12	22	14-56-59-61-62-63-66-71-73-75-76-78-80-82-87-88-89-114-122-124-130-132	Ant Colony Optimization – (Project Management)

Table D.10: Results for SOM 4x3.

Cluster	No of Elements	Studies	Character
1	14	15-19-20-23-24-25-27-36-39-40-111-115-128-129	Particle Swarm Optimization – Robotics/Electronics/Mechanics – (Product Development)
2	11	93-94-96-98-99-102-105-106-112-120-131	Particle Swarm Optimization - Historical Studies – Unspecified Business Function
3	18	4-7-10-22-28-37-49-54-81-92-95-97-100-103-108-119-123-127	(Particle Swarm Optimization) – Unspecified Industry
4	7	34-38-42-45-70-116-117	Particle Swarm Optimization – (Historical Studies) – (Unspecified Business Function)
5	10	16-21-29-30-31-32-52-53-75-135	Banking – Finance
6	12	9-12-17-26-35-44-46-47-50-107-109-110	Particle Swarm Optimization – (Unspecified Industry) – Project Management
7	7	41-43-51-60-84-86-126	(Hybrid Particle Swarm Optimization) – Supply Chain Management
8	7	1-5-18-33-69-104-118	(Energy)
9	10	2-8-13-48-55-64-67-85-101-133	Project Management
10	15	56-57-59-61-62-63-66-71-73-76-82-87-89-113-114	Ant Colony Optimization – Supply Chain Management
11	13	6-11-58-65-72-74-77-79-90-91-121-125-134	Ant Colony Optimization
12	13	6-11-58-65-72-74-77-79-90-91-121-125-134	Ant Colony Optimization – Project Management

Table D.11: Results for SOM 6x2.

Cluster	No of Elements	Studies	Character
1	20	56-57-59-60-61-62-63-66-71-73-76-78-82-87-88-89-113-114-130-132	Ant Colony Optimization – Supply Chain Management
2	5	14-68-83-122-124	Ant Colony Optimization – (Historical Studies) – (Product Development)
3	10	16-21-29-30-31-32-52-75-80-135	Banking – Finance
4	11	18-58-65-72-74-77-79-90-121-125-134	Ant Colony Optimization – Project Management
5	15	1-2-3-5-6-8-11-33-41-51-84-104-111-118-126	(Hybrid Particle Swarm Optimization)
6	9	13-48-55-64-67-85-91-101-133	(Historical Studies) – Project Management
7	10	4-7-10-43-53-69-81-86-100-123	Unspecified Industry
8	7	9-17-35-44-47-50-110	(Particle Swarm Optimization) – Unspecified Industry – Project Management
9	9	37-49-92-95-97-103-108-119-127	Particle Swarm Optimization – Unspecified Industry – (Unspecified Business Function)
10	8	12-22-26-28-54-107-109-120	Particle Swarm Optimization
11	18	34-38-42-45-46-70-93-94-96-98-99-102-105-106-112-116-117-131	Particle Swarm Optimization – Historical Studies
12	13	15-19-20-23-24-25-27-36-39-40-115-128-128	Particle Swarm Optimization – Robotics/Electronics/Mechanics – Product Development

Table D.12: Results for SOM 12x1.

Cluster	No of Elements	Studies	Character
1	12	15-19-20-23-24-25-27-36-39-40-128-129	Particle Swarm Optimization – Robotics/Electronics/Mechanics – Product Development
2	16	34-45-46-70-93-94-96-98-99-102-105-106-112-116-117-131	Particle Swarm Optimization – Historical Studies – (Unspecified Business Function)
3	7	12-26-38-42-107-109-120	Particle Swarm Optimization – (Project Management)
4	17	17-22-28-35-37-44-47-49-54-92-95-97-103-108-110-119-127	Particle Swarm Optimization – Unspecified Industry
5	9	4-7-10-53-69-81-86-100-123	Unspecified Industry
6	9	16-21-29-30-31-32-52-75-135	Banking – Finance
7	10	33-41-43-51-84-104-111-115-118-126	Hybrid Particle Swarm Optimization
8	16	1-2-5-6-8-9-11-48-50-55-64-67-85-91-101-133	(Project Management)
9	7	3-13-18-65-77-90-125	(Ant Colony Optimization) – Project Management
10	11	58-72-74-78-79-80-88-121-130-132-134	Ant Colony Optimization – (Project Management)
11	5	14-68-83-122-124	Ant Colony Optimization – (Historical Studies) – (Product Development)
12	16	56-57-59-60-61-62-63-66-71-73-76-82-87-89-113-114-	Ant Colony Optimization – Supply Chain Management

Table D.13: Results for Fuzzy K-Means, *k*=10.

Cluster	No of Elements	Studies	Character
1	13	12-13-26-46-48-64-67-85-91-101-107-109-133	Project Management
2	16	9-14-17-35-44-47-50-53-55-65-69-77-81-90-110-123	Unspecified Industry – (Project Management)
3	18	34-38-42-45-70-93-94-96-98-99-102-105-106-112-116-117-120-131	Particle Swarm Optimization – Historical Studies
4	8	56-59-60-66-71-73-76-87	Ant Colony Optimization – Web-IT – Risk Management
5	17	18-58-68-72-74-78-79-80-83-88-121-122-124-125-130-132-134	Ant Colony Optimization
6	9	16-21-29-30-31-32-52-75-135	Banking – Finance
7	9	57-61-62-63-82-86-89-113-114	Ant Colony Optimization – (Unspecified Industry) – Supply Chain Management
8	12	15-19-20-23-24-25-27-36-39-40-128-129	Particle Swarm Optimization – Robotics/Electronics/Mechanics – Product Development
9	10	33-41-43-51-84-104-111-115-118-126	Hybrid Particle Swarm Optimization
10	23	1-2-3-4-5-6-7-8-10-11-22-28-37-49-54-92-95-97-100-103-108-119-127	(Particle Swarm Optimization) – (Unspecified Industry)

Table D.14: Results for Fuzzy K-Means, *k*=11.

Cluster	No of Elements	Studies	Character
1	13	12-13-26-46-48-64-67-85-91-101-107-109-133	Project Management
2	11	9-17-35-44-47-50-55-65-77-90-110	Unspecified Industry – Project Management
3	13	34-38-41-45-56-59-60-66-70-71-73-76-87	(Ant Colony Optimization) – Historical Studies – Supply Chain Management
4	8	43-53-62-63-86-89-114-123	Unspecified Industry –Supply Chain Management
5	14	58-68-72-74-78-79-83-88-121-124-125-130-132-134	Ant Colony Optimization – (Historical Studies)
6	9	14-22-28-54-69-81-104-115-118	(Unspecified Industry) – Product Development
7	7	18-57-61-80-82-113-122	Ant Colony Optimization– (Supply Chain Management)
8	25	15-19-20-23-24-25-27-36-39-40-93-94-96-98-99-102-105-106-111-112-116-117-128-129-131	Particle Swarm Optimization – (Robotics/Electronics/Mechanics) – (Historical Studies)
9	12	1-2-3-5-6-8-11-42-51-84-120-126	
10	13	4-7-10-37-49-92-95-97-100-103-108-119-127	(Particle Swarm Optimization) – Unspecified Industry – (Unspecified Business Function)
11	10	16-21-29-30-31-32-33-52-75-135	Banking – Finance

Table D.15: Results for Fuzzy K-Means, *k*=12.

Cluster	No of Elements	Studies	Character
1	12	15-19-20-23-24-25-27-36-39-40-128-129	Particle Swarm Optimization – Robotics/Electronics/Mechanics – Product Development
2	11	12-18-26-46-64-67-85-107-109-120-133	(Particle Swarm Optimization) – (Energy) – Project Management
3	23	56-58-59-66-68-71-72-73-74-76-78-79-80-83-87-88-121-122-124-125-130-132-134	Ant Colony Optimization – (Historical Studies)
4	11	93-94-96-98-99-102-105-106-112-117-131	Particle Swarm Optimization – Historical Studies – Unspecified Business Function
5	9	43-57-61-62-63-82-89-113-114	Ant Colony Optimization – (Unspecified Industry) – Supply Chain Management
6	8	14-22-28-54-104-111-115-118	(Hybrid Particle Swarm Optimization) – Product Development
7	13	34-38-41-42-45-48-51-60-70-84-101-116-126	(Hybrid Particle Swarm Optimization) – (Historical Studies) – Supply Chain Management
8	10	16-21-29-30-31-32-33-52-75-135	Banking, Finance
9	11	9-17-35-44-47-50-55-65-77-90-110	Unspecified Industry – Project Management
10	13	4-7-10-37-49-92-95-97-100-103-108-119-127	(Particle Swarm Optimization) – Unspecified Industry – (Unspecified Business Function)
11	5	53-69-81-86-123	Hybrid Ant Colony Optimization – Unspecified Industry – (Finance) – (Manufacturing)
12	9	1-2-3-5-6-8-11-13-91	(Collective Intelligence)

Table D.16: Results for PSO clustering, *k*=10.

Cluster	No of Elements	Studies	Character
1	6	29-30-31-52-75-135	Banking – Finance
2	3	6-11-91	Hybrid Collective Intelligence – Environment – (Risk Management)
3	3	13-111-115	(Simulation) – (Hybrid Particle Swarm Optimization) - Robotics/Electronics/Mechanics
4	22	1-4-7-9-10-14-35-43-50-53-55-62-81-86-92-95-97-100-103-114-119-123	Unspecified Industry
5	9	15-20-23-24-25-39-104-128-129	Particle Swarm Optimization – Robotics/Electronics/Mechanics – Product Development
6	8	37-94-96-98-99-102-106-131	Particle Swarm Optimization – Historical Studies – Unspecified Business Function
7	26	18-57-58-61-63-64-65-67-71-72-74-77-78-79-80-82-88-89-90-113-121-122-125-130-132-134	Ant Colony Optimization
8	3	51-84-126	Hybrid Particle Swarm Optimization – (Energy) – Supply Chain Management
9	26	12-17-19-21-22-26-27-28-34-36-38-40-42-44-45-46-47-49-54-70-107-108-109-110-120-127	Particle Swarm Optimization
10	29	2-3-5-8-16-32-33-41-48-56-59-60-66-68-69-73-76-83-85-87-93-101-105-112-116-117-118-124-133	Historical Studies

Table D.17: Results for PSO clustering, *k*=11.

Cluster	No of Elements	Studies	Character
1	29	1-3-5-8-19-35-36-37-40-46-49-92-93-94-95-96-97-98-99-102-103-105-106-107-109-112-117-119-131	Particle Swarm Optimization
2	10	16-21-26-29-30-31-32-52-75-135	Finance – Banking
3	14	18-57-61-68-78-80-82-88-89-113-122-124-130-132	Ant Colony Optimization
4	6	2-6-11-42-91-120	Environment
5	9	15-20-23-24-25-27-39-54-104	Particle Swarm Optimization – Robotics/Electronics/Mechanics – Product Development
6	22	4-7-9-10-17-22-43-44-47-62-63-65-69-77-81-86-90-108-110-114-123-127	Unspecified Industry
7	12	34-38-45-56-59-60-66-70-71-73-76-87	(Ant Colony Optimization) – Historical Studies – Supply Chain Management
8	3	13-64-67	(Hybrid Ant Colony Optimization) – (Energy) – Project Management
9	10	12-58-72-74-79-85-121-125-133-134	(Ant Colony Optimization) – (Historical Studies) – Project Management
10	5	14-28-83-128-129	(Particle Swarm Optimization) – (Historical Studies) – Product Development
11	15	33-41-48-50-51-53-55-84-100-101-111-115-116-118-126	Hybrid Particle Swarm Optimization

Table D.18: Results for PSO clustering, *k*=12.

Cluster	No of Elements	Studies	Character
1	5	68-78-88-130-132	Ant Colony Optimization – (Public Services)
2	12	14-15-20-23-24-28-39-54-81-104-115-118	(Particle Swarm Optimization) - Product Development
3	6	9-48-55-91-101-133	(Historical Studies) – Project Management
4	19	12-17-19-22-26-27-34-35-38-42-44-45-47-49-70-108-109-110-127	Particle Swarm Optimization
5	3	2-3-8	Collective Intelligence
6	28	56-57-58-59-62-63-65-66-72-73-74-75-76-77-79-80-82-83-87-89-90-113-114-121-122-124-125-134	Ant Colony Optimization
7	10	5-18-25-33-61-64-67-69-85-120	Energy
8	6	7-43-51-84-86-126	(Hybrid Particle Swarm Optimization) – Supply Chain Management/Inventory
9	29	1-6-11-13-16-21-29-30-31-32-36-37-40-46-93-94-96-98-99-102-105-106-107-112-116-117-128-129-131	Particle Swarm Optimization
10	3	52-111-135	Hybrid Particle Swarm Optimization – (Banking) – (Finance)
11	11	4-10-50-53-92-95-97-100-103-119-123	Unspecified Industry – (Unspecified Business Function)
12	3	41-60-71	Historical Studies – Supply Chain Management/Inventory

APPENDIX E: The united synergy fuzzy cognitive matrix

Table E.1: The united synergy fuzzy cognitive matrix.

	Factors														
Factors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	0	0	0	0	0	0	5	4	2	0	3	4	4	0
2	2	0	4	13	5	4	0	0	3	5	2	3	3	4	0
3	0	0	0	0	0	4	3	4	0	4	0	0	0	10	6
4	4	0	4	0	10	3	0	0	0	10	0	4	0	4	7
5	5	0	4	0	0	7	4	0	0	10	0	2	0	5	8
6	0	0	4	0	0	4	4	4	7	0	0	3	0	6	0
7	5	0	9	0	0	0	0	3	10	4	0	4	5	10	4
8	0	0	5	0	0	5	4	0	3	3	0	5	3	10	4
9	0	0	5	0	0	4	9	5	0	0	0	4	7	10	0
10	9	0	0	0	0	0	0	0	0	0	1	0	0	0	4
11	0	0	0	0	0	0	0	0	0	0	0	5	5	4	0
12	0	2	3	0	5	0	4	0	0	3	10	5	8	5	0
13	0	0	3	0	3	3	4	0	0	3	12	8	0	0	0
14	0	0	7	0	4	3	4	0	10	3	2	4	5	0	8
15	0	0	0	3	4	3	4	0	5	4	0	0	0	0	0
16	0	0	7	0	7	3	10	8	5	3	0	6	3	9	4
17	0	6	5	0	12	0	5	7	4	3	3	3	3	4	3
18	4	0	0	0	0	0	0	0	3	0	4	9	12	5	0
19	3	3	3	0	0	4	4	0	4	3	6	5	6	5	1
20	8	0	5	0	5	0	2	8	0	4	5	9	8	9	0

Table E.1(continued): The united synergy fuzzy cognitive matrix.

	Factors														
Factors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
21	4	2	3	0	0	3	5	3	0	3	8	10	7	0	0
22	2	0	2	2	2	2	3	5	2	6	4	13	8	8	5
23	0	0	0	0	0	0	0	0	0	0	0	7	8	0	0
24	2	2	2	2	2	2	5	2	5	2	10	11	9	2	2
25	5	0	4	0	8	4	4	0	0	5	4	5	3	5	5
26	5	0	6	0	0	0	0	5	0	0	0	2	9	15	5
27	5	0	4	0	1	0	5	0	5	4	2	6	4	5	8
28	0	0	3	5	3	3	0	0	0	0	5	1	0	0	0
29	4	0	0	0	0	0	8	8	0	8	0	6	4	5	4
30	4	0	3	0	0	0	3	3	4	2	0	8	10	4	3
31	0	0	1	0	3	0	4	4	0	7	0	0	7	9	0
32	0	0	0	5	3	5	4	2	9	7	0	9	4	4	0

Table E.1(continued): The united synergy fuzzy cognitive matrix.

	Factors																
Factors	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
1	0	6	6	0	3	5	0	4	3	5	0	0	0	4	4	6	6
2	0	5	5	5	0	0	0	0	0	0	0	0	5	0	4	3	5
3	4	5	4	0	0	9	5	1	0	0	10	0	0	3	0	4	0
4	0	4	0	0	0	4	0	0	0	0	5	10	0	8	0	0	0
5	0	4	0	0	0	1	5	3	0	12	4	10	0	9	0	0	4
6	9	0	4	6	0	4	0	0	10	0	0	0	0	0	0	0	7
7	10	5	4	0	0	4	4	0	4	0	8	5	1	0	4	0	4
8	10	4	3	5	0	7	0	3	5	5	3	0	0	0	0	0	5
9	10	4	3	0	0	5	0	0	4	5	7	0	0	0	8	4	4
10	0	2	0	0	0	0	0	0	5	0	5	0	0	0	0	0	0
11	0	5	5	0	5	5	5	0	5	0	0	3	0	5	3	0	4
12	0	0	10	0	5	0	5	0	3	5	0	0	2	0	9	0	10
13	0	5	10	5	5	0	10	0	8	0	0	0	5	0	9	0	10
14	5	4	7	0	5	8	4	2	4	0	7	0	0	0	7	0	7
15	0	5	0	3	3	0	4	0	0	0	0	3	5	4	5	3	0
16	0	7	0	8	7	0	4	0	5	0	0	5	0	0	9	3	8
17	0	0	0	5	0	3	0	0	0	5	4	5	0	3	0	0	4
18	0	4	2	3	12	4	5	0	4	0	0	0	4	0	10	0	7
19	3	4	3	0	9	3	4	0	8	3	0	5	0	0	4	0	10
20	0	0	11	4	5	5	0	5	5	0	0	0	4	0	8	0	0
21	0	3	9	0	8	0	6	5	8	4	3	0	0	4	9	4	6
22	2	2	10	5	14	6	2	5	10	11	2	8	9	4	7	2	8

Table E.1(continued): The United Synergy Fuzzy Cognitive Matrix.

	Factors																
Factors	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
23	0	3	7	0	6	3	10	0	7	5	0	0	0	0	3	0	8
24	2	2	11	2	10	6	4	3	5	6	2	2	5	2	9	2	10
25	0	4	5	9	3	6	10	7	4	0	8	12	0	7	2	0	7
26	5	0	3	8	2	2	0	0	1	3	0	4	0	5	2	0	4
27	8	14	7	0	4	4	10	4	4	5	4	0	0	5	9	4	4
28	0	0	1	0	10	0	3	2	5	5	5	0	0	0	1	0	5
29	0	4	0	3	1	4	7	6	5	3	0	9	0	0	9	0	0
30	0	3	5	7	8	5	9	7	8	4	0	5	3	0	0	0	4
31	0	4	0	1	0	5	9	7	3	0	0	0	8	0	2	0	0
32	8	4	9	5	10	7	9	2	8	9	3	5	7	0	6	0	0

APPENDIX F: The fuzzy synergy questionnaire.

Aşağıdaki soru formu, "**KOBİ'lerde AR_GE İşbirliklerinin Sinerji Potansiyeli**"ni konu alan bir tez çalışmasına veri sağlamak amacıyla hazırlanmıştır. Çalışmanın güvenilirliği açısından **tüm soruları eksiksiz** olarak cevaplandırmanız önemlidir. Çalışmaya gösterdiğiniz ilgi, ayırdığınız zaman ve değerli katkılarınız için teşekkür ederiz.

Doç. Dr. Gülgün Kayakutlu

İTÜ İşletme Fakültesi

Endüstri Mühendisliği Bölümü

e-posta: kayakutlu@itu.edu.tr

M.Sc. Ayça Altay

İ.T.Ü. İşletme Fakültesi

Endüstri Mühendisliği Bölümü

e-posta: altaya@itu.edu.tr

1. Firmanız hangi sektörde faaliyet göstermektedir?

2. Firmanızın bir Ar-Ge işbirliği yapma isteğini nasıl değerlendirirsiniz?

Hiç ihtiyacımız yok		Olsa da olur, olmasa da		Kesinlikle yapılmalı
1	2	3	4	5

3. Firmanız, başka firmalarla iletişim halinde olunması konusuna ne derece açıktır?

Hiç açık değildir		Ne açıktır ne de değil		Kesinlikle açıktır
1	2	3	4	5

4. Firmanızın vizyon ve yenilikçilik hedeflerini açıklayınız.

5. Firmanızın yönetim şeklini aşağıdaki ölçeği kullanarak nasıl değerlendirirsiniz?

Tamamen hiyerarşik					Hiyerarşi ve Demokrasi dengelidir					Tamamen demokratik
1	2	3	4	5	6	7	8	9	10	11

6. Radikal müşteri taleplerine cevap verme hızınızı aşağıdaki ölçeğe göre nasıl tanımlarsınız?

Sektör ortalamasından çok yavaş					Sektör ortalaması ile aynı					Sektör ortalamasından çok hızlı
1	2	3	4	5	6	7	8	9	10	11

7. Firmanızın finansal durumunu belirtiniz?

BİRDEN FAZLA CEVAP İŞARETLEYEBİLİRSİNİZ

Halka arzımız yapılmıştır/yapılmaktadır……………..(1)

Hissedarlar tarafından finanse edilmektedir…………(2)

Yan şirketleri bulunmaktadır………………………....(3)

Diğer ***(Belirtin)***

8. Bir Ar-Ge işbirliğine karşı tutumunuz ne olur?

İşbirliklerine katılmak istiyoruz ama bu konuda tecrübemiz az / yok					İşbirliğine katkıda bulunabiliriz ancak kaynaklarımız sınırlıdır					Şirkete özgün bilgileri paylaşmadan, işimizi aksatmadan yürüyecek işbirliklerine hazırız
1	2	3	4	5	6	7	8	9	10	11

9. Mevcut işiniz için ne tür Ar-Ge işbirlikleri daha uygundur?

İşimiz işbirliklerine uygun değildir					Kısa dönemli işbirlikleri daha uygundur					Uzun dönemli işbirlikleri daha uygundur
1	2	3	4	5	6	7	8	9	10	11

10. Size göre, Ar-Ge işbirliklerinde sorun çıkmaması için ne yapılmalıdır?

Herkes her işin bir ucundan tutmalıdır					Bazı ortaklar kendi sorunlarını çözüp, başka ortaklara karışmamalıdırlar					Herkes kendi sorumluluğunu yerine getirirse sorun çıkmaz
1	2	3	4	5	6	7	8	9	10	11

11. Bir Ar-Ge işbirliğindeki önceliklerinizi nasıl tanımlarsınız?

Bizim kültürümüze uyabilecek ortakları tercih ederiz					Firma kültürümüz ve işimiz katıdır ancak esnek bir çalışma takımı çıkarabiliriz					Ortak bir zemin yaratmaya istekliyiz, mevcut iş ve çalışanlarımız bu yapıya uyabilir
1	2	3	4	5	6	7	8	9	10	11

12. Eğer bir Ar-Ge işbirliğinde olsanız, işbirliği içinde yer alan çalışanlarınız bu durumu nasıl karşılar?

Genel olarak karşı tarafın yaptıklarına uyarlar					Bu işbirliği işlerini kolaylaştırırsa gönüllü çalışırlar					Bu işbirliği maaşlarına yansır ise gönüllü çalışırlar
1	2	3	4	5	6	7	8	9	10	11

13. Size göre, Ar-Ge işbirliklerinde yatırımlar nasıl dengelenir?

Yatırımların dağıtımı şirket zenginliğine göre yapılmalıdır. Çoğunluk daha zengin ortaklar tarafından ödenmelidir					Bazı şirketler kısa sürede yapılacak yatırımları, kalan şirketler uzun sürede yapılacak yatırımları yerine getirmelidir					Her şirket kendisine ait yatırımları yapmalıdır. Ortak işler için paylar sözleşme ile belirlenmedir
1	2	3	4	5	6	7	8	9	10	11

14. Başka firma(lar) ile yapabileceğiniz bir Ar-Ge işbirliğinde, firmanızın nasıl konumlanabileceğini değerlendiriniz.

Rollerin açık olup olmadığı baştan belirlenemez, firmaların işbirliğindeki rolleri proje adımları belirlendikçe belirlenir					Örnek kullanmadan, özgün bir işbirliğinde firmamızın rolünün yeterince açık olacağını düşünüyorum					Başarılı işbirliklerini örnek alarak firmamızın rolünün yeterince açık olacağını düşünüyorum
1	2	3	4	5	6	7	8	9	10	11

15. Bir Ar-Ge işbirliği sürecinde iletişim, koordinasyon ve bilgi paylaşım sistemi açısından firmanızla ilgili nasıl sorunlar çıkabilir?

Diğer ortaklar ile kültürel uyumsuzluk ortaya çıkarsa, yapısal zorluklar çıkabilir					Diğer ortaklar ile teknolojik uyumsuzluk ortaya çıkarsa, teknik zorluklar olabilir					Eğer işbirliğindeki tüm firmalar iyi düzenlenmiş bir iletişim, koordinasyon ve bilgi paylaşım sistemi kurabilecekse, bizce bir sorun olmayacaktır
1	2	3	4	5	6	7	8	9	10	11

16. Firmanızın performans ölçüm sistemini nasıl tanımlarsınız?

BİRDEN FAZLA CEVAP İŞARETLEYEBİLİRSİNİZ

Performans ölçümü için çıktıları kullanıyoruz. (Kar, ürün adedi, vb…)…(1)

Performans ölçümü için çabayı kullanıyoruz. (Çalışma saatleri, vb…)…..(2)

Performans ölçüm sistemimiz bulunmamaktadır…………………………..(3)

Diğer ***(Belirtin)***

17. İnsan Kaynakları Sisteminizi nasıl tanımlarsınız?

BİRDEN FAZLA CEVAP İŞARETLEYEBİLİRSİNİZ

Ödül sistemi kullanıyoruz…………………………………………………..(1)

Ceza sistemi kullanıyoruz…………………………………………………..(2)

Belirli bir sistemimiz bulunmamaktadır……………………………………(3)

Diğer ***(Belirtin)***

18. Aşağıdaki ifadelerin firma vizyon, hedef ve amaçları hakkında firmanıza ne derece uygun olduğunu 1 ile 7 arası puan vererek belirtir misiniz?

	Hiç uygun değil			Ne uygun ne değil			Ke-sinlik-le Uygun
Yazılı vizyon, hedef ve amaçlar gerçeği yansıtmakta ve çalışanlar tarafından benimsenmektedir	1	2	3	4	5	6	7
Yazılı vizyon, hedef ve amaçlar çalışanların çoğu tarafından benimsenmemektedir	1	2	3	4	5	6	7
Vizyon, hedef ve amaçlar sektör ve piyasa durumuna göre değişmektedir	1	2	3	4	5	6	7

19. Firmanızdaki liderlik anlayışını nasıl tanımlarsınız?

Kararlar ortak verilir ancak uygulama yetkisi tek kişi/kuruldadır					Karar ve yetkiler tek kişi/kurulda toplanır					Yetkiler tüm çalışanlara dağıtılır, acil durumlarda tüm çalışanlar üstünlük alabilir
1	2	3	4	5	6	7	8	9	10	11

20. Aşağıdaki ifadelere ne derece katıldığınızı 1 ile 7 arası puan vererek belirtir misiniz?

	Kesinlikle			Ne katılıyorum			Kesinlikle
Yöneticinin çalışanlara yaklaşımı sayesinde şirket verimi artmaktadır	1	2	3	4	5	6	7
Yöneticinin çalışanlara yaklaşımı sayesinde departman bazında verimi artmaktadır	1	2	3	4	5	6	7
Yöneticinin çalışanlara yaklaşımı sayesinde kişiler bazında verimi artmaktadır	1	2	3	4	5	6	7

21. Firmanızın ününü nasıl tanımlarsınız?

Sektördeki tüm firmalar gibi bizim de ünümüz sınırlıdır					Firmaların sektördeki ünü ile ilgili bir bilgi bulunmamaktadır					Genel kabul görmüş, iyi ünü olan bir firmayız
1	2	3	4	5	6	7	8	9	10	11

22. Bir işbirliğinde aşağıdaki genel/teknolojik kaynaklardan hangilerini ne derecede temin edebilirsiniz?

	Hiç Temin Edemeyiz			Firmamızın üzerine düşeni temin edebiliriz			Tamamını kaşılayabiliriz
Nitelikli personel	1	2	3	4	5	6	7
Makine/Teçhizat	1	2	3	4	5	6	7
Ticaret sözleşmeleri	1	2	3	4	5	6	7
Sermaye	1	2	3	4	5	6	7
Prosedür ve süreçler	1	2	3	4	5	6	7
Bilgisayarlar	1	2	3	4	5	6	7
İletişim ekipmanı	1	2	3	4	5	6	7
Otomatik Veri İşleme	1	2	3	4	5	6	7
Veri Tabanı Yönetim Sistemi	1	2	3	4	5	6	7
Yönetim Bilişim Sistemleri	1	2	3	4	5	6	7
Bilgi, ekipman ve çeşitli hizmetler	1	2	3	4	5	6	7

APPENDIX G: The characters of visions, goals and objectives.

Table G.1: The characters of visions, goals and objectives.

Firm No	Word / Expression (in Turkish)									
	ürün	hizmet	yenilik	teknoloji	gelişim	değişim	mükemmel	çağ/zaman/ayak uydurma	büyüme	AB
1	1	0	0	1	0	0	0	0	0	0
2	0	0	0	0	1	1	1	0	0	0
3	0	0	0	1	0	0	0	1	0	0
4	0	1	1	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0
6	0	0	1	0	0	0	0	0	0	0
7	0	0	0	1	0	0	0	1	0	0
8	0	0	1	0	0	0	0	0	0	0
9	1	0	0	1	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	1	1
11	0	0	1	0	0	0	0	0	0	0
12	0	0	0	1	0	0	0	0	0	0
13	1	0	0	0	0	0	0	0	0	0
14	0	1	0	0	0	0	0	0	0	0
15	0	1	0	1	0	0	0	0	0	0
16	0	0	1	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0
18	0	0	1	0	0	0	0	0	0	0
19	0	0	1	0	1	0	0	0	0	0
20	0	1	0	0	0	0	0	0	0	0
21	1	0	0	0	0	0	0	0	0	0
22	0	0	0	0	1	1	0	0	0	0

Table G.1 (continued): The ,characters of visions, goals and objectives.

	ürün	hizmet	yenilik	teknoloji	gelişim	değişim	mükemmel	çağ/zaman/ayak uydurma	büyüme	AB
23	0	0	0	0	0	0	0	0	1	0
24	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	1
26	1	0	0	0	0	0	0	0	0	0
27	1	0	0	0	0	0	0	0	0	0
28	0	1	0	0	0	0	0	0	0	0
29	0	0	1	0	0	0	0	0	0	0
30	0	1	1	0	0	0	0	0	0	0
31	1	0	0	0	0	0	0	0	0	0
32	0	0	1	0	0	0	0	0	0	0
33	1	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	1	0
35	1	0	1	0	0	0	0	1	0	0
36	0	0	1	0	0	0	0	0	0	0
37	0	0	0	1	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0
39	1	0	0	0	0	0	0	0	0	0
40	1	0	1	0	0	0	0	1	0	0
41	0	0	0	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	1	0	0
43	0	0	0	0	0	0	0	0	0	0
44	0	0	1	0	0	0	1	0	0	0
45	0	0	0	0	1	0	0	0	0	0
46	0	0	1	0	0	0	0	0	0	0
47	0	0	1	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	1	0
49	0	1	0	0	0	0	1	0	0	0
50	0	0	1	0	0	0	0	0	0	0
51	0	1	0	0	0	0	1	0	0	0

Table G.1 (continued): The characters of visions, goals and objectives.

Firm No	Word / Expression (in Turkish)									
	kalite	Pazar	şube	markalaşma	bilinç	eğlence	samimiyet	bayilik	ucuz	tasarım
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0
4	1	0	0	0	0	0	0	0	0	0
5	0	0	1	0	0	0	0	0	0	0
6	0	0	0	1	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0
8	1	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	1	0
14	1	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	1	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0
20	1	0	0	0	0	0	0	0	0	0
21	1	0	0	0	0	0	0	0	0	0
22	1	0	0	1	0	0	0	0	0	0
23	1	0	1	0	0	0	0	0	0	0
24	1	0	0	0	1	0	0	0	0	0
25	0	0	1	1	0	0	0	0	0	0

Table G.1 (continued): The characters of visions, goals and objectives.

	kalite	Pazar	şube	markalaşma	bilinç	eğlence	samimiyet	bayilik	ucuz	tasarım
26	1	0	0	0	0	0	0	0	0	0
27	1	0	0	0	0	0	0	0	0	0
28	1	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	1
30	0	0	0	0	0	0	0	0	0	0
31	1	0	0	0	0	0	0	0	0	0
32	1	0	0	0	0	0	0	0	0	1
33	1	0	0	0	0	0	0	0	1	0
34	0	0	1	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0
39	1	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0
41	0	0	1	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	1	0	0	0
44	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0

Table G.1 (continued): The characters of visions, goals and objectives.

Firm No	sektör	satış	rekabet	Hız	eleman	öncü	doğal	global	vizyon	garanti
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0
6	1	0	1	1	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0
10	0	0	0	1	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0
13	0	0	0	1	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	1	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	1	0	0	0	0	0
18	0	0	0	0	0	1	0	0	0	0
19	1	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	1	0	0	0
22	0	0	1	0	0	0	0	1	0	0
23	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0

Table G.1 (continued): The characters of visions, goals and objectives.

	sektör	satış	rekabet	hız	eleman	öncü	doğal	global	vizyon	garanti
25	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0
27	1	0	0	0	0	0	0	0	0	0
28	1	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	1
30	0	0	0	0	0	0	0	0	0	0
31	1	0	0	0	0	0	0	0	0	0
32	1	0	0	0	0	0	0	0	0	1
33	1	0	0	0	0	0	0	0	1	0
34	0	0	1	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0	0	0
39	1	0	0	0	0	0	0	0	0	0
40	0	0	0	0	0	0	0	0	0	0
41	0	0	1	0	0	0	0	0	0	0
42	0	0	0	0	0	0	0	0	0	0
43	0	0	0	0	0	0	1	0	0	0
44	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0
46	0	0	0	0	0	0	0	0	0	0
47	0	0	0	0	0	0	0	0	0	0
48	0	0	0	0	0	0	0	0	0	0
49	0	0	0	0	0	0	0	0	0	0
50	0	0	0	0	0	0	0	0	0	0
51	0	0	0	0	0	0	0	0	0	0

APPENDIX H: The united innovation and risk fuzzy cognitive matrix.

Table H.1: The united innovation and risk fuzzy cognitive matrix.

	factors																
Factors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0	8	7	5	13	0	0	0	-1	1	2	6	3	-2	1	3	2
2	4	0	2	7	8	10	0	6	6	-1	-1	3	4	-2	2	3	4
3	9	4	0	7	11	2	7	10	12	4	6	4	12	8	2	1	-2
4	0	5	3	0	11	2	0	1	-3	5	5	8	7	3	2	1	4
5	0	5	-5	-3	0	3	-2	-1	0	8	-2	-6	7	-2	-2	2	3
6	0	0	0	0	0	0	0	-3	-3	8	2	2	-1	-2	1	3	3
7	0	0	5	3	0	0	0	4	4	10	7	2	-1	6	2	-1	-3
8	0	0	0	0	0	-5	0	0	13	0	3	4	0	7	2	0	0
9	0	0	0	0	0	-4	0	5	0	5	1	5	0	-4	0	0	2
10	0	0	0	0	0	0	0	9	9	0	10	4	10	12	11	0	0
11	0	0	0	9	0	0	0	9	9	10	1	0	10	12	7	0	0
12	0	0	5	0	0	0	4	0	6	5	10	0	5	1	1	0	5
13	0	0	0	0	1	0	0	0	0	10	0	0	0	3	8	0	3
14	0	0	5	0	0	0	5	8	3	10	4	0	10	0	9	-3	0
15	0	3	0	10	5	3	0	5	8	10	0	3	8	10	0	5	5
16	0	0	0	5	0	0	0	0	0	0	2	5	0	0	0	0	12
17	0	0	0	5	5	0	0	0	0	1	2	0	0	0	0	5	0
18	0	3	0	5	5	5	0	4	9	10	10	8	10	10	0	0	6
19	0	4	0	4	0	0	0	0	3	0	0	1	0	4	0	4	4
20	0	0	0	0	0	4	0	4	5	5	3	0	0	5	0	0	3
21	0	0	0	3	0	0	0	0	0	0	0	4	0	0	0	0	3
22	0	0	5	0	-3	0	0	0	0	0	1	4	0	0	0	0	4
23	0	0	5	4	5	0	0	0	0	0	7	7	0	0	0	0	6

Table H.1 (continued): The united innovation and risk fuzzy cognitive matrix.

	Factors																
Factors	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
24	0	0	3	3	0	0	0	0	0	0	5	5	0	0	0	0	5
25	0	3	0	0	4	0	0	0	4	0	5	4	4	0	0	0	4
26	0	5	0	3	5	0	0	0	-4	0	5	5	0	0	0	0	5
27	0	3	3	0	3	0	0	0	0	0	0	0	0	0	0	0	4
28	0	0	4	3	0	0	0	3	3	0	0	-4	1	0	0	0	0
29	0	0	0	5	3	0	0	0	5	0	1	4	0	0	0	0	4
30	1	0	0	2	3	3	0	0	0	0	0	4	0	0	0	0	4
31	0	0	0	0	0	0	0	0	0	0	-2	0	0	0	0	0	1
32	0	0	0	0	5	0	0	0	5	0	0	4	0	0	0	0	4
33	0	0	0	0	3	0	0	0	5	0	0	5	0	0	0	5	4
34	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0
35	0	0	0	4	4	0	0	0	-4	0	7	7	0	1	0	4	7
36	0	0	5	0	4	0	0	0	-5	0	7	7	0	1	0	0	2
37	0	0	0	0	0	0	0	0	-5	-4	-6	-6	0	0	0	0	0
38	0	0	0	0	0	0	5	0	0	3	0	0	3	0	0	5	4
39	0	0	0	0	0	0	5	0	0	3	0	0	3	0	0	5	4
40	0	0	0	0	0	0	5	0	0	3	0	0	3	0	0	5	4
41	0	2	0	0	0	0	5	0	-4	0	1	5	0	0	0	4	7
42	0	2	0	0	0	0	5	0	-4	0	1	5	0	0	0	4	9
43	0	2	0	0	0	0	5	0	-4	0	1	5	0	0	0	4	9
44	0	0	2	0	0	0	3	3	3	0	0	3	2	3	0	0	0
45	0	0	0	0	-4	0	0	0	-4	-5	-5	4	5	1	4	0	0
46	0	0	0	0	5	0	0	0	0	0	0	0	0	6	0	0	0
47	0	0	0	0	4	0	0	0	5	0	0	0	0	0	0	0	4

48	0	0	0	4	4	0	0	0	0	0	0	4	0	0	0	0	4

Table H.1 (continued): The united innovation and risk fuzzy cognitive matrix.

	Factors																
Factors	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1	2	4	2	2	1	6	2	4	3	2	4	6	8	2	8	-2	4
2	3	2	0	4	3	4	3	2	3	4	2	1	2	3	5	4	5
3	3	6	2	0	0	-3	1	6	5	5	2	3	7	1	4	6	4
4	7	-2	0	0	0	3	2	5	5	-5	5	2	2	-1	8	-3	2
5	5	3	0	2	1	1	4	-3	3	4	15	-1	9	8	-1	8	2
6	-3	2	3	2	2	5	-1	10	-3	2	-1	2	8	3	7	7	1
7	2	5	1	0	0	5	3	1	3	-4	-3	5	2	-4	6	-5	4
8	5	0	0	0	0	0	0	0	0	0	0	0	1	-5	1	0	0
9	6	4	0	0	0	2	0	-3	-4	0	0	0	0	0	0	5	7
10	12	7	5	0	5	3	5	8	4	-4	-5	0	2	-5	0	1	0
11	5	5	0	0	0	4	5	5	5	-4	0	0	3	-5	6	7	7
12	7	8	0	0	0	5	0	2	5	-5	0	5	0	-5	5	0	4
13	9	3	0	0	0	6	1	1	-2	-4	0	-1	0	-6	-1	3	0
14	9	5	0	0	0	0	0	0	-1	-5	0	0	3	-5	0	-1	5
15	9	5	1	0	3	5	0	8	10	-4	1	1	8	-2	1	9	5
16	4	11	0	0	0	4	1	6	7	0	0	0	1	2	4	1	4
17	3	12	0	3	0	8	9	2	9	-3	0	7	3	-1	5	1	0
18	0	4	0	0	0	11	8	11	10	5	3	8	1	10	8	10	9
19	4	0	0	0	0	2	1	7	7	0	0	1	1	2	2	2	1
20	5	5	0	7	8	11	10	8	7	0	6	2	4	2	3	0	3
21	0	3	0	0	3	10	11	2	5	1	-7	0	0	0	2	1	1

22	0	4	0	0	0	13	12	2	0	0	-3	0	0	0	1	1	0
23	0	4	0	0	5	0	14	1	6	0	-7	1	2	0	1	2	0
24	0	5	0	0	4	5	5	1	0	0	-7	0	1	0	1	2	0

Table H.1 (continued): The united innovation and risk fuzzy cognitive matrix.

	Factors																
Factors	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
25	5	0	0	4	5	0	8	2	4	9	1	0	0	0	0	5	0
26	0	0	0	0	5	5	0	2	0	2	0	0	0	1	0	0	0
27	0	0	0	2	4	3	2	0	0	12	1	0	0	0	0	0	0
28	0	0	0	0	-4	2	-2	-2	0	-4	1	1	1	0	0	0	0
29	0	0	0	4	5	0	5	2	0	0	1	0	1	0	0	0	0
30	0	0	0	3	3	0	4	0	0	0	0	3	9	3	0	0	0
31	0	0	0	0	0	0	0	0	-1	-1	-5	-2	2	1	0	0	0
32	0	0	0	4	4	0	0	0	0	3	0	0	0	1	2	0	0
33	0	0	0	3	0	0	3	0	0	4	0	0	4	0	3	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
35	0	0	0	4	5	0	0	0	0	5	0	0	5	0	0	0	0
36	0	0	0	4	4	0	4	0	0	0	0	0	0	0	0	0	0
37	0	0	0	-4	-4	0	0	0	0	-4	0	0	-4	-5	0	0	0
38	0	0	0	0	4	0	0	0	0	4	0	0	4	0	0	0	0
39	0	0	0	0	4	0	0	0	0	4	0	0	4	0	0	0	0
40	0	0	0	0	4	0	0	0	0	4	0	0	4	0	0	0	0
41	0	0	0	5	5	0	5	0	0	5	0	0	5	0	0	0	0
42	0	0	0	5	5	0	5	0	0	5	0	0	5	0	0	0	0
43	0	0	0	5	5	0	5	0	0	5	0	0	5	0	0	0	0
44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	-2	0	0	0	0	0	-3	0	0	0	0	0	0	0

46	0	0	0	0	0	0	0	0	0	0	0	0	0	-2	0	0	0
47	0	4	0	0	0	0	0	0	0	5	0	0	5	0	0	0	4
48	0	0	0	0	4	0	0	0	0	5	0	0	5	0	0	0	0

Table H.1 (continued): The united innovation and risk fuzzy cognitive matrix.

	Factors													
Factors	35	36	37	38	39	40	41	42	43	44	45	46	47	48
1	8	3	8	2	2	3	6	5	2	4	0	8	6	5
2	3	3	7	4	4	4	3	3	2	3	0	4	5	5
3	6	7	-9	1	-1	-1	-2	3	-3	-2	0	3	3	3
4	7	7	5	5	5	5	11	6	3	2	0	0	10	10
5	0	-3	12	4	3	2	7	7	8	4	1	3	2	2
6	9	-2	3	3	2	2	-1	4	2	3	6	1	5	3
7	7	4	-6	-1	2	2	3	4	2	7	0	5	5	5
8	0	0	0	0	0	0	-4	6	0	0	0	0	0	0
9	10	0	9	1	1	1	1	1	1	0	0	0	0	0
10	10	-5	0	5	2	2	0	11	0	0	0	0	7	7
11	7	5	-5	4	2	2	5	6	0	0	0	0	7	8
12	6	8	-7	2	1	1	7	7	2	0	0	0	8	8
13	3	0	-4	-2	-2	-2	4	5	-1	3	0	0	0	0
14	-1	0	-2	0	0	0	4	4	0	0	0	0	0	0
15	5	1	-2	3	1	1	5	9	5	0	4	5	8	9
16	5	7	-3	5	5	5	9	4	8	4	0	0	7	7
17	6	9	-1	8	8	8	10	5	14	2	0	0	14	14
18	9	7	0	4	6	1	6	7	8	7	1	1	8	9
19	2	9	3	2	2	2	6	6	7	2	0	0	7	7
20	3	5	0	0	0	0	0	0	4	0	0	0	6	5
21	5	5	-5	2	2	2	7	5	6	0	0	0	1	1

22	5	5	-5	1	1	1	5	9	1	0	0	0	1	1
23	5	6	-3	3	3	3	8	9	3	1	0	0	1	1
24	6	6	-5	3	3	3	7	9	9	2	0	0	4	4

Table H.1 (continued): The united innovation and risk fuzzy cognitive matrix.

	Factors													
Factors	35	36	37	38	39	40	41	42	43	44	45	46	47	48
25	5	0	0	0	0	0	7	5	4	0	0	0	0	0
26	1	0	0	1	1	1	7	5	6	0	0	0	6	6
27	0	0	-3	2	2	1	5	3	2	1	0	0	0	1
28	1	0	0	0	0	0	-3	-4	1	0	0	0	1	1
29	1	5	0	2	2	2	9	7	5	0	0	0	2	2
30	0	3	0	1	1	1	1	0	5	0	0	0	1	4
31	2	-2	0	1	1	1	2	0	-2	1	0	0	2	-1
32	1	3	0	2	2	2	6	6	3	2	0	0	3	6
33	11	8	6	4	4	4	6	4	13	7	0	0	7	7
34	1	8	5	0	0	0	2	1	2	0	0	0	0	0
35	0	13	-3	7	9	9	9	5	11	3	0	0	7	7
36	5	0	-3	3	5	5	9	5	6	3	0	0	8	8
37	-5	-5	0	-3	-3	-3	-5	-6	-5	0	0	0	-4	-4
38	0	0	-4	0	1	5	3	3	5	0	0	0	2	3
39	0	0	-4	5	0	13	10	9	13	4	0	1	9	9
40	0	0	-4	5	5	4	9	9	13	4	0	1	9	9
41	0	5	-4	4	4	4	0	9	15	3	4	7	14	14
42	0	5	-4	5	5	5	5	0	15	3	0	10	14	15
43	0	5	-4	5	5	5	5	5	0	4	2	7	15	15
44	0	4	-4	3	3	3	5	5	0	0	0	0	2	2
45	0	0	0	3	3	3	3	3	1	0	0	0	-1	-1

46	-4	0	0	3	3	3	7	7	-4	-4	4	0	4	4
47	0	5	0	4	4	4	10	10	5	0	0	0	0	7
48	0	4	0	4	4	4	10	10	5	0	0	0	0	0

APPENDIX I: The fuzzy innovation / risk questionnaire.

Aşağıdaki soru formu, "**KOBİ'lerde inovasyon potansiyelinin ölçülmesi**"ni konu alan bir tez çalışmasına veri sağlamak amacıyla hazırlanmıştır. Çalışmanın güvenilirliği açısından **tüm soruları eksiksiz** olarak cevaplandırmanız önemlidir. Çalışmaya gösterdiğiniz ilgi, ayırdığınız zaman ve değerli katkılarınız için teşekkür ederiz.

Assist. Prof. Dr. Gülgün Kayakutlu

ITU Management Faculty

Industrial Engineering Department

e-mail: kayakutlu@itu.edu.tr

M.Sc. Ayça Altay

ITU Management Faculty

Industrial Engineering Department

e-mail: altaya@itu.edu.tr

1. Firmanız hangi tür KOBİ'dir?

a. Orta büyüklüktedir.(250 çalışandan az)
b. Küçük firmadır. (50 çalışandan az)
c. Mikro firmadır. (10 çalışandan az)

UYARI:

Bundan sonraki ölçek bulunan sorularımızı cevaplarken; size en uygun seçeneği veya iki seçenek arasında kalmanız durumunda iki seçenek arasında görüşünüze en yakın puanı işaretlemenizi rica ederiz.
Cevapların dışında sizin eklemek istediğiniz noktalar olması durumunda sorunun altına cevabınızı ifade edebilirsiniz.

2. Firmanızdaki beyaz yakalı çalışan oranı nedir?

%30'undan azı beyaz yakalıdır					Çalışanlarımızın yarısı beyaz yakalıdır.					%70'inden fazlası beyaz yakalıdır
1	2	3	4	5	6	7	8	9	10	11

3. Firmanızın yaşını nasıl tanımlarsınız.

Eski ve köklü bir firmayız					Endüstrideki birçok firma ile hemen hemen aynı yaştayız.					Yeni bir firmayız
1	2	3	4	5	6	7	8	9	10	11

4. Sektörünüzü teknolojik açıdan nasıl tanımlarsınız?

Üretimimiz düşük teknoloji/el yapımıdır					İleri teknoloji üretim süreçlerimize yardımcıdır					İleri teknoloji içeren bir sektörde çalışıyoruz
1	2	3	4	5	6	7	8	9	10	11

5. Sermaye yapınızı nasıl tanımlarsınız.

1.Kısım

Krediler ile çalışmaktayız					Nakit ve kredi arasında dengeli bir dağılım vardır					Sermayemiz girişimcilerin yatırımlarından oluşmaktadır
1	2	3	4	5	6	7	8	9	10	11

2.Kısım

Tüm finansal kaynaklarımız ödünç sermayeye dayanmaktadır										Tüm finansal kaynaklarımız yatırımcılarımız ve diğer girişimciler tarafından sağlanmaktadır
1	2	3	4	5	6	7	8	9	10	11

6. Firmanızın hissedar yapısı ne durumdadır?

Halka açık bir firmayız					Hisse senedi kullanırlar					Devlet tahvili kullanırlar
1	2	3	4	5	6	7	8	9	10	11

7. Firmanızın kaç patenti bulunmaktadır?

Birden fazla patenti bulunmaktadır......................................1

Bir patenti bulunmaktadır...2

Firmamızın patenti bulunmaktadır.......................................3

8. Şu ana kadar başvurduğunuz patent sayısı nedir?

Birden fazla patent için başvurumuz bulunmaktadır. 1

Bir patent için başvurumuz bulunmaktadır. 2

Şu ana kadar patent için başvuruda bulunmadık. 3

9. Müşteri sorunlarını değerlendirmek için aşağıdaki yollardan hangisini kullanıyorsunuz?

BİRDEN FAZLA CEVAP İŞARETLEYEBİLİRSİNİZ

Çağrı merkezimiz bulunmaktadır. ....

Müşteri ilişkileri ile ilgilenen bir çalışanımız bulunmaktadır. ....

Müşteri bilgilerini ara müşteri, satış kanalı gibi kaynaklardan alıyoruz. ....

Diğer ***(Belirtin)***...

Diğer ***(Belirtin)***...

10. Satış kanallarınızı nasıl tanımlarsınız?

BİRDEN FAZLA CEVAP İŞARETLEYEBİLİRSİNİZ

Doğrudan satış yapıyoruz………………………………………(1)

Dağıtımcılar aracılığı ile satış yapıyoruz……………………….(2)

Tek bir firmaya satış yapıyoruz. ………………………………(3)

Diğer ***(Belirtin)***)

11. Aşağıdaki satış kanallarından hangisini kullanıyorsunuz?

	Kullanıyoruz	Kullanmıyoruz	Oran
Dijital satış kanallarını	1	2	………………..
Geleneksel satış kanallarını	1	2	………………..
			100

12. Gözlemlerinize göre, sektörünüzün yaşam ömrü nasıldır?

Bulunduğumuz bölgede azalan bir talep göstermektedir					Bulunduğumuz bölgede gelecekte de aynı talebi gösterecektir					Bulunduğumuz bölgede artan bir talep göstermektedir
1	2	3	4	5	6	7	8	9	10	11

13. Sektörünüzün değişme hızı nasıldır?

Sektörümüz değişmemektedir					Yavaş değişen bir sektörde çalışıyoruz					Hızlı değişen bir sektörde çalışıyoruz
1	2	3	4	5	6	7	8	9	10	11

14. Gözlemlerinize göre, sektördeki firmaların birbirine yaklaşımı nasıldır?

Firmalar birbirlerine karşı ilgisizdirle r, başka firma bilgileri bilinmez					Firmalar rekabetçi davranış göstermektedirl er					Firmalar işbirlikçi davranış göstermektedirl er
1	2	3	4	5	6	7	8	9	1 0	11

15. Firmanızda Ar-Ge faaliyetleri sürdürülüyor mu?

Evet, sürdürülüyor...1

Hayır, Ar-Ge faaliyetimiz yok ....2***(17.SORUYA gEÇİNİZ)***

16. Firmanızın Ar-Ge yapısını aşağıdaki seçeneklerden hangileri en tanımlar?

BİRDEN FAZLA CEVAP İŞARETLEYEBİLİRSİNİZ

Bir Ar-Ge laboratuarımız bulunmaktadır…………………………….(1)

Bir Ar-Ge bölümümüz/birimimiz bulunmaktadır…………………..(2)

Ar-Ge araştırmaları dış firmalarca yapılmakta, bu firmalar bizi bilgilendirmektedir…………………………………………………...(3)

Diğer ***(Belirtin)***)

17. Firmanızın işçi devir oranını nasıl tanımlarsınız?

Çalışanların çoğu eğitimden / işe alıştıktan kısa bir süre sonra ayrılmaktadır					İşçi devir oranı sektör ortalamasındadır					Çalışanların büyük bir kısmı firmamızın uzun süreli elemanıdır
1	2	3	4	5	6	7	8	9	10	11

18. Firmanızın yenilikçilik yaklaşımını nasıl tanımlarsınız?

BİRDEN FAZLA CEVAP İŞARETLEYEBİLİRSİNİZ

Bize pazar payı veya gelir artışı getirebilecek işbirliklerine hazırız. ….(1)

Yeni ürünler için araştırma yapıyoruz ancak bu bilgileri firma dışında paylaşmıyoruz. ……………………………………………………..(2)

Yenilikçilik adına bir girişimimiz yok……………………………...(3)

Diğer ***(Belirtin)***

19. Aşağıdakilerden ifadelerin firmanıza ne derece uygun olduğunu 1 ile 7 arası puan vererek belirtir misiniz?

	Hiç uygun değil			Ne uygun ne değil			Kesinlikle Uygun
Firmamız içinde yeni fikirlerin yaratılması ve paylaşılması desteklenir	1	2	3	4	5	6	7
Firma kültürümüz yeni fikirler yaratılmasına ve paylaşılmasına uygun değildir	1	2	3	4	5	6	7

Teknolojik kaynaklarımız yeni fikirler yaratılmasına ve paylaşılmasına uygun değildir	1	2	3	4	5	6	7
Hem firma kültürümüzde hem de teknolojik kaynaklarımızda iyileştirme yapılırsa, yeni fikirlerin yaratılması ve paylaşılması desteklenebilir	1	2	3	4	5	6	7

20. Firmanızın kaynak dağılımı sistemini nasıl tanımlarsınız?

1.Kısım

Bulunduğumuz sektörde, kaynakların miktarı kısıtlıdır. Bu nedenle acil olanı yerine getirmeye çalışarak günü kurtarırız					Çeyrek ve yarım yıllık bütçe dağılımı planlarımız yapılmaktadır, ancak günlük ihtiyaçlar nedeni ile planımızı değiştirmek zorunda kalabiliyoruz					Çeyrek ve yarım yıllık bütçe dağılımı planlarımız yapılmaktadır ve küçük sapmalar dışında plandan şaşılmamaktadır
1	2	3	4	5	6	7	8	9	10	11

2.Kısım

Ana harcamalar yapıldıktan sonra, diğer acil durumlara sıra gelmektedir					Harcamalar kontrol edildikten sonra, acil durumlar için kaynaklarımız bulunmakta ve nasıl kullanılacağı planlanmaktadır					Harcamalar yapılmadan önce planımız kesinlikle hazırlanmıştır
1	2	3	4	5	6	7	8	9	10	11

21. Firmanızın laboratuarlar, nitelikli danışmanlar ve/veya ulusal/uluslar arası bilimsel kuruluşlar ile ilişkileri ne sıklıktadır?

Bu kişi/kuruluşlar ile nadir olarak işbirlikleri kurar ve araştırmalar yaparız					Bu kişi/kuruluşlar ile ara sıra işbirlikleri kurar ve araştırmalar yaparız					Bu kişi/kuruluşlar ile sık sık işbirlikleri kurar ve araştırmalar yaparız
1	2	3	4	5	6	7	8	9	10	11

22. Firmanızın üniversiteler ile ilişkileri ne sıklıktadır?

Üniversiteler ile nadir olarak işbirlikleri kurar ve araştırmalar yaparız					Üniversiteler ile ara sıra işbirlikleri kurar ve araştırmalar yaparız					Üniversiteler ile sık sık işbirlikleri kurar ve araştırmalar yaparız
1	2	3	4	5	6	7	8	9	10	11

23. Firmanızın, şirket içi rekabet açısından durumu nasıldır?

Firma kültürümüzde şirket içi rekabetin çalışanları rahatsız etme riski arttıracağı düşünülmektedir, bu nedenle rekabeti teşvik etmeyiz					Firmamızda bir işin tam ve kaliteli olarak bitirilmesi şirket içi rekabetten önce gelmektedir					Firmamızda çeşitli performans değerlendirme sistemleri ve ödüller, şirket içi rekabeti teşvik etmek üzere uygulanmaktadır
1	2	3	4	5	6	7	8	9	10	11

24. Gözlemlerinize göre çalışanlarınızın üretkenlik derecesi nasıldır?

Çalışanlarımızın %30'undan azı yüksek verimlilik ile çalışmaktadır					Çalışanlarımızın yarısı yüksek verimlilikle çalışmaktadır					Çalışanlarımızın %70'inden fazlası yüksek verimlilik ile çalışmaktadır
1	2	3	4	5	6	7	8	9	10	11

25. Aşağıdakilerden ifadelerin firmanıza ne derece uygun olduğunu 1 ile 7 arası puan vererek belirtir misiniz?

	Hiç uygun değil			Ne uygun ne değil			Kesinlikle Uygun
Yeni ürün/hizmet/süreçler, firmanın ayakta kalabilmesi için zorunlu olduğundan talebe göre düzenlenebilir	1	2	3	4	5	6	7
Ürün/hizmet/süreçlerin farklılaştırılması zordur ve müşterilerden bu konuda gelen talep çok azdır / yoktur	1	2	3	4	5	6	7
Ürün/hizmet/süreçlerin farklılaştırılamaz çünkü müşteri talepleri standarttır	1	2	3	4	5	6	7

26. Yeni ürün/süreç çıkarma hızınızı aşağıdaki ölçeğe göre nasıl tanımlarsınız?

Sektör ortalamasından çok yavaş					Sektör Ortalaması ile aynı hızda					Sektör ortalamasından çok hızlı
1	2	3	4	5	6	7	8	9	10	11

27. Nitelik açısından sektör ortalaması ile karşılaştırıldığında çalışanlarınızın durumu aşağıdaki ölçeğe göre nasıldır?

Sektör ortalamasından çok daha az nitelikli					Sektör Ortalaması ile aynı nitelikte					Sektör ortalamasından çok daha fazla nitelikli
1	2	3	4	5	6	7	8	9	10	11

28. Üretkenlik açısından sektör ortalaması ile karşılaştırıldığında firmanızın durumu aşağıdaki ölçeğe göre nasıldır?

Sektör ortalamasından çok daha az üretken					Sektör Ortalaması ile aynı üretkenlikte					Sektör ortalamasından çok daha fazla üretken
1	2	3	4	5	6	7	8	9	10	11

29. Karlılık açısından sektör ortalaması ile karşılaştırıldığında firmanızın durumu nasıldır?

Sektör ortalamasından çok daha az karlı					Sektör Ortalaması ile aynı karlılıkta					Sektör ortalamasından çok daha fazla karlı
1	2	3	4	5	6	7	8	9	10	11

30. Tedarikçileriniz için hangisi daha uygundur?

Yenilikçilik araştırmalarımıza katılmamaktadırlar					Firmamıza fikir getirmektedirler					Birlikte yürüttüğümüz yenilikçilik araştırmalarımız bulunmaktadır
1	2	3	4	5	6	7	8	9	10	11

31. Satış kanallarınız için hangisi daha uygundur?

Yenilikçilik araştırmalarımıza katılmamaktadırlar					Firmamıza fikir getirmektedirler					Birlikte yürüttüğümüz yenilikçilik araştırmalarımız bulunmaktadır
1	2	3	4	5	6	7	8	9	10	11

CURRICULUM VITAE

Name Surname: Ayça Altay

Place and Date of Birth: Bergama / 18.08.1983

Address: İTU Isletme Fakultesi Endustri Muhendisligi Bolumu A304 Macka / Istanbul

E-Mail: altaya@itu.edu.tr

B.Sc.: Istanbul Technical University / Industrial Engineering

M.Sc.: Istanbul Technical University / Industrial Engineering

List of Publications and Patents:

PUBLICATIONS/PRESENTATIONS ON THE THESIS

Altay, A., and Kayakutlu, G., 2012: The Foraging Search for Combinatorial Optimization Problems, *25th Conference of European Chapter on Combinatorial Optimization - ECCO XXV*, April 26-28, Antalya, Turkey, 1.

Altay, A., and Kayakutlu, G., 2011: Fuzzy Cognitive Mapping in Factor Elimination: A Case Study for Innovative Power and Risks. *Procedia Computer Science*, 1111-1119.

Altay, A., and Kayakutlu, G., 2011: Animal Food Chain Based Particle Swarm Optimization, *World Congress on Engineering 2011*, Proceedings Edited by S. I. Ao, Len Gelman, David WL Hukins, Andrew Hunter, A. M. Korsunsky, Volume II, July 6-8, London, UK, 1094-1099.

Altay, A., and Kayakutlu, G., 2010: Risks in SME Collaboration for Research Supply Chain. *International Conference on Value Chain Sustainability*, November 15-17, Valencia, Spain, 304 -312.

Altay, A., and Kayakutlu ,G., 2010: Evaluating Cognitive Clustering: Application on Collective Intelligence, *5th International Conference on Production Research*, July 21-23, Bogota, Colombia, 43.