DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

A FUZZY APPROACH FOR TOTAL PRODUCTIVE MAINTENANCE PERFORMANCE MEASUREMENT IN MANUFACTURING SYSTEMS

by
Ebru TURANOĞLU BEKAR

December, 2016
İZMİR

A FUZZY APPROACH FOR TOTAL PRODUCTIVE MAINTENANCE PERFORMANCE MEASUREMENT IN MANUFACTURING SYSTEMS

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İZMİR

Ph.D. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"A FUZZY APPROACH FOR TOTAL PRODUCTIVE MAINTENANCE PERFORMANCE MEASUREMENT IN MANUFACTURING SYSTEMS"** completed by **EBRU TURANOĞLU BEKAR** under supervision of **PROF. DR. LATİF SALUM** and **PROF. DR. CENGİZ KAHRAMAN** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

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A FUZZY APPROACH FOR TOTAL PRODUCTIVE MAINTENANCE PERFORMANCE MEASUREMENT IN MANUFACTURING SYSTEMS

ABSTRACT

Total Productive Maintenance (TPM), which recognized as a strategic maintenance technique, has been widely and successfully implemented in many organizations. In this context, evaluation of TPM performance can make a great contribution to organizations in advancing their manufacturing operations. Therefore, this thesis aims to develop a new framework for the performance measurement of TPM based on quantitative and qualitative performance indicators. Within the scope of this thesis, the proposed TPM performance measurement system (TPM PMS) is divided into four phases namely design, evaluation, implementation, and review. In the design phase, novel performance indicators having impact on TPM performance are identified and analyzed. In the evaluation phase, these indicators are evaluated using a fuzzy multiattribute decision making (FMADM) method improved on the basis of fuzzy arithmetic and ranking. Moreover, the improved method is compared with the most popular FMADM methods in the literature and its applicability and reliability are determined by carrying out sensitivity analysis. In the implementation phase, TPM performance is measured with novel performance indicators using fuzzy data envelopment analysis (FDEA). In this context, different generalized fuzzy data envelopment analysis with assurance regions models are proposed in the presence of desirable and undesirable inputs and outputs. Thus, the proposed models make a significant contribution into TPM literature. In the review phase, TPM performance should be monitored periodically, and preventive and predictive decisions or actions should be taken if it is needed. Finally, the proposed TPM PMS is implemented in an international manufacturing company operating on automotive industry.

Keywords: Performance measurement, total productive maintenance (TPM), novel performance indicators in TPM, fuzzy multiattribute decision making (FMADM), fuzzy data envelopment analysis (FDEA), fuzzy optimization.

ÜRETİM SİSTEMLERİNDE TOPLAM VERİMLİ BAKIM PERFORMANS ÖLÇÜMÜ İÇİN BULANIK BİR YAKLAŞIM

ÖZ

Stratejik bir bakım tekniği olan Toplam Verimli Bakım (TVB) birçok organizasyon tarafından başarılı bir şekilde yaygın olarak uygulanmaktadır. Bu bağlamda TVB performansının değerlendirilmesi de organizasyonların üretim süreçlerinin ve performanslarının geliştirilmesine büyük katkı sağlamaktadır. Bu nedenle, bu tez, niceliksel ve nitel performans göstergelerine dayalı TVB performans ölçümü için yeni bir çerçeve geliştirmeyi amaçlamaktadır. Bu tez kapsamında önerilen TVB performans ölçüm sistemi (TVB PÖS) tasarım, değerlendirme, uygulama ve gözden geçirme olmak üzere dört aşamadan oluşmaktadır. Tasarım aşamasında, TVB performansı üzerinde etkili olabilecek yeni performans göstergeleri belirlenmiş ve analiz edilmiştir. Değerlendirme aşamasında, bu göstergeler, bulanık aritmetik ve sıralamaya dayalı iyileştirilmiş bir bulanık çok ölçütlü karar verme yöntemi (BÇÖKV) kullanılarak değerlendirilmiştir. Ayrıca, iyileştirilen yöntem literatürdeki en popüler BÇÖKV yöntemleriyle karşılaştırılmış ve iyileştirilen yöntemin uygulanabilirliği ve güvenilirliği duyarlılık analizi yapılarak belirlenmiştir. Uygulama aşamasında, TVB performansı bulanık veri zarflama analizi (BVZA) kullanılarak yeni performans göstergeleri ile ölçülmüştür. Bu bağlamda, arzu edilen ve edilmeyen girdi ve çıktıların varlığında güvenli bölge kısıtlarını dikkate alan farklı genelleştirilmiş bulanık veri zarflama analizi modelleri önerilmiştir. Böylece önerilen modeller, TVB literatürüne önemli katkı sağlamıştır. Gözden geçirme aşamasında ise TVB performansının periyodik olarak izlenmesi ve gerektiğinde koruyucu ve önleyici karar ya da eylemlerin alınması gerektiği vurgulanmıştır. Son olarak, önerilen TVB PÖS, otomotiv endüstrisinde faaliyet gösteren uluslararası bir imalat şirketinde uygulanmıştır.

Anahtar kelimeler: Performans ölçümü, toplam verimli bakım (TVB), TVB' de yeni performans ölçütleri, bulanık çok ölçütlü karar verme (BÇÖKV), bulanık veri zarflama analizi (BVZA), bulanık optimizasyon.

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CHAPTER ONE
INTRODUCTION

1.1 Motivation

In today's dynamic environment, having a consistent production system is crucial for competitiveness; accordingly, Total Productive Maintenance (TPM) becomes a prominent subject as a strategic power for manufacturing organizations (Brah & Chong, 2004; Pinjala, Pintelon, & Vereecke, 2006). In the literature, a number of studies present the relationships between TPM and manufacturing performance (Bartz, Siluk, & Bartz, 2014; Belekoukias, Garza-Reyes, & Kumar, 2014; Brah & Chong, 2004; McKone, Schroeder, & Cua, 2001; Singh & Ahuja, 2015; Wickramasinghe & Perera, 2016, and etc.). According to the results of these studies, the proper implementation of TPM has a positive impact on the manufacturing performance. Thus, the relevant literature has defined several critical success factors for TPM implementation (Bamber, Sharp, & Hides, 1999; Ireland & Dale, 2006). In this regard, the measurement of TPM performance is significantly required for continuous improvement of the TPM implementation program (Piechnicki, Sola, & Trojan, 2015). When it comes to performance evaluation in TPM, overall equipment effectiveness (OEE) has widely been used as a performance measure because TPM aims to maximize equipment effectiveness (Schippers, 2001; Waeyenbergh & Pintelon, 2002). Although OEE has been considered as a standard measure for equipment performance, it captures only effectiveness of TPM, not its efficiency (Chan, Lau, Ip, Chan, & Kong, 2005).

OEE provides productivity behaviour of only individual equipment. However, the evaluation of TPM performance should include an objective and comprehensive method based on multiple inputs and outputs instead of OEE and its extensions (Muchiri & Pintelon, 2008). Thus, the motivation of this thesis is to measure TPM performance by developing a systematic framework based on novel performance indicators including quantitative and qualitative data (e.g., availability of maintenance personnel, human-oriented indicators such as "competence of maintenance personnel", "experience of operators in a production line", "operator reliability”, “training and continuing education”, “new ideas generated and implemented” , “level of 5S” and employee satisfaction indicators such as “employee absenteeism”, “employee turn-over rate” and “refusal of extended hours or overtimes”). In this context, the developed framework is called “Total Productive Maintenance Performance Measurement System (TPM PMS)”. The proposed TPM PMS is reinforced with a real manufacturing case study on an international automotive company.

1.2 Framework of the Thesis

Nowadays, it has been recognized by many researchers and practitioners that maintenance is a crucial support function for the manufacturing processes with significant investment in physical assets and a main and contributor to the performance and profitability of a manufacturing system. Thus, many organizations involved in the manufacturing system desire the measurement of their maintenance performances to plan and control their maintenance processes in order to remain in the competitive environment (Kumar & Parida, 2008).

Maintenance performance measurement (MPM) can be used as an influential scheme in the business for effective management of maintenance, which allows maintenance engineer/managers to plan, monitor and control their operation/business (Parida, Kumar, Galar, & Stenström, 2015). MPM provides organizations to understand the value created by maintenance, to re-evaluate and revise their maintenance policies and techniques, to justify investment in new trends and techniques, revise resource allocations, and change in organizational structural and to understand the effects of maintenance on other functions and stakeholders as well as on health safety and environmental (HSE), etc. (Parida & Kumar, 2006).

In order to develop an MPM system, there is a requirement for identifying and analyzing different concerns related to maintenance performance and developing a framework (Parida & Kumar, 2009).

There are different maintenance performance measures/indicators (MIPs) and MPM frameworks proposed in the literature. The different categories of indicators display different areas of interest in maintenance performance in both the literature and practice. Moreover, in the available literature on MPM and MPI, some shortcomings have been observed. One of them is that the proposed MPM frameworks and systems are too generic and superficial and do not consider the business specific environment of the organization and specific maintenance objectives, strategies, practices or techniques. Additionally, the proposed MPIs have the lack of methodological approach to determine which one is the most important and how they are selected, evaluated and measured into the MPM system according to maintenance strategy, practice or technique. Considering these shortcomings, TPM, which is widely used maintenance strategy/practice/technique, is selected for the development of performance measurement system. Furthermore, in the literature, a few studies have been made related to the performance measurement in TPM implementation. In these studies, Wang (2006) and Jeon, Chulhyun, and Hakyeon (2011) used Data Envelopment Analysis (DEA) to measure the efficiency of TPM implementation. Also a number of studies were conducted to identify significant factors in TPM (Ahuja & Khamba, 2008c; Cua, McKone, & Schroeder, 2001; Ljungberg, 1998; McKone et al., 2001; Sharma, D. Kumar, & P. Kumar, 2006; Swanson, 2001; Wang, 2006).

In this thesis, the proposed TPM PMS provides a comprehensive and systematic way to measure TPM performance, since it covers all phases of performance measurement system; namely, design, evaluation, implementation and review.

In the design phase, various types of indicators which tend to impact on TPM performance are designed based on the theoretical and practical aspects. Then, these TPM performance indicators (TPM PIs) are analyzed by the decision makers to identify the most important ones using nominal group technique which is a group decision making (GDM) method and conjoint analysis which is a multiattribute decision making (MADM) method based on experimental design.

In the evaluation phase, the TPM PIs proposed in the design phase are evaluated by using COmplex PRoportional ASsessment of alternatives with Grey relations (COPRAS-G), which is one of the recently developed and most popular multiattribute decision making (MADM) method. Since the proposed TPM PIs includes both quantitative and qualitative data, these data are obtained by the linguistic variables. To evaluate these TPM PIs, fuzzy COmplex PRoportional ASsessment of alternatives (FCOPRAS) method based on fuzzy group decision making (FGDM) is also proposed in this phase. In the proposed FCOPRAS method, all fuzzy judgments and numbers are not converted to crisp values (or real numbers) and all calculations are performed in accordance with the fuzzy arithmetic operations and fuzzy ranking method. The innovative side of the proposed FCOPRAS method is that it does not include any deffuzification step for avoiding information loss. Furthermore, in this phase, the comparisons are made between the proposed FCOPRAS and most popular fuzzy multiattribute decision making (FMADM) methods using the Spearman’s rank correlation coefficient. Lastly, sensitivity analysis is performed to demonstrate the applicability and reliability of the proposed FCOPRAS method.

In the implementation phase, the proposed TPM PIs are used to evaluate TPM performance using fuzzy data envelopment analysis (FDEA) which is a very effective method to evaluate the relative efficiency of decision making units (DMUs) on the basis of multiple fuzzy inputs and outputs. The fuzzy relative significance of the proposed TPM PIs obtained by FCOPRAS method are integrated to the FDEA models based on assurance region (AR) and undesirability approaches. In this regard, different generalized fuzzy data envelopment analysis with AR (GFDEA/AR) in the presence of desirable and undesirable inputs and outputs are proposed to measure TPM performance.

In the review phase, the proposed TPM PMS is periodically monitored and reviewed. Afterwards, required improvements, preventive, predictive decisions and actions should be made for successful implementation of TPM.

1.3 Outline of the Thesis

This thesis consists of six chapters. The introduction is the first chapter. The remaining chapters are organized as in the following.

Chapter two initially presents the basic concepts, definitions and frameworks of performance measurement. Afterwards, detailed literature reviews about MPM frameworks, MPIs and performance measurement in TPM are presented.

Chapter three presents the background information and detailed literature survey on methods employed in the different phases of the proposed TPM PMS to gain a more comprehensive understanding.

Chapter four explains the proposed TPM PMS with the phases of design, evaluation, implementation, and review in detail.

Chapter five focuses on a real manufacturing case study to demonstrate the applicability and the novelty of the proposed TPM PMS.

Finally, the summary and the contributions of this thesis are discussed and the recommendations for future research are given in Chapter six.

CHAPTER TWO
PROBLEM DEFINITION AND LITERATURE REVIEW

2.1 Introduction

Maintenance plays a key role in an organization's long-term profitability, success and survivability and has increasingly become a part of a total performance approach, together with other topics such as productivity, quality, safety, and environment (Groote, 1995). This has been reflected in the desire of organizations to improve maintenance performance. The efficiency and effectiveness of the maintenance system should be measured by using a proper performance measurement (PM) technique. Within this context, MPM is perceived as an important function to achieve sustainable performance of any manufacturing plant (Ahren & Parida, 2009; Parida, 2007).

MPM is explained as a multidisciplinary approach to the process of measuring and justifying the values provided by maintenance investment, and considers the organization's stockholders' demands stated strategically from the overall business view (Parida & Chattopadhyay, 2007). Maintenance managers need a good track of maintenance process performance, which can be achieved by a rigorously defined MPM system and MPIs that are able to measure maintenance performance. This is reflected and supported by the many proposed MPM approaches in the literature (Muchiri, Pintelon, Gelders, & Martin, 2011).

TPM is a strategic tool that is widely used to make manufacturing industries competitive and effective in the field of maintenance (Sharma, Gera, Kumar, Chaudhary, & Gupta, 2012a; Sharma, Jain, & Jain, 2012b). In the literature, a number of studies present the relationships between TPM and manufacturing performance. According to the results of these studies, the proper implementation of TPM has a positive impact on the manufacturing performance. Thus, the relevant literature has defined several critical success factors for TPM implementation. In this manner, the measurement of TPM performance is significantly required for continuous improvement of the TPM implementation program (Piechnicki et al., 2015).

The rest of this chapter is organized as follows. Following section starts with the definitions and current status for PM and its frameworks and indicators. Section 2.3 gives information about the definitions of MPM and MPI and also briefly explains the literature review on MPM frameworks and MPIs. In section 2.4, firstly, the detailed information is presented on TPM framework. Secondly, a detailed literature review about TPM is given. Thirdly, implementation of TPM in manufacturing systems is explained in depth. Section 2.4 is completed by providing a detailed information and literature survey on performance measurement in TPM. Finally, concluding remarks about this chapter are provided in Section 2.5.

2.2 An Overview of PM Frameworks

In this section, primarily the key terms of performance measurement are defined. Neely, Gregory, and Platts (1995) define performance as the efficiency and effectiveness of actions within a business context. While efficiency is an ability of an organization to perform a task, effectiveness is an ability of an organization to plan for output from its processes (Nudurupati, Bititci, Kumar, & Chan, 2011). PM is the process of quantifying efficiency and effectiveness. To do this, performance measures should be chosen, implemented, and monitored. Before the meaning of a performance measure is given, some terms related to performance measure are needed to be explained. For example, Folan and Browne (2006) describe a measure as a quantitative expression which is composed of a number. The Institute of Electrical and Electronic Engineers (IEEE) (1990) expresses a measure ‘‘is to ascertain or appraise by comparing to a standard.” and ‘‘A standard or unit of measurement; the extent, dimensions, capacity, etc., of anything, especially as determined by a standard; an act or process of measuring; a result of measurement.” Additionally, The IEEE (1990) defines a metric “is a quantitative measure of the degree to which a system, component, or process possesses a given attribute.’’

Choong (2013) defines a metric as a “quantitative expression, and it is based on a standard or unit of measurement, like cost per unit”. From these definitions, it is obvious that a metric is more precise and clearly defined than a measure on the account the former is based on a standard unit of measurement-which is effectively a fraction (Choong, 2013). Consequently, performance measures are the metric used to quantify the efficiency and/or effectiveness of actions of part or of an entire process or a system in relation to a pattern or target (Franceschini, Galetto, Maisano, & Mastrogiacomo, 2008; Neely et al., 2000).

Another definition of PM is “the development of the indicators and the process of measuring the performance of an organization, a program, a function, or a process with gathering data.” (Marshall et al., 1999; US Department of Energy (DOE), 2012). Based on this definition Franco-Santos et al. (2007) explains the meaning of an indicator that “it consists of a combination of qualitative and quantitative attributes, collected and processed using multidimensional scaling and cluster analysis to create an ambiguous and valid tool to inform users of direction or measure.” Poll (2006) states that indicator is more general than metric and measure. Choong (2013) identifies the properties of a good indicator such as (1) relevant to the goal; (2) easily measured and understandable to users; and (3) provide reliable information, either in quantitative or qualitative (characteristic) form – financial or nonfinancial. The US DOE (2012) gives the following description of performance indicator:

“Performance indicator is a particular value or characteristic used to measure output or outcome. It is a parameter useful for determining the degree to which an organization has achieved its goals and a quantifiable expression used to observe and track the status of a process.”

To summarize, a performance measurement system (PMS) can be figured out as the process of calculating the efficiency and effectiveness of a task using performance measures that is predefined set of metrics. The set of metrics interact with the actions of people, groups, teams, and functions in organizations and extend multiple dimensions (such as the six elements of the Results/Determinants Matrix (Fitzgerald, Johnston, Brignall, Silvestro, & Voss, 1991), or the four perspectives of the Balanced Scorecard, (Kaplan & Norton, 1992) and reveal the strategy or strategic plan of the organization.

A literature review illustrates a huge amount of research on PM. According to Ghalayini and Noble (1996), the evolution of PM consists of two stages in the literature. The first stage was began in late 1880s and identified as “cost accounting orientation stage”, which aided managers to assess the relevant costs of operation and the second stage began after 1980, which tried to provide a balanced and integrated perspective of PM (Micheli & Mari, 2014).

In the 1980s, the term “productivity” was taken the place of “performance”, because the criteria of productivity paradigm were not sufficient to various stakeholders (Parida & Chattopadhyay, 2007). A number of studies expressed the weaknesses of common PMSs based on only financial measures (Johnson & Kaplan, 1987; Dixon, Nanni, & Vollmann, 1990); focused internal rather than externally; had a little relation with competitors or customers (Kaplan & Norton, 1992; Neely et al. 1995). Moreover, some researchers proposed different approaches in order to deal with the weaknesses of the existent traditional measures of PMSs (Al-Turki & Duffuaa, 2003; Dixon et al., 1990; Eccles, 1991; Ghalayini & Noble, 1996; Meyer & Gupta, 1994; Neely, 1999).

Towards the late 1980s and 90s many researchers criticized the problems with the traditional financial measures, which are internal and historical based, and employed to improve a balanced PM framework, which is related to both financial and non-financial perspectives (Nudurupati et al., 2011; Parida & Chattopadhyay, 2007;). A large number of frameworks and models for PM have arisen in the literature and significant ones are given chronologically in Table 2.1.

Table 2.1 Major PM models/frameworks developed by various researchers

Researchers	PM Model/Framework	Researchers	PM Model/Framework
Chandler (1977); Skousen et al. (2001)	Du Pont pyramid	Sveiby (1997)	Intangible asset-monitor (IAM)
Sink and Tuttle (1989)	Shink and Tuttle	Ghalayini et al. (1997)	Integrated dynamic PM system
Keegan et al. (1989)	PM matrix	Edvinsson and Malone (1997); Sveiby (1997)	Skandia Navigator
Dixon et al. (1990)	PM questionnaire	Oliver and Palmer (1998)	Integrated measurement model
Fitzgerald et al. (1991)	Results and determinants matrix	Kanji (1998)	Comparative Business Scorecard
Lynch and Cross (1991)	SMART pyramid (Performance pyramid)	Bititci, Turner, & Begemann (2000)	Dynamic PM systems
Kaydos (1991)	Kaydos's framework	Medori & Steeple (2000)	Integrated PM framework
Wisner and Fawcett (1991)	Wisner and Fawcett's framework	Laitinen (2002)	Framework for small business PM
Kaplan and Norton (1992)	Balanced Scorecard (BSC)	Abran & Buglione (2003)	Balanced IT Scorecard (BITS)
Bititci (1994)	Integrated PM system	Abran and Buglione (2003)	BSC of Advanced Information (AIBSC)
Bradley (1996)	AMBITE performance measurement cube	Abran and Buglione (2003)	QUEST
Brown (1996)	Brown's framework	Wongrassamee et al. (2003)	European Foundation for Quality Management (EFQM)
Flapper, Fortuin, and Stoop (1996)	Consistent PM system	Rouse and Putterill (2003)	An integral framework
Neely, Richards, Mills, Platts, and Bourne (1997)	Cambridge PM process	Stenström (2012)	Link and effect model

As can be seen from Table 2.1, one of the first frameworks for PM was developed by Sink and Tuttle (1989), which defines a six-step procedure for PM in the planning phase. Keegan, Eiler, and Jones (1989) proposed "the structural performance measurement matrix" that analyzed external/internal and cost/non-cost performance measures. Dixon et al. (1990) critiqued strategies, actions and measures using "PM questionnaire" and analyzed that extent to which they are supportive. The results and determinants framework proposed by Fitzgerald et al. (1991) has as its core performance measure management typology the distinction between measures of results and measures of the determinants of the results.

Some of the other known frameworks/models are: "the BSC approach (Kaplan & Norton, 1996)", "performance pyramid models (Lynch & Cross, 1991)" and "performance prism (Neely et al., 1997)", and etc. Lynch and Cross (1991) suggested “the structural performance pyramid”, which emphasizes a hierarchical view of business performance measurement and a 10-step procedural model to identify the requirements of PM. Both Kaydos (1991) and Wisner and Fawcett (1991) offered “procedural stepwise framework models”, while the structural balanced scorecard developed by Kaplan and Norton (1996) attempts to introduce the concept of producing a “balanced” set of measures (i.e. non-financial measures balanced against financial measures). Bradley (1996) presented “the structural AMBITE performance measurement” based on three dimensions: business processes, competitive priorities and manufacturing typology.

The other PM models/frameworks which are cause and effect relationship relating measures (“macro process model of organization, (Brown, 1996)”; “the consistent PM system, (Flapper et al., 1996)”; “the framework for small business PM, (Laitinen, 1996)”; “the Cambridge PM or the performance prism, (Neely et al., 1997)”; “integrated dynamic PM, (Ghalayini et al., 1997)”; “integrated PM system (Bititci, 1994)”; and “the integrated measurement model, (Oliver & Palmer, 1998)”. Brown (1996) proposed “a structural framework” which seeks distinct between input, process, output and outcome measures; while the structural PM framework of the EFQM contains two segments as enablers and results. Neely et al. (1997) presented the structural performance prism, which involves five weighted faces such as stakeholder satisfaction, strategies, processes, capabilities and stakeholder contribution. Rouse and Putterill (2003) offered “the structural integrated PM framework”, which attempts an integration of a number of structural frameworks, and comprises a set of principles that should be considered alongside the framework. Stenström (2012) suggested “a link and effect model” for performance improvement that provides continuous methodology for breaking down objectives into operational requirements and linking them to results.

The PM frameworks could also be classified as five types of PM frameworks. These frameworks are “traditional accounting-based”, “balanced and multicriteria”, “multicriteria hierarchical”, “function specific”, and “business specific” (Parida et al., 2015). While “the traditional accounting-based frameworks” were established on financial perspective, the balanced and multi-criteria frameworks were introduced considering financial and non-financial measurements. Next, "multicriteria hierarchical frameworks" were proposed to satisfy the expectation of the management from several industries regarding with strategic, tactical and operational perspectives. "The function specific frameworks" were categorized according to the desired function to be measured such as maintenance, human factor, and etc. Finally, the business specific frameworks were also considered to operating industries like nuclear, infrastructure, and etc. (Parida et al., 2015).

All these models and frameworks deal with what to measure and how to structure the PMS, i.e. they attempt to answer the question ‘‘how to design the PMS?’’(Nudurupati et al., 2011). Additionally, in comparison to PM frameworks, there are very few PMSs in existence that were academically proposed and most of the PMSs developed in companies are a collection of best practices that adapted various PM frameworks (Folan & Browne, 2005).

A PMS includes the process (or processes) for setting goals (developing the metric set) and collecting, analyzing, and interpreting performance data. The main purpose of the system is to translate an organization's data into valuable information, to evaluate the effectiveness and efficiency of an action and to support decision makers (Melnyk, Bititci, Platts, Tobias, & Andersen, 2014).

The improvement of a new PMS is theoretically divided into four stages such as design, implementation, use, and review (Lohman, Fortuin, & Wouters, 2004; Pinheiro de Lima, Gouvea da Costa, Angelis, & Munik, 2013). Despite the great attention of scholars and practitioners to designing a PMS, design is not the most important process. There are three other important processes: implementation, use, and review (Franco-Santos et al., 2007; Nudurupati et al., 2011). *In the design stage*, key objectives and a framework for performance measures are defined in depth. *The implementation stage* provides procedures which contain of collecting and analyzing data for the measurements to be made regularly. *In the use stage*, decision makers examine the measurement results to evaluate whether operations are efficient and effective, and the strategy is successfully implemented (Lohman et al., 2004). When there is an existing PMS, the use stage is the initial point for any change, and then it is followed by the reflection, modification, and deployment stages (Braz, Scavarda, & Martins, 2011). The design, implementation, and use of a set of performance measures should not be a onetime effort and continuous review of the PMS should be done regularly. Therefore, the review process should be added to the end of the use stage. When new measures are added, old measures are rarely deleted, which raises the PMS complexity (Kennerley & Neely, 2002; Neely, 1999), making the review process very important. This process explains that a measure may be deleted or replaced; the target and the definition of measures may be changed (Micheli & Mari, 2014).

PM is an essential principle of management. Like other manufacturing functions, it is also required for properly managing the maintenance function. MPM advice to maintenance managers for concentrating maintenance staff and resources which are particular areas of the production system and they have a significant impact on manufacturing performance (Muchiri et al., 2011). Detailed information about MPM will be given in the next section.

2.3 Performance Measurement in Maintenance

Maintenance is a significant support process for the business system and plays a critical role in an organization’s long-term profitability and competitiveness. It has gradually become an important part of a manufacturing performance (Groote, 1995). Since the performance of manufacturing companies is bound up the reliability, availability and productivity of their production facilities, MPM is required for the sustainable performance of any manufacturing plant using with properly defined MPIs (Muchiri et al., 2011).

2.3.1 An overview of MPM and MPIs

To begin with the definition of maintenance, British Standards Institute (BSI) describes maintenance as "a combination of all technical and associated administrative activities required to keep equipment, installations and other physical assets in the desired operating condition or restore them to this condition" (BSI, 1984). Maintenance Engineering Society of Australia (MESA) also defines as "maintenance is about achieving the required asset capabilities within an economic or business context" (MESA, 1995). Maintenance is also identified as "the engineering decisions and associated actions, necessary and sufficient for optimization of specified equipment capability" by Tsang (1999). The capability in this definition is "the ability to perform a specified function within a range of performance levels that may relate to capacity, rate, quality, safety and responsiveness" (Muchiri, Pintelon, Martin, & De Meyer, 2010). In a similar manner, the main scope of maintenance is to obtain the desired output level and track an operation plan at minimum resource cost providing with high availability of equipment and safety of technical system (Visser & Pretorious, 2003).

An MPM is defined as "the multidisciplinary process of measuring and justifying the value created by maintenance investment, and taking care of the organization's stockholder's requirements viewed strategically from the overall business perspective" (Parida & Kumar, 2006). An MPM system is a vital part of the organization's operational system and contains all related MPIs and their interrelationship within the whole maintenance process (Kumar & Parida, 2008). MPM is an important process for evaluation of maintenance performance, identification of the opportunities and deciding priorities for continuous improvement (Parida & Chattopadhyay, 2007). In an MPM system, data are collected, analyzed and relevant information extracted for timely decision making. MPM is a complex task involving measurement of varying inputs and multiple outputs of the maintenance process (Parida & Kumar, 2009). An MPM system can be classified as three phases such as "the design of the performance measures", "the implementation of the performance measures", and "the use of the performance measures to perform analysis/reviewing" (Pun & White, 1996). The reviewing of the MPM system provides a feedback and validation in a dynamic environment.

MPIs are defined "a set of measures used for the measurement of maintenance impact on the process performance" by Wireman (1998). MPIs are performed to simplify the understanding and measurement of the past performance of maintenance, so that future prediction can be visualized resulting in appropriate decision making. In other words, MPIs provide valuable information about the current status of maintenance process and play a vital role as pre warning system so as to enable evaluation, prediction and corrective action in this process (Simoes, Gomes, & Yasin, 2011). Additionally, MPIs can be employed0 for financial reports, to monitor employees' performance satisfaction of customer, rating of the health safety and environmental (HSE), and overall equipment effectiveness (OEE), as well as many other applications (Parida & Kumar, 2006). The definition of MPI needs to involve both the process inputs and the process outputs. If this is employed correctly, then MPIs can (Kumar & Ellingsen, 2000):

- Determine basic concepts for resource allocation and control,
- Enable to identify the problem areas,
- Make available teams/individuals with the means to measure his/their contribution to the business objectives,
- Enable easy benchmarking of performance,
- Provide trends in performance,
- Designate the contribution of maintenance to overall business objectives.

There are a large number of MPIs used by various industries today which should be carefully defined and chosen to meet the specific requirements of the organization. For example, some of the MPIs are crucial for the industries like nuclear and thermal power plants where safety aspects act a significant role since they give quality information for monitoring operational safety performance during the implementation phase of the MPM system (Kumar & Parida, 2008).

2.3.2 Literature Review on MPM Frameworks and MPIs

Many MPM approaches are used for the improvement of the organizational specific MPM frameworks. Some of these are classified in Table 2.2 (Parida et al., 2015).

Table 2.2 Summary of the MPM frameworks according to their corresponding categories and scopes

Category of the MPM Frameworks	**Researchers**	**Scope of the MPM Frameworks**
Value-driven Performance (VDM) measures for MPM	Dwight (1995) Haarman and Delahay (2006) Simoes et al. (2011) Stenström, Parida, Kumar, and Galar (2013)	It focuses on four values such as “asset utilization”, “resource allocation”, “cost control” and “HSE”.
The BSC approach-based MPM	Tsang (1998) Tsang, Jardine, and Kolodny (1999) Ahlmann (2002) Parida, Ahren, and Kumar (2003) Liyanage and Kumar (2003) Alsyouf (2006) Galar, Parida, Kumar, Stenström and Berger (2011) Kumar, Galar, Parida, and Stenström (2011)	It considers both “financial” and “non-financial” measures.
Integrated MPM system corporate strategy and BSC	Kumar and Ellingsen (1999) Kumar and Ellingsen (2000) Galar, Parida, Kumar, Baglee, and Morant (2012)	It focuses corporate objectives such as “different divisions”, “departments” and “down to employee level”.
Multi-criteria hierarchical framework for MPM	Arts, Knapp, and Mann (1998) Parida (2006, 2007) Parida and Chattopadhyay (2007) Ahren (2008) Stenström (2012) Van Horenbeek and Pintelon (2014)	It includes stakeholders at various levels such as “strategic, tactical, and operational”.
MPM using quality function deployment (QFD) technique	Kutucuoglu, Hamali, Irani, and Sharp (2001) Kutucuoglu, Hamali, Irani, and Sharp (2002)	It uses a type of three-stage matrix diagram and also referred to as “a house of quality”.
eMaintenance frameworks for MPM	Davies (1990) Labib (1998, 2004) Lee (2001) Tsang (2002) Pinjala et al. (2006) Hwang, Tien, and Shu (2007) Kans (2008)	It considers a maintenance plan which includes “condition monitoring”, “proactive maintenance” and “remote maintenance”.

Table 2.2 Summary of the MPM frameworks according to their corresponding categories and scopes (cont.)

Category of the MPM Frameworks	**Researchers**	**Scope of the MPM Frameworks**
Audits for MPM	Wireman (1990) Dixon et al. (1990) Kaiser (1991) Westerkamp (1993) Venezuelan Commission for Industrial Standards (COVENIN) (1993) Duffuaa and Raouf (1996) Al-Zahrani (2001)	It includes a comprehensive review of maintenance system.
Plant/equipment health management system (PHMS) for MPM	Mobley (1990) Campbell and Jardine (2001) Soderholm and Akersten (2002)	It deals with supportive activities such as "e-condition monitoring", "diagnostics" and "prognostics".
Strategic asset performance approach for MPM	Weber and Thomas (2006) Parida and Kumar (2009)	It combines enterprise asset management's measuring criteria with "condition monitoring".
Maintenance Productivity Index	Löftsen (2000)	It focuses on "expected changes in the prices of outputs and inputs".

Another popular classification of MPIs was proposed by Weber and Thomas (2006) for management of maintenance function. A large number of key MPIs were classified into two categories, namely "*maintenance process (leading*)" and "*maintenance results (lagging)*" indicators. Leading indicators are lead to perform task and contain of four phases such as "*work identification*, *work planning*, *work scheduling* and *work execution*". Lagging indicators controls the results or outcomes that have been achieved and contains of two classes as "*equipment performance*" and "*cost related measures*". Muchiri et al. (2011) summarized the widely used MPIs into two major categories as shown in Figure 2.1.

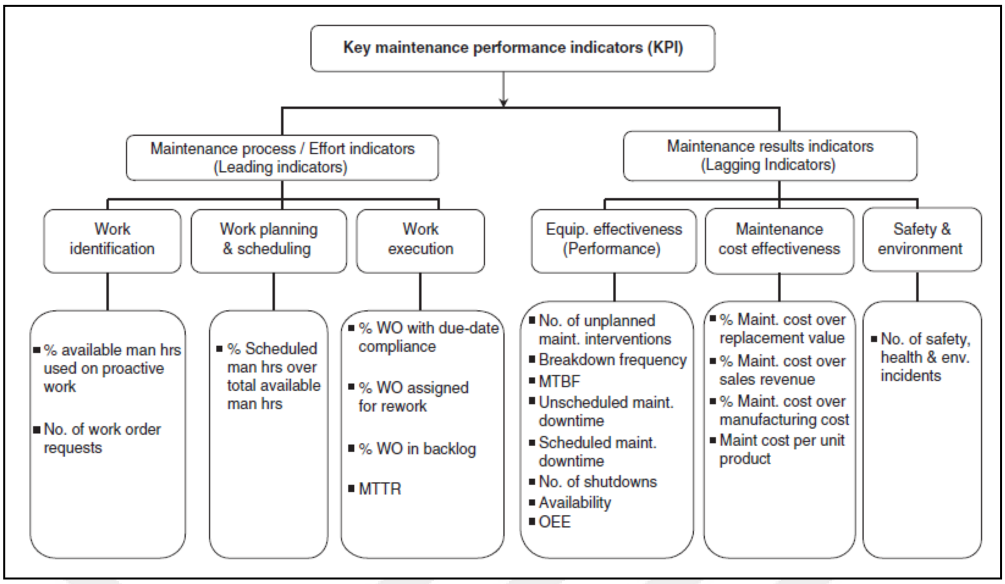

Figure 2.1 Key MPIs (Muchiri et al., 2011)

According to the literature review, various models, methodologies and frameworks on MPM have been proposed by a number of authors. When the available literature on MPM and MPI was analyzed, some shortcomings have been observed. For example, the proposed MPM frameworks are too generic and do not consider the business specific environment of the company and maintenance objectives, strategies or techniques. Additionally, the proposed MPIs have the lack of methodological approach to select or derive business specific MPI. Within the scope of this thesis, a new framework is developed for performance measurement of TPM, which is a commonly used maintenance technique. The detailed information about performance measurement in TPM is given in the next section.

2.4 Performance Measurement in TPM

In this section, firstly general information and the literature review based on statistics for TPM are presented, and then the implementation issues within and beyond the basic TPM theory in manufacturing systems, and the critical success factors for achieving TPM are discussed and analyzed. Finally, the section is completed with the explanation of KPIs and PM literature in TPM.

2.4.1 Framework of TPM

Seiichi Nakajima, vice-chairman of the Japanese Institute of Plant Engineers (JIPE), the predecessor of the Japan Institute of Plant Maintenance (JIPM), promoted TPM throughout Japan and has become known as the father of TPM. In 1971, TPM was defined by JIPE as follows (Mckone et al., 2001):

“TPM is designed to maximize equipment effectiveness (improving overall efficiency) by establishing a comprehensive productive maintenance system covering the entire life of the equipment, spanning all equipment-related fields, and, with the participation of all employees from the top management down to shop-floor workers, to promote productive maintenance through motivation management or voluntary small-group activities.”

TPM is a maintenance system defined by Nakajima (1988) in Japan, which covers the whole life of equipment in each division including planning, manufacturing, and maintenance. It defines an interactive connection among all organizational functions, but especially between production and maintenance, in order to improve product quality, operational efficiency, capacity assurance and safety, continuously. According to the Nakajima (1989), the word “total” in TPM has three meanings: total effectiveness, total maintenance system, and total participation of all employees.

A more detailed definition of TPM is given by Rhyne (1990) as “a partnership between the maintenance and production organizations to improve product quality, reduce waste, reduce manufacturing cost, increase equipment availability, and improve the company’s overall state of maintenance.”

The concept of TPM includes the following elements (Chan et al., 2005):

- TPM purposes to maximize equipment effectiveness.
- TPM sets up a thorough system of preventative maintenance for the equipment’s entire life span.
- TPM is applied by different departments in an organization.

- TPM covers every single employee, from the top management to workers on the shop floor.
- TPM is based on the promotion of preventative maintenance through “motivation management” involving small group activities.

The main practices of TPM are generally called “the pillars or elements of TPM”. The concept of TPM has been conceived on eight pillars shown in Figure 2.2 (Sangameshwran & Jagannathan, 2002).

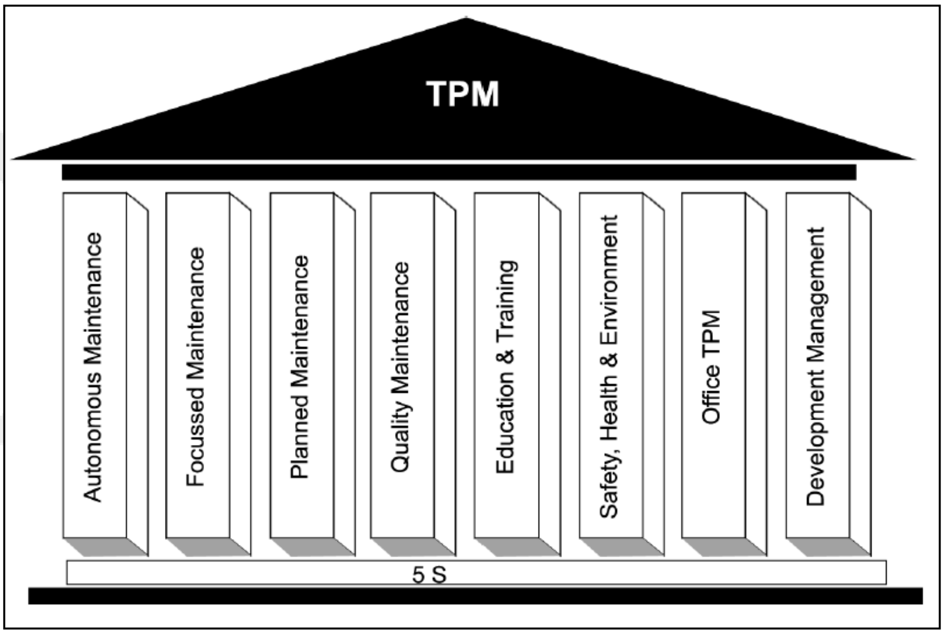

Figure 2.2 Eight pillars approach for TPM implementation (suggested JIPM) (Sangameshwran & Jagannathan, 2002)

Fuentes (2006) extended the eight pillars approach for TPM implementation suggested JIPM and presented the relationship between the eight pillars of TPM and also stated the meaning of each of these pillars illustrated in Figure 2.3.

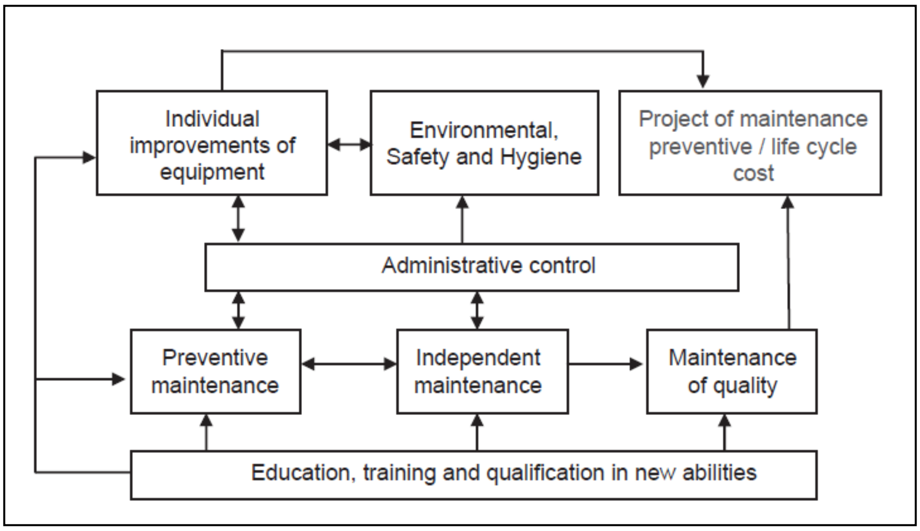

Figure 2.3 Implementation of TPM (Bartz et al., 2014)

According to Figure 2.3, the training, education and development of new skills stands for evaluation of the capability of human resources involved, defining what the training necessities are and assess in them after their implementation. In the pillar of preventive maintenance types of maintenance, the criteria to adopt in maintenance, planning, inventory control and others are described. Autonomous maintenance considers the awareness of everyone involved with the meaning of that the equipment operator takes care of the equipment as if it were “yours.” Quality maintenance assesses the effect of the equipment on the quality of the product and sets control parameters. Administrative control contains all different areas of maintenance that are involved in the production process, such as purchasing, quality and others. Individual improvements in equipment search for elimination, especially, the six big losses in the production process. The pillar of environment, health and safety addresses prevention policies and the assessment of risks and costs from these areas. The analysis of investment viability in equipment replacement is carried out by the pillar of preventive maintenance projects and life cycle cost (Bartz et al., 2014). It is observed that to successfully deploy TPM, it is necessary to have all the pillars interlinked, forming a continuous, orderly, step-by-step process.

TPM searches for maximizing equipment effectiveness throughout the entire life of the equipment including the involvement of individuals and corporations, through the use of autonomous maintenance and small group activities for the development of equipment reliability, maintainability and productivity. It satisfies to sustain the equipment in optimum conditions for the prevention of unexpected breakdown, speed losses, and quality defects resulting from process activities. There are three basic aims of TPM; namely, “zero defects”, “zero accident”, and “zero breakdowns” (Khanlari, Mohammadi, & Sohrabi, 2008; Nakajima, 1988; Noon, Jenkins, & Lucio, 2000; Willmott, 1997). Swanson (2001) defined the four vital elements of TPM namely “*worker training*”, “*operator involvement*”, “t*eams and preventive maintenance*”. According to Rodrigues & Hatakeyama (2006), TPM was designed as a response to a competitive market which forced companies to adjust some activities; eliminating waste, reducing downtime and implementing defined maintenance goals. Ahuja & Khamba (2008a) presented that TPM is a methodology of continuous improvement that aims to improve confidence in equipment while increasing management efficiency through the involvement of people and which also seeks to integrate the activities of production, maintenance and engineering. Moreover, Ahuja & Kumar (2009) stressed the importance of TPM to increase morale and satisfaction of people from all organizational levels. According to Ahuja and Khamba (2008b), TPM is a methodology that covers the entire company to achieve maximum utilization of existing equipment, using the philosophy of management-oriented equipment. In brief, TPM has arisen as a powerful strategic tool for improvement of quality in maintenance activities (Ollila & Malmipuro, 1999; Pramod, Devadasan, & Raj, 2007). Moreover, it provides a comprehensive methodology to manage maintenance, which is separated into long-term activities, e.g., eliminating of causes of lost equipment time, designing of new equipment, and the participation of many areas of the organization and short-term activities, e.g., determination of autonomous and planned maintenance programs).

2.4.2 Statistical Review of the TPM Literature

A systematic search of the literature related to TPM and its implementation is conducted in this section. The time period for this literature review is chosen from 1988 to September 2016. When the search for literature review for TPM is conducted using “Scopus”, it gives 3710 published papers in all fields. Among these, 790 published papers mention TPM in their “article title, abstract, keywords”. Figure 2.4 demonstrates the number of published papers that mentioned TPM in their “article title, abstracts or keywords”. A Total of 790 papers published in TPM are categorized by the document type, the subject areas, the authors and the sources per year, respectively shown in Figures 2.5-2.8.

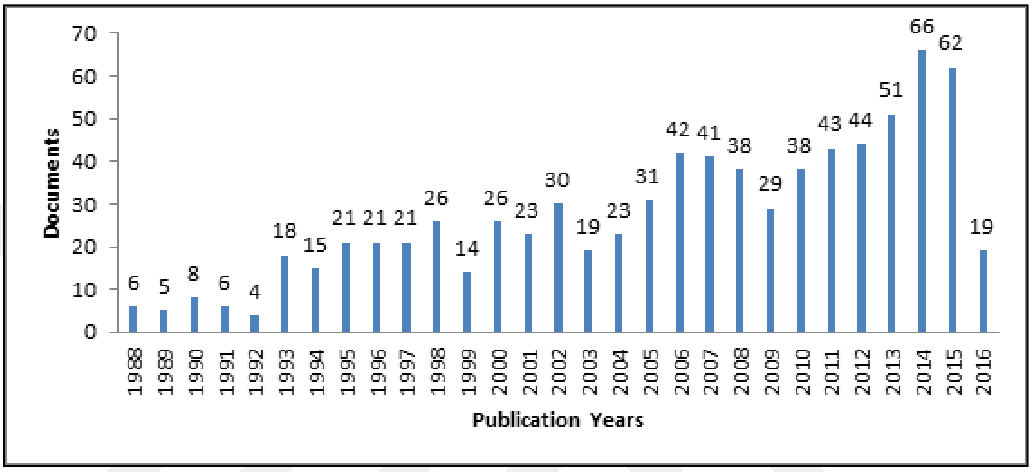

Figure 2.4 Published documents in TPM over years

According to Figure 2.4, it could be seen that there is an increasing trend by years with respect to studies related to TPM along with 2014 and 2015 being the years with the most studies. Figure 2.5 classifies the TPM publications according to document types.

According to Figure 2.5, 510 papers on TPM are published as an article, 187 papers as a conference paper, 47 papers as a review, 17 papers as a book chapter, 10 papers as a conference review, six papers as a short survey, six papers as an article in press, three papers as a book, two paper as a report, 1 paper as an editorial and one paper as a note. The journals such as “Journal of Quality in Maintenance Engineering”, “Applied Mechanics and Materials”, “International Journal of Productivity and Quality Management”, “International Journal of Production Research”, “International Journal of Quality and Reliability Management”, “Manufacturing Engineer” and “International Journal of Technology Policy and

Management" have the most publishing TPM papers. "IEEE Semi Advanced Semiconductor Manufacturing Conference and Workshop" and "Annual Quality Congress Transactions" have the most publishing TPM conference papers. Figure 2.6 illustrates the journals publishing TPM based articles. Figure 2.7 presents the subject areas of the examined papers on TPM.

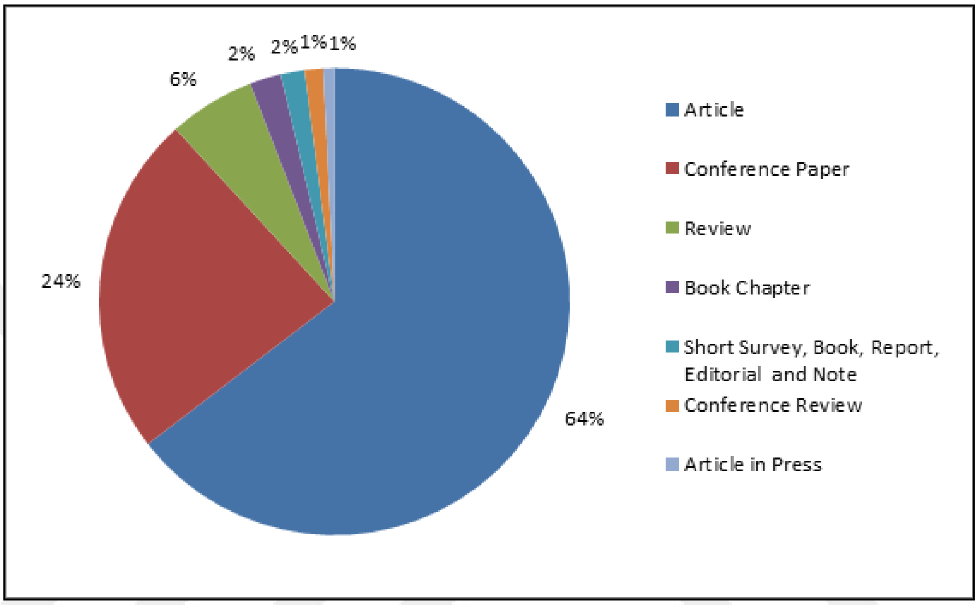

Figure 2.5 The classification of published documents in TPM according to document types

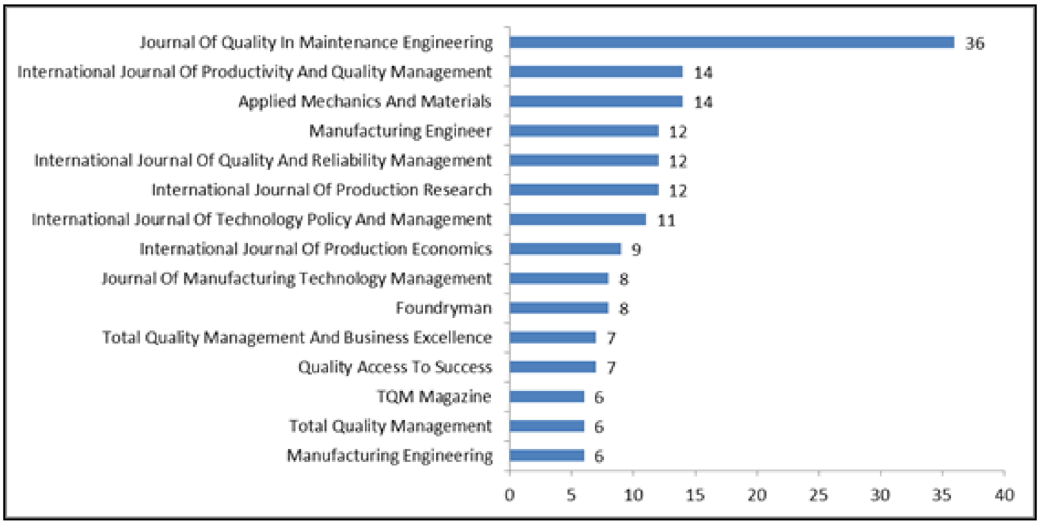

Figure 2.6 Journals that publish TPM based articles

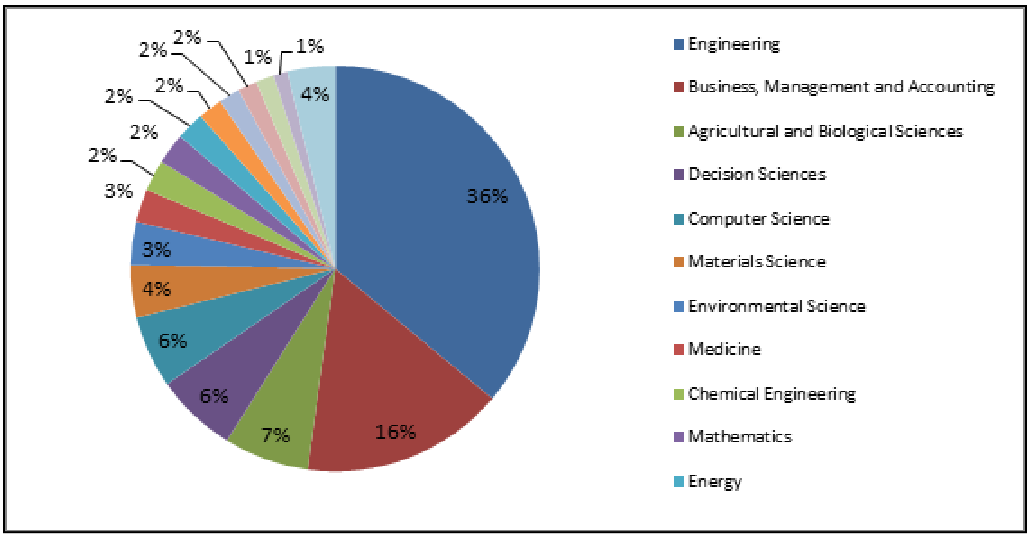

Figure 2.7 Subject areas of the examined papers on TPM

According to Figure 2.7, the areas of engineering (451 papers) and business management and accounting (201 papers) are the most studied research fields on TPM. Another classification for reviewed papers on TPM is performed according to author names illustrated as in Figure 2.8.

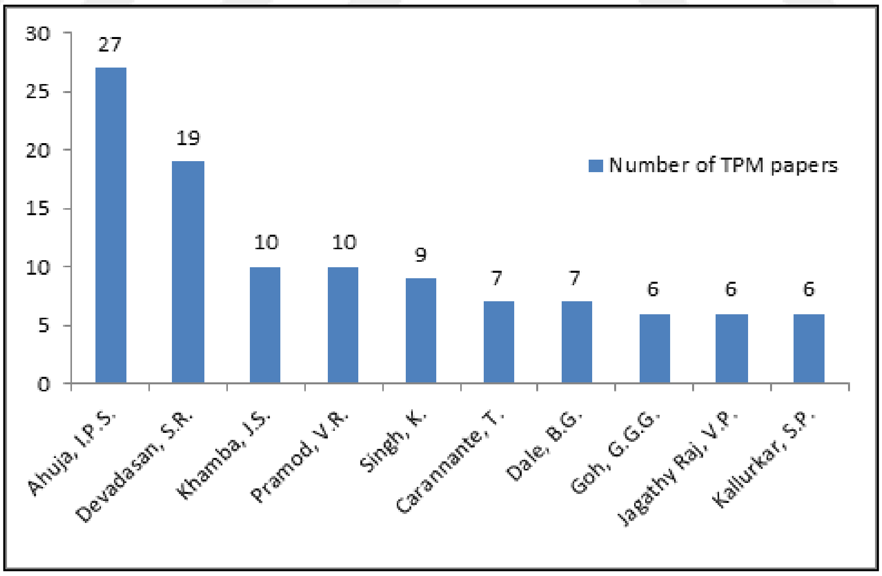

Figure 2.8 The number of TPM papers according to author names

According to Figure 2.8, I. P. S. Ahuja (with 27 publications) from Punjabi University and S. R. Devadasan (with 19 publications) from PSG College of Technology are the most productive researchers on TPM.

Another different search for literature review of TPM using “Scopus” gives 166 published articles (only titles). The results of this research are given in Table 2.3. According to Table 2.3, out of the total of 166 papers, 94 papers (near about 57 % of total articles) are of TPM implementation and case study types, 39 papers (near about 24% of total articles) are of empirical research on TPM, 23 papers (near about 14% of total articles) are of model and simulation type studies and 10 papers (near about 6% of total articles) are of literature type study.

As seen from Table 2.3, the most of TPM research papers have been presented on TPM implementation plans, procedures or steps and development of TPM activities based on case studies in plants (Ahuja & Kumar, 2009; Blanchard, 1997; Bamber et al., 1999; Bekar, Cakmakci, & Kahraman, 2015, in-press; Chan et al., 2005; Cigolini & Turco, 1997; Gupta & Vardhan, 2016; Hartmann, 1992; Hj. Bakri et al., 2014; Kilenstam & Odenrick, 2000; Lin, Lin, & Zhang, 2015; Nakajima 1988, 1989; Ng, Goh, & Eze, 2012, 2014; Ohunakin & Leramo, 2012; Patterson, Kennedy, & Fredendall, 1997; Piechnicki et al., 2015; Singh & Ahuja, 2015; Singh, Gohil, Shah, & Desai 2013; Sun, Yam, & Wai-Keung, 2003; Suzuki, 1992; Tsarouhas, 2007, 2015; Wakjira & Singh, 2012; Van der Wal & Lynn, 2002). Subsequently, the implementation of TPM in manufacturing systems is explained in detail.

Table 2.3 Classification of research papers on TPM

Years	Empirical Research	Literature Review	Implementation and Case study	Modeling and Simulation
1994 and below	9		15	2
1995-2000	9	1	14	4
2001-2002	2		6	1
2003-2004	3		5	1
2005			3	1
2006	1	1	6	2
2007			1	
2008	1	2	6	1
2009	2		2	
2010	1		6	1
2011	2	1	7	3
2012	1	1	11	1
2013	1	1	1	1
2014	1	2	2	1
2015	6	1	7	3
2016			2	1

2.4.3 Implementation of TPM in Manufacturing Systems

2.4.3.1 An Overview of TPM Implementation Practices

Nakajima (1988) outlined twelve steps that involve the basic requirements and the supportive and constructive activities in order to develop and implement a TPM program. Hartmann (1992) extended the Nakajima' (1988) implementation model by adding the contextual issues to simplify differences in several dimensions of TPM. Naguib (1993) introduced a five-phase roadmap to implementing TPM which contain "an awareness program", "a restructuring of the manufacturing organization to incorporate maintenance in production modules", "planning maps", "an implementation process" and "an assessment process for continuous improvements". Willmott (1994) suggested a three-phase, nine-step TPM improvement plan. Suzuki (1994) also mentioned the impacts of TPM to business excellence, and the eight essential TPM development activities. Pirsig (1998) emphasized upon seven unique broad components and four main subjects in any TPM implementation program. Carannante, Haigh, and Morris (1996) developed an approach including eight steps to the implementation of TPM. Mcadam and Duffner (1996) discussed how TPM can be effectively implemented within an organization. The strategy and benefits of TPM implementation were also shown based on a case study data on a company operating in semiconductor industry. Bamber et al. (1999) proposed a six-step TPM implementation program for organizations. Ireland and Dale (2001) examined TPM implementation for three companies to observe the main differences in their TPM implementation. Leflar (2001) offered a five-step plan to lead the TPM implementation. McKone et al. (2001) defined six major activities of TPM implementation such as training, early equipment design, early product design, focused improvement teams, and autonomous and planned maintenance.

Sector-wise studies have also been performed to assess TPM implementation practices. For example, Sun et al. (2003) carried out an evaluation of a successful TPM implementation in a pilot project in Chinese manufacturing company. Chan et al. (2005) analyzed a TPM program implementation in an electronics manufacturing company in China, and measured tangible and intangible benefits. Sharma, Kumar, and Kumar (2005) examined the TPM implementation in semi-automated cells in India and measured the performance by means of an OEE index. Tsarouhas (2007) proposed a TPM implementation methodology including four steps for food industry and especially in bakery products. Ahuja and Khamba (2008d) highlighted achievements of TPM implementation in an Indian manufacturing organization. Shahanaghi and Yazdian (2009) showed the effectiveness and usefulness of TPM implementation using system dynamics concept. Alsyouf (2009) investigated the maintenance practices in Swedish industries, by conducting a cross-sectional survey within firms with employees. Ahuja and Khamba (2009) investigated that has successfully implemented TPM and has reaped significant benefits as a result of TPM implementation at a precision tube mills in an Indian manufacturing organization. Lazim and Ramayah (2010) carried out a cross-sectional study focusing on manufacturing companies in Malaysia in order to examine the extent of TPM practices and to study the relationship between TPM practices and manufacturing performance. Ohunakin and Leramo (2012) examined the production performance of a beverage manufacturing plant after adopting TPM strategy. Attri, Sandeep, Dev, and Kumar (2013) proposed an interpretive structural modeling (ISM) to determine some key enablers and their managerial implications in the implementation of TPM. Ananth and Vinayagam (2015) developed a TPM implementation system for tiny industries. As a conclusion, numerous researchers deal with TPM implementation practices that have been implemented by many companies and can be adopted by companies in different environments and within various types of organizations in manufacturing systems.

2.4.3.2 The Need for TPM Implementation

The involvement of all the employees in the organization is the most significant requirement of TPM in order to increase OEE, reliability and safety (Kulkarni & Dabade, 2012). The following lists significant requirements for the application of TPM in manufacturing systems (Ahuja & Khamba, 2008c; Jain, Bhatti, & Singh, 2014):

- enhancing productivity and quality;
- making the job simpler and safer;
- improving employee skills;
- becoming world class, satisfying global customers and achieving sustained organizational growth;
- changing and remaining competitive;
- realizing pre-eminent reliability and flexibility requirements of the organizations;
- improving work culture and mindset of the organizations;
- reducing significant cost regarding maintenance-related expenses;
- ensuring appropriate manufacturing quality and productivity;
- optimizing life cycle costs for realizing competitiveness in the global marketplace;
- reducing problems encountered by organizations in terms of external factors such as "tough competition, globalization, increase in raw material costs and energy cost";
- reducing problems encountered by organizations in terms of internal factors such as "low productivity, high customer complaints, high defect rates, non-adherence to delivery time, increase in wages and salaries, lack of knowledge, skill of workers and high production system losses";
- liquidating the unsolved tasks (breakdown, setup time and defects);
- and making good use of human resources, assisting personal growth and advancing human resource competencies by providing sufficient training and multi-skilling.

In the literature, many articles have argued the benefits of TPM implementation, see, e.g., Ahuja & Khamba, 2007, 2008c; Bohoris, Vamvalis, Tracey, & Ignatiadou, 1995; Carannante, 1995; Chan et al., 2005; Chowdhury, 1995; Fernandes, Mills, & Fleury, 2005; Hamrick, 1994; Jain et al., 2014; Koelsch, 1993; McKone, Schroeder, & Cua, 1999; Nakajima, 1988; Panneerselvam, 2012; Park & Han, 2001; Rolfsen &

Langeland, 2012; Teresko, 1992; Tripathi, 2005; Willmott, 1994; Windle, 1993; Yamashina, 2000. According to the literature review, the direct benefits of TPM are given as follows:

- satisfying economic efficiency or profitability;
- providing maintenance prevention;
- developing maintainability;
- using of preventive maintenance and total participation of all employees;
- planning and controlling the maintenance expenses;
- reducing maintenance workforce by allocating certain maintenance activities to the operator themselves;
- providing the more reliable equipment, and more repeatable process;
- providing easier scheduling the flow of work through the process;
- decreasing operating and overall maintenance costs;
- extending equipment life;
- decreasing in number of equipment breakdowns, tool replacement time, and cost of defectives;
- reducing the need for safety stock and time buffer, and;
- improving availability of machines, OEE and total productivity.

TPM implementation can also facilitate achieving the indirect benefits such as (Arunraj, Maran, & Manikandan, 2014; Jain et al., 2014):

- increased employees confidence and job satisfaction levels;
- workers feel ownership toward the machine;
- encouraging a clean and attractive workplace;
- providing favorable changes in the attitude of the operators;
- increasing share of the knowledge and experiences among all the employees;
- working together with all employees to achieve organizational goals; and
- providing horizontal deployment in all areas of the organization.

Furthermore, successful TPM implementation programs can contributes towards realization of intangible benefits; namely, "continuous improvement of workforce skills and knowledge, explanation of the roles and responsibilities for employees, a system for continuously maintaining and controlling equipment and manual work, an enhanced quality of work life, an improved participation rate, and reduced absenteeism caused by stress, and more open communication within and among workplaces" (Carannante, 1995; Kodali & Chandra, 2001; Suzuki, 1994).

Although TPM provides a large number of benefits, its implementation has some difficulties. For example, since the application of TPM needs the change of the organizational culture and existing behaviors of all employees, operators, engineers, maintenance technicians, and managers, it involves various obstacles such as resistance to culture change, limited application of TPM, lack of management support and consensus, lack of involvement of production associates, lack of resources, lack of term vision, lack of sustained momentum, and lack of education and training for employees (Attri et al., 2013).

Cooke (2000) demonstrated that applying TPM is not an easy job, which is extremely blocked by political, financial, departmental and interoccupational barriers. Moreover, numerous other researchers defined different types of barriers in the implementation of TPM (Bakerjan, 1994; Becker, 1993; Blanchard, 1997; Chan et al., 2005; Crawford, Blackstone, Jr, & Cox, 1988; Dal, Tugwell, & Greatbanks, 2000; Davis & Willmott, 1999; Fredendall, Patterson, Kennedy, & Griffin, 1997; Ireland & Dale, 2001; Jonsson & Lesshammar, 1999; Jostes & Helms, 1994; Lawrence, 1999; Ljungberg, 1998; Maggard & Rhyne, 1992; McAdam & Duffner, 1996; Patterson et al., 1995; Rodrigues & Hatakeyama, 2006). Attri, Grover, Dev, and Kumar (2012a, b) examined the barriers of TPM implementation by interpretive structural modelling (ISM) approach. Singh, Gohil, Shah, and Desai (2013) also handled the TPM barriers, which affects adversely TPM implementation, using ISM approach. Ahuja and Khamba (2008d), Majumdar and Manohar (2012) and Panneerselvam (2012) outlined the different challenges faced by Indian manufacturing organizations in the application of TPM. Baglee and Knowles (2010) determined barriers to the implementation of TPM by extending the study of Bamber et al. (1999) for Small and Medium Enterprises in United Kingdom. Ahuja and Khamba (2008c) categorized barriers into different classes such as organizational, cultural, behavioral, technological, operational, financial and departmental barriers. Attri, Grover, and Dev (2014) also proposed a graph theoretic approach to evaluate the nature and impact of TPM barriers categorized as behavioral, human and culture, strategic, operational, and technical.

2.4.3.3 Impact of TPM Implementation on Manufacturing Performance

In the literature, a number of studies present the relationships between TPM and manufacturing performance (Ahuja & Khamba, 2008a; Badli Shah, 2012; Bartz et al., 2014; Belekoukias et al., 2014; Brah & Chong, 2004; Cua et al., 2001; Eti, Ogaji, & Probert, 2006; Lazim & Ramayah, 2010; Maier, Milling, & Hasenpusch 1998; McKone et al., 1999; McKone et al., 2001; Miyake & Enkawa, 1999; Sangameshwran & Jagannathan, 2002; Seth & Tripathi, 2005; Shah & Ward, 2003; Singh & Ahuja, 2015; Wickramasinghe & Perera, 2016).

Maier et al. (1998) demonstrated the impact of TPM implementation program on production system and also categorized various measures into two groups like *subjective measures* and *objective measures* for evaluation of the contributions of TPM program on manufacturing performance.

McKone et al. (1999) explained the critical dimensions of TPM and their impact on manufacturing performance and illustrated a strong relationship among TPM and the contextual issues; namely, *environmental context* and *managerial context*. McKone et al. (2001) also found a positive relationship between TPM and manufacturing performance using by structural equation modeling (SEM). Cua et al. (2001) presented an integrated framework to understand the relationship between implementation of TQM, JIT, and TPM and manufacturing performance.

Miyake and Enkawa (1999) conducted the application of JIT, TQM and TPM paradigms to increase the performance of manufacturing systems and also emphasized that TPM is very important tool to the realization of developments at shop floor level and involvement of the technical personnel.

Sangameshwran and Jagannathan (2002) mentioned that TPM implementation is a vital part of business process improvement. Brah and Chong (2004) reported the gaining insights into the impact of TPM on performance of the organization. They also investigated a positive correlation between TPM and business performance shown with respect to constructs of corporate planning, top management leadership, human resource focus, process focus, total quality management focus and information system focus, and the three specific constructs of TPM strategies, TPM teams and TPM process focus.

Shah and Ward (2003) empirically showed that lean bundles such as JIT, TQM, TPM and human resource management contribute substantially to the operating performance of plants.

Seth and Tripathi (2005) determined the strategic effects of TQM and TPM and also examined the correlation between factors influencing the application of TQM and TPM pillars with business performance in an Indian manufacturing company.

Eti et al. (2006) reported the methods in which Nigerian manufacturing industries can apply TPM as a strategy and culture for increasing their performance in their manufacturing environments.

Ahuja and Khamba (2008a) illustrated the important contributions of TPM implementation success factors; namely, “top management leadership and involvement”, “traditional maintenance practices” and “holistic TPM implementation initiatives towards affecting improvements in manufacturing performance” in the Indian industry.

Lazim and Ramayah (2010) carried out a cross-sectional study focusing on manufacturing companies in Malaysia to determine the extent of TPM practices and to demonstrate the relationship between TPM practices and manufacturing performance.

Badli Shah (2012) reported that the successful implementation of a TPM program improves manufacturing performance. It guides the organization to obtain a competitive edge and provides multifarious benefits.

Belekoukias et al. (2014) demonstrated the impact of five essential lean practices, i.e. JIT, autonomation, kaizen, TPM and value stream mapping on contemporary measures of operational performance like cost, speed, dependability, quality and flexibility. A linear regression analysis and structural equation modeling were performed to analyze correlation and the relationship between these lean practices and the performance of their operations.

Bartz et al. (2014) presented the results of the implementation of a TPM-based maintenance management model in a production line in order to improve the performance and competitiveness of a metalworking company.

Singh and Ahuja (2015) investigated the contributions of TPM initiatives towards improving manufacturing performance in an Indian manufacturing company. The study showed that proactive TPM initiatives have aided the manufacturing organization extremely in improving synergy between the maintenance department and rest of the manufacturing functions.

Wickramasinghe and Perera (2016) illustrated the effects of TPM practices on widely used measures of manufacturing performance like cost effectiveness, product quality, on-time delivery and volume flexibility for labor intensive manufacturing industries such as textile and apparel since it has not been researched adequately.

According to the literature review summarized in this section, an effective TPM implementation program can help manufacturing organizations to achieve improved manufacturing performance. Additionally, it can facilitate to carry out core competencies for sustainability efforts in a competitive environment.

2.4.3.4 Critical Success Factors for TPM implementation

TPM literature presents many success criteria for effective and systematic TPM implementation. Some examples from the related literature are explained as the following paragraphs.

Bamber et al. (1999) studied the factors affecting successful TPM implementation from a United Kingdom manufacturing case study perspective and developed a conceptual framework, which is shown in Figure 2.9.

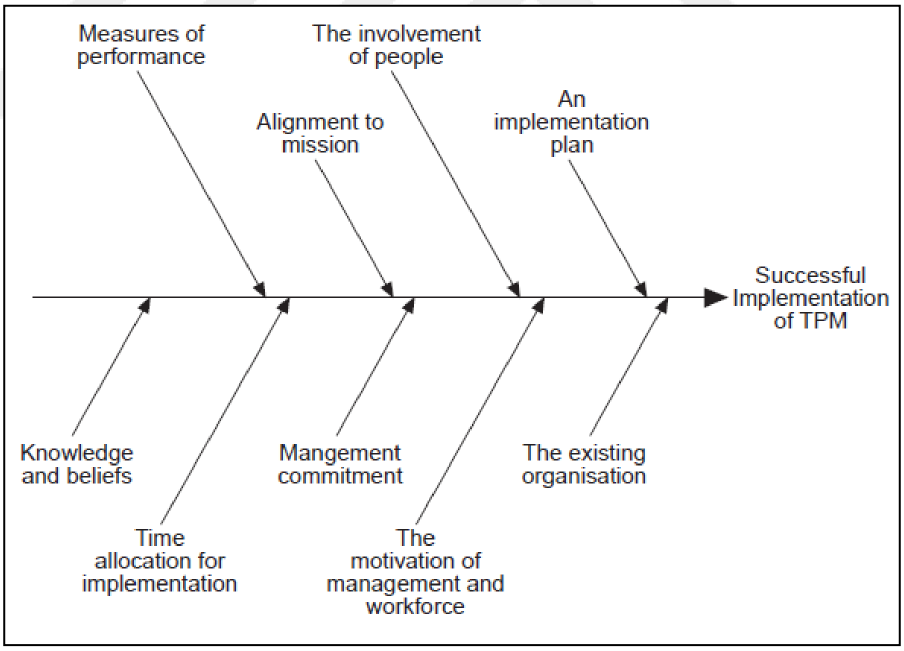

Figure 2.9 Cause and effect diagram-a generic model of factors affecting successful implementation of TPM (Bamber et al.,1999)

Davis and Willmott (1999) suggested two important enablers, e.g., “a structured approach which uses different tools and techniques to succeed highly effective plants and production equipment and to quantify its effectiveness", and "a philosophy which is based on the empowerment and encouragement of factory floor-based personnel from all areas" for successful implementation of TPM in the manufacturing organizations.

Lawrence (1999) proposed the use of linear programming, integer programming, and other related operation research techniques to optimize the maintenance management process and to turn an unsuccessful TPM effort into a successful one.

Finlow-Bates, Visser, and Finlow-Bates (2000) illustrated three strong tools, i.e., "seven simple tools of TQM", four thinking models of "Kepner-Tregoe" and "Root cause analysis" to implement TPM successfully. Ben-Daya (2000) explained that equipment management and employee empowerment and involvement are defined as basic issues of successfully TPM implementation program.

Park and Han (2001) outlined two significant factors that are crucial to successful implementation of TPM. Firstly, to apply TPM successfully, organizations should establish their strategy and their basis of competition, and systematic preliminary planning. Secondly, organizations should recognize simple application of the operational aspects of TPM, and TPM practitioners in the organizations should construct a supportive culture and environment based on human aspects for TPM implementation. Particularly, "training for TPM" and "employee participation in maintenance-related decision making" are significant factors for successful TPM program.

Sun et al. (2003) carried out an evaluation of a successful TPM implementation in a pilot project in a Chinese manufacturing company.

Chan et al. (2005) determined some factors that contributed to the success of TPM implementation; namely, determination of a specific guideline/training for realizing the benefits in the production and maintenance department during TPM implementation, the selection of team members which have a positive attitude and be willing to accept new changes, a well-designed maintenance training system, top management support and commitment for giving morale to production operators and maintenance personnel, and model machine implementation.

Gupta, Tiwari, and Sharma (2006) stated that top management support, employee involvement, TPM teams, continuous improvement and education and training of employees are also critical to successful implementation of TPM. Lazim, Ahmad, Hamid, and Ramayah (2009) also defined that the top management commitment and support is one of the most important success factors to improve the morale and motivation of the personnel in TPM implementation.

Seng, Jantan, and Ramayah (2005) stated that the human-oriented approaches have a greater impact than process-oriented approach. The management should balance both these approaches to provide maximum benefit from TPM implementation.

Rodrigues and Hatakeyama (2006) proposed that an effective TPM program is exactly related to employee management. In this context, it is essential to design indicators for the evaluation of performance of the program.

Panneerselvam (2012) conducted a survey in order to identify the critical success factors for TPM implementation in an Indian industrial rubric. Badli Shah (2012) also demonstrated critical success factors in TPM implementation in Malaysian automotive industries by means of a survey with engineers and managers.

Attri et al. (2013) determined ten enablers based on the literature in the implementation of TPM like top management commitment and support, cultural change, coordination, communication, cooperation, total employee involvement, training and education, integration of TPM goals and objectives into business plans, motivation, and empowerment and encouragement. Then, the ranking of these enablers were done by a questionnaire-based survey and ISM approach were utilized in analyzing their mutual interaction.

Piechnicki et al. (2015) firstly explained the critical success factors in TPM implementation previously determined in the literature. Then, a model was proposed to prioritize the critical success factors in the phases of TPM implementation process using Analytical Hierarchy Process (AHP), and the results showed different degrees of priorities of critical success factors in each phase of the process. The main critical success factors for TPM implementation found in the literature are summarized in Table 2.4.

Table 2.4 Summarization of the literature review on critical success factors for TPM implementation

Critical Success Factors	**References**
Training and education	Maggard and Rhyne (1992), Turbide (1995), Moore (1997), Swanson (1997), Blanchard (1997), Thiagarajan and Zairi (1997), Sun et al., (2003), Eti, Ogaji, and Probert (2004), Chan et al. (2005), Gupta et al. (2006), Ahuja and Khamba (2008a), Alsyouf (2009), Panneerselvam (2012), Attri et al. (2013), Piechnicki et al. (2015)
Working in teams	Park and Han (2001), Sun et al. (2003), Baird, Hu, and Reeve (2011), Santandreu-Mascarell, Garzon, and Knorr (2013), Piechnicki et al. (2015)
Planning and preparation	Park and Han (2001), Chan et al. (2005), Sharma et al. (2006), Ahuja and Khamba (2008a), Lazim and Ramayah (2010), Piechnicki et al. (2015)
Top management commitment and support	Nakajima (1989), Patterson et al. (1995), Patterson, Fredendall, Kennedy, and McGee (1996), Bamber et al. (1999), Tsang and Chan (2000), Park and Han (2001), Sun et al. (2003), Chan et al. (2005), Bititci, Mendibil, Nudurupati, Garengo, and Turner (2006), Gupta et al. (2006), Ward, McCreery, and Anand (2007), Ahuja and Khamba (2008a), Arca and Prado (2008), Alsyouf (2009), Lazim et al. (2009), Lazim and Ramayah (2010), Tung, Baird, and Schoch (2011), Shavarini, Salimian, Nazemi, and Alborzi (2013), Attri et al. (2013), Piechnicki et al. (2015)
Resistance to change	Park and Han (2001), Eti et al. (2004), Chan et al. (2005), Ahuja and Khamba (2008a), Kuula, Putkiranta, and Toivanen (2012), Poduval, Pramod, and Raj (2013), Piechnicki et al. (2015)
Culture change	Bamber et al. (1999), Park and Han (2001), Hansson, Backlund, and Lycke (2003), Ahuja and Khamba (2008a), Ronnenberg, Graham, and Mahmoodi (2011), Naranjo-Valencia, Jimenez-Jimenez, and Sanz-Valle (2011), Prajogo and McDermott (2011), Panneerselvam (2012), Aspinwall and Elgharib (2013), Poduval et al. (2013), Attri et al. (2013), Piechnicki et al. (2015)
Employee involvement	Chen (1997), Nakajima (1989), Rodrigues and Hatakeyama (2006), Gupta et al. (2006), Ahuja and Khamba (2008a), Arca and Prado (2008), Panneerselvam (2012), Attri et al. (2013), Piechnicki et al. (2015)
Effective communication	Park and Han (2001), Eti et al. (2004), Ahuja and Khamba (2008a), Alsyouf (2009), Panneerselvam (2012), Attri et al. (2013), Piechnicki et al. (2015)
Monitoring results	Lawrence (1999), Park andHan (2001), Sharma et al. (2006), Piechnicki et al. (2015)
Coordination	Badiru and Schlegel (1994), Park and Han (2001), Attri et al. (2013)
Cooperation	Agyris (1998), Davis and Willmott (1999), Patterson et al. (1995), Ben-Daya (2000), Eti et al. (2004), Attri et al. (2013)
Integration of TPM goals and objectives into business plans	Ahuja and Khamba (2008b), Attri et al. (2013)
Empowerment and encouragement	Bamber et al. (1999), Attri et al. (2013)
Motivation	Park and Han (2001), Attri et al. (2013)

2.4.4 Measurement of TPM Performance

Many factors have been drawn from a review of literature and case studies on manufacturing organizations' efforts to implement TPM successfully which has been summarized in the previous section. According to these studies, the measurement of TPM performance is significantly required for continuous improvement of the TPM implementation program. Moreover, it is necessary to establish appropriate metrics for measurement purposes (Piechnicki et al., 2015).

Quality improvement experts Deming (1986), Tenner and DeToro (1992) and Spenley (1992) all emphasized the need for appropriate measures of performance, to provide management focus and fact based decision making for the implementation of change to be successful. Groote (1995) suggested a maintenance performance evaluation approach based on a quality audit and quantifiable MPIs to allow the maintenance manager for monitoring the progress of maintenance performance and to make decisions necessary for improved maintenance management. Hansen (2002) also stated that accurately measuring and driving key success parameters contributes to higher productivity for the maintenance function.

Leblanc (1995) proposed that the evaluation of TPM can be measured for realizing the true potential of TPM. Davis (1996) provided a vital addition to the understanding of implementation issues related to the TPM program and reported that relevant measures of performance should be established and continually monitored and publicized benefits achieved in financial terms. It is considered extremely important to measure performance since it gives managers the possibility to base their decisions on facts, not opinions (Maskell, 1994). Ljungberg (1998) remarked that if measurable results are not provided within a rather short period, the management and operators can loose reliance in TPM.

In measuring TPM implementation, Maier et al. (1998) recommended preventive maintenance, teamwork shop floor employee competencies, measurement and information availability work environment, work documentation, and extent of operator involvement in maintenance activities such as factors reflecting TPM implementation.

McKone et al. (1999) considered both autonomous and planned maintenance variables selected from Word Class Manufacturing (WCM) database for assessing the TPM activities at various plants in three different countries using a five question scale selected from the WCM database. While the autonomous maintenance variables include three perceptual measures for *housekeeping* on the production line, *cross-training* of operators to perform maintenance tasks and *teams* of production and maintenance personnel, and an objective measure for *operator involvement* in the maintenance delivery system, the planned maintenance variables contains three measures like two perceptual measures for *disciplined planning* of maintenance tasks and *information tracking* equipment and process condition and plans, and an objective measure for *schedule compliance* to the maintenance plan. McKone et al. (2001) extended the study of McKone et al. (1999) and also considered the seven variables of TPM explained as in McKone et al. (1999) to measure TPM effectiveness and explore the relationship TPM and manufacturing performance through SEM. Das (2001) presented a case study where TPM is implemented in a step-by-step manner and also developed some parameters for measuring the effectiveness of TPM.

Brah and Chong (2004) summarized the internal and external environments and provided a macro view of the factors affecting TPM performance. External factors are beyond the control of an organization and management, while some of the internal factors are critical to the success of TPM implementation. In this study, it is also stated that morale and performance of employees is another performance aspect of TPM.

Rodrigues and Hatakeyama (2006) noted that it is crucial to establish key indicators for the evaluation of TPM performance in order to provide successfully implementation of TPM. Also, it is stated that the key performance indicators used to verify the progress of TPM are productivity, cost, quality, customer satisfaction, safety, shop floor morale issues, total number of suggestions contributed by the shop floor and the participation rate of employees in small group activities.

Recent studies have investigated that companies should also consider the human factors of TPM in combination with the technical and financial impacts (Arunraj et al., 2014; Peach et al., 2016). Human factors are examined thoroughly in the design phase of the proposed TPM PMS (see Section 4.2).

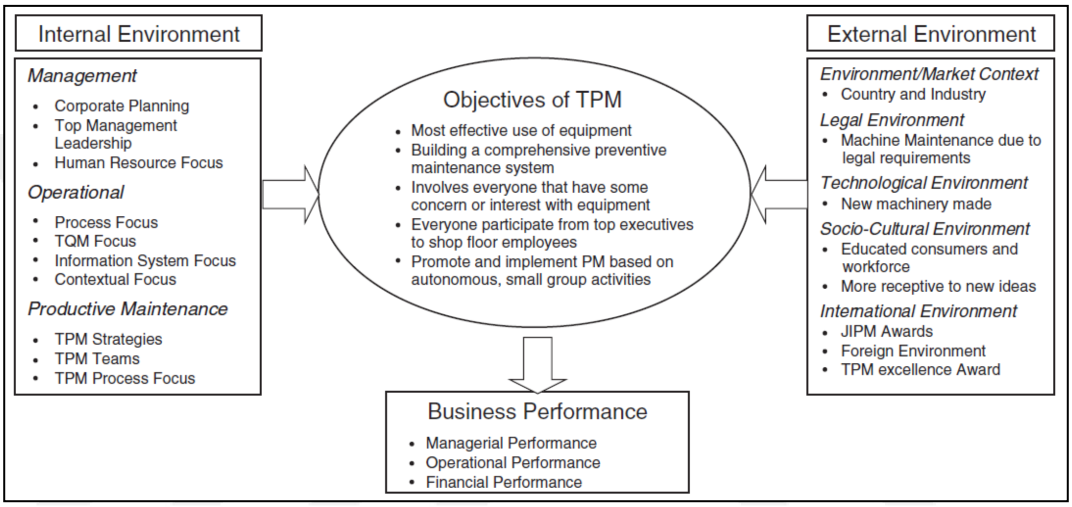

Figure 2.10 Macro view of factors affecting TPM (Brah and Chong, 2004)

The fundamental measure of TPM performance is the OEE value which as defined by Nakajima (1989) should be the driving force and provides direction for improvement based activities with manufacturing organizations (Bamber et al., 1999). Detailed information and literature review on OEE and its extensions are given in the following section.

2.4.4.1 OEE and Its Extensions

From a generic perspective, TPM can be identified in terms of OEE which in turn can be considered as a combination of the operation maintenance, equipment management, and available resources. The goal of TPM is to maximize equipment effectiveness, and the OEE is used as a core metric for measuring the success of TPM implementation program in an organization (Jeong & Phillips, 2001;

Waeyenbergh & Pintelon, 2002). Definition of OEE includes six big losses, including downtime and other production losses that reduce output/machine hour or capacity utilization and does not include factors that reduce capacity utilization, e.g. plan downtime, lack of material input, lack of labor, etc. The six large losses are given as follow (De Ron & Rooda, 2006):

Downtime losses: 1) Breakdown losses categorized as time losses and quantity losses caused by equipment failure or breakdown. 2) Set up and adjustment losses occur when production is changing over from requirement of one item to another. *Speed losses:* 3) Idling and minor stoppage losses occur when production is interrupted by temporary malfunction or when a machine is idling. 4) Reduced speed losses refer to the difference between equipment design speed and actual operating speed. *Quality losses:* 5) Quality defects and rework are losses in quality caused by malfunctioning production equipment. 6) Reduced yield during start-up are yield losses that occur from machine start-up to stabilization. These losses are activities that absorb resources but create no value shown in Figure 2.11.

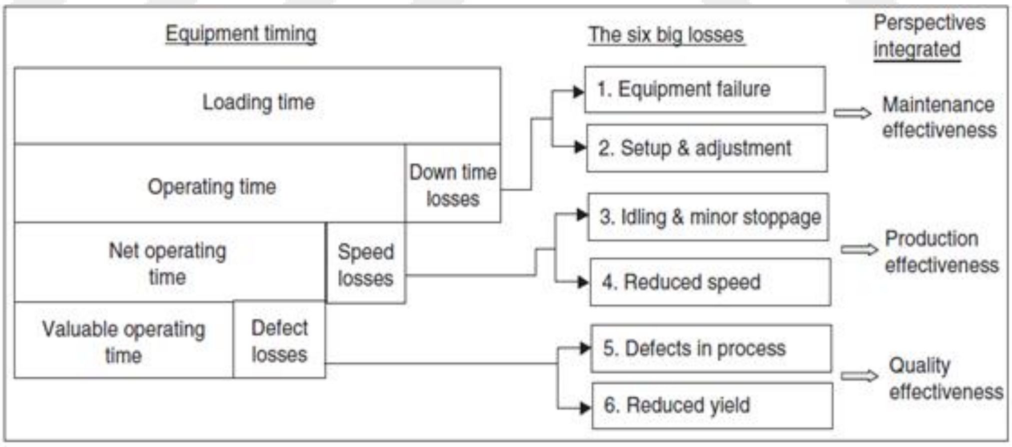

Figure 2.11 OEE measurement tool and the perspectives of performance integrated in the tool (Muchiri & Pintelon, 2008)

According to Nakajima (1988), the six large losses are measured by OEE, which is a function of availability (A), performance efficiency (P) and rate of quality (R).

$$OEE = A \times P \times R, \tag{2.1}$$

where

$$A = \frac{Loading\,time - Down\,time}{Loading\,time}, \tag{2.2}$$

$$P = \frac{\Pr ocess\,amount \times Thereotical\,cycle\,time}{Operating\,time}, \tag{2.3}$$

$$R = \frac{\Pr ocess\,amount - defect\,amount}{\Pr ocess\,amount}. \tag{2.4}$$

This metric has become widely accepted as a quantitative tool essential for measurement of productivity in manufacturing operations. The OEE measure is central to the formulation and execution of a TPM improvement strategy (Dal et al., 2000).

According to the literature review, a large number of studies focused on OEE, a well-known efficiency metric that allows evaluation of the impact of several hidden losses, by comparing the actual performance of equipment with respect to its theoretical potential. When the search for literature review for OEE is conducted using “Scopus”, 459 published papers mention OEE in their “article title, abstracts, or keywords”. Figure 2.12 shows the publication frequencies of OEE according to years between 1993 and September 2016. Some of these publications are articles, conference papers, and book chapters. Figure 2.13 also illustrates the distribution of these publications according to publication categories.

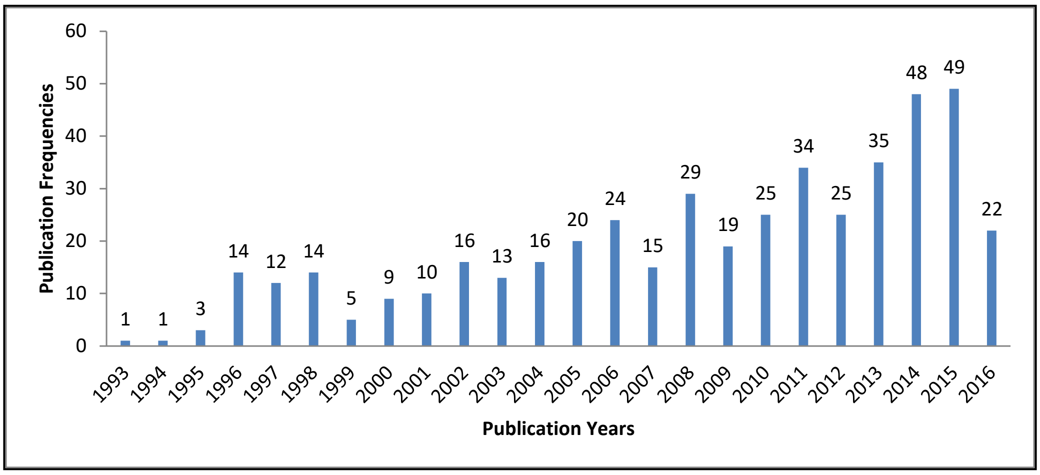

Figure 2.12 Publication frequencies of OEE according to years

According to Figure 2.13, most of the studies on OEE have been published as an article with 224 studies and as a conference paper with 168 studies. Rest are as follows as a review with 34 papers, as a short survey with 14 papers, as a note with a rate of six studies, as a book chapter, conference review and article in press with a rate of four studies, and as a letter with one study, respectively.

As seen from Figures 2.12 and 2.13, there is a considerable amount of literature published in relation to the definition of OEE and its various applications. Additionally, researches on OEE improvements and relationships with other measures of performance and approaches, and empirical researches on OEE have been conducted to understand its managerial implications. Some examples of the OEE literature are explained in the following paragraphs.

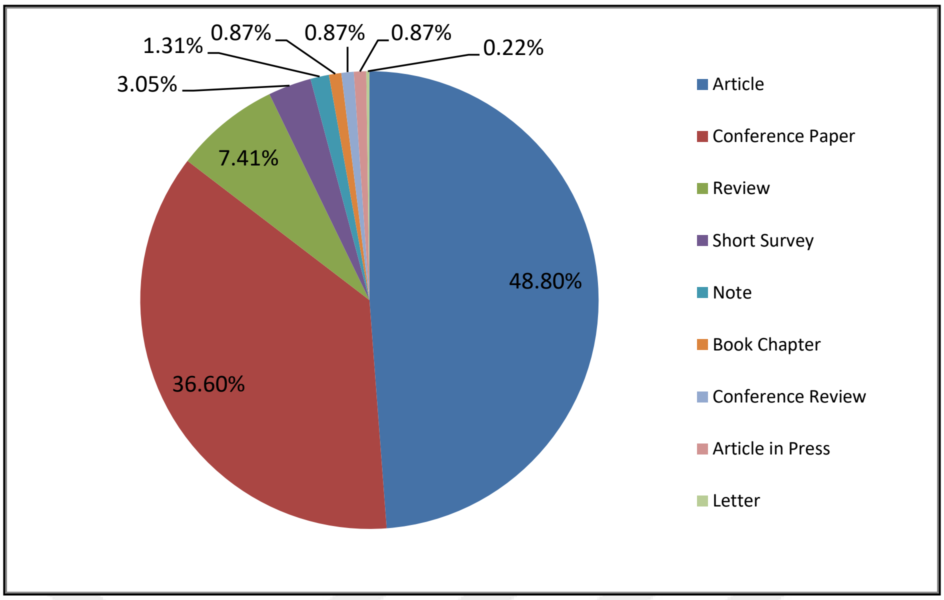

Figure 2.13 Percentages of publication categories of OEE

Ljungberg (1998) argued that it should be beneficial to change focus and use a comprehensive model for losses and proposes a TPM model with eight equipment losses. The author also explained that the data collection problem has not been sufficiently treated in the literature and has suggested a method for collecting disturbance data where computerized systems are combined with manual recording.

Jeong and Phillips (2001) explained that accurate estimation of equipment utilization is very essential. They presented a new loss classification scheme for computing OEE for a capital-intensive industry and provide justification for this scheme. They also presented the methodology for designing the necessary data collection system that can serve as a template for any industry.

Bamber, Castka, Sharp, and Motara (2003) explored the purpose of the OEE concept in modern operations. This paper discussed that in order to effectively address all six big losses and improve OEE, cross-functional team is necessary. Additionally, through the use of cross-functional team, it is more likely that the responsibility and authority to carry out improvements is gained from management.

Holmgren (2005) identified maintenance related losses, and their causes, in order to describe different deviations in the maintenance process that contributes to incidents and accidents at the Swedish Railway.

Nachiappan and Anantharaman (2006) expressed the importance of the quantitative OEE analysis for the whole factory in a continuous product line manufacturing system.

Sarkar (2007) pointed out how six sigma methodology has been applied for process improvement considering OEE as a parameter. Raja and Kannan (2007) optimized the OEE parameters using Evolutionary Programming using MATLAB. They analyzed the impact of yield in calculation of OEE in casting industry and suggested to the practicing industry to run the process with the given optimum conditions.

Braglia, Frosolini, and Zammori (2008) developed an alternative losses classification structure to divide the losses that can be directly ascribed to equipment, from the ones that are spread in the line for engine basements production. Starting from this losses classification structure, an approach based on OEE is developed to evaluate the criticalities and the effectiveness of the line. Results show that it successfully highlights the progressive degradation of the ideal cycle time, explaining it in terms of: bottleneck inefficiency, quality rate, and synchronization-transportation problems.

Garza-Reyes, Eldridge, Barber, Archer, and Peacock (2010) demonstrated the relationship between OEE and Process Capability (PC) and suggested the existence of a “cut-off point” beyond which improvements in PC have little impact on OEE. They developed a discrete-event simulation model of a bottling line.

Sharma and Trikhab (2011) concluded that TPM was chosen as an effective maintenance strategy to improve the OEE of production machines. OEE can also be improved in any manufacturing company through the implementation of innovative maintenance strategies and also reduces the operating cost of the industry. OEE has increased by 4 per cent even after a small implementation of TPM in a company.

Shahin and Attarpour (2011) estimated a linear relationship between OEE and mean time between failures in order to develop decision making grid for making more accurate maintenance policies.

Zammori, Braglia, and Frosolini (2011) took into account the stochastic nature of the OEE, and presented an approximated procedure based on the application of the Central Limit Theorem. The results obtained demonstrate that the stochastic OEE can help in battling variation, for it allows one to identify the hidden losses that account for most of the variability and to estimate the impacts of potential corrective actions in terms of both efficiency and efficacy.

Relkar and Nandurkar (2012) simulated a manufacturing scenario by using WITNESS software to identify bottleneck machine with different combinations of mean time between failures and repair time results into variation in output. They used MiniTab15 software for regression analysis which establishes relation between OEE and time between failures (repair time). The process of OEE was optimized by using response surface methodology to identify optimized zone for maximizing output.

Puvanasvaran, Teoh, and Tay (2013a) and Puvanasvaran, Mei, and Alagendran (2013b) explained the inclusion of customer demand in obtaining OEE value of any particular equipment. Besides, the equipment without ideal cycle time, which means those processes carried out in constant cycle time were evaluated with performance ratio. As a consequence, the machine utilization and capacity were used as the performance ratio data in the calculation of the OEE index.

Tsarouhas (2013) carried out the analysis of failure and repair data of the limoncello production line over a period of 8 months. Descriptive statistics at machine and line level were computed, and also all the components of the OEE were calculated. As a conclusion in this study, the statistical analysis provided a useful perspective and helped managers make better decisions about how to run and improve their processes more efficiently and effectively.

Raguram (2014) presented the implementation of OEE at a small enterprise finishing product specification according to customer specifications in India. After full implementation, OEE performances improved by over 75 percentages, since availability rate and performance efficiency were improved over 79 percentages and quality rate was maintained at the same level.

Bekar et al. (2015) proposed an ANFIS modeling to obtain forecasted results for OEE parameter in TPM through some predetermined inputs such as availability, performance efficiency and rate of quality. Triangular type of membership functions were used and defined as low, medium, and high and also their membership degrees were determined using fuzzy c-means clustering algorithm for each input parameter in the model. As a conclusion in this study, the statistical analysis provided a useful perspective and helped managers make better decisions about how to run and improve their processes more efficiently and effectively. Bekar et al. (in-press) have extended the study of Bekar et al. (2015) by developing a simulation model and using response surface methodology.

Zammori (2015) proposed fuzzy overall equipment effectiveness (FOEE) to capture the day-to-day performance fluctuations using LR fuzzy numbers and fuzzy transformation model. An industrial application was also performed for an important Italian manufacturing firm. Since the FOEE made it possible to trace back the share of the overall fluctuations, it provided the basis for setting improvement priorities and directed the lean team toward the selection of appropriate corrective actions.

Gupta ans Vardhan (2016) proposed a framework for improvement of operational effectiveness with the applications of OEE as a tool, increment of productivity through capability building and decreasing production cost after minimizing the main losses also were argued.

Binti Aminuddin (2016) analyzed the managerial issues related to the implementation and use of OEE in the manufacturing industry. In the study, five hypotheses and four research questions were formulated and then data were collected through a survey questionnaire responded by 139 manufacturing organization's worldwide and finally gathered data were tested using a combination of descriptive statistics and cross-tabulation, chi-square, analysis of variance, Tukey's pairwise comparison, Z-test and correlation tests. The results investigated the relation of OEE implementation with that of TPM and lean manufacturing, drivers, most critical factors, barriers and the role of management in its implementation as well as how manufacturing organizations employ the information provided by OEE and how the data for its computation is collected.

Though the OEE tool has become increasingly popular and has been widely used as a quantitative tool essential for measurement of productivity, it is only limited productivity behavior of individual equipment (Huang et al. 2003).

In the literature, some of researchers have tried to expand the application scope of OEE from individual equipment to either entire processes/factories or through the inclusion of more elements of performance than just availability, performance and quality. This has led to broadening of OEE to Overall process effectiveness (Sherwin, 2000), Overall line effectiveness (Nachiappan & Anantharam, 2006), Overall equipment effectiveness of a manufacturing line (Braglia, Frosolini, & Zammori, 2009), Overall fab effectiveness (Oechsner et al., 2003), Total equipment effectiveness performance (Ivancic, 1998), Production equipment effectiveness (Raouf, 1994), Overall asset effectiveness (Muchiri & Pintelon, 2008), Overall resource effectiveness (Garza-Reyes, 2015; Garza-Reyes, Eldridge, Barber, Archer, & Peacock, 2008; Garza-Reyes et al., 2010), Overall equipment effectiveness market-based (Anvari, Edwards & Starr, 2010), Integrated equipment effectiveness (Anvari & Edwards, 2011), Overall throughput effectiveness (Muthiah & Huang, 2007), Overall tool group efficiency (Chien, Chen, Wu, & Hu, 2007), and Overall equipment cost loss (Wudhikarn, 2016). Some of the modified formulations are limited to effectiveness at the equipment level (e.g. production equipment effectiveness, total equipment effectiveness performance), while others have been extended to factory level effectiveness (e.g. overall fab effectiveness, overall process effectiveness, overall asset effectiveness, overall throughput effectiveness) (Muchiri & Pintelon, 2008).

2.4.4.2 Detailed Literature Review on Measurement of TPM Performance

When it comes to performance evaluation in TPM, OEE has widely been used as a performance measure because TPM aims to maximize equipment effectiveness (Schippers, 2001; Waeyenbergh & Pintelon, 2002). Although OEE has been considered as a standard measure for equipment performance, it captures only effectiveness of TPM, not its efficiency (Chan et al., 2005).

OEE provides productivity behaviour of only individual equipment. However, the evaluation of TPM performance should include an objective and comprehensive method based on multiple inputs and outputs instead of OEE and its extensions (Muchiri & Pintelon, 2008). For this context, in the literature, a few studies have been made related to the performance measurement in TPM implementation explained as the following paragraphs.

Park (2002) proposed a TPM analysis model including three stages. The first stage represents the effect of TPM factors on TPM performance. The second stage represents how TPM performance factors influence productivity. The third stage also represents the testing of TPM analysis model with univariate and multivariate regression and correlation analyses and the results show that TPM performance factors improve productivity through TPM activity’s characteristics.

F.-K. Wang (2006) suggested a simple methodology for efficiency evaluation in TPM. In this study, DEA was used to evaluate the efficiency score when the utility function considers many attributes. A prediction model by the multiple regression method was performed to obtain the expected efficiency score for checking the performance of implementing TPM. F.-K. Wang (2006) measured TPM efficiency at the factory level using DEA method, which has some limitations. Therefore, Jeon et al. (2011) measured three types of TPM efficiency by self-directed work teams (SDWTs) using DEA. Firstly, DEA efficiency scores of SDWTs were measured for three stages (Stage 1: from TPM input to TPM intermediate output; Stage 2: from TPM intermediate output to TPM final output, and Stage 3: from TPM input to TPM final output). Then, the relationships between the three types of efficiency scores were analyzed by Spearman correlation analysis (Gibbons, 1971). SDWTs were also clustered by the three types of TPM efficiency.

2.5 Conclusion

This chapter begins with the explanation of general overview PM frameworks and indicators. Then, the next sections present information in detail about the background and a brief introduction to MPM, an overview of MPM frameworks and MPIs, TPM framework and its detailed literature review, need, impact and critical successes for TPM implementation in manufacturing systems. In the final section, a review on performance measurement of TPM and OEE which is a quantitative metric for measuring the performance of TPM are expressed in detail.

According to results of this chapter, tracking the performance of maintenance is a key management issue for many organizations and a structured approach of measuring maintenance performance should be developed. Moreover, it is concluded that the area of maintenance performance and management is in need of more future systematic research efforts aimed at solidifying theoretical constructs and promoting the implementation of more practical approaches.

A strategic approach to improve the performance of maintenance activities is to effectively adapt and implement TPM program in the manufacturing organizations. TPM brings maintenance into focus as a necessary and vitally important part of the business (Ahuja & Khamba, 2008b). However, a few studies have been made related to the performance measurement in TPM implementation (see Section 2.4.4.2). Thus, the motivation of this thesis is to measure TPM performance by developing a systematic program based on different quantitative and qualitative factors having impact on TPM performance. Proposed TPM PMS and its positioning in the literature are presented in detail in Chapter 4. In the subsequent chapter, the background information about the methods used in this thesis is presented.

CHAPTER THREE
UNDERYLING TOOLS FOR
THE PROPOSED METHODS

3.1 Introduction

As stated in the previous chapter, this thesis aims to develop a new framework for measurement of TPM performance based on novel performance indicators which include uncertain information or imprecise data. Fuzzy set theory, introduced by Zadeh in 1965, provides a new mathematical tool to deal with uncertainty of information (Zadeh, 2008). In the proposed TPM PMS, after the design of new performance indicators, these indicators can be evaluated and measured using some methods under fuzzy environment. For example, in the evaluation phase of the proposed TPM PMS, since the evaluation involves multiple criteria, it can be thought of as a multi-criteria decision-making (MCMD) problem. Therefore, in this phase, COmplex PRoportional ASsessment of alternatives with Grey relations (COPRAS-G), which is one of the most popular multiattribute decision making (MADM) methods, and proposed fuzzy COmplex PRoportional ASsessment of alternatives (FCOPRAS) are used. Then, in the implementation phase of the proposed TMP PMS, fuzzy data envelopment analysis (FDEA), which is a mathematical programming approach for evaluation of performance with uncertainty pertinent to existence of qualitative data set, is utilized to evaluate TPM performance based on novel performance indicators. The Generalized Fuzzy Data Envelopment Analysis with Assurance Region (GFDEA/AR) models are integrated with the proposed FCOPRAS method. In these models, desirable and undesirable performance indicators (inputs and outputs) are also considered. To gain a more comprehensive understanding, these methods employed in the different phases of the proposed TPM PMS are explained in detail in this chapter.

The rest of this chapter is organized as follows. Following section starts with the definition and basic concepts of fuzzy set theory. Subsequent sections review the standard operation and properties of fuzzy set, fuzzy numbers and membership functions, fuzzy arithmetic operations, linguistic variables and fuzzy ranking methods, respectively. Section 3.3 introduces the fuzzy multicriteria decision making (FMCDM) and fuzzy multiattribute decision making (FMADM) and also briefly explains the literature review on COPRAS-G, COPRAS-G methodology and FCOPRAS method. In section 3.4, firstly, the fundamentals of data envelopment analysis (DEA) are presented. Secondly, the principles and a detailed literature review about FDEA are given. Thirdly, the FDEA approaches are explained in depth. Then, FDEA/AR approach, undesirable inputs and outputs and integrated methods in FDEA are explained. This section is finished by a review on FDEA based performance measurement studies. Finally, the context of this chapter is summarized in Section 3.5.

3.2 Fuzzy Set Theory

Fuzzy set theory and its attendant fuzzy logic were developed by Zadeh in 1965 to handle semantic and subjective ambiguity (Zadeh, 2008). Then a large number of papers dealt with this theory and a compilation of some of the most interesting articles published by Zadeh were presented in Yager, Ovchinnikov, Tong, & Nguyen (1987). Moreover, Dubois and Prade (1980, 1989) and Zimmerman (1991) bring together the most important aspects behind the theory of fuzzy sets and the theory of possibility.

The original interpretation of fuzzy sets arises from a generalization of the classic concept of a subset extended to embrace the description of “vague” and “imprecise” notions. This generalization is formed in the following way (Galindo, Urrutia, & Piattini, 2006):

- The membership of an element to a set becomes a “fuzzy” or “vague” concept. In the case of some elements, the issue of whether they belong to a set may not be clear.
- The membership of an element may be measured by a degree, commonly known as the “membership degree” of that element to the

set, and it takes a value in the interval [0, 1] by agreement.

In the classical logic the membership of an element to a set is represented by zero if it does not belong and one if it does, having the set {0, 1}. On the other hand, in fuzzy logic this set extends to the interval [0, 1]. Therefore, it could be said that fuzzy logic is an extension of the classic systems (Zadeh, 1975, 1978).

Fuzzy set theory provides a strict mathematical framework in which vague conceptual phenomena can be precisely and rigorously studied. It also can be considered as a powerful modeling language that can cope with a large fraction of uncertainties in real life-applications and engineering problems (Zimmermann, 1991; Babuska, 2001).

Since then, a considerable body of literature has blossomed around the concept of fuzzy sets in an incredible wide range of areas, from mathematics and logics to traditional and advanced engineering methodologies. The applications of fuzziness are uncountable and varied in many contexts (Dubois, Ostasiewicz, & Prade, 2000; Dubois & Prade, 2001). For example, additionally to consumer applications in Japanese electronics, auto industry in Germany, and home appliances; Fuzzy logic is applied to finance, stock market, biomedicine, ecology, philosophy, agriculture, geography, rheology, satellite remote control, nuclear science, weather prediction, elevators, robotics and rocket science, to mention a few of them. In general fuzziness is applied to engineering and control theory very widely and now currently used in the industrial practice of advanced information technology (Anastassiou, 2010). Wong and Lai (2011) showed the applications of the fuzzy set theory in production and operations management. A comprehensive literature review and recent applications of fuzzy sets in the last decades has been presented in the study of Kahraman, Öztayşi, and Çevik Onar (2016).

3.2.1 Definition of Fuzzy Sets

In the classical set theory, an element of a set either belongs or does not belong to the set. In fuzzy set theory, an element belongs with a *membership grade* in the interval [0, 1]. All membership grades together form the *membership function*. A classical set is often called crisp as opposed to fuzzy (R. Zhang, Phillis, & Kouikoglou, 2005).

Let X be classical (ordinary) set of objects, called the universe of discourse, whose generic elements are denoted by x, namely, $X = \{x\}$. Then a fuzzy set $\tilde{A}$ is defined by a membership function $\mu_{\tilde{A}}(x)$ which associates with each element in X a real number in the interval [0, 1]. If X is a collection of objects denoted by x, the fuzzy set $\tilde{A}$ in X is a set of ordered pairs of elements x (Zimmermann, 1991):

$$\tilde{A} = \left\{ \left(x, \mu_{\tilde{A}}(\mathrm{x}) \right) \mid x \in X \right\}. \tag{3.1}$$

$\mu_{\tilde{A}}(x)$ is called the membership function or grade membership (sometimes degree of compatibility or degree of truth) of x in $\tilde{A}$ which maps X to the membership space M. Membership function is not limited to values between 0 and 1. The range of the membership function is a subset of the nonnegative real numbers whose supremum is finite. Elements with a zero degree of membership are normally not listed in $\tilde{A}$.

When X is countable or a finite set, a fuzzy set $\tilde{A}$ on X is expressed as follows (Lu, Zhang, Ruan, & Wu, 2007; Ross, 2010):

$$\tilde{A} = \sum_{x_i \in X} \mu(\mathrm{x}_i)/x_i. \tag{3.2}$$

When X is a finite set whose elements are $x_1, x_2, \ldots, x_n$, a fuzzy set $\tilde{A}$ on X is expressed as follows:

$$\tilde{A} = \left\{ \left(x_1, \mu_{\tilde{A}}(\mathrm{x}_1) \right), \left(x_2, \mu_{\tilde{A}}(\mathrm{x}_2) \right), \ldots, \left(x_n, \mu_{\tilde{A}}(\mathrm{x}_n) \right) \right\}. \tag{3.3}$$

When X is an infinite and uncountable set, a fuzzy set $\tilde{A}$ on X is expressed as follows:

$$\tilde{A} = \int_X \mu(\mathrm{x})/x. \tag{3.4}$$

These expressions mean that the grade of x is $\mu_{\tilde{A}}(\mathrm{x})$ and the operations '+', 'Σ', and '$\int$ ' do not refer to algebraic addition and integral but they are union, and '/' does not indicate an algebraic division but it is as merely a maker.

As an example, consider the temperature of a patient in degrees Celsius. Let X = {36.5, 37, 37.5, 38, 38.5, 39, 39.5}. The fuzzy set $\tilde{A}$ = *"High temperature"* may be defined as follows (R. Zhang et al., 2005):

$$\begin{aligned}\tilde{A} &= \left\{\left(x, \mu_{\tilde{A}}(\mathrm{x})\right) \mid x \in X\right\} \\ &= 0/36.5 + 0/37 + 0.1/37.5 + 0.5/38 + 1/39 + 1/39.5,\end{aligned}$$

where the numbers 0, 0.1, 0.5, 0.8, and 1 express the degree to which the corresponding temperature is high.

As another example for fuzzy sets, let's define a fuzzy set $\tilde{A}$ = *{real number near 0}*. The boundary for set "real number near 0" is pretty ambiguous. The possibility of real number x to be a member of prescribed set can be defined by the following membership function (Lee, 2005).

$$\tilde{A} = \int \mu_A(\mathrm{x})/x \quad \textit{where} \quad \mu_A(\mathrm{x}) = \frac{1}{1+x^2}$$

Figure 2.1 shows this membership function. According to this, the membership degree of 1 is $\frac{1}{1+1^2} = 0.5$. The possibility of 2 is 0.2 and that of 3 is 0.1.

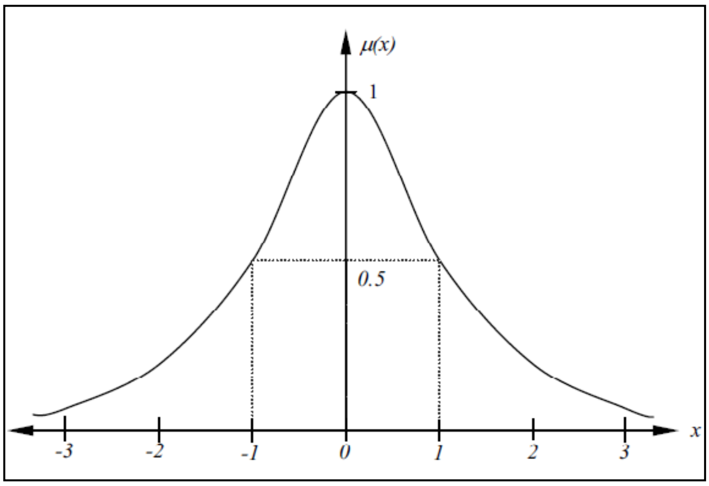

Figure 3.1 Membership function of fuzzy set “real number near 0” (Lee, 2005)

The membership functions can be represented with very different shapes of graphs (See Section 3.2.4). It cannot be said a particular shape is much suitable (Klir & Yuan, 1995).

3.2.2 Basic Concepts of Fuzzy Sets

In this section, a number of properties of fuzzy sets are defined to establish the mathematical framework for computing with fuzzy sets.

Given a fuzzy set $\tilde{A}$ defined on X and any number $\alpha \in [0, 1]$, *the α-cut* A_α is a crisp subset of the universe of discourse X whose elements all have membership grades greater than or equal to α (Buckley & Eslami, 2002; Klir & Yuan, 1995):

$$A_\alpha = \left\{ x \in X \mid \mu_{\tilde{A}}(\mathrm{x}) \geq \alpha \right\}. \tag{3.5}$$

The α-cut operator is also denoted by *α-cut (A)* or *α-cut (A, α)*. The value of α is called the *α-level*. A more general and even more useful notation is that of *α-level-set* (Zimmermann, 1991*)*.

The more restricted variant of α-cut is the *strong α-cut*. It is defined as a crisp set that contains all the elements of the universal set whose membership grades in the given set are greater than (but do not include) the specified value of α. For a fuzzy set

$\tilde{A}$, *the strong α-cut*, $A_{+\alpha}$ is presented as follows (Babuska, 2001):

$$A_{+\alpha} = \{x \in X \mid \mu_{\tilde{A}}(\mathrm{x}) > \alpha\}. \tag{3.6}$$

The *support* of a fuzzy set $\tilde{A}$ is the crisp set of all elements of X with nonzero membership in A, or symbolically shown as follows (Babuska, 2001):

$$S(\tilde{\mathrm{A}}) = \{x \in X \mid \mu_{\tilde{A}}(\mathrm{x}) > 0\}. \tag{3.7}$$

The support of fuzzy set $\tilde{A}$ is also denoted by *supp(A)* and defined as the strong α-cut for α=0.

The *core* of a fuzzy set $\tilde{A}$ is a crisp subset of X consisting of all elements with membership grades equal to one (Babuska, 2001):

$$core(\mathrm{A}) = \{x \in X \mid \mu_{\tilde{A}}(\mathrm{x}) = 1\}. \tag{3.8}$$

The support and core of a fuzzy set are thus particular cases of the strong α-cut and α-cut, respectively. Figure 2.2 depicts the core, support and α-cut of a fuzzy set.

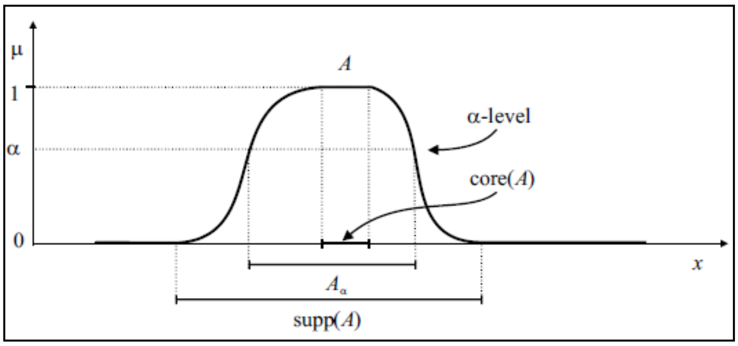

Figure 3.2 Core, support and α-cut of a fuzzy set (Babuska, 2001)

Given a fuzzy set $\tilde{A}$ defined on X, the height of $\tilde{A}$ is the supremum (the least upper bound) of the membership grades of elements in $\tilde{A}$ or the largest membership degree among all elements of the universe shown as follows (Lu et al., 2007):

$$hgt(\tilde{\mathrm{A}}) = \sup_{x \in X} \mu_{\tilde{A}}(\mathrm{x}). \tag{3.9}$$

If $hgt(\tilde{A}) = 1$, then the fuzzy set $\tilde{A}$ is called *normal fuzzy set*, otherwise it is called *subnormal*.

A fuzzy set $\tilde{A}$ is *empty*, denoted by $\emptyset$, if and only if its membership function is identically zero, $\mu_{\tilde{A}}(x) = 0$ for all $x \in X$ (Lee, 2005).

The convexity of a fuzzy set is an important property from the point of view of the application aspect. A fuzzy set $\tilde{A}$ on R^n is called *convex fuzzy set* if and only if

$$\mu_{\tilde{A}}(\lambda x_1 + (1-\lambda)\,x_2) \geq \min(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2)) \tag{3.10}$$

for any $x_1, x_2 \in R^n$ and $\lambda \in [0, 1]$. Moreover, a fuzzy set is convex if all α-level sets are convex (Lee, 2005).

Given a fuzzy set $\tilde{A}$ on R^n, $\tilde{A}$ is called a *bounded fuzzy set* if its α-cuts, A_α, are the crisp bounded sets for all $\alpha \in [0, 1]$ (Lu et al., 2007).

3.2.3 Standard Operations and Properties of Fuzzy Sets

Definitions of set-theoretic operations such as the complement, union and intersection can be extended from classical set theory to fuzzy sets (Babuska, 2001). In this section, the following definitions concerning with these operations and some properties for fuzzy sets as introduced by Zadeh (1965) are presented.

Let $\tilde{A}$ and $\tilde{B}$ be two fuzzy sets on X. The fuzzy set $\tilde{A}$ is called *subset* of $\tilde{B}$ (or $\tilde{A}$ is contained in $\tilde{B}$), denoted by $\tilde{A} \subset \tilde{B}$, if $\mu_{\tilde{A}}(x) \leq \mu_{\tilde{B}}(x)$ for all $x \in X$.

Let $\tilde{A}$ and $\tilde{B}$ be two fuzzy sets on X. The fuzzy set $\tilde{A}$ and $\tilde{B}$ are *equal*, denoted by $\tilde{A} \cong \tilde{B}$, if $\tilde{A} \subset \tilde{B}$ and $\tilde{B} \subset \tilde{A}$.

Let $\tilde{A}$ and $\tilde{B}$ be two fuzzy sets on X. The *union* of two fuzzy set $\tilde{A}$ and $\tilde{B}$, denoted by $\tilde{A} \cup \tilde{B}$, if for all $x \in X$,

$$\mu_{\tilde{A}\cup\tilde{B}}(\mathrm{x}) = \max(\mu_{\tilde{A}}(\mathrm{x}), \mu_{\tilde{B}}(\mathrm{x})) \ \mathit{or} \\ \mu_{\tilde{A}\cup\tilde{B}}(\mathrm{x}) = \mu_{\tilde{A}}(\mathrm{x}) \vee \mu_{\tilde{B}}(\mathrm{x}). \tag{3.11}$$

where '∨' is the maximum operator. The union of $\tilde{A}$ and $\tilde{B}$ is the smallest fuzzy set containing both $\tilde{A}$ and $\tilde{B}$ (Zadeh, 1965).

Let $\tilde{A}$ and $\tilde{B}$ be two fuzzy sets on X. The intersection of two fuzzy set $\tilde{A}$ and $\tilde{B}$, denoted by $\tilde{A} \cap \tilde{B}$, if for all $x \in X$,

$$\mu_{\tilde{A}\cap\tilde{B}}(\mathrm{x}) = \min(\mu_{\tilde{A}}(\mathrm{x}), \mu_{\tilde{B}}(\mathrm{x})) \ \mathit{or} \\ \mu_{\tilde{A}\cap\tilde{B}}(\mathrm{x}) = \mu_{\tilde{A}}(\mathrm{x}) \wedge \mu_{\tilde{B}}(\mathrm{x}). \tag{3.12}$$

where '∧' is the minimum operator. The intersection of $\tilde{A}$ and $\tilde{B}$ is the largest fuzzy set containing both $\tilde{A}$ and $\tilde{B}$ (Zadeh, 1965).

Let $\tilde{A}$ be a fuzzy set on X. The complement of a fuzzy set $\tilde{A}$, denoted by $\tilde{A}^c$, if for all $x \in X$,

$$\mu_{\tilde{A}^c}(\mathrm{x}) = 1 - \mu_{\tilde{A}}(\mathrm{x}). \tag{3.13}$$

Fuzzy sets have the same properties as crisp sets because classical sets can be thought of as a special case of fuzzy sets (Ross, 2010). Let $\tilde{A}$, $\tilde{B}$ and $\tilde{C}$ be fuzzy sets on X. The following properties are given for fuzzy sets (Ross, 2010).

1. $\emptyset \subset \tilde{A} \subset X$;
2. (Reflexive Law): $\tilde{A} \subset \tilde{A}$;
3. (Transferability Law): If $\tilde{A} \subseteq \tilde{B}$ and $\tilde{B} \subseteq \tilde{C}$, then $\tilde{A} \subseteq \tilde{C}$;
4. (Commutativity Law): $\tilde{A} \cup \tilde{B} = \tilde{B} \cup \tilde{A}$ and $\tilde{A} \cap \tilde{B} = \tilde{B} \cap \tilde{A}$
5. (Associativity Law): $(\tilde{A} \cup \tilde{B}) \cup \tilde{C} = \tilde{A} \cup (\tilde{B} \cup \tilde{C})$ and $(\tilde{A} \cap \tilde{B}) \cap \tilde{C} = \tilde{A} \cap (\tilde{B} \cap \tilde{C})$;

6. (Distributivity Law): $(\tilde{A} \cup \tilde{B}) \cap \tilde{C} = (\tilde{A} \cap \tilde{C}) \cup (\tilde{B} \cap \tilde{C})$ and $(\tilde{A} \cap \tilde{B}) \cup \tilde{C} = (\tilde{A} \cup \tilde{C}) \cap (\tilde{B} \cup \tilde{C})$;
7. (Absorption): $(\tilde{A} \cup \tilde{B}) \cap \tilde{A} = \tilde{A}$ and $(\tilde{A} \cap \tilde{B}) \cup \tilde{A} = \tilde{A}$;
8. (De Morgan's Laws): $(\tilde{A} \cup \tilde{B})^c = \tilde{A}^c \cap \tilde{B}^c$ and $(\tilde{A} \cap \tilde{B})^c = \tilde{A}^c \cup \tilde{B}^c$;
9. (Involution): $(\tilde{A}^c)^c = \tilde{A}$.

It should be noted that the complementarity law and mutually exclusive law are no longer valid for fuzzy sets:

$\tilde{A} \cap \tilde{A}^c \neq \emptyset$ and $\tilde{A} \cup \tilde{A}^c \neq X$.

Let $\tilde{A}$ be a fuzzy set, defined in universe of discourse X, and f is a nonfuzy transformation function between universes X and Y, so that $f: X \to Y$ (it is a mapping from a set X to a set Y). Let X be a cartesian product of n universes such as $X = X_1 \times X_2 \times \ldots \times X_n$, and $\tilde{A} = \tilde{A}_1 \times \tilde{A}_2 \times \ldots \times \tilde{A}_n$ are n fuzzy sets in those n universes, respectively. The mapping for these sets can now be defined as $\tilde{B} = f(\tilde{A}_1 \times \tilde{A}_2 \times \ldots \times \tilde{A}_n)$, where the membership function of the image $\tilde{B}$ is given by (Bector & Chandra, 2005; Ross, 2010):

$$\mu_{\tilde{B}}(\mathrm{y}) = \max_{\mathrm{y}=\mathrm{f}(\mathrm{x}_1,\mathrm{x}_2,\ldots,\mathrm{x}_n)} \left\{ \min[\mu_{\tilde{A}_1}(\mathrm{x}_1), \mu_{\tilde{A}_2}(\mathrm{x}_2), \ldots, \mu_{\tilde{A}_n}(\mathrm{x}_n)] \right\}. \tag{3.14}$$

In the literature Equation (3.14) is generally called Zadeh's *extension principle*. Equation (3.14) is expressed for a discrete-valued function, *f*. If the function *f* is a continuous-valued expression, the max operator is replaced by the sup (supremum) operator (the supremum is the least upper bound) (Bector & Chandra, 2005).

3.2.4 Fuzzy Numbers and Membership Functions

The concept of a fuzzy number arises from the fact that many quantifiable phenomena do not lend themselves to be characterized in terms of absolutely precise numbers (Klir & Yuan, 1995). It was first introduced in Zadeh (1975a, 1975b, 1975c) with the purpose of analyzing and manipulating approximate numeric values, for example “near 0,” almost 5,” “close to 12” and so forth. The concept has since been refined (Dubois & Prade, 1980, 1985), and several definitions exist (Galindo et al., 2006).

Let $\tilde{A}$ be a fuzzy set on R. It is called the *fuzzy number* if it satisfies the following properties (Bector & Chandra, 2005; Lee, 2005):

(i) $\tilde{A}$ is a normalized fuzzy set ($\exists x$: $\mu_{\tilde{A}}(x) = 1$),
(ii) $\tilde{A}$ is a convex fuzzy set,
(iii) A_α is a closed interval for every $\alpha \in (0, 1]$,
(iv) $\tilde{A}$ has the bounded support.

A Fuzzy number should be normalized. Here the condition of normalization implies that the maximum membership value is one. The support of a fuzzy number must be bounded and all α-cuts of $\tilde{A}$ (for $\alpha \neq 0$) must be closed intervals to define meaningful arithmetic operations on fuzzy numbers in terms of standard arithmetic operations on a closed interval (Klir & Yuan, 1995). The convex condition is that the line by α-cut is continuous and α-cut interval satisfies the condition $(\alpha' < \alpha) \Rightarrow (A_\alpha \subset A_{\alpha'})$ (Lee, 2005).

While every fuzzy number $\tilde{A}$ is expressed by a membership function of the form $\tilde{A}: \mathbb{R} \to [0, 1]$, not all membership functions of this form represent fuzzy numbers. To qualify as a fuzzy number, the membership function must capture intuitive conception of a set of numbers that are around a given real number or, possibly, around an interval of real numbers. Membership functions that conform to this intuitive conception must be expressed in the general form (Klir & Yuan, 1995)

$$\mu_{\tilde{A}}(x) = \begin{cases} \mu_{\tilde{A}}^{L}(x), & \text{for } x \in [a, b] \\ 1, & \text{for } x \in [b, c] \\ \mu_{\tilde{A}}^{R}(x), & \text{for } x \in [c, d] \\ 0, & \text{otherwise.} \end{cases} \tag{3.14}$$

$$\mu_{\tilde{A}}(x) = \begin{cases} \mu_{\tilde{A}}^{L}(x), & \text{for } x \in [a,b] \\ 1, & \text{for } x \in [b,c] \\ \mu_{\tilde{A}}^{R}(x), & \text{for } x \in [c,d] \\ 0, & \text{otherwise}. \end{cases} \tag{3.15}$$

where $a \leq b \leq c \leq d$, $\mu_{\tilde{A}}^{L}$ (x) is left membership function or increasing part of fuzzy number $\tilde{A}$ that increases to 1 at point b, and $\mu_{\tilde{A}}^{R}$ (x) is right membership function or decreasing part of fuzzy number $\tilde{A}$ that decreases from 1 at point c. A fuzzy number can be represented in discrete or continuous form (Chen & Hwang, 1992).

There are a great variety of shapes of membership functions for representing fuzzy numbers, as shown in Figure 3.3.

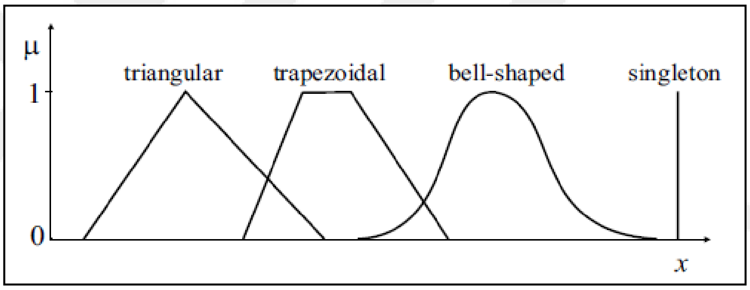

Figure 3.3 Different shapes of membership functions (Babuska, 2001)

Among the various shapes of fuzzy number, triangular fuzzy number (TFN) is the most popular one and so it is used within the scope of the thesis.

A TFN $\tilde{A}$ can be defined by a triplet (a, b, c) in which a and b are the lower and upper bounds of $\tilde{A}$ as illustrated in Figure 3.4 and the membership function $\mu_{\tilde{A}}(x)$ is identified as follows (Bector & Chandra, 2005; Lu et al., 2007):

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & \text{for } x < a \\ \dfrac{x-a}{b-a}, & \text{for } b \leq x \leq c \\ \dfrac{c-x}{c-b}, & \text{for } b \leq x \leq c \\ 0, & \text{for } x > c. \end{cases} \tag{3.16}$$

The α-cut of the TFN $\tilde{A} = (a, b, c)$ is the closed interval (Zimmermann, 1991)

$$A_\alpha = [a_\alpha^L, a_\alpha^R] = [(a-b)\alpha + a, c-(b-c)\alpha], \quad \alpha \in [0,1]. \tag{3.17}$$

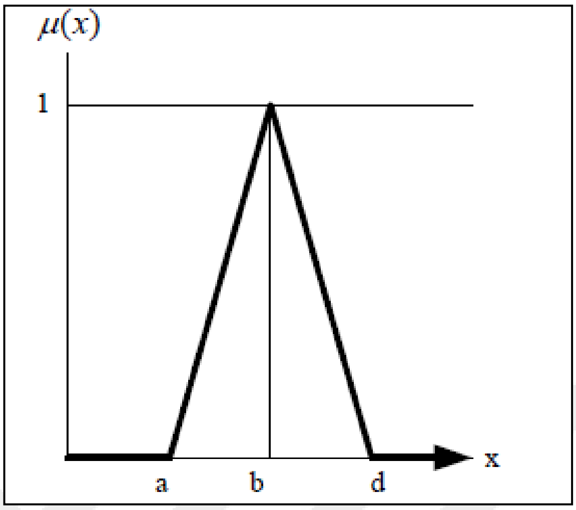

Figure 3.4 A triangular-shaped fuzzy number

3.2.5 Fuzzy Arithmetic Operations

Fuzzy arithmetic can be implemented by means of interval arithmetic. But there is a difference between them. While interval arithmetic has one (constant) level only, fuzzy arithmetic has several levels in the closed range of 0 and 1. That is, all α-cuts of a fuzzy number are considered as an interval (Bector & Chandra, 2005).

There are two basic approaches for arithmetic of fuzzy numbers that are: (1) the extension principle of Zadeh that allows to extend the classic arithmetical operations to the treatment of fuzzy numbers; and (2) the interval arithmetic on α–cuts (Buckley, 2005; Galindo et al., 2006).

3.2.5.1 Fuzzy Arithmetic Based on α-cuts

In this section, firstly a brief introduction to interval arithmetic is given and then the interval arithmetic on α-cuts for understanding the fuzzy arithmetic is explained.

Let $[a_1, b_1]$ and $[a_2, b_2]$ be two closed, bounded intervals of real numbers. If $*$ denotes the four basic arithmetic operations such as addition, subtraction, multiplication, and division, then $[a_1, b_1] * [a_2, b_2] = [\alpha, \beta]$ where (Buckley, 2005; Klir & Yuan, 1995)

$$[\alpha, \beta] = \{a * b \mid a_1 \le a \le b_1, a_2 \le a \le b_2\}. \tag{3.18}$$

If $*$ is division, it must be assumed that zero does not belong to $[a_2, b_2]$. Equation (3.18) is simplified as follows:

$$[a_1, b_1] + [a_2, b_2] = [a_1 + a_2, b_1 + b_2], \tag{3.19}$$

$$[a_1, b_1] + [a_2, b_2] = [a_1 - b_2, b_1 - a_2], \tag{3.20}$$

$$[a_1, b_1] \cdot [a_2, b_2] = [\mathrm{x}, \mathrm{y}], \tag{3.21}$$

where $x = min(a_1b_1, a_1b_2, a_2b_1, a_2b_2)$ and $y = max(a_1b_1, a_1b_2, a_2b_1, a_2b_2)$.

$$[a_1, b_1] / [a_2, b_2] = [a_1, b_1] \cdot [\frac{1}{b_2}, \frac{1}{a_2}] = [\mathrm{x}, \mathrm{y}], \tag{3.22}$$

where $x = min(a_1/b_2, a_1/a_2, b_1/b_2, b_1/a_2)$ and $y = max(a_1/b_2, a_1/a_2, b_1/b_2, b_1/a_2)$.

One approach to formulate the four basic arithmetic operations on fuzzy numbers is to represent the numbers by their α-cuts and employ interval arithmetic to the α-cuts. Consider two fuzzy numbers $\tilde{A}$ and $\tilde{B}$, and denote $*$ for any of the four interval arithmetic operations. Then for each $\alpha \in (0, 1]$, the α-cut of $A * B$ is defined in terms of the α-cuts of A and B by the formula (Klir & Yuan, 1995)

$$(\mathrm{A} * B)_\alpha = A_\alpha * B_\alpha, \tag{3.23}$$

which is not applicable when $*$ is division and $0 \in B_\alpha$ for any $\alpha \in (0, 1]$. Once the α-cuts $(A * B)_\alpha$ are determined, the resulting fuzzy number $\tilde{A} * \tilde{B}$ is readily expressed as (Klir & Yuan, 1995)

$$\tilde{A} * \tilde{B} = \bigcup_{\alpha} \alpha(A * B)_{\alpha}. \tag{3.24}$$

If $\tilde{A}$ and $\tilde{B}$ are fuzzy numbers, the α-level sets A_α and B_α can be written as $A_\alpha = [a_\alpha^L, a_\alpha^R]$ and $B_\alpha = [b_\alpha^L, b_\alpha^R]$. For a given $\alpha \in (0, 1]$, the basic arithmetic operations can be computed by applying the interval arithmetic on the closed intervals A_α and B_α as follows (Bector & Chandra, 2005):

$$A_\alpha (+) B_\alpha = [a_\alpha^L + b_\alpha^L, a_\alpha^R + b_\alpha^R], \tag{3.25}$$

$$A_\alpha (-) B_\alpha = [a_\alpha^L - b_\alpha^R, a_\alpha^R - b_\alpha^L], \tag{3.26}$$

$$A_\alpha (\cdot) B_\alpha \cong [a_\alpha^L b_\alpha^L, a_\alpha^R b_\alpha^R], \tag{3.27}$$

$$A_\alpha (\div) B_\alpha \cong [\frac{a_\alpha^L}{b_\alpha^R}, \frac{a_\alpha^R}{b_\alpha^L}], \quad 0 \notin [b_\alpha^L, b_\alpha^R]. \tag{3.28}$$

The multiplication of a fuzzy number by a real number k > 0 can be defined as follows:

$$(k \cdot A)_\alpha = k \cdot A_\alpha = [ka_\alpha^L, ka_\alpha^R]. \tag{3.29}$$

3.2.5.2 Fuzzy Arithmetic Based on Extension Principle

Let $\tilde{A}$ and $\tilde{B}$ be two fuzzy numbers. The basic arithmetic operations can be computed by applying the extension principle as follows (Buckley & Eslami, 2002).

If $\tilde{A} + \tilde{B} = \tilde{C}$, then the membership function for $\tilde{C}$ is defined as

$$\mu_{\tilde{C}}(z) = \sup_{x,y} \{\min(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y)) \mid x + y = z\} \text{ for } all \;\; z \in R. \tag{3.30}$$

If $\tilde{A} - \tilde{B} = \tilde{C}$, then the membership function for $\tilde{C}$ is defined as

$$\mu_{\tilde{C}}(z) = \sup_{x,y} \{\min(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y)) \mid x - y = z\} \text{ for } all \;\; z \in R. \tag{3.31}$$

Similarly, if $\tilde{C} = \tilde{A} \cdot \tilde{B}$, then

$$\mu_{\tilde{C}}(z) = \sup_{x,y} \left\{ \min(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y)) \mid x \cdot y = z \right\} \text{ for } all \ z \in R, \tag{3.32}$$

and if $\tilde{C} = \tilde{A}/\tilde{B}$, then

$$\mu_{\tilde{C}}(z) = \sup_{x,y} \left\{ \min(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y)) \mid x / y = z \right\} \text{ for } all \ z \in R. \tag{3.33}$$

In all cases $\tilde{C}$ is also a fuzzy number. It is assumed that zero does not belong to the support of $\tilde{B}$ in $\tilde{C} = \tilde{A}/\tilde{B}$.

3.2.5.3 Fuzzy Arithmetic Operations for TFNs

This section explains the fuzzy arithmetic operations for TFNs which are used in this thesis. Let $\tilde{A} = (a_l, a, a_u)$ and $\tilde{B} = (b_l, b, b_u)$ be two TFNs. Then, the arithmetic operations on TFNs are given by (Chen, 1994; Chen & Hwang, 1992;)

Image of $\tilde{A}$,

$$-\tilde{A} = (-a_l, -a, -a_u). \tag{3.34}$$

Inverse of $\tilde{A}$,

$$\tilde{A}^{-1} = \left(\frac{1}{a_l}, \frac{1}{a}, \frac{1}{a_u}\right). \tag{3.35}$$

Addition of $\tilde{A}$ and $\tilde{B}$,

$$\tilde{A}(+)\tilde{B} = (a_l + b_l, a + b, a_u + b_u). \tag{3.36}$$

Subtraction of $\tilde{A}$ and $\tilde{B}$,

$$\tilde{A}(-)\tilde{B} = (a_l - b_u, a - b, a_u - b_l). \tag{3.37}$$

Multiplications of $\tilde{A}$ and $\tilde{B}$,

$$\tilde{A}(\cdot)\tilde{B} \cong (a_l b_l, ab, a_u b_u) \quad if \quad \tilde{A} > 0, \tilde{B} > 0, \tag{3.38}$$

$$\tilde{A}(\cdot)\tilde{B} \cong (a_l b_u, ab, a_u b_l) \quad if \quad \tilde{A} < 0, \tilde{B} > 0, \tag{3.39}$$

$$\tilde{A}(\cdot)\tilde{B} \cong (a_u b_u, ab, a_l b_l) \quad if \quad \tilde{A} < 0, \tilde{B} < 0. \tag{3.40}$$

Division of $\tilde{A}$ and $\tilde{B}$,

$$\tilde{A}(\div)\tilde{B} \cong (\frac{a_l}{b_u}, \frac{a}{b}, \frac{a_u}{b_l}) \quad if \quad \tilde{A} > 0, \tilde{B} > 0, \tag{3.41}$$

$$\tilde{A}(\div)\tilde{B} \cong (\frac{a_u}{b_u}, \frac{a}{b}, \frac{a_l}{b_l}) \quad if \quad \tilde{A} < 0, \tilde{B} > 0, \tag{3.42}$$

$$\tilde{A}(\div)\tilde{B} \cong (\frac{a_u}{b_l}, \frac{a}{b}, \frac{a_l}{b_u}) \quad if \quad \tilde{A} < 0, \tilde{B} < 0. \tag{3.43}$$

Scalar Multiplications of $\tilde{A}$,

$$k\tilde{A} = (ka_l, ka, ka_u) \quad \forall k > 0, \ k \in \mathrm{R}, \tag{3.44}$$

$$k\tilde{A} = (ka_u, ka, ka_l) \quad \forall k < 0, \ k \in R. \tag{3.45}$$

3.2.6 Linguistic Variables

Any linguistic explanation is a formal illustration of systems made through fuzzy set theory, fuzzy relations, and fuzzy operators. It proposes an alternative way to define and utilize human languages in related analysis models and systems that contain linguistic and/or imprecise variables and constraints. Informal linguistic descriptions used by humans in daily life and in the performance of skilled tasks, namely control of industrial facilities, troubleshooting, aircraft landing, decision making, text searching and so on, are generally the initial point for the improvement of linguistic descriptions (Lu et al., 2007).

In the real life applications, the information cannot be defined and evaluated exactly in a quantitative way but can be in a qualitative one because of the unstable environment. In these applications, decision makers might not be able to express his/her goals or constraints precisely but rather in a fuzzy sense in terms of linguistic variables more easily and properly (Ross, 2010). For example, when the satisfactory for a product are evaluated, the terms like “very good”, “good”, “medium”, or “bad” can be used instead of numerical values. In a similar way, when the decision makers' preference for an alternative is expressed, linguistic terms such as “low” and “high” could be use (Lu et al., 2007).

Consider a variable, which in general takes numbers as its value. If the variable takes linguistic terms, it is called “*linguistic variables*” (Lee, 2005). That is, a *linguistic variable* is a variable “whose values are words or sentences in a natural or artificial language,” as Zadeh (1965) has put it. Take, for example the concept “Height,” which can be seen as a linguistic variable with values “very tall,” “tall,” “not tall,” “average,” “short,” “very short,” and so on. To each of these values, it may be assigned a membership function. Let the height range over a region [0, 230 cm] and assume that the linguistic terms are governed by a given set of rules. Then it is defined formally a linguistic variable (R. Zhang et al., 2005). In this thesis, the linguistic variables are used in the evaluation and implementation phases of proposed TPM PMS (For details see Chapter 5).

3.2.7 Fuzzy Ranking Methods

Ranking of fuzzy numbers plays a very important role in decision making and many other fuzzy application systems (Z. X. Wang, Liu, Fan, & Feng, 2009). For example, the concept of optimum or best choice to come true is completely based on ranking or comparison. Therefore, a key issue is how to set the rank of fuzzy numbers (Cheng, 1998).

For a finite set of real numbers there is no problem in ranking them from smallest to largest (Buckley, 2005). Unlike real numbers, fuzzy numbers have not natural and linear order (Wang & Kerre, 2001). In ranking fuzzy numbers, it does not always allow to achieve a totally ordered set and also so fuzzy numbers cannot be easily compared to each other (Chang & Lee, 1994). Since the study of fuzzy ranking began, various approaches that yield a totally ordered set have been developed (Cheng, 1998). However, there is no universally accepted way to do this and many of them produce different ranking outcomes for the same problem (Buckley, 2005). All the proposed fuzzy ranking methods have advantages as well as disadvantages (Allahviranloo, Abbasbandy, & Saneifard, 2011).

Since Jain (1976, 1977) employed the concept of maximizing set to order the fuzzy numbers in 1976, several researchers have investigated numerous fuzzy ranking methods (Abbasbandy & Hajjari, 2009). These methods range from the trivial to the complex, from including one fuzzy number attribute to including many fuzzy number attributes (Abbasbandy & Hajjari, 2009). In the literature, comparison and classification of these methods are made in different manners by some researchers (Abbasbandy & Asady, 2002; Bortolan & Degani, 1985; Chen & Hwang, 1992; Chang & Lee, 1994; Delgado, Verdegay, & Vila, 1988; Lee & Li, 1988; Zimmermann, 1987). Wang and Kerre (2001) suggested some axioms as reasonable properties to define the rationality of a fuzzy number ranking approach and systematically compared a wide array of the existing fuzzy number ranking methods. As a result, almost each approach, however, has pitfalls in some aspect, such as inconsistency with human intuition, indiscrimination, and difficulty of interpretation. So far, none of them is commonly accepted (Z. X. Wang et al., 2009).

Chen and Hwang (1992) categorized fuzzy ranking methods into four major groups namely *preference relation*, *fuzzy mean and spread*, *fuzzy scoring* and *linguistic expression* and determined various illogical conditions that arise among them. Figure 3.5 illustrates a classification of fuzzy ranking methods.

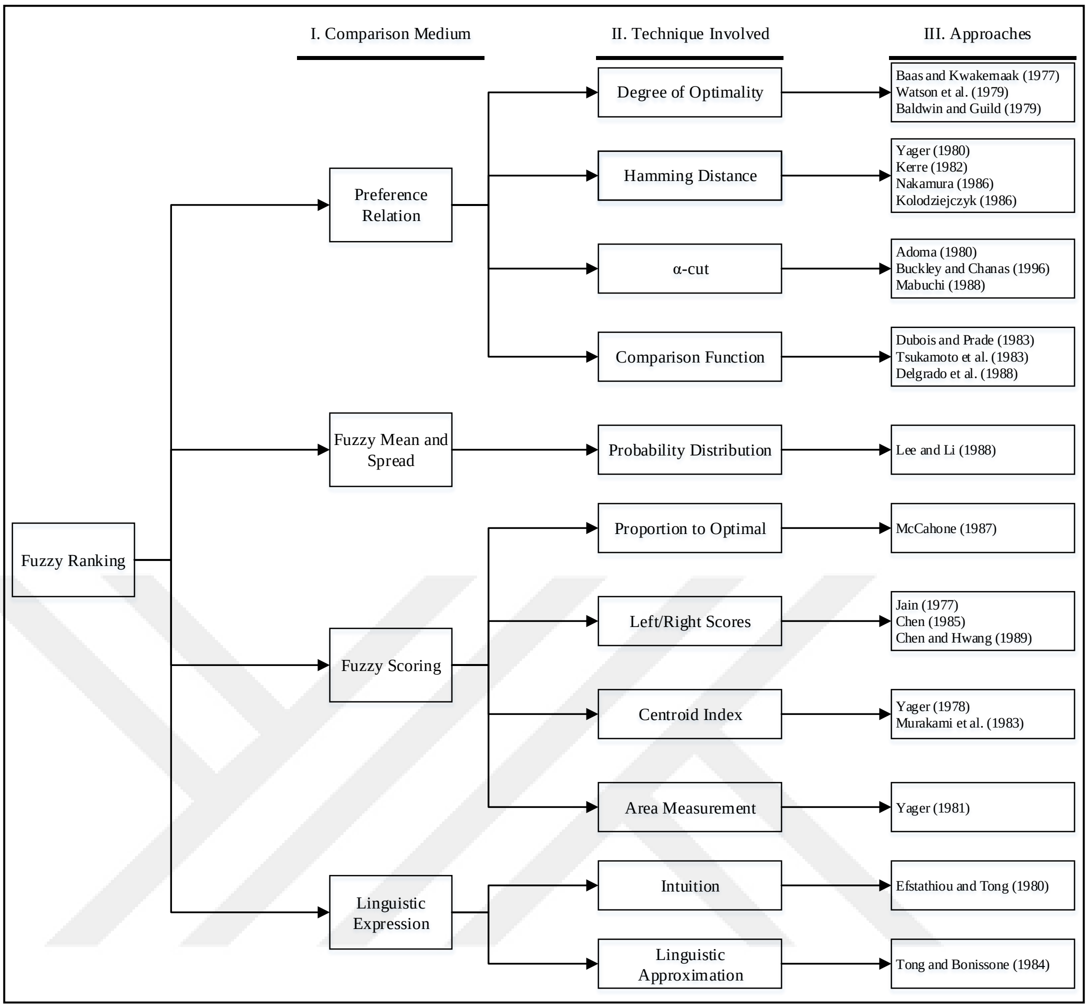

Figure 3.5 A classification of fuzzy ranking methods (Chen & Hwang, 1992)

Jain (1976, 1977) proposed a method which the decision maker takes into account only the right side membership function using the concept of maximizing set to rank the fuzzy numbers. A standard way to extend the natural ordering of real numbers to fuzzy numbers was proposed by Bass and Kwakernaak (1977). Dubios and Prade (1978) utilized maximizing sets to rank fuzzy numbers. Then, Baldwin and Guild (1979) investigated some disturbing disadvantages of these two methods. Moreover, in approaches (Adamo, 1980; Basirzadeh & Abbasi, 2008; Buckley & Chanas, 1996; Chang, 1981; Chen & Lu, 2001, 2002; Cheng & Mon, 1993; Liu, 2001; Liu & Han, 2005; Mabuchi, 1988) α-cut set and decision-maker's preference are performed for the constructing of fuzzy ranking function. Additionally, another widely used technique is the centroid-based fuzzy number ranking approach (Cheng, 1998; Chu & Tsao, 2002; Lee & Li, 1988; Murakami, Maeda, & Imamura, 1983; Wang & Lee, 2008; Yager, 1978; Y.-M. Wang, Yang, Xu, & Chin, 2006). Another commonly used technique is involved the construction of proper maps in order to transform a fuzzy number into a real number based on the area measurement (Abbasbandy & Asady, 2006; Abbasbandy & Hajjari, 2009, 2011; Asady, 2010; Deng & Liu, 2005; Deng, Zhu, & Liu, 2006; Hajjari, 2011; Hajjari & Abbasbandy, 2011; S. J. Chen & Chen, 2003, 2007; S. M. Chen & Chen, 2009; Watson, Weiss, & Donnell, 1979; Z. X. Wang et al., 2009; Yager, 1981). Negi and Lee (1993) and Iskander (2002) presented the possibility programming approach to rank of fuzzy numbers. Hashemi, Modarres, Nasrabadi, & Nasrabadi (2006) proposed a ranking method for fuzzy numbers based on comparison of mean and standard deviation of fuzzy numbers. Some researchers also proposed various approaches based on different distance functions to compare and to rank fuzzy numbers (Abbasbandy & Amirfakhrian, 2006; Abbasbandy & Abbasbandy, Lucas, & Asady, 2003; Asady, 2006; Asady & Zendehnam, 2007; Facchinetti & Ricci, 2004; Tsukamoto, Nikiforuk, & Gupta, 1983; Yao & Wu, 2000).

In the literature, as mentioned in the paragraphs above, there are different approaches and methods in order to rank fuzzy numbers and there is no best method agreed. In the selection of the appropriate fuzzy ranking method, the shape (triangular) of the fuzzy numbers and consistency in fuzzy arithmetic method used in this thesis are taken into account. Accordingly, the fuzzy ranking method based on α-cut which is proposed by Basirzadeh and Abbasi (2008) is employed within the scope of the thesis.

Basirzadeh and Abbasi (2008) introduced an effective parametric method for comparison and ranking of fuzzy numbers. This method recommends significant advantages over similar methods, in the comparison of intersected fuzzy numbers, rendering the comparison between fuzzy numbers possible in different decision levels that are related to α-cuts. This method is explained as below.

Let $\tilde{A}_{\omega} = (\underline{A}(r),\ \overline{A}(r))$, $0 \leq r \leq \omega$ be a fuzzy number. Then, the value $Q_{\alpha}\big(\tilde{A}_{\omega}\big)$, is assigned to $\tilde{A}_{\omega}$ for a decision level higher than "α" which is calculated as follows:

$$Q_\alpha(\tilde{A}_\omega) = \int_\alpha^\omega \left\{ \underline{A}(\mathrm{r}) + \overline{A}(\mathrm{r}) \right\} dr, \quad where\ 0 \le \alpha \le 1. \tag{3.46}$$

This quantity will be used as a basis for comparing fuzzy numbers in decision level higher than α. It is clear that if $\alpha \ge \omega$, then $Q_\alpha(\tilde{A}_\omega) = 0$. In order to explain the concept of the above mentioned quantity, consider the following fuzzy number shown as in Figure 3.6.

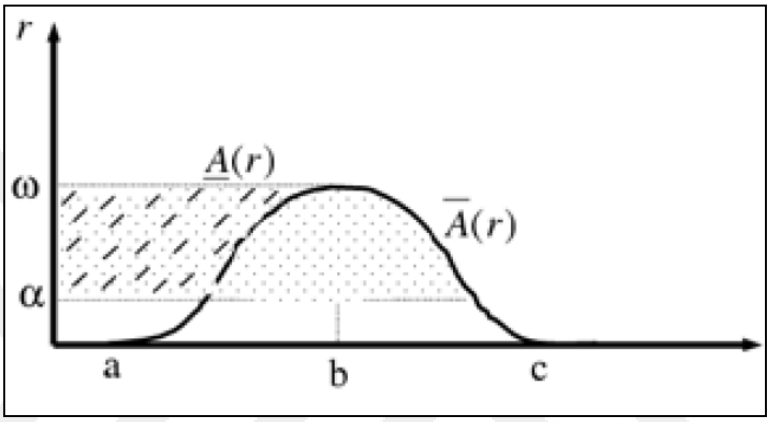

Figure 3.6 $Q_\alpha(\tilde{A}_\omega)$ Quantity (Basirzadeh & and Abbasi, 2008)

As shown in Figure 3.6, the presented quantity is the summation of the dotted area and the cross-hatched area given in the following equation.

$$\begin{aligned} Q_\alpha(\tilde{A}_\omega) &= \int_\alpha^\omega \left\{ \underline{A}(\mathrm{r}) + \overline{A}(\mathrm{r}) \right\} dr = \int_\alpha^\omega \underline{A}(\mathrm{r}) dr + \int_\alpha^\omega \overline{A}(\mathrm{r}) dr \\ &= (cross - hatched\, area) + (dotted\, area). \end{aligned} \tag{3.47}$$

If $\tilde{A}_\omega$ and $\tilde{B}_\omega$ are two fuzzy numbers and ω, $\omega' \in [0,1]$, then the following definitions are given:

(1) $\tilde{A}_\omega \le \tilde{B}_{\omega'} \iff \forall \alpha \in [0,1]\ Q_\alpha(\tilde{A}_\omega) \le Q_\alpha(\tilde{B}_{\omega'})$,

(2) $\tilde{A}_\omega = \tilde{B}_{\omega'} \iff \forall \alpha \in [0,1]\ Q_\alpha(\tilde{A}_\omega) = Q_\alpha(\tilde{B}_{\omega'})$,

(3) $\tilde{A}_\omega \ge \tilde{B}_{\omega'} \iff \forall \alpha \in [0,1]\ Q_\alpha(\tilde{A}_\omega) \ge Q_\alpha(\tilde{B}_{\omega'})$.

If two arbitrary fuzzy numbers including $\tilde{A}_{\omega}$ and $\tilde{B}_{\omega'}$ at decision levels higher than "α" and $\alpha, \omega, \omega' \in [0, 1]$ are compared, then the following definitions are given:

(1) $\tilde{A}_{\omega} \leq_{\alpha} \tilde{B}_{\omega'} \Leftrightarrow \forall\alpha \in [0, 1]\ Q_{\alpha}(\tilde{A}_{\omega}) \leq_{\alpha} Q_{\alpha}(\tilde{B}_{\omega'})$,
(2) $\tilde{A}_{\omega} =_{\alpha} \tilde{B}_{\omega'} \Leftrightarrow \forall\alpha \in [0, 1]\ Q_{\alpha}(\tilde{A}_{\omega}) =_{\alpha} Q_{\alpha}(\tilde{B}_{\omega'})$,
(3) $\tilde{A}_{\omega} \geq_{\alpha} \tilde{B}_{\omega'} \Leftrightarrow \forall\alpha \in [0, 1]\ Q_{\alpha}(\tilde{A}_{\omega}) \geq_{\alpha} Q_{\alpha}(\tilde{B}_{\omega'})$,

where $\tilde{A}_{\omega} \leq_{\alpha} \tilde{B}_{\omega'}$, i.e., at decision levels higher than α, $\tilde{B}_{\omega'}$is greater than or equal to $\tilde{A}_{\omega}$.

If α is close to one, the pertaining decision is called a "*high level decision*", in which case only parts of the two fuzzy numbers, with membership values between "α", and "*1*", will be compared. Likewise, If α is close to zero, the pertaining decision is called a "*low level decision*", since members with membership values lower than both the fuzzy numbers are involved in the comparison. If $\tilde{A}_{\omega} = \left(\underline{A}(r),\ \overline{A}(r)\right) = (x_0 - \delta + \frac{\delta}{\omega}r, x_0 + \beta - \frac{\beta}{\omega}r)$ is a TFNs, then $Q_{\alpha}^{Tri}(\tilde{A}_{\omega})$ is calculated as in Equation (3.48):

$$\begin{aligned} Q_{\alpha}^{Tri}(\tilde{A}_{\omega}) &= \int_{\alpha}^{\omega} \left\{\underline{A}(r) + \overline{A}(r)\right\} dr \\ &= \int_{\alpha}^{\omega} \left(2x_0 + (\beta - \delta)(1 - \frac{r}{\omega}) \right) dr = 2x_0[\omega - \alpha] + \frac{(\beta - \delta)}{2\omega}(\omega - \alpha)^2 \end{aligned} \tag{3.48}$$

where the value corresponding to the TFN $\tilde{A}_{\omega}$ pertains to a decision level higher than α.

Obviously, if $\alpha \geq \omega$, then Equation (3.48) equals to zero. It can also be seen that if $\tilde{A}$ is a normal TFN ($\omega = 1$) and denoted by $\tilde{A} = (x_0, \delta, \beta)$, then Equation (3.48) reduces to:

$$Q_{\alpha}^{Tri}(\tilde{A}) = 2x_0(1 - \alpha) + \frac{(\beta - \delta)}{2}(1 - \alpha)^2. \tag{3.49}$$

3.3 Fuzzy Multicriteria Decision Making

Multicriteria decision making (MCDM) is one of the research fields of operations research and management science that develops and implements the decision support tools and approaches to solve complex decision problems containing multiple criteria, goals, or objectives of conflicting nature (Zopounidis & Doumpos, 2002). It deals with screening, evaluating, prioritizing, ranking, or selecting a set of alternatives (also referred to as "candidates" or "actions") under usually independent, incommensurate or conflicting criteria with respect to decision maker(s) preferences (Belton & Steward, 2002; Carrizosa, Conde, Munoz-Marquez, & Puerto, 1995; Herrera & Herrera-Viedma, 2000; Herrera, Herrera-Viedma, & Martinez, 2000; Mardani, Jusoh, & Zavadskas, 2015).

The MCDM framework makes decision and scores or ranks the performance of alternative decision options in the presence of multiple and conflicting criteria which are typically measured in different units (Sadiq & Tesfamariam, 2009). The MCDM problems usually share the following common features (Hwang & Yoon, 1981; Lu et al., 2007):

- "*Multiple criteria*: each problem has multiple criteria, which can be objectives or attributes.
- *Conflicting among criteria*: multiple criteria conflict with each other.
- *Incommensurable unit*: criteria may have different units of measurement.
- *Design/selection*: solutions to an MCDM problem are either to design the best alternative(s) or to select the best one among previously specified finite alternatives."

The MCDM problems are broadly categorized in two groups such as multi-objective decision making (MODM) and MADM, depending on whether the problem is a selection problem or a design problem (Chen & Hwang, 1992; Rao, 2007). MODM methods have decision variable values that are determined in a continuous or integer domain with either an infinitive or a large number of alternative choices, the best of which should satisfy the decision maker's constraints and preference priorities. MADM methods, on the other hand, are generally discrete, with a limited number of pre-specified alternatives. These methods require both intra- and inter-attribute comparisons, and involve explicit tradeoffs that are appropriate for the problem considered (Rao, 2007). The basic difference between MODM and MADM is that the former concentrates on continuous decision spaces, primarily on mathematical programming with several objective functions, while the latter focuses on problems with discrete decision spaces (Lu et al., 2007). In MCDM problems, some basic concepts such as criteria, objectives, goals, attributes and alternatives are defined by Hwang and Masud (1979) and Hwang and Yoon (1981) the following (Figueira, Greco, & Ehrgott, 2005; Lu et al., 2007).

"***Criteria** are the standard of judgment or rules to test acceptability. In the MCDM literature, it indicates attributes and/or objectives. In this sense, any MCDM problem means either MODM or MADM, but is more used for MADM*."

"***Objectives** are the reflections of the desire of decision makers and indicate the direction in which decision makers want to work. An MODM problem, as a result, involves the design of alternatives that optimizes or most satisfies the objectives of decision makers.*"

"***Goals** are things desired by decision makers expressed in terms of a specific state in space and time. Thus, while objectives give the desired direction, goals give a desired (or target) level to achieve*."

"***Attributes** are the characteristics, qualities, or performance parameters of alternatives. An MADM problem involves the selection of the 'best' alternative from a pool of pre-selected alternatives described in terms of their attributes*."

"***Alternatives** correspond to the particular case in which modeling is such that two distinct potential actions, which constitute the object of the decision, or that* *which decision aiding is directed towards, can in no way be conjointly put into operation*."

In real world, problems in regard to decision making generally involve uncertainties which arise from unquantifiable information, incomplete information, unobtainable information, and partial ignorance. These uncertainties can be addressed using the fuzzy sets theory. Therefore, Bellman and Zadeh (1970) and Zimmermann (1978) introduced fuzzy sets into the MCDM field (Kahraman, 2008).

An MCDM problem at tactical and strategic levels often involves fuzziness in its criteria (attributes) and decision makers' judgments. This kind of decision problems is called *Fuzzy Multicriteria Decision Making (FMCDM)* (Lu et al., 2007).

FMCDM has been one of the fastest growing areas in decision making during the last two decades. In that, the development of FMCDM is related to a large number of criteria that decision makers are hoped to integrate in their actions and the difficulty of stating decision makers' opinions by crisp values in practice (Kahraman, 2008).

In the literature, various FMCDM methods have been proposed, which are different in areas such as the type of questions asked, theoretical background, and type of obtained results (Mardani et al., 2015). These methods are used to evaluate alternatives according to predetermined criteria through either a single decision maker or a committee of decision makers, where suitability of alternatives versus criteria, and the importance weights of criteria can be assessed using linguistic variables expressed by fuzzy numbers (Chen & Hwang, 1992; Kahraman, Cevik Onar, & Oztaysi, 2015). Numerous review papers were reported on the use of FMCDM methods in various fields of application (Abdullah, 2013; Baas & Kwakernaak, 1977; Carlsson & Fuller, 1996; Chen & Hwang, 1992; Dubois & Prade, 1980; Fodor & Roubens, 1994; Kahraman, 2008; Kickert, 1978; Liou, 2013; Liou & Tzeng, 2012; Luhandjula, 1989; Ribeiro, 1996; Sakawa, 1993; Triantaphyllou & Lin, 1996; Zavadskas & Turskis, 2011; Zimmermann, 1987, 1991; Yager, 1978). Recently, a comprehensive literature review of FMCDM techniques and applications in the last two decades has been presented in the studies of Kahraman et al. (2015) and Mardani et al. (2015).

3.3.1 Fuzzy Multi Attribute Decision Making

MADM refers to making preference decision (evaluation, prioritization, and selection) over the available alternatives that are characterized by multiple, usually conflicting, attributes (Chen & Hwang, 1992). The main feature of MADM is that there are usually a limited number of predetermined alternatives, which are associated with a level of the achievement of the attributes (Lu et al., 2007). Based on the attributes, the final decision is to be made. Also, the final selection of the alternative is made with the help of inter- and intra-attribute comparisons. The comparison may involve explicit or implicit trade-off (Rao, 2007).

An MADM problem can be concisely expressed in a matrix format called a decision matrix. Each decision matrix in MADM problems has four main parts, namely: (a) alternatives, (b) attributes, (c) weight or relative importance of each attribute, and (d) measures of performance of alternatives with respect to the attributes (Chen & Hwang, 1992; Rao, 2007). Mathematically, a typical MADM problem can be modeled as follows (Lu et al., 2007):

$$\text{(MADM)}\begin{cases} Select: A_1, A_2, ..., A_m \\ s.t.: C_1, C_2, ..., C_n \end{cases} \tag{3.50}$$

where $A = (A_1, A_2, \dots, A_n)$ denotes m alternatives, $C = (C_1, C_2, \dots, C_n)$ represents n attributes (often called criteria) for characterizing a decision situation. The *select* here is normally based on maximizing a multi attribute value (or utility) function elicited from the stakeholders. The basic information involved in this model can be represented by the decision matrix as follows (Lu et al., 2007):

where $A_1, A_2, \dots, A_n$ are alternatives from which decision maker choose; $C_1, C_2, \dots, C_n$ are attributes with which alternative performances are measured; x_{ij}, $i = 1, \dots, m, j = 1, \dots, n$, is the rating of alternative A_i with respect to attribute C_j; w_j is the weight of attribute C_j.

$$D = \begin{array}{c|cccc|} & C_1 & C_2 & \cdots & C_n \\ \hline A_1 & x_{11} & x_{12} & \cdots & x_{1n} \\ A_2 & x_{12} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_M & x_{1m} & x_{2m} & \cdots & x_{nm} \end{array}$$

$$W = \begin{bmatrix} w_1 & w_2 & \cdots & w_n \end{bmatrix} \quad and \quad \sum_{j=1}^{n} w_j = 1 \tag{3.51}$$

An MADM method specifies how attribute information is to be processed in order to arrive at a choice. In the literature, there are numerous MADM methods and each of them has its own characteristics and applicability (Chen & Hwang, 1992). A review and classification of the various MADM methods have been presented in (Chen & Hwang, 1992; Figueira et al., 2005; Gul, M., Celik, Aydin, Taskin Gumus, & Guneri, 2016; Hwang & Yoon, 1981; Kabir, Sadiq, & Tesfamariam, 2014; Kahraman, 2008; Ölçer & Odabaşi, 2005; Olson, 1992, 2000; Stewart, 1992; Triantaphyllou & Sanchez, 1997; Triantaphyllou, 2000; Yoon & Hwang, 1995; Zanakis, Solomon, Wishart, & Dublish, 1998; Zavadskas & Turksis, 2011). Various classifications have been proposed by different researchers according to information type, solution aimed at, data type and so on. For example, Kahraman (2008) stated that the classical MADM methods can be classified as to whether if they are compensatory (methods which incorporate tradeoffs between high and low performance into the analysis) or noncompensatory (those methods which do not as compensatory methods). Another wider overview of MADM methods, classification and applications were presented by Zavadskas and Turskis (2011). Figure 3.7 illustrates a classification of the classical MADM methods according to the information type from the decision maker and the salient features of the information (Hwang & Yoon, 1981; Zavadskas & Turksis, 2011).

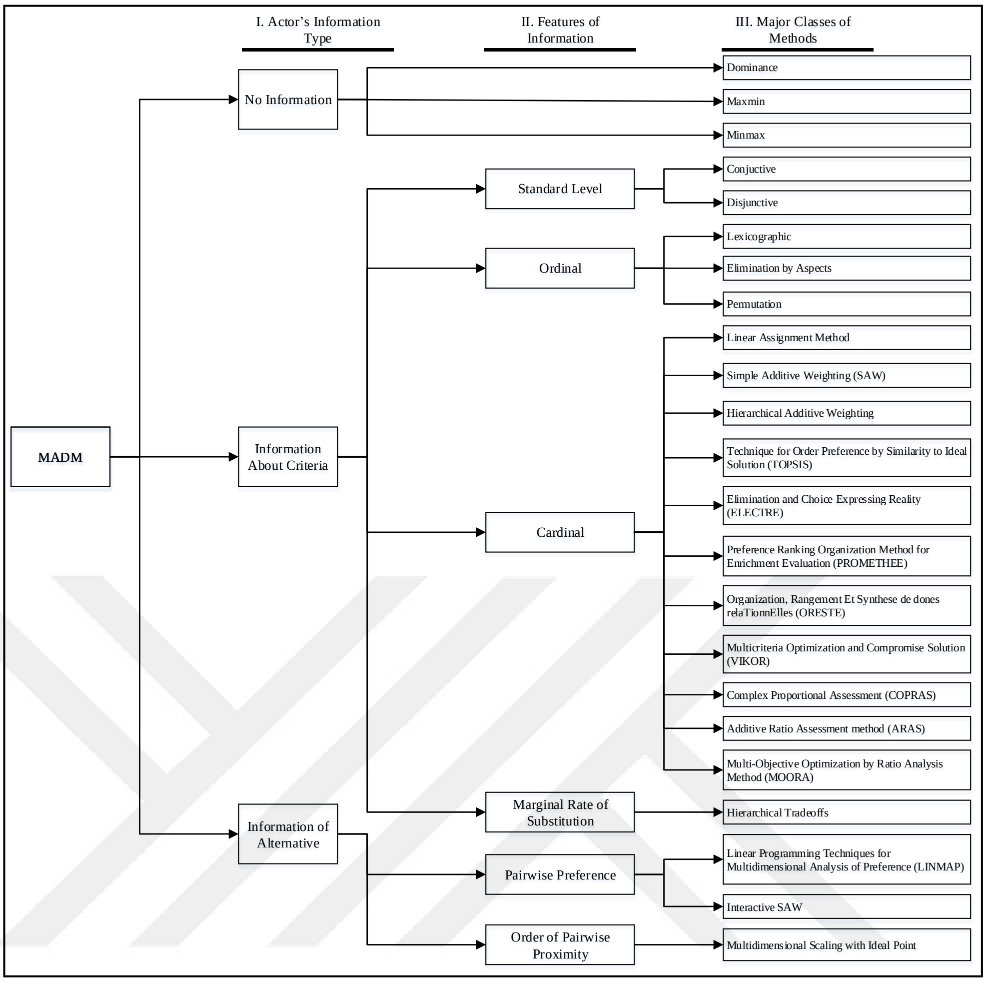

Figure 3.7 A classification of classical MADM methods (Hwang & Yoon, 1981; Zavadskas & Turksis, 2011)

Classical MADM methods cannot effectively handle problems with such imprecise information. To resolve this difficulty, FMADM methods are used (Rao, 2007). FMADM methods basically consist of two phases. In *phase (1)*, the aggregation of the performance ratings (or the degree of satisfactions) with respect to all attributes for each alternative is made. In *phase (2)*, the alternatives according to the overall aggregated performance ratings are ranked (Chen & Hwang, 1992). The methods for solving *phase (1)* problems are referred to as "fuzzy ranking methods" (See Section 3.2.7), and methods for solving *phase (2)* and/or both phases of FMADM problems are referred to as FMADM methods (Chen & Hwang, 1992; Ölçer & Odabaşi, 2005). It is worth emphasizing that many of the basic concepts of these classical MADM methods (mentioned in the paragraphs above) are used in

FMADM methods. Hence, an FMADM problem can be modeled by redesigning of Equation (3.51) and illustrated as follows (Lu et al., 2007):

$$
\begin{array}{c}
\tilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_M \end{array}
\begin{array}{c}
\begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\
\begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{12} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{1m} & \tilde{x}_{2m} & \cdots & \tilde{x}_{nm} \end{bmatrix}
\end{array} \\
\tilde{W} = \begin{bmatrix} \tilde{w}_1 & \tilde{w}_2 & \cdots & \tilde{w}_n \end{bmatrix}
\end{array}
\tag{3.52}
$$

where $\tilde{x}_{ij}\ \forall i,j$ and $\tilde{w}_j,\ j = 1, \dots, n$ can be linguistic variables that are described by any form of fuzzy numbers. For example, in TFNs, $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and $\tilde{w}_{ij} = (w_{j1}, w_{j2}, w_{j3})$.

During the last two decades, several FMADM methods have been proposed and reviewed. For example, Chen and Hwang (1992) presented the taxonomy of FMADM methods. In this taxonomy, the classification was made in five stages such as problem size (characterized by the number of attributes and the number of alternatives), data type (all fuzzy, all fuzzy singleton, all crisp or a mixture of fuzzy and crisp), corresponding classical MADM methods (SAW, Analytic Hierarchical Process (AHP) method, Conjunctive method, Disjunctive method, Multiple Attribute utility Function (MAUF) theory, Outranking method, Maximin, TOPSIS, and general classical MADM methods), technique involved (α-cut, fuzzy arithmetic operations, weight assessing method (Eigenvector method), possibility and necessity measures, human intuition, fuzzy outranking relation, maximum and minimum operators, and semantic modeling (linguistic data as fuzzy data and crisp number).

Ölçer and Odabaşi (2005) also classified the most of the FMADM methods according to type of performance ratings, type of attribute weights, result of the phase (1), and group decision making (GDM) means. Table 3.1 gives this classification.

Table 3.1 Classification of the most of the FMADM methods in the literature

FMADM Approaches	Performance Ratings		Attributes Weights		Result of the Phase (1)	GDM
	Crisp	**Fuzzy**	**Crisp**	**Fuzzy**		
SAW based techniques						
Baas and Kwakernaak (1977)		√		√	Fuzzy	X
Kwakernaak (1979)		√		√	Fuzzy	X
Dubois and Prade (1983)		√		√	Fuzzy	X
Cheng and McInnis (1980)		√		√	Fuzzy	X
Bonissone (1982)	√	√	√	√	Fuzzy	X
AHP based techniques						
Laarhoven and Pedrycz (1983)		√		√	Fuzzy	√
Buckley (1985)		√		√	Fuzzy	√
Ruoning and Xiaoyan (1992)		√		√	Fuzzy	√
Chang (1996)		√		√	Fuzzy	√
Outranking relation based techniques						
Roy (1977)	√		√		Crisp	X
Siskos, Lochard, & Lombard (1984)	√		√		Crisp	X
Brans, Mareshal, & Vincke (1984)	√		√		Crisp	X
Takeda (1982)	√		√		Crisp	X
Wang (1997)		√		√	Crisp	X
Implied conjunction techniques						
Bellman and Zadeh (1970)		√			Crisp	X
Yager (1978)		√	√		Crisp	X
Fuzzy linguistic approaches						
Liang and Wang (1991, 1993)		√		√	Fuzzy	√
Chang and Chen (1994)		√		√	Fuzzy	√
Wang and Chang (1995)		√		√	Fuzzy	√
Chen (1997)		√		√	Fuzzy	√
Rangone (1998)		√		√	Fuzzy	X
Liang (1999)		√		√	Fuzzy	√
Yeh, Deng, & Chang (2000)		√		√	Crisp	X
Chen (2001)	√	√		√	Fuzzy	√
Miscellaneous FMADM techniques						
Efstathiou (1979)		√			Fuzzy	√
Dubois, Prade, & Testemale (1988)		√	√		Crisp	X
Negi (1989)	√	√		√	Crisp	X
Chen and Hwang (1992)	√	√	√		Crisp	X

Kahraman et al. (2015) classified and summarized the FMADM methods as outranking methods (fuzzy ELECTRE, fuzzy PROTHEMEE, fuzzy ORESTE), distance based methods (fuzzy VIKOR, fuzzy TOPSIS), pairwise comparison based methods (fuzzy AHP, fuzzy Analytic Network Process (ANP), fuzzy Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH)) and other FMADM methods (fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL), fuzzy axiomatic design, fuzzy Choquet integral).

Literature review also indicates that recently developed MADM methods such as COPRAS, ARAS, Step-Wise Weight Assessment Ratio Analysis (SWARA), MOORA, Weighted Aggregated Sum Product Assessment (WASPAS) and etc., and their modifications have been applied to solve different kinds of problems using fuzzy and grey number theory (Zavadskas, Turskis, & Kildiene, 2014).

As seen above paragraphs, there are a lot of different MADM and FMADM methods. The selection of appropriate decision method depends on the aim of the problem, available information, costs of decision and actors' (persons which are making decisions) qualification (Zavadskas & Turksis, 2011). In this thesis, COPRAS-G and improved FCOPRAS methods are applied in the evaluation phase of proposed TPM PMS, since it has the following advantages:

- it uses not certain, unclear information about the alternatives' criterion values stated in terms of intervals;
- it is more appropriate in real life applications;
- its calculations are not complex and very proper for the fuzzy arithmetic based on α-cuts;
- it needs smaller samples not involving a typical distribution; and
- it is an effective method in taking care of discrete and interval data.

3.3.2 COPRAS-G Method

3.3.2.1 Literature Review on COPRAS-G Method

The COPRAS-G method which presented in this section employs a stepwise ordering and assessing procedure of the alternatives with respect to importance and utility degree based on the Grey systems theory (Zavadskas et al., 2014).

A literature review for COPRAS-G method using "Scopus" gives 222 published papers (all fields) among these, 39 papers mention COPRAS-G method in "article title, abstract, keywords". This literature review includes the period of between 2008 and September 2016. The papers mentioned COPRAS-G method in "article title, abstract, keywords" are surveyed by analyzing the publishing frequencies with respect to years, the document type; the research areas and the journals publishing COPRAS-G method, respectively shown as in Figures 3.8, 3.9 and 3.10 and Table 3.2.

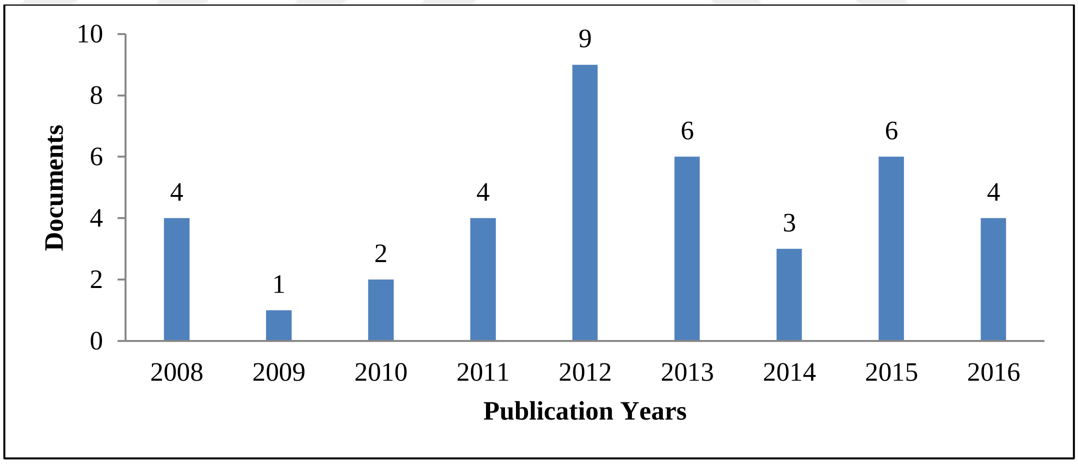

Figure 3.8 Published papers using COPRAS-G method over years

According to Figure 3.9, 30 papers using COPRAS-G are published as an article, 8 papers as a conference paper and 1 paper as a book chapter. The areas of *Engineering*, *Business Management and Accounting*, *Economics*, *Econometrics and Finance* are the most studied research fields on COPRAS-G shown in Figure 3.10.

The *Journals of Civil Engineering and Management* and *Technological and Economic Development of Economy* have the most publishing papers using COPRAS-G method given as in Table 3.2. Moreover, E. K. Zavadskas (with 16 publications), S. Hashemkhani Zolfani (with 11 publications), Z. Turksis (with 8 publictions), N. Rezaeiniya (with 7 publications), M. H. Aghdaie (with 6 publications) and A. Kaklauslas (with 5 publications) are the most productive researchers on COPRAS-G.

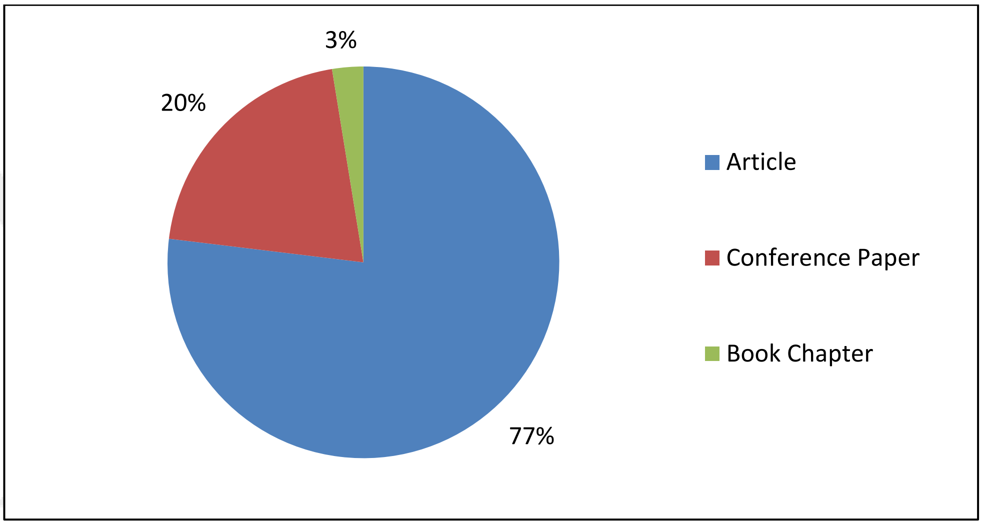

Figure 3.9 The classification of published papers using COPRAS-G according to document types

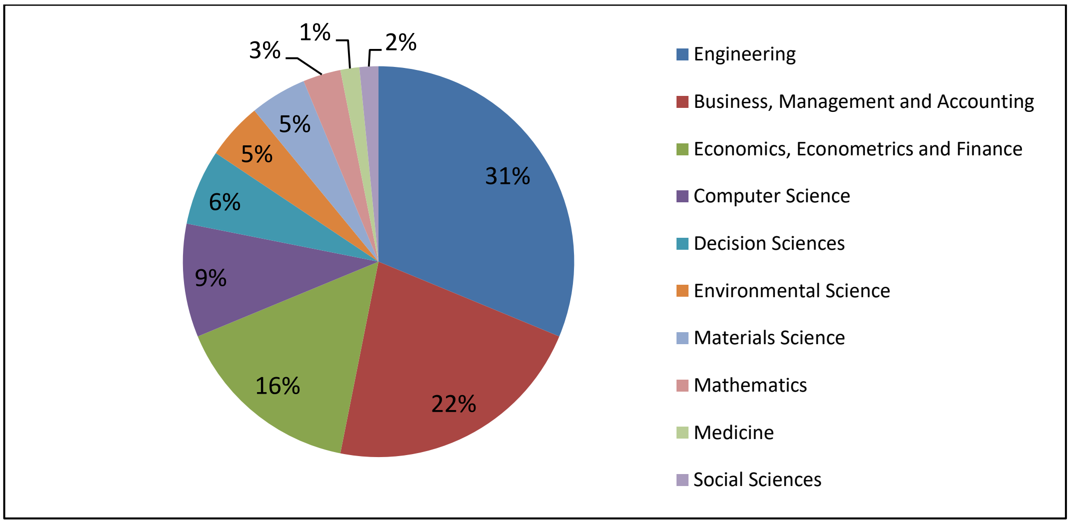

Figure 3.10 Research areas of the examined papers using COPRAS-G

Table 3.2 Journals that publish COPRAS-G based articles

Journal	Total
Journal of Civil Engineering and Management	3
Technological and Economic Development of Economy	3
Engineering Economics	2
Environmental Monitoring and Assessment	2
Expert Systems with Applications	2
Materials and Design	2
Others	16

The COPRAS-G method has been applied for the solution of many and complicated MCDM problems by several researchers in the literature as given in the following paragraph.

Zavadskas and Vilutiene (2006) proposed a model based on a multiattribute evaluation of dwelling maintenance contractors by applying COPRAS-G. Zavadskas, Turskis, and Tamosaitiene (2008a) considered the application of grey relations methodology for contractors' assessment and selection in a competitive and risky environment. Zavadskas, Kaklauskas, Turskis, and Tamosaitiene (2008b) used COPRAS-G method to assess external walls. Zavadskas, Turskis, Tamosaitiene, and Marina (2008c) presented a model based on multicriteria evaluation of project managers. Ginevicius and Podvezko (2008) evaluated some banks from the perspective of their reliability for customers using COPRAS-G.

Datta, Beriha, Patnaik, and Mahapatra (2009) and Hashemkhani Zolfani, Rezaeiniya, Aghdaie, and Zavadskas (2012a) used COPRAS-G method for employee selection. Bindu Madhuri, Anand Chandulal, and Padmaja (2010) selected the best websites based on COPRAS-G. Zavadskas, Vilutiene, Turskis, and Tamosaitiene (2010) applied the COPRAS-G method in the contractor selection problem.

Aghdaie, Hashemkhani Zolfani, Rezaeinia, and Mehri-Tekmeh (2011) studied on the evaluation of the segmentation of the market using with the real data of a chair manufacturer in Iran. They used COPRAS-G in the evaluation of alternatives whose weights were determined by fuzzy AHP.

Bitarafan, Hashemkhani Zolfani, Arefi, and Zavadskas (2012) used COPRAS-G method to select proper construction methods when the emergency situations are used to convert into the normal state by considering sustainable development and all safety regulations in the reconstruction of the damaged areas. Rezaeiniya, Hashemkhani Zolfani, and Zavadskas (2012) described the research and development of hybrid MCDM methods for greenhouse locating. In this study, ANP was applied to find the relative weights among the criteria and to emphasize the interdependent relationships, and then COPRAS -G method was applied to rank for five regions in Amol city in Iran to increase the accuracy of their results. Maity, Chatterjee, and Chakraborty (2012) applied COPRAS-G method to select the most appropriate cutting tool material with the desired properties for enhanced machining performance. Sahu, Datta, and Mahapatra, (2012) and Hashemkhani Zolfani, Chen, Rezaeiniya, and Tamosaitiene (2012b) presented the evaluation and selection of suppliers. Barysien (2012) applied COPRAS-G method for the evaluation of container terminal technologies.

Aghdaie, Hashemkhani Zolfani, and Zavadskas (2013a) proposed an integrated approach with COPRAS-G and SWARA methods for the selection of machine tools. Aghdaie, Hashemkhani Zolfani, and Zavadskas (2013b) proposed a model based on fuzzy AHP and COPRAS-G methods for the evaluation and selection of market segment. Additionally, Aghdaie, Hashemkhani Zolfani, and Zavadskas (2013c) extended the study of Aghdaie et al. (2013b) by adding data mining concept. Tamosaitiene and Gaudutis (2013) used the COPRAS-G method to select a structural system for a high-rise building. Tavana, Momeni, Rezaeiniya, Mirhedayatian, and Rezaeiniya (2013a) proposed a hybrid model based on fuzzy ANP and COPRAS-G methods for the selection of proper social media platform.

Ecer (2014) proposed a hybrid model based on AHP and COPRAS-G methods to evaluate the quality of banking websites. Adhikary, Bose, Bose, and Mitra, (2014) used the COPRAS-G method for a multi criterion failure mode effect and criticality analysis for coal-fired thermal power plant.

Nguyen, Dawal, Nukman, and Aoyama (2014) proposed the hybrid approach of the fuzzy ANP and COPRAS-G to select machine tools.

Ecer (2015) suggested a hybrid model including two techniques, namely the fuzzy AHP and COPRAS-G to evaluate the performance of internet banking branches. Miranda Lakshmi, Prasanna Venkatesan, and Martin, (2015) applied COPRAS-G method to find better hospital for cardiology treatment.

Pancholi and Bhatt (2016) have performed the COPRAS-G method to identify the weights of major failure causes for bearings, gears, and shafts of aluminum wire rolling mill plant. Saha and Majumder (2016) have carried out considering hybrid approach comprehensive COPRAS-G to determine optimal machining parameters in turning operation. Liou, Tamosaitiene, Zavadskas, & Tzeng (2016) have presented a new hybrid COPRAS-G MADM model for selecting suppliers in green supply chain management. Additionally, the most cited papers on COPRAS-G method are also presented in Table 3.3. AHP is the most used MADM method integrated with COPRAS-G.

Table 3.3 The most cited articles on COPRAS-G according to application problem

References	Publication Journal	Cited Times	Application Problem	Other MADM methods integrated with COPRAS-G
Zavadskas et al. (2008a)	Journal of Civil Engineering and Management	163	Selection of the effective dwelling house walls	-
Zavadskas et al. (2010)	Journal of Civil Engineering and Management	147	Risk assessment of construction projects	TOPSIS
Zavadskas, Kaklauskas, Turskis, and Tamosaitiene (2009)	Informatica	113	General contractor choice	-
Zavadskas et al. (2008b)	Technological and Economic Development of Economy	89	Selection of project managers	-
Chatterjee and Chakraborty (2012)	Materials and Design	64	Material selection	-
Maity et al. (2012)	Materials and Design	42	Cutting tool material selection	Operational Competitiveness Rating Analysis (OCRA), PROMETHEE II, ORESTE
Nguyen et al. (2014)	Expert Systems with Applications	34	Machine tool selection	Fuzzy ANP
Hashemkhani Zolfani et al. (2012b)	Technological and Economic Development of Economy	32	Company supplier selection	AHP (Analytic Hierarchical Process)
Bitarafan et al. (2012)	Archives of Civil and Mechanical Engineering	31	Evaluating the construction methods of cold-formed steel structures in reconstructing the areas damaged in natural crises	AHP
Aghdaie et al. (2013a)	Engineering Economics	27	Machine tool selection	SWARA
Aghdaie et al. (2013b)	Journal of Business Economics and Management	23	Market segment evaluation and selection	Fuzzy AHP
Rezaeiniya et al. (2012)	International Journal of Strategic Property Management	22	Greenhouse locating problem	ANP
Tavana et al. (2013a)	Expert Systems with Applications	21	Social media platform selection	Fuzzy ANP
Aghdaie, Hashemkhani Zolfani, and Zavadskas (2012)	Baltic Journal of Road and Bridge Engineering	21	Selecting area for constructing footbridges	AHP
Hashemkhani Zolfani, Rezaeiniya, Zavadskas, and Turskis (2011)	E a M: Ekonomie a Management	17	Forest roads locating	AHP
Tamosaitiene and Gaudutis (2013)	Journal of Civil Engineering and Management	15	Assessment of high-rise building	-
Zavadskas, Kaklauskas, Turskis, Tamosaitiene, and Kalibatas (2011)	Environmental Engineering and Management Journal	15	Assessment of the indoor environment of dwelling houses	-

3.3.2.2 COPRAS-G Methodology

Zavadskas et al. (2008a, 2009) represented the basic notions of the COPRAS-G method as the following steps:

1. Selecting the set of the most important attributes, describing the alternatives.
2. Constructing the decision-making matrix $\otimes X$:

$$\otimes X = \begin{bmatrix} x_{11} & \dots & \otimes x_{1m} \\ \dots & \ddots & \dots \\ \otimes x_{n1} & \dots & \otimes x_{nm} \end{bmatrix}, \tag{3.53}$$

$$= \begin{bmatrix} [w_{11}; b_{11}] & \dots & [w_{1m}; b_{1m}] \\ \dots & \ddots & \dots \\ [w_{n1}; b_{n1}] & \dots & [w_{nm}; b_{nm}] \end{bmatrix}; j = \overline{1,n}; i = \overline{1,m}, \tag{3.54}$$

where $\otimes x_{ji}$ is determined by w_{ji} (the smallest value, the lower limit) and b_{ji} the biggest value, the upper limit).

3. Determining weights of the attributes q_i.
4. Normalizing the decision-making matrix$\otimes X$:

$$\overline{w_{j1}} = \frac{w_{ji}}{\frac{1}{2}\left(\sum_{j=1}^{n} w_{ji} + \sum_{j=1}^{n} b_{ji}\right)} = \frac{2w_{ji}}{\left(\sum_{j=1}^{n} w_{ji} + \sum_{j=1}^{n} b_{ji}\right)},$$
$$\overline{b_{j1}} = \frac{b_{ji}}{\frac{1}{2}\left(\sum_{j=1}^{n} w_{ji} + \sum_{j=1}^{n} b_{ji}\right)} = \frac{2b_{ji}}{\left(\sum_{j=1}^{n} w_{ji} + \sum_{j=1}^{n} b_{ji}\right)}, \tag{3.55}$$
$$\mathrm{i} = \overline{1,n} \, and \; j = \overline{1,m}.$$

In Equation (3.55), w_{ji} is the lower value of the *i* attributes in the alternatives *j* of the solution; w_{ji} is the upper value of the attribute *i* in the alternative *j* of the solution; *m* is the number of attributes; *n* is the number of the alternatives compared. Then, the decision-making matrix is denoted by Equation (3.56):

$$\otimes \hat{X} = \begin{bmatrix} \otimes\overline{x_{11}} & \dots & \otimes\overline{x_{1m}} \\ \dots & \ddots & \dots \\ \otimes\overline{x_{n1}} & \dots & \otimes\overline{x_{nm}} \end{bmatrix}$$

$$= \begin{bmatrix} \left[\overline{w_{11};b_{11}}\right] & \dots & \left[\overline{w_{1m};b_{1m}}\right] \\ \dots & \ddots & \dots \\ \left[\overline{w_{n1};b_{n1}}\right] & \dots & \left[\overline{w_{nm};b_{nm}}\right] \end{bmatrix}; j = \overline{1,n}; i = \overline{1,m}. \tag{3.56}$$

5. Calculating the weighted normalized decision-making matrix $\otimes \hat{X}$. The weighted normalized values $\otimes \hat{x}_{ji}$ are calculated as follows:

$$\otimes\hat{x}_{j1} = \otimes\hat{x}_{j1}.\mathrm{q}_i;\ \hat{w}_{j1} = \bar{w}_{j1}.\mathrm{q}_i;\ \hat{b}_{j1} = \bar{b}_{j1}.\mathrm{q}_i.\mathrm{a} \tag{3.57}$$

In Equation (3.57), q_i is the weight of the *ith* attribute. Then, the weighted normalized decision-making matrix is shown as follows:

$$\otimes \hat{X} = \begin{bmatrix} \otimes\hat{x}_{11} & \dots & \otimes\hat{x}_{1m} \\ \dots & \ddots & \dots \\ \otimes\hat{x}_{n1} & \dots & \otimes\hat{x}_{nm} \end{bmatrix}$$

$$= \begin{bmatrix} \left[\hat{w}_{11};\hat{b}_{11}\right] & \dots & \left[\hat{w}_{1m};\hat{b}_{1m}\right] \\ \dots & \ddots & \dots \\ \left[\hat{w}_{1n};\hat{b}_{1n}\right] & \dots & \left[\hat{w}_{nm};\hat{b}_{nm}\right] \end{bmatrix}. \tag{3.58}$$

6. Calculating the sums P_j of the attribute values, whose larger values are more preferable:

$$P_j = \frac{1}{2}\sum_{i=1}^{k}\left(\hat{w}_{j1} + \hat{b}_{j1}\right). \tag{3.59}$$

7. Calculating the sums R_j of attribute values, whose smaller values are more preferable:

$$R_j = \frac{1}{2}\sum_{i=k+1}^{m}\left(\hat{w}_{j1} + \hat{b}_{j1}\right); i = \overline{k,m}. \tag{3.60}$$

8. Determining the minimal value of R_j:

$$R_{\min} = \min_i R_j;\ j = \overline{j,n}. \tag{3.61}$$

9. Calculating the relative weight of each alternative Q_j:

$$Q_j = P_j + \frac{\sum_{j=1}^{n} R_j}{R_j \sum_{j=1}^{n} \frac{1}{R_j}}. \tag{3.62}$$

10. Determining the optimality criterion K:

$$K = \max_j Q_j;\ j = \overline{1,n}. \tag{3.63}$$

11. Determining the priority of the project.

12. Calculating the utility degree of each alternative using Q_j and Q_{max} which the weights of projects are obtained from Equation (10).

$$N_j = \frac{Q_j}{Q_{\max}} 100\%. \tag{3.64}$$

3.3.3 FCOPRAS Method

In recent years, the COPRAS-G method and its hybrid modifications have been applied to the solution of complicated MADM problems using fuzzy sets theory.

Zavadskas and Antucheviciene (2007) firstly suggested multiple-criteria complex proportional evaluation under fuzzy environment to assess the rural building's regeneration alternatives. Yazdani, Alidoosti, and Zavadskas (2011) developed a risk based methodology for critical infrastructures using FCOPRAS extended of COPRAS method. Antucheviciene, Zavadskas, and Zakarevicius (2012) applied fuzzy TOPSIS, FCOPRAS and fuzzy VIKOR to rank the redevelopment decisions of derelict buildings. Chatterjee and Bose (2012), Nguyen, Dawal, Nukman, Aoyama, and Case (2015) and also Akhavan, Barak, Maghsoudlou, and Antucheviciene (2015) studied different MADM problems using FCOPRAS method. Turanoglu Bekar, Cakmakci, and Kahraman (2016) have evaluated the newly developed performance measures in TPM using proposed FCOPRAS method. Proposed FCOPRAS method is explained in detail in Section 4.3.

FCOPRAS method has also been handled by new extensions of fuzzy sets such as interval type-2, intuitionistic or hesitant fuzzy sets (Bausys, Zavadskas, & Kaklauskas, 2015; Ghorabaee, Amiri, Sadaghiani, & Goodarzi, 2014; Gitinavard, Mousavi, & Vahdani, 2016; Razavi Hajiagha, Akrami, Zavadskas, & Hashemi, 2013).

3.4 Fuzzy Data Envelopment Analysis

3.4.1 The Fundamentals of DEA

Efficiency measurement is known to arise in modern age with the Farrell (1957) who drew upon the work of Debreu (1951) and Koopmans (1951). Farrell (1957) aimed to define a simple measure of firm efficiency which could account for multiple inputs (Coelli, 1996). Several studies has been conducted after Farrell's study on the measurement of the efficiency and finally in 1978, during doctoral dissertation about the efficiency of a public education program of Edwardo Rhodes under the consultancy of W.W Cooper, DEA method has been developed.

As is generally acknowledged, DEA is a non-parametric approach to efficiency measurement based on Farrell’s (1957) original work that was later popularized by Charnes, Cooper, & Rhodes (1978) who propose a novel method that combines and transforms multiple inputs and outputs into a single efficiency index (Lo & Tzeng, 2006). Charnes et al. (1978) defined DEA as “a mathematical programming model applied to observational data [which] provides a new way of obtaining empirical estimates of extremal relations – such as the production functions and/or efficient production possibility surfaces that are a cornerstone of modern economics.”

DEA is a mathematical programming and data oriented approach which is directed to frontiers rather than central tendencies for measuring and evaluating the performance or efficiencies of a set of entities called Decision Making Units (DMUs), to incorporate multiple inputs and outputs into a single value, without the need to convert them into a common unit of measure (Cooper, 2004; Cooper, Seiford, & Tone, 2007). This approach first establishes an ‘‘efficient frontier’’ formed by asset of DMUs that exhibit best practices and then assigns the efficiency level to other non-frontier units according to their distances to the efficient frontier (J. S. Liu, Lu, Lu, & Lin, 2013).

In the theory of DEA, a DMU is relatively efficient as long as the combination of input and output from the DMU is within the boundary of DEA; otherwise, a DMU is relatively inefficient since its combination is outside the boundaries. The summarization of main features of DEA is given as follows (Lo & Tzeng, 2006):

- “it can easily handle the evaluation problem of multiple inputs and multiple outputs without facing the difficulty of parameter estimation so it can handle real world problems”;
- “it has the characteristic of unit invariance, i.e. changing the scale of input or output quantities that does not alter the results”;
- “it calculates a single aggregative index to measure the efficiency that may properly describe the concept of total factors of productivity in economics”;
- “its weighting factors are generated by mathematical design”;
- “it has flexible data processing that can simultaneously handle various data with different dimensions”;
- “it can handle the external variances that are based on the data characters of Ratio and Non-Ratio in DEA.”

DEA has some advantages which can be listed as follows (Cooper et al., 2007; Liu et al., 2013):

- “DEA does not need to have specific functional forms of relations between inputs and outputs;
- In DEA applications a large number of inputs and outputs can be considered at the same time;
- Inputs and outputs can be expressed in different units;
- DEA directed to frontiers rather than central tendencies.”

The steps to be followed in the implementation of DEA are determination of DMUs to be analyzed, determination of appropriate inputs and outputs, measurement of relative efficiency, determination of the reference sets, and evaluation of the results (Ramanathan, 2003).

DEA can be described as a series of models, whereas the type of returns to scale is what characterizes the two main ones: (a) CRS (constant returns to scale), or CCR which is an acronym for Charnes, Cooper, and Rhodes (Charnes et al., 1978); and (b) VRS (variable returns to scale) or BCC which is an acronym for Banker, Charnes, and Cooper (Banker, Charnes, & Cooper, 1984) which is one of the broadening of the CCR model where the efficient frontiers set is characterized by a convex curve passing through all efficient DMUs and structured by both constant and decreasing returns to scale (Faizrahnemoona, Hosseinzadeh Lotfi, & Alimardani Jondabeh, 2012). In brief, while the CCR model assumes that outputs always grow proportionally to inputs, in the BCC model this proportionality is not required, as a DMU may display returns to scale: (a) *increasing:* where outputs grow proportionally more than inputs; (b) *constant:* where there is proportionality; or (c) *decreasing:* where outputs grow proportionately less than inputs (Mariano, Sobreiro, & Nascimento Rebelatto, 2015).

DEA is defined either input- or output-orientated. In the input-oriented case, the DEA method describes the frontier by searching “the maximum possible proportional reduction” in input usage, while output levels are held constant, for each DMU. On the other hand, for the output-orientated case, the DEA method searches “the maximum proportional increase” in output production, while input levels are held fixed. For example, a basic input-oriented CCR model with m input variables $(x_1, x_2 \dots, x_m)$, s output variables $(y_1, y_2 \dots, y_s)$ and n DMUs $(j = 1, .., n)$ is presented in Model (3.65) (Emrouznejad, Tavana, & Hatami-Marbini, 2014).

$$\begin{aligned}
\min \quad & \theta_p \\
s.t. \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_p x_{ip}, \quad \forall_i, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rp}, \quad \forall_r, \\
& \lambda_j \geq 0, \quad \forall_j.
\end{aligned} \tag{3.65}$$

A basic input-oriented BCC model is also given as follows:

$$\begin{aligned}
\min \quad & \theta_p \\
s.t. \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_p x_{ip}, \quad \forall_i, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rp}, \quad \forall_r, \\
& \sum_{j=1}^{n} \lambda_j = 1, \quad \lambda_j \geq 0, \quad \forall_j.
\end{aligned} \tag{3.66}$$

The only difference between CRR and BCC models is the inclusion of the convexity constraints of $\sum_{j=1}^{n} \lambda_j = 1$ and in the BCC model (Emrouznejad et al., 2014).

The graphical representation of a simple VRS output oriented DEA model is shown in Figure 3.11.

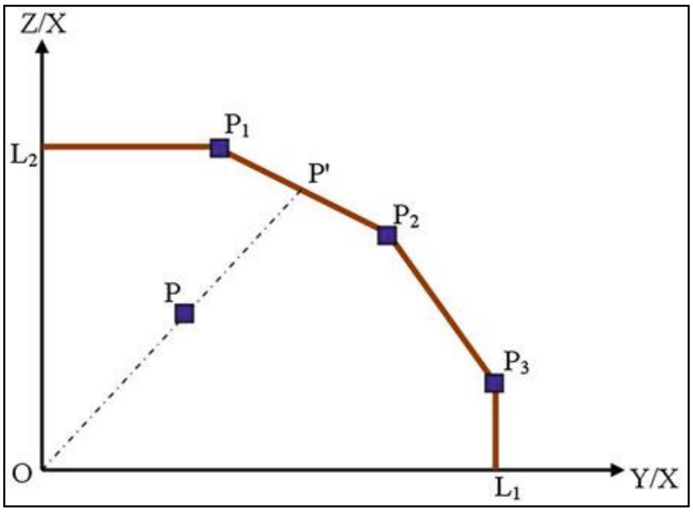

Figure 3.11 An output-oriented DEA with two outputs and one input (Emrouznejad et al., 2014).

According to Figure 3.11, Y and Z are the outputs, and, X is the input in the DEA problem. The isoquant L_1L_2 denotes the technical efficient frontier comprising P_1, P_2, and P_3 which are technically efficient DMUs and hence on the frontier. If a given DMU utilizes one unit of input and yields outputs defined by point P, the technical inefficiency of that DMU is denoted as the distance PP', that is the amount by which all outputs could be comparatively increased without increasing the input. In percentage terms, it is explained by the ratio OP/OP', which is the ratio by which all the outputs could be increased (Emrouznejad et al, 2014).

The CCR and BCC models are categorized as radial models that require first selecting an orientation, which can be 'input orientation' or 'output orientation'. In addition to these models, there are the non-radial models, whose efficiency is based on the slack concept, which represents how much each input and each output, respectively, should be reduced or increased until the DMU reaches the frontier (Cook & Seiford, 2009).

The additive or Pareto-Koopmans model was introduced by Charnes, Clark, Cooper, and Golany (1984) which can work with both CRS and VRS. An improvement of this model was the *Slack Based Measure*, proposed by Tone (2001), which is invariant to the units of measurement and is monotone increasing in each input and output slack. Another widely used non-radial model is the *Russell*

Measure model named by Fare and Lovell (1978), and later revisited by Pastor, Ruiz, and Sirvent (1999). Finally, *the multiplicative models*, which were originally presented in Charnes, Cooper, Seiford, and Stutz (1982) and not a linear combination of inputs and outputs, but rather is a geometric combination between variables (Mariano et al., 2015).

Numerous applications in recent years have been accompanied by new extensions and developments in expanding the concept and methodology of DEA. Moreover, it has been applied to various industrial and non-industrial environments, such as banking, education, hospital, etc. (J. S. Liu et al., 2013). As a result, a large number of published research papers and surveys have performed in the DEA literature (see Cook & Seiford, 2009; Emrouznejad, Parker, & Tavares, 2008; Gattoufi, Oral, Kumar, & Reisman, 2004a; Gattoufi, Oral, & Reisman, 2004b; J. S. Liu et al., 2013; Seiford, 1996; Seiford & Thrall, 1990).

3.4.2 The Principles of FDEA

3.4.2.1 Fuzzy Set Theory and DEA

The traditional DEA models require accurate and precise performance data since it is a methodology focused on frontiers or boundaries (Gua & Tanaka, 2001). However, in real-world applications such as in a manufacturing system, a production process or a service system, the observed data are volatile and complex and generally include uncertainty (Zerafat Angiz, Emrouznejad, & Mustafa, 2012a). In this context, imprecise or vague data can be represented with bounded intervals, ordinal (rank order) data or fuzzy numbers (Hatami-Marbini, Emrouznejad, & Tavana, 2011a). Fuzzy set theory, established by Zadeh (1965), has been proven to be useful as a way to quantify imprecise and vague (expressed by linguistic variables) data in DEA models. Therefore, the DEA models with fuzzy data can more realistically represent real-world applications than the conventional DEA models (Lertworasirikul, Fang, Joines, & Nuttle, 2003a).

The general formulations of fuzzy CCR and BCC models are presented in the following Models (3.67)-(3.70) (Hatami-Marbini et al., 2011a). If it is assumed that *n* DMUs consume varying amounts of *m* different inputs to produce *s* different outputs. Moreover, $\tilde{x}_{ij} = (i = 1, 2, \dots, m)$ and $\tilde{y}_{ij} = (i = 1, 2, \dots, s)$ represent, respectively, *the fuzzy input* and *fuzzy output of the j*th $DMU_j = (1, 2, \dots, n)$. The primal and its dual fuzzy CCR models in input-oriented versions are formulated as follows:

Primal CCR model (input-oriented)

$$
\begin{aligned}
\min \quad & \theta_p \\
s.t. \quad & \sum_{j=1}^{n} \lambda_j \tilde{x}_{ij} \le \theta_p \tilde{x}_{ip}, \quad \forall_i, \\
& \sum_{j=1}^{n} \lambda_j \tilde{y}_{rj} \ge \tilde{y}_{rp}, \quad \forall_r, \\
& \lambda_j \ge 0, \quad \forall_j.
\end{aligned}
\tag{3.67}
$$

Dual CCR model (input-oriented)

$$
\begin{aligned}
\max \quad & \theta_p = \sum_{r=1}^{s} u_r \tilde{y}_{rp} \\
s.t. \quad & \sum_{i=1}^{m} v_i \tilde{x}_{ip} = 1, \\
& \sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij} \le 0, \quad \forall_j, \\
& u_r, v_i \ge 0, \quad \forall_{r,i}.
\end{aligned}
\tag{3.68}
$$

where v_i and u_r in (fuzzy Dual CRR model input-oriented) are the input and output weights assigned to the *i*th input and *r*th output. If the constraint $\sum_{j=1}^{n} \lambda_j = 1$ is adjoined to (primal CRR model-input oriented), a fuzzy BCC model is obtained and this added constraint produces an additional variable, $\tilde{u}_0$, into the dual model where these models are respectively presented as Models (3.69) and (3.70):

Primal BCC model (input-oriented)

$$
\begin{aligned}
\min \quad & \theta_p \\
s.t. \quad & \sum_{j=1}^{n} \lambda_j \tilde{x}_{ij} \le \theta_p \tilde{x}_{ip}, \quad \forall_i, \\
& \sum_{j=1}^{n} \lambda_j \tilde{y}_{rj} \ge \tilde{y}_{rp}, \quad \forall_r, \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \ge 0, \quad \forall_j.
\end{aligned}
\tag{3.69}
$$

Dual BCC model (input-oriented)

$$
\begin{aligned}
\max \quad & \theta_p = \sum_{r=1}^{s} u_r \tilde{y}_{rp} + u_0 \\
s.t. \quad & \sum_{i=1}^{m} v_i \tilde{x}_{ip} = 1, \\
& \sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij} + u_0 \le 0, \quad \forall_j, \\
& u_r, v_i \ge 0, \quad \forall_{r,i}.
\end{aligned}
\tag{3.70}
$$

Several approaches have been proposed by various researchers to deal with fuzzy data in DEA. These approaches are explained in depth in Section 3.4.3.

3.4.2.2 Statistical Review of FDEA Literature

A systematic search of the literature related to FDEA is conducted in this section. The time period for this literature review is chosen from 1992 to September 2016. When the search for literature review for FDEA is carried out using “Scopus”, it gives 4575 published papers in all fields. Among these, 576 published papers use FDEA in their “article title, abstract, keywords”. Figure 3.12 demonstrates the number of published papers used FDEA in their “article title, abstract, keywords” over years. Total of 576 papers published using FDEA are categorized by the document type; the subject areas; the authors and the sources per year, respectively shown in Figures 3.13-3.16.

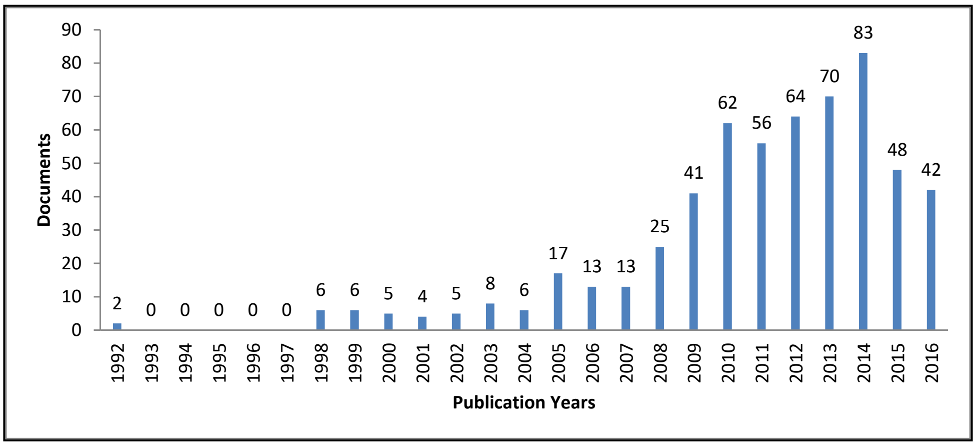

Figure 3.12 Published documents using FDEA over years

As for the year of publication, which can also be seen in Figure 3.12, the first article that proposed a fuzzy mathematical programming approach by incorporating fuzzy input and output data into a DEA model and defining tolerance levels for the objective function and constraint violations was the work of Sengupta (1992a, b), which was published over 24 years ago. Between 1992 and 1997, however, the subject had no major developments and no documents were published in these years. It can be observed that the last 7 years have concentrated 80.90% of the studies selected, demonstrating that this is a dynamic research area.

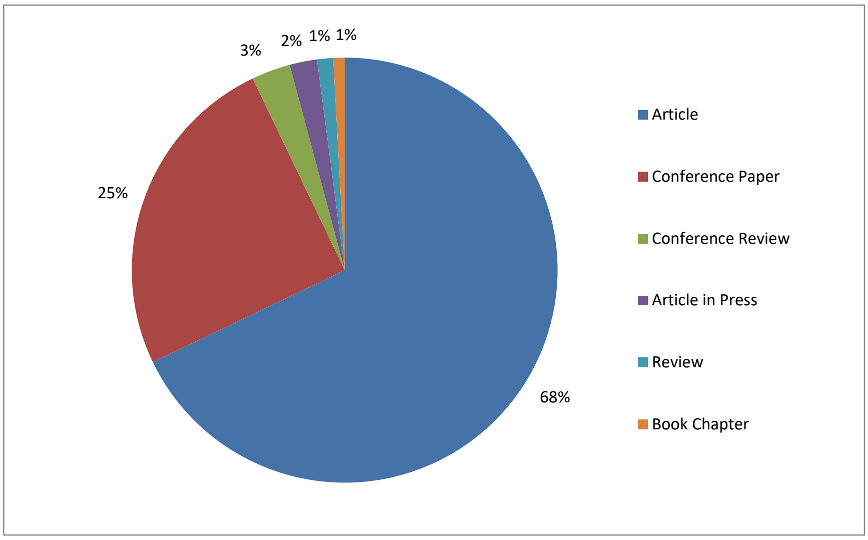

Figure 3.13 Classification of published documents using FDEA according to document types

According to Figure 3.13, 391 papers using FDEA are published as an article, 144 papers as a conference paper, 17 papers as a conference review, 12 papers as an article in press, 7 papers as a review, and 5 papers as a book chapter.

The journals such as “Expert System with Applications”, “Computers and Industrial Engineering”, “Studies in Fuzziness and Soft Computing”, “Europen Journal of Operation Research”, “International Journal of Advanced Manufacturing Technology”, and “Applied Mathematical Science” have the most publishing FDEA papers. “IEEE International Conference on Fuzzy Systems” has the most publishing FDEA conference papers. Figure 3.14 illustrates the journals publishing FDEA based articles. Figure 3.15 presents the subject areas of the examined papers using FDEA.

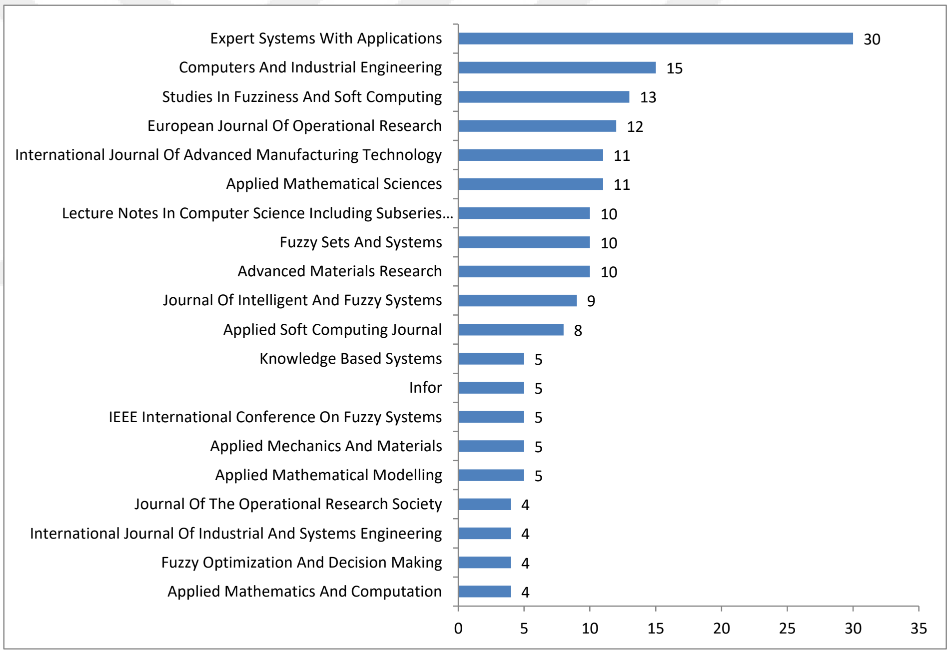

Figure 3.14 Journals that publish FDEA based articles

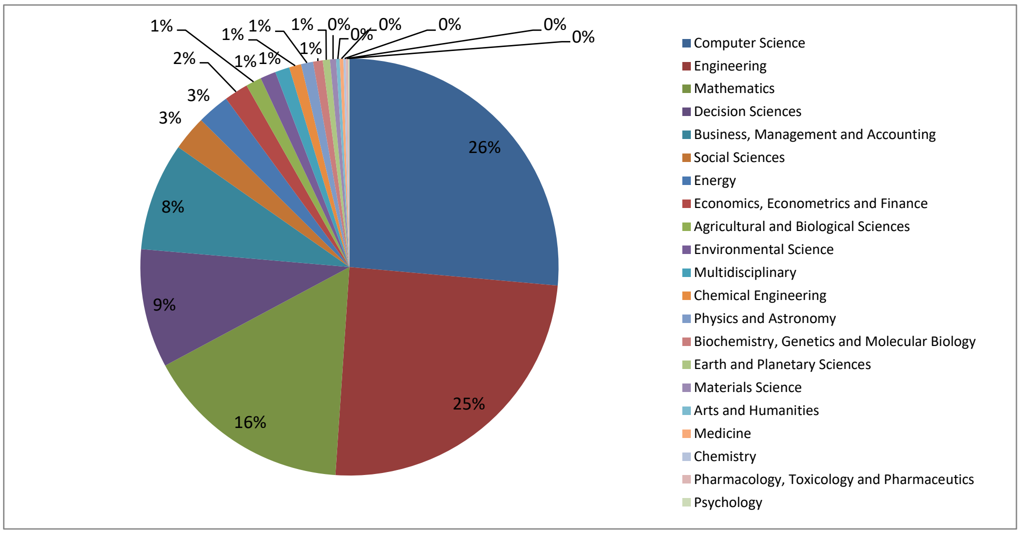

Figure 3.15 Subject areas of the examined papers using FDEA

According to Figure 3.15, the areas of computer science (284 papers), engineering (265 papers) and mathematics (173 papers) are the most studied research fields on FDEA. Another classification for reviewed papers on FDEA is performed according to author names (Figure 3.16).

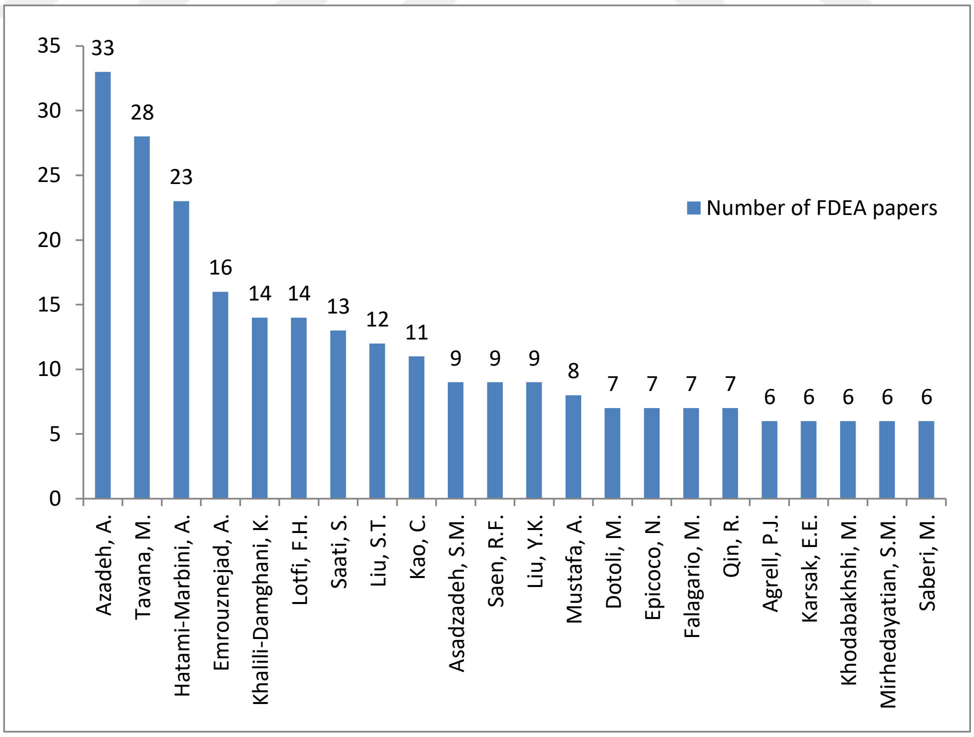

Figure 3.16 Number of FDEA papers according to author names

According to Figure 3.16, A. Azadeh (with 33 publications) from Tehran University, M. Tavana (with 28 publications) from La Salle University, A. Hatami-Marbini (with 23 publications) from Islamic Azad University, and A. Emrouznejad (with 16 publications) from Aston University are the most productive researchers on FDEA.

When it comes to identify the most important works, a useful parameter to classify them is the number of citations. Nevertheless, it is important to remember that the most recent articles have not yet time to become prominent in this regard. Table 3.4 gives the twenty most cited papers using FDEA, together with the total citation counts in the Scopus until September 2016.

According to Table 3.4, the articles published in Fuzzy Sets and Systems by the authors Guo and Tanaka (2001), Kao and Liu (2000) and Lertworasirikul et al. (2003a) are the most cited articles using FDEA. Recent publishing articles in European Journal of Operational Research by the authors Hatami-Marbini et al. (2011a), Wu (2009) and Tan (2013) are also the most cited articles using FDEA.

3.4.3 FDEA Approaches

The applications of fuzzy set theory in DEA are generally classified into four groups (Lertworasirikul et al., 2003a, 2003b; Lertworasirikul, 2002; Karsak, 2008) such as "*the tolerance approach*", "*the α-level based approach*", "*the fuzzy ranking approach*", "*the possibility approach*". Emrouznejad et al. (2014) extended this classification and attached two new groups: "*the fuzzy arithmetic*" and "*the fuzzy random variables and other extensions of fuzzy sets*". In this section, a general mathematical formulation of some approaches (used within the scope of the thesis) and also a summary review of the most widely used literature according to each of the six approaches are provided.

Table 3.4 Twenty most cited papers using FDEA

References	Publication Year	Publication Journal	Cited Times
Guo and Tanaka	2001	Fuzzy Sets and Systems	206
Kao and Liu	2000a	Fuzzy Sets and Systems	202
Lertworasirikul et al.	2003a	Fuzzy Sets and Systems	181
Entani, Maeda, and Tanaka	2002	European Journal of Operational Research	148
Sengupta	1992a	Computers & Mathematics with Applications	142
Y.-M. Wang, Greatbanks, and Yang	2005	Fuzzy Sets and Systems	141
Sarkar and Mohapatra	2006	Journal of Purchasing and Supply Management	141
Leon, Liern, Ruiz, and Sirvent	2003	Fuzzy Sets and Systems	105
Liu	2008	Computers and Industrial Engineering	92
Hatami-Marbini et al.	2011a	European Journal of Operational Research	91
Saati, Memariani, and Jahanshahloo	2002	Fuzzy Optimization and Decision Making	87
Wu	2009	European Journal of Operational Research	78
Garcia, Schirru, and Frutuoso e Melo	2005	Progress in Nuclear Energy	71
Tan	2013	International Journal of Applied Mathematics and Statistics	59
Kao and Liu	2003	International Journal of Production Economics	57
Wen and Li	2009	Journal of Computational and Applied Mathematics	55
Y.-M Wang, Luo, and Liang	2009	Expert Systems with Applications	54
Jahanshahloo et al.	2004	Applied Mathematics and Computation	53
Triantis and Girod	1998	Journal of Productivity Analysis	53
Guo	2009	Information Sciences	49
Wu, Yang, and Liang	2006	Applied Mathematics and Computation	46
Lertworasirikul, Fang, Nuttle, and Joines	2003b	Fuzzy Optimization and Decision Making	42

3.4.3.1 The Tolerance Approach

Sengupta (1992a) firstly proposed the tolerance approach in FDEA models. Afterwards, Kahraman and Tolga (1998) improved this approach and Kahraman, Ziya, and Tolga (1999) employed this approach for evaluating two alternative computer integrated systems.

The main idea of this approach is incorporation of uncertainty into the DEA model by describing tolerance levels for constraints. In this manner, it provides only the fuzzification of the inequality or equality signs, however fuzzy coefficients are not considered directly in the model. Sengupta (1992b) proposed a new design of this approach to deal with fuzzy objective function and fuzzy constraints. As a conclusion, the tolerance approach provides flexibility by relaxing the DEA relationships while the input and output coefficients are treated as crisp (Triantis & Girod, 1998).

3.4.3.2 The α-level Based Approach

Numerous publications based on α-level approach are founded in FDEA literature. Therefore, this approach is the most popular FDEA approach and it has been studied by the various researchers. The main concept of this approach is to transform the FDEA model into a pair of parametric programs in order to obtain the lower and upper bounds of the α-level of the membership functions of the efficiency scores (Emrouznejad et al., 2014). A summary of FDEA reference based on the α-level approach is listed in Table 3.5.

In the α-level based approach, the FDEA model is solved by parametric programming using α-cuts. Solving the model at a given α-level produces corresponding interval efficiency for the target DMU. A number of such intervals can be used to construct the corresponding fuzzy efficiency. Kao and Liu (2000a) proposed a solution method to measure the efficiencies of the DMUs with fuzzy observations in the BCC model following the basic idea of converting a FDEA model to a family of conventional crisp DEA models. In this method, α-level approach and Zadeh's extension principle were applied and obtained approximately the membership functions of the fuzzy efficiency measures. The general mathematical description of the model proposed by Kao and Liu (2000a) is provided in this section. Since this model is one of the mathematical models used within the scoped of the thesis, it is also explained in detail in Chapter 4 (See Section 4.4).

Table 3.5 A summary of FDEA literature based on the α-level based approach

Years	The α-level based Approach References		
From 1999 to 2004 (including 2004)	Girod and Triantis (1999)	Guh (2001)	Kao and Liu (2003)
	Kao and Liu (2000a)	Chen (2001)	Triantis (2003)
	Kao and Liu (2000b)	Entani et al. (2002)	
	Kao (2001)	Saati et al. (2002)	
From 2005 to 2010 (including 2010)	Hsu (2005)	Y. P. Liu, Gao, and Shen (2007)	Tlig and Rebai (2009)
	Kao and Liu (2005)	Saneifard, Allahviranloo, Hosseinzadeh Lotfi, and Mikaeilvand (2007)	C.-H. Wang, Chuang, and Tsai (2009)
	Wu, Yong, Zhang, Liu, and Dai (2005)	Azadeh, Ghaderi, Javaheri, and Saberi (2008)	Azadeh and Alem (2010)
	L. Zhang, Mannino, Ghosh, and Scott (2005)	Ghapanchi, Jafarzadeh, and Khakbaz (2008)	Azadeh, Anvari, Ziaei, and Sadeghi. (2010)
	Allahviranloo, Hosseinzade Lotfi, and Adabitabar (2007)	Karsak (2008)	Hatami-Marbini, Saati, and Tavana (2010a)
	Azadeh, Anvari, and Izadbakhsh (2007)	Li and Yang (2008)	Mansourirad, Rizam, Lee, and Jaafar (2010)
	Hosseinzadeh Lotfi, Jahanshahloo, Rezai Balf, and Zhiani Rezai (2007c)	Jahanshahloo et al. (2009a)	Noura, Natavan, Poodineh, and Abdolalian (2010)
	Jahanshahloo, Hosseinzadeh Lotfi, Adabitabar Firozja, and Allahviranloo (2007b)	S.-T. Liu and Chuang (2009)	Zerafat Angiz, Emrouznejad, and Mustafa (2010a)
	Kuo and Wang (2007)	Noura and Saljooghi (2009) Saati and Memariani (2009)	Z. Zhou, Yang, Ma, and Liu (2010)
From 2011 to 1 September 2016	Abtahi and Khalili-Damghani (2011)	Z. Zhou, Lui, Ma, Liu, D., and Liu (2012a)	Kao (2014)
	Kao and Lin (2011)	Ghapanchi, Tavana, Khakbaz, and Low (2012)	Lan, Chiou, and Yen (2014)
	Kao and Liu (2011)	Azadeh, Saberi, Asadzadeh, Hussain, and Saberi (2013a)	Muren, Ma, and Cui (2014)
	Khalili-Damghani and Abtahi (2011)	Chen, Chiu, Huang, and Tu (2013)	Şafak et al. (2014)
	Khoshfetrat and Daneshvar (2011)	Fathi and Izadikhah (2013)	Puri and Yadav (2014a, 2014b)
	Mostafaee (2011)	Hatami-Marbini et al. (2013)	Aydın and Zorturk (2015)
	Zerafat Angiz, Emrouznejad, and Mustafa (2012a)	Khalili-Damghani and Taghavifard (2013)	Azadi, Jafarian, Saen, and Mirhedayatian (2015a)
	Azadeh, Hasani Farmand, and Jiryaei Sharahi (2012)	Khalili-Damghani and Tavana (2013)	Kao (2015)
	Hatami-Marbini, Tavana, Emrouznejad, and Saati (2012)	Mugera (2013)	Bagherzadeh Valami, and Raeinojehdehi (2016)
	Kao and Lin (2012)	Puri and Yadav (2013)	Chen and Wang (2016)
	Khalili-Damghani and Hosseinzadeh Lotfi (2012)	Rezaie, Majazi Dalfard, Hatami-Shirkouhi, and Nazari-Shirkouhi (2013)	Çakir (2016)
	Khalili-Damghani and Taghavifard (2012)	Saati, Hatami-Marbini, Tavana, and Agrell (2013)	Liu (2016)
	Khalili-Damghani, Taghavi,-Fard, and Abtahi (2012)	Srinivasa Raju and Nagesh Kumar (2013)	Wanke, Barros, and Emrouznejad (2016)

Consider n DMUs and each of these DMUs consumes varying amounts of m different fuzzy inputs to produce s different fuzzy outputs. In the model formulation, $\tilde{x}_{ip}$ and $\tilde{y}_{rp}$ denote, respectively, the fuzzy input and fuzzy output values for the DMU_p. In order to solve the fuzzy BCC model, Kao and Liu (2000a) suggested a pair of two-level mathematical models to obtain the lower bound $(w_p)_\alpha^L$ and upper bound $(w_p)_\alpha^U$ of the fuzzy efficiency score for a specific α-level as follows:

$$(\mathrm{w}_p)_\alpha^L = \min_{\substack{(X_{ij})_\alpha^L \le x_{ij} \le (X_{ij})_\alpha^U \\ (Y_{rj})_\alpha^L \le y_{rj} \le (Y_{rj})_\alpha^U \\ \forall r,i,j}} \begin{cases} \tilde{w}_p = \max \sum_{r=1}^{s} u_r y_{rp} + u_0 \\ \quad s.t. \ \sum_{i=1}^{m} v_i x_{ip} = 1, \\ \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + u_0 \le 0, \quad \forall_j, \\ \quad u_r, v_i \ge 0, \quad \forall_{r,i}. \end{cases} \tag{3.71}$$

$$(\mathrm{w}_p)_\alpha^U = \max_{\substack{(X_{ij})_\alpha^L \le x_{ij} \le (X_{ij})_\alpha^U \\ (Y_{rj})_\alpha^L \le y_{rj} \le (Y_{rj})_\alpha^U \\ \forall r,i,j}} \begin{cases} \tilde{w}_p = \max \sum_{r=1}^{s} u_r y_{rp} + u_0 \\ \quad s.t. \ \sum_{i=1}^{m} v_i x_{ip} = 1, \\ \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + u_0 \le 0, \quad \forall_j, \\ \quad u_r, v_i \ge 0, \quad \forall_{r,i}. \end{cases} \tag{3.72}$$

where $[(X_{ij})_\alpha^L, (X_{ij})_\alpha^U]$ and $[(Y_{rj})_\alpha^L, (Y_{rj})_\alpha^U]$ are α-level form of the fuzzy inputs and the fuzzy outputs respectively. This two-level mathematical model can be simplified to the conventional one-level model as follows:

$$\begin{aligned} (\mathrm{w}_p)_\alpha^L = \ & \max \sum_{r=1}^{s} u_r (\mathrm{Y}_{rp})_\alpha^L + u_0 \\ s.t. \ & \sum_{r=1}^{s} u_r (\mathrm{Y}_{rp})_\alpha^L - \sum_{i=1}^{m} v_i (\mathrm{X}_{ip})_\alpha^U + u_0 \le 0, \\ & \sum_{r=1}^{s} u_r (\mathrm{Y}_{rj})_\alpha^U - \sum_{i=1}^{m} v_i (\mathrm{X}_{ij})_\alpha^L + u_0 \le 0, \quad \forall_j, j \ne p, \\ & \sum_{i=1}^{m} v_i (\mathrm{X}_{ip})_\alpha^U = 1, \qquad u_r, v_i \ge 0, \quad \forall_{r,\mathrm{i}}. \end{aligned} \tag{3.73}$$

$$
\begin{aligned}
(\mathrm{w}_p)_\alpha^U = \quad & \max \sum_{r=1}^{s} u_r (\mathrm{Y}_{rp})_\alpha^U + u_0 \\
s.t. \quad & \sum_{r=1}^{s} u_r (\mathrm{Y}_{rp})_\alpha^U - \sum_{i=1}^{m} v_i (\mathrm{X}_{ip})_\alpha^L + u_0 \le 0, \\
& \sum_{r=1}^{s} u_r (\mathrm{Y}_{rj})_\alpha^L - \sum_{i=1}^{m} v_i (\mathrm{X}_{ij})_\alpha^U + u_0 \le 0, \quad \forall_j,\, j \ne p, \\
& \sum_{i=1}^{m} v_i (\mathrm{X}_{ip})_\alpha^L = 1, \qquad u_r, v_i \ge 0, \quad \forall_{r,\mathrm{i}}.
\end{aligned}
\tag{3.74}
$$

Next, a membership function is built by solving the lower and upper bounds $[(w_p)_\alpha^L, (w_p)_\alpha^U]$ of the α-levels for each DMU using Models (3.73) and (3.74).

As seen from Table 3.5, various researches suggested FDEA models based on the α-level method proposed by Kao and Liu (2002a) for measuring efficiency of various problems in different areas (Chen et al., 2013; Chiang & Che, 2010; Guh, 2001; Kao & Lin, 2011, 2012; Kao & Liu, 2000b; Kao & Liu, 2003, 2005; Kao, 2001; Khalili-Damghani & Tavana, 2013; Kuo & Wang, 2007; L. Zhang et al., 2005; Li & Yang, 2008; Mugera, 2013; Puri & Yadav, 2013). Furthermore, in recent years, some researches also employed the FDEA model proposed by Kao and Liu (2000a) to evaluate efficiency of of various problems in different areas. For example, Şafak et al. (2014) employed Kao and Liu's (2000a) technique to evaluate the efficiency of the forest sub-districts in the Denizli Forestry Regional Directorate. Aydın and Zorturk (2015) performed to Kao and Liu's (2000a) technique for measuring efficiency of foreign direct investment in 12 transition economies. Additionally, the mini-max regret method was used to compare and rank efficiency intervals of DMUs. However, according to literature review on the α-level based approach, various FDEA models which are independent from Kao and Liu's (2000a) model have also been developed by different authors.

For example, Saati et al. (2002) proposed a fuzzy CCR model as a possibilistic programming problem and converted it into an interval programming problem using the α-level based approach shown as the following model.

$$
\begin{aligned}
&\max\ w_p = \sum_{r=1}^{s} y'_{rp} \\
&s.t.\ \ \sum_{r=1}^{s} y'_{rj} - \sum_{i=1}^{m} x'_{ij} \le 0, \\
&\qquad v_i(\alpha x_{ij}^m + (1-\alpha) x_{ij}^l) \le x'_{ij} \le v_i(\alpha x_{ij}^m + (1-\alpha) x_{ij}^u),\ \forall i, j, \\
&\qquad u_r(\alpha y_{rj}^m + (1-\alpha)\, y_{rj}^l) \le y'_{rj} \le u_r(\alpha y_{rj}^m + (1-\alpha)\, y_{rj}^u),\ \forall r, j, \\
&\qquad \sum_{i=1}^{m} x'_{ip} = 1, \qquad u_r, v_i \ge 0,\ \ \forall r, j.
\end{aligned}
\tag{3.75}
$$

where $\tilde{x}_{ij} = (x_{ij}^l, x_{ij}^m, x_{ij}^u)$ and $\tilde{y}_{rj} = (y_{rj}^l, y_{rj}^m, y_{rj}^u)$ are the triangular fuzzy inputs and the triangular fuzzy outputs, and x'_{ij} and y'_{rj} are the decision variables obtained from variable substitutions used to transform the original fuzzy model into a parametric linear programming model with $\alpha \in [0, 1]$.

Various researches have suggested FDEA models based on the α-level method proposed by Saati et al. (2002) for measuring efficiency of various problems in different areas (Azadeh et al., 2007; Azadeh et al., 2010; Azadeh et al., 2012; Azadeh et al., 2013a; Fathi & Izadikhah, 2013; Ghapanchi et al., 2008; Ghapanchi et al., 2012; Hatami-Marbini & Saati, 2009; Hatami-Marbini et al., 2010a; Hatami-Marbini et al., 2012; Hatami-Marbini et al., 2013; Rezaie et al., 2013; Saati & Memariani, 2005; Saati & Memariani, 2009; Saati et al., 2011; Saati et al., 2013; Srinivasa Raju & Nagesh Kumar, 2013; Wu et al., 2005; Zerafat Angiz et al., 2010a).

Liu (2008) proposed a FDEA method to obtain the efficiency measures embedded the assurance region (AR) concept using fuzzy numbers. This concept (used within the scope of the thesis) is explained in detail in Section 3.4.4.

Recent studies have suggested novel procedures based on the α-level approach. For example, Kao (2014) discussed network DEA for fuzzy observations and also proposed the membership grade and the α-cut for measuring the system and process efficiencies through two-level mathematical programming. Then the model was transformed into a conventional one-level program. Moreover, a simple network system with three processes was used to investigate the proposed idea. Muren et al.

(2014) proposed a generalized FDEA model which can evaluate sample DMU model including five evaluation methods which not only improve the types of FDEA model, the types of fuzzy number, the α-cut approach but also propose a new evaluation method based on vector. Lan et al. (2014) proposed novel integrated fuzzy data envelopment analysis models where in both efficiency frontiers are integrated into a single modeling formulation in ways that the slack values for lower- and upper-bound input/output variables are determined simultaneously. Azadi et al. (2015a) developed an integrated DEA enhanced Russell measure model in fuzzy context to select the best sustainable suppliers. Puri and Yadav (2014a, b) have extended the idea of mix-efficiency to fuzzy environments and developed a slack based measurement FDEA model. The α-cut approach has been used to measure the fuzzy input as well as fuzzy output mix-efficiencies of each DMU. Finally, a numerical example has been applied the proposed methodology to the banking sector in India. Kao (2015) proposed two approaches based on the extension principle. One views the membership function of the fuzzy data vertically, and the results were represented by membership grades. The other views it horizontally, and the results were represented by α-cuts. Additionally, an example was given to explain the development and implementation of these two approaches. Wanke et al. (2016) have suggested new FDEA α-level models based on bootstrap truncated regression using an application in Mozambican banks to handle the underlying uncertainty. Çakır (2016) have conducted the FDEA model developed by Lertworasirikul et al. (2002) to measure efficiency in the tea industry. Bagherzadeh Valami and Raeinojehdehi (2016) have introduced a new α-level based approach based on fuzzy linear programming. Chen and Wang (2016) have developed the fuzzy cross efficiency DEA model that combines self-evaluation with peer-evaluation to eliminate the weaknesses of traditional FDEA. This model solves the efficiency evaluation problem in fuzzy environments from a new perspective.

3.4.3.3 Fuzzy Ranking Based Approaches

The fuzzy ranking approach is also another widely used method that has drawn attention in the FDEA literature. In this approach the basic concept is to obtain the fuzzy efficiency scores of the DMUs using fuzzy linear programs which need to rank the fuzzy set. A summary of FDEA literature based on the fuzzy ranking approach is presented in Table 3.6.

Table 3.6 A summary of FDEA literature based on the fuzzy ranking approach

Years	**Fuzzy Ranking based Approaches**		
		References	
From 2001 to 2008 (including 2008)	Guo and Tanaka (2001)	Molavi, Aryanezhad, and Shah Alizadeh (2005)	Guo and Tanaka (2008)
	Lertworasirikul (2002)	Saati and Memariani (2006)	Hosseinzadeh Lotfi and Mansouri (2008)
	Leon et al. (2003)	Soleimani-damaneh, Jahanshahloo, and Abbasbandy (2006)	Jahanshahloo et al. (2008)
	Dia (2004)	Hosseinzadeh Lotfi, Jahanshahloo, and Alimardani (2007b)	Noora and Karami (2008)
	Jahanshahloo et al. (2004)	Hosseinzadeh Lotfi, Jahanshahloo, Allahviranloo, Noroozi, and Hosseinzadeh Lotfi (2007a)	Soleimani-damaneh (2008)
	K. H. Lee (2004)	Jahanshahloo, Hosseinzadeh Lotfi, Nikoomaram, and Alimardani (2007a)	P. Zhou, Ang, and Poh (2008)
	H. S. Lee, Shen, and Chyr (2005)	Pal, Mitra, and Pal (2007)	
From 2009 to 1 September 2016	Bagherzadeh Valami (2009)	Hatami-Marbini, Saati, and Makui (2010b)	Sefeedpari, Rafiee, and Akram (2012)
	Guo (2009)	Azadeh, Asadzadeh, Bukhari, and Izadbakhsh (2011a)	Ahmady, Azadi, Sadeghi, and Saen (2013)
	Hatami-Marbini, Saati, and Makui (2009)	Azadeh, Moghaddam, Asadzadeh, and Negahban (2011b)	Amindoust, Ahmed, and Saghafinia (2013)
	Hosseinzadeh Lotfi, Allahviranloo, Mozaffari, and Gerami (2009a)	Azadeh, Sheikhalishahi, and Asadzadeh (2011c)	Azadeh et al. (2013b)
	Hosseinzadeh Lotfi, Jahanshahloo, Vahidi, and Dalirian (2009b)	Emrouznejad, Rostamy-Malkhalifeh, Hatami-Marbini, Tavana, and Aghayi (2011)	Beiranvand, Khodabakhshi, Yarahmadi, and Jalili (2013)
	Jahanshahloo et al. (2009b)	Hatami-Marbini, Saati, and Tavana. (2011b)	Puri and Yadav (2014c)
	Juan (2009)	Hatami-Marbini, Tavana, and Ebrahimi (2011c)	Shen, Hermans, Brijs, and Wets (2014)
	Sanei, Noori, and Saleh (2009)	Moheb-Alizadeh, Rasouli, and Tavakkoli-Moghaddam (2011)	Payan (2015)
	Soleimani-damaneh (2009)	Chang and Lee (2012)	Ignatius, Ghasemi, Zhang, Emrouznejad, and Hatami-Marbini (2016)

Guo and Tanaka (2001) firstly proposed the fuzzy ranking approach for efficiency measurement. They suggested a fuzzy CCR model in which fuzzy constraints were changed to crisp constraints by a predefined possibility level and using the comparison rule for fuzzy numbers which is described in Model (3.76).

Consider n DMUs under evaluation, the efficiency of the $\mathrm{DMU_j}$with m symmetrical triangular fuzzy inputs and s symmetrical triangular fuzzy outputs is denoted by $\tilde{\mathrm{x}}_{\mathrm{ij}} = (\mathrm{x_{ij}}, \mathrm{c_{ij}})$ and $\tilde{\mathrm{y}}_{\mathrm{rj}} = (y_{rj}, d_{rj})$, respectively, where x_{ij} and $y_{rj}$are the center, and c_{ij} and d_{rj} are the spread of fuzzy numbers.

$$
\begin{aligned}
&\left.\begin{aligned}
&\max_{u,v} \quad \theta_p = \sum_{r=1}^{s} (\mathrm{u}_r\, y_{rp} - (1-\alpha)\,\mathrm{u}_r\, d_{rp}) \\
&s.t. \quad \max_{v} \sum_{i=1}^{m} v_i c_{ip} \\
&s.t. \quad \sum_{i=1}^{m} (v_i x_{ip} - (1-\alpha) v_i c_{ip} = 1-(1-\alpha)e, \\
&\qquad\quad \sum_{i=1}^{m} (v_i x_{ip} - (1-\alpha) v_i c_{ip} \le 1+(1-\alpha)\,\mathrm{e},
\end{aligned}\right\} \text{Model (3.76-1)} \\
&\qquad\quad v_i \ge 0, \quad \forall_i . \\
&\qquad\quad \sum_{r=1}^{s} (\mathrm{u}_r\, y_{rj} + (1-\alpha)\,\mathrm{u}_r\, d_{rj}) \le \sum_{i=1}^{m} (\mathrm{v}_i \mathrm{x}_{ij} + (1-\alpha)\,\mathrm{v}_i \mathrm{c}_{ij}), \quad \forall_j , \\
&\qquad\quad \sum_{r=1}^{s} (\mathrm{u}_r\, y_{rj} - (1-\alpha)\,\mathrm{u}_r\, d_{rj}) \le \sum_{i=1}^{m} (\mathrm{v}_i \mathrm{x}_{ij} - (1-\alpha)\,\mathrm{v}_i \mathrm{c}_{ij}), \quad \forall_j , \\
&\qquad\quad u_r \ge 0, \quad \forall_r .
\end{aligned}
\tag{3.76}
$$

where $\alpha \in [0,1]$ is a prearranged possibility level by decision-makers and the unity number in the right hand side of the first constraint of model is purportedly a symmetrical TFN *1 = (1, e)*. Note that if $c_{ij} = d_{ij} = 0$, then the traditional CCR is obtained and if max $[c_{p1}/x_{p1}, \ldots, c_{p1}/x_{ps}] \le e$ in (3.76-1), there exists an optimal solution in (3.76).

The fuzzy efficiency of each DMU under evaluation with the symmetrical triangular fuzzy inputs $\tilde{x}_{ip}$ and outputs $\tilde{y}_{rp}$ is achieved for each possibility level as a non-symmetrical TFN $\tilde{\theta}_p = (e_p^l,\ e_p^m, e_p^u)$ as follows:

$$
e_p^m = \frac{u_r^* y_{rp}}{v_i^* x_{ip}}, \quad e_p^l = e_p^m - \frac{u_r^*(y_{rp} - d_{rp}(1-\alpha))}{v_i^*(\mathrm{x}_{ip} + \mathrm{c}_{ip}(1-\alpha))}, \quad e_p^u = \frac{u_r^*(y_{rp} + d_{rp}(1-\alpha))}{v_i^*(\mathrm{x}_{ip} - \mathrm{c}_{ip}(1-\alpha))} - e_p^m
$$

where u_r^* and v_i^* are obtained from (3.12), and, e_p^l, e_p^m and e_p^u are the left, right spreads and the center of the fuzzy efficiency $\tilde{\theta}_p$, respectively. Because of using a predefined $\alpha \in [0,1]$ Guo and Tanaka (2001)'s method can also be classified within α-level approaches.

Recent studies have suggested novel procedures based on the fuzzy ranking approach. For example, Puri and Yadav (2014c) have proposed a dual slack based measurement model with fuzzy weights for input and output data using a new ranking method.

Shen et al. (2014) presented the extension of the basic DEA-based composite indicator model by integrating fuzzy ranking approach for modeling qualitative data. Payan (2015) have proposed a FDEA model including an extension of fuzzy ranking approach and also have used the common set of weights to evaluate the performances of chief executive officers of U.S. public banks and thrifts. Ignatius et al. (2016) have developed a DEA-based framework where the input and output data are characterized by symmetrical and asymmetrical fuzzy numbers and adapted the fuzzy ranking approach to measure energy efficiency.

3.4.3.4 Possibility Based Approaches

The main bases of the possibility theory are embedded in Zadeh’s (1978) fuzzy set theory. Zadeh (1978) recommended that a fuzzy variable is linked to a possibility distribution in a similar way that a random variable is linked to a probability distribution. In fuzzy linear programming models, fuzzy coefficients are regarded as fuzzy variables and the constraints are viewed to be fuzzy events. Hence, the possibilities of fuzzy events (i.e., fuzzy constraints) are identified using possibility theory. Dubois and Prade (1988) presented a broad outline of possibility theory. Some researchers have proposed various FDEA models based on the possibility approach given Table 3.7.

Guo, Tanaka, and Inuiguchi (2000) firstly proposed FDEA models based on possibility and necessity measures and then Lertworasirikul (2002) and Lertworasirikul et al. (2002a, 2002b) developed the ‘‘possibility approach’’ and the ‘‘credibility approach’’ for the ranking of DMUs in FDEA models. Then, Lertworasirikul et al. (2003a) suggested a possibility approach in order to solve a fuzzy CCR model where fuzzy constraints were treated as fuzzy events represented as the following model.

$$
\begin{aligned}
\max \quad & \theta_p = \overline{f} \\
s.t. \quad & (\sum_{r=1}^{s} u_r \tilde{y}_{rp})_{\beta}^{U} \geq \overline{f}, \\
& (\sum_{i=1}^{m} v_i \tilde{x}_{ip})_{\alpha_0}^{U} \geq 1, \\
& (\sum_{i=1}^{m} v_i \tilde{x}_{ip})_{\alpha_0}^{L} \leq 1, \\
& (\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij})_{\alpha}^{L} \leq 0, \quad \forall_j, \\
& \mathrm{u}_r, v_i \geq 0, \quad \forall_{r,i}.
\end{aligned}
\tag{3.77}
$$

where $\beta \in [0,1]$, $\alpha_0 \in [0,1]$ and $\alpha \in [0,1]$ are predefined admissible levels of possibility. The aim of Model (3.77) is to maximize $\bar{f}$ so that $\sum_{r=1}^{s} u_r y_{rp}$ of the first constraint can obtain with a ‘‘possibility’’ level β or higher, subject to the possibility levels being at least α_0 and α in other constraints. For the optimal solution, the value of $\sum_{r=1}^{s} u_r y_{rp}$ is achieved at least equal to $\bar{f}$ the possibility level β; while at the same time all constraints are satisfied at the predefined possibility levels.

Lertworasirikul et al. (2003b) improved possibility and credibility approaches in order to solve the primal and dual of the fuzzy BCC models. According to this study, the proposed primal fuzzy BCC model is given in Model (3.78).

$$
\begin{aligned}
\max \quad & \theta_p = (\sum_{r=1}^{s} u_r \tilde{y}_{rp})_{\beta}^{U} - u_0 \\
s.t. \quad & (\sum_{i=1}^{m} v_i \tilde{x}_{ip})_{\alpha_0}^{U} \geq 1, \\
& (\sum_{i=1}^{m} v_i \tilde{x}_{ip})_{\alpha_0}^{L} \leq 1, \\
& (\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij})_{\alpha}^{L} - u_0 \leq 0, \quad \forall_j, \\
& \mathrm{u}_r, v_i \geq 0, \quad \forall_{r,i}.
\end{aligned}
\tag{3.78}
$$

where $\beta \in [0,1]$, $\alpha_0 \in [0,1]$ and $\alpha \in [0,1]$ are predetermined admissible levels of possibility. Similarly, the proposed dual fuzzy BCC model is as follows:

$$
\begin{aligned}
\max \quad & \theta_B \\
s.t. \quad & (\theta_B \tilde{x}_{ip} - \sum_{j=1}^{n} \lambda_j \tilde{x}_{ij})^U_{\bar{\alpha}_1} \geq 0, \quad \forall_i, \\
& (\sum_{j=1}^{n} \lambda_j \tilde{y}_{rj} - \tilde{y}_{rp})^U_{\bar{\alpha}_2} \geq 0, \quad \forall_r, \\
& \sum_{j=1}^{n} \lambda_j = 1 \quad \forall_j, \\
& \lambda_j \geq 0, \quad \forall_j.
\end{aligned} \tag{3.79}
$$

where $\bar{\alpha}_1 \in [0,1]$ and $\bar{\alpha}_2 \in [0,1]$ are predetermined admissible levels of possibility.

As seen from Table 3.7, various researches have suggested FDEA models based on the possibility approach proposed by Lertworasirikul et al. (2003a, 2003b) for measuring efficiency of various problems in different areas (Garcia et al., 2005; Hossainzadeh et al., 2011; Jiang & Yang, 2007; Khodabakhshi et al., 2010; Lin, 2010; Nedeljkovic & Drenovac, 2012; Payan & Sharifi, 2013; Ruiz & Sirvent, 2016; Valami et al., 2013; Wen & Li, 2009; Wu et al., 2006; Zhao & Yue, 2012.)

Table 3.7 A summary of FDEA literature based on the possibility approach

Years	**Possibility based Approach**	
	References	
From 2000 to 2010 (including 2010)	Guo et al. (2000)	Wu et al. (2006)
	Lertworasirikul (2002)	Jiang and Yang (2007)
	Lertworasirikul et al. (2002a, 2002b)	Wen and Li (2009)
	Lertworasirikul et al. (2003a, 2003b)	Khodabakhshi, Gholami, and Kheirollahi (2010)
	Garcia et al. (2005)	H.-T. Lin (2010)
	Ramezanzadeh, Memariani, and Saati (2005)	Wen, You, and Kang (2010)
From 2011 to 1 September 2016	Hossainzadeh Lotfi, Jahanshahloo, Kodabakhshi, and Moradi (2011)	Agarwal (2014)
	Wang and Chin (2011)	Paryab, Shiraz, Jalalzadeh, and Fukuyama (2014)
	Wen, Qin, and Kang (2011)	Shiraz, Charles, and Jalalzadeh (2014)
	Nedeljkovic and Drenovac (2012)	Feng, Meng, and Liu (2015)
	Zhao and Yue (2012)	Way (2015)
	Payan and Sharifi (2013)	Ruiz and Sirvent (2016)
	Bagherzadeh Valami, Nojehdehi, Abianeh, and Zaeri (2013)	

Recent studies have suggested novel procedures for possibility based approach. For example, Agarwal (2014) have attempted to extend the conventional DEA model to a fuzzy framework, thus proposing a fuzzy slack based measurement DEA model based on possibility approach to cope with the efficiency measuring problem with the given fuzzy input and output data. Paryab et al. (2014) have introduced a non-deterministic chance constrained DEA model by treating the input-output data as bifuzzy variables which are fuzzy variables with fuzzy parameters. Finally, two numerical examples were also given to show the applicability of the proposed framework. Shiraz et al. (2014) have created a fuzzy rough DEA model by incorporating the classical DEA, fuzzy set theory, and rough set theory and provided a pavement to measure the relative efficiency of any given DMUs in line with the possibility approach along with the fuzzy rough expected value operator. Feng et al. (2015) have studied the input-oriented and the output-oriented fuzzy DEA models, in which the input data and output data were characterized by fuzzy variables with known possibility distributions and also designed a hybrid heuristics algorithm for solving their FDEA models.

3.4.3.5 Fuzzy Arithmetic Based Approaches

Researches concentrate on fuzzy arithmetic to deal with the fuzziness of the input and output data in the DEA models in this approach. A summary of FDEA literature based on the fuzzy arithmetic approaches is given in Table 3.8.

Table 3.8 A summary of FDEA literature based on the fuzzy arithmetic approaches

Years	**Fuzzy Arithmetic based Approaches**	
	References	
From 2005 to 1 September 2016	Y.-M. Wang, Greatbanks, and Yang (2005)	Azadi, Mirhedayatian, and Saen (2013)
	Y.-M. Wang et al. (2009)	Khalili-Damghani and Taghavifard (2013)
	Abdoli, Shahrabi, and Heidary (2011)	Mirhedayatian, Jelodar, Adnani, Akbarnejad, and Saen (2013a)
	Jafarian-Moghaddam and Ghoseiri (2012)	Mirhedayatian, Vahdat, Jelodar, and Saen (2013b)
	Khalili-Damghani and Taghavifard (2012)	Razavi Hajiagha et al. (2013)
	Raei Nojehdehi, Maleki Moghadam Abianeh, and Bagherzadeh Valami (2012)	Mirhedayatian, Azadi, & Saen (2014)
	Alem, Jolai, and Nazari-Shirkouhi (2013)	

As seen from Table 3.8, various researches have suggested FDEA models based on the fuzzy arithmetic approach proposed by Y.-M. Wang et al. (2009) for measuring efficiency of various problems in different areas (Abdoli et al., 2011; Azadi et al., 2013; Khalili-Damghani and Taghavifard, 2012, 2013; Mirhedayatian et al., 2013a, 2013b, 2014; Razavi Hajiagha et al., 2013).

3.4.3.6 Fuzzy Random Variables and Other Extensions of Fuzzy Sets

Several extensions and generalizations of fuzzy sets have been introduced in the literature; namely, type 2 fuzzy sets proposed by Zadeh (1978), Atanassov's intuitionistic fuzzy sets proposed by Atanassov (1986), fuzzy multisets proposed by Yager (1986) and hesitant fuzzy sets (Torra, 2010). Moreover, many complicated systems usually include randomness and fuzziness simultaneously. In response, Kwakernaak (1978) offered fuzzy random variables to deal with performance measurement in such systems. Different researchers have proposed various FDEA models based on the fuzzy random and other extensions of fuzzy sets theory given in Table 3.9.

According to Table 3.9, FDEA studies based on the fuzzy random are more than FDEA studies based on the other extensions of the fuzzy sets. In this class, Ramezanzadeh et al. (2005) initially deal with the fuzzy random variables for inputs and outputs in DEA. In their study, these variables were considered as fuzzy random flat LR numbers with known distribution. To solve the problem, firstly defuzzification of imprecise probability by constructing a suitable membership function and defuzzification of parameters using an α-cut were done, respectively. Finally the chance-constrained DEA was converted into a crisp model using the method of Cooper (1996). Meng and Liu (2007) provided the input-oriented credibility data envelopment analysis model, where the concept of fuzzy chance constrained programming were adopted on objective function and all constraints with fuzzy inputs and fuzzy outputs. Azadeh et al. (2009) introduced a framework including three models as DEA, FDEA and Chance Constraint DEA based on Monte Carlo simulation analysis for decision making about the vendor selection problem.

Table 3.9 A classification of FDEA literature based on the fuzzy random variables and other extensions of fuzzy sets

Classes	Reference
Fuzzy Random	Ramezanzadeh et al. (2005), Meng and Liu (2007), Azadeh, Alem, Nazari-Shirkoohi, and Rezaie (2009), Azadeh and Alem (2010), Qin and Liu (2010a), Qin and Liu (2010b), Eslami, Khodabakhshi, Jahanshahloo, Hosseinzadeh Lotfi, and Khoveyni (2012), Tavana, Khanjani Shiraz, Hatami-Marbini, Agrell, and Paryab (2012), Tavana, Khanjani Shiraz, Hatami-Marbini, Agrell, and Paryab (2013b), Azadeh, Rahimi, Zarrin, Ghaderi, and Shabanpour (2016a).
Type-2 Fuzzy Sets	Qin, Liu, Liu, and Wang (2009), Qin, Liu, and Liu (2011a), Qin, Liu, and Liu (2011b), Figueroa-Garcia and Castro-Cabrera (2015), X. Zhou, Pedrycz, Kuang, and Zhang (2016).
Intuitionistic Fuzzy Sets	Gandotra, Bajaj, and Gupta (2012), Hajiagha, Akrami, Zavadskas, and Hashemi (2013), Puri and Yadav (2015a), and Wang (2016).
Fuzzy Multisets	No documents have been found.
Hesitant Fuzzy Sets	No documents have been found.
Nonstationary Fuzzy Sets	No documents have been found.
Neutrosophic Sets	No documents have been found.

Azadeh and Alem (2010) also proposed a Chance Constraint DEA model for two levels of probabilities to evaluate supply chain risk and select proper vendor. Qin and Liu (2010a, 2010b) presented different formulas of chance distributions for triangular and trapezoidal fuzzy random variables and their functions. Afterwards, they developed a new class of fuzzy random DEA models, in which the inputs and outputs are assumed to be characterized by fuzzy random variables with known possibility and probability distributions. Eslami et al. (2012) formulated varieties of DEA models to assess the performance of DMUs in various fields with different data such as deterministic, intervals, fuzzy, and etc. They especially deal with a realistic decision problem that contains fuzzy constraints and uncertain information (stochastic data) that most productive scale size was estimated in imprecise-chance constrained DEA model. Tavana et al. (2012) proposed three fuzzy DEA models in respect of probability-possibility, probability-necessity and probability-credibility constraints. In addition to addressing the possibility, necessity and credibility constraints in the DEA model and also presented a case study for the base realignment and closure decision process at the U.S. Department of Defense to show the features and the applicability of the proposed models. Tavana et al. (2013b) improved three DEA models for measuring the radial efficiency of DMUs when the input and output data are fuzzy random variables with Poisson, uniform and normal distributions. Afterwards, they extend the formulations proposed by Tavana et al. (2012) for a production possibility set where the fuzzy random inputs and outputs have normal distributions with fuzzy means and variances. Azadeh et al. (2016a) implemented a decision-making scheme for selecting appropriate method for supplier selection under certainty, uncertainty, and stochastic conditions. In their study, when data were not crisp but sufficient historical data were available, stochastic DEA was used. Finally, average efficiency scores of DMUs for each model under different random types of inputs were calculated and the results were analyzed.

Type-2 fuzzy sets are the mostly used sets after the classical fuzzy sets in FDEA literature. For example, Qin et al. (2009) firstly extended the traditional DEA model and established a DEA model with type-2 fuzzy inputs and outputs and then provided a numerical example to illustrate the efficiency of the proposed DEA model. Qin et al. (2011a) presented three kinds of critical values for a regular fuzzy variable, and proposed three novel methods of reduction for a type-2 fuzzy variable. Then applied the reduction methods to DEA models with type-2 fuzzy inputs and outputs, and developed a new class of generalized credibility DEA models. Qin et al. (2011b) extended the study of Qin et al. (2011a) and added the mean reduction methods for type-2 fuzzy variables in their model. Figueroa-Garcia and Castro-Cabrera (2015) proposed a method that is an extension of the classic CCR model based on the opinion of multiple experts. They defined the values of inputs and outputs using the interval type-2 fuzzy sets for solving DEA problems. X. Zhou et al. (2016) developed a multi-objective DEA model in a setting of type-2 fuzzy modeling to evaluate and select the most appropriate sustainable suppliers.

Some researchers have also studied the intuitionistic fuzzy sets for modeling FDEA. For example, Gandotra et al. (2012) proposed a new algorithm for DMUs in context of intuitionistic fuzzy weighted entropy in order to rank decision making units in DEA. Hajiagha et al. (2013) used the intuitionistic fuzzy sets in the classical DEA method and presented a case of a finance and credit institution for the proposed method. Puri and Yadav (2015) developed models to measure optimistic and pessimistic efficiencies of each DMU in which the input/output data are represented by triangular intuitionistic fuzzy numbers and also presented an application of the proposed approach to the banking sector. Wang (2016) employed a FDEA model to construct evaluation of innovative design for green products based on intuitionistic fuzzy sets. As seen from Table 3.9, fuzzy multisets, hesitant fuzzy sets, nonstationary fuzzy sets and neutrosophic sets have not used yet for modeling FDEA.

3.4.3.7 Other Developments in FDEA

In this section, some FDEA models are examined, that do not take place in the summarized FDEA approaches in the previous subsequent sections.

Sheth and Triantis (2003) presented a fuzzy goal DEA method to assess the goals of efficiency and effectiveness under fuzzy environment. Hougaard (2005) proposed a simple approximation that has no requirement of the use of fuzzy linear programming techniques for the evaluation of efficiency scores according to fuzzy production plans. Uemura (2006) suggested a fuzzy goal based DEA model to obtain the ratings of individual outputs using the fuzzy loglinear analysis. Luban (2009) recommended a method motivated by Sheth and Triantis’s (2003) study and performed the fuzzy dimension of the DEA models to choose the membership function. Jafarian-Moghaddam and Ghoseiri (2011) presented a fuzzy dynamic multi-objective DEA model in which data are changing sequentially to assess the performance of the railways.

Zerafat Angiz, Emrouznejad, Mustafa, and Al-Eraqi (2010b) developed an alternative ranking approach based on DEA under fuzziness for the aggregation of preference rankings of a group of decision makers. Zerafat Angiz, Mustafa, and Emrouznejad (2010c) offered a multi-objective mathematical model using the fuzzy sets theory on the multipliers to rank the efficient units. Moreover, Zerafat Angiz, Tajaddini, Mustafa, and Jalal Kamali (2012b) introduced a ranking method in the preferential voting system using DEA under fuzziness.

Some researchers demonstrated that the standard DEA model can be performed to improve the performance via increasing the desirable outputs and decreasing the undesirable outputs (Jahanshahloo, Hosseinzadeh Lotfi, Shoja, Tohidi, & Razavyan, 2005; Liang, Li, & Li, 2009; Liu, Meng, Li, & Zhang, 2010; Puri & Yadav, 2014a; Saen, 2010; Seiford & Zhu, 2002, and so on). This concept, (used within the scope of the thesis), is explained in detail in Section 3.4.5.

Hatami-Marbini, Tavana, and Ebrahimi (2011c) suggested a novel fully fuzzified DEA model by utilizing a fully fuzzified linear programming model, where all decision parameters and variables are fuzzy numbers. Kazemi and Alimi (2014) presented a fully fuzzy DEA model and a ranking function approach to solve this model. Puri and Yadav (2015b) developed multi-component fully fuzzy DEA model in the presence of undesirable outputs. They also proposed a new ranking function approach to transform fully fuzzy DEA and multi-component fully fuzzy DEA models. Puri and Yadav (2016) also extended the conventional cost efficiency and revenue efficiency models under fully fuzzy environments and illustrated the practicality of the proposed models with an application to the banking sector in India.

3.4.4 The FDEA/AR Approach

In a conceptual manner, conventional DEA methodology permits individual DMU to select the weights that are most favorable to themselves in calculating the ratio of the aggregated output to the corresponding aggregated input. In truth, there are cases where each factor must be maintained at a minimum level for the production mechanism to work. To deal with this, weights restrictions and value judgments cover a considerable part of the DEA research literature (Allen, Athanassopoulos, Dyson, & Thanassoulis, 1997). Although there are various methods presented in the literature about the integration of weights constraints to DEA, it is often faced in the studies that the concept of the AR initially proposed by Thompson, Singleton, Thrall, and Smith (1986) and Thompson, Langemeier, Lee, Lee, and Thrall (1990). It was applied to restrict some weights to reasonable ranges, which are based upon a priori information such as previous experience, expert opinion, and common sense (Thompson, Brinkmann, Dharmapala, Gonzalez-Lima, & Thrall, 1997; Thompson, Dharmapala, and Thrall, 1995; Thompson, Dharmapala, Rothenberg, & Thrall; Thompson, Lee, & Thrall, 1992). The MCDM methods can be used integrating with DEA when evaluation of the expert options (for a detailed information, see Section 3.4.6).

Liu (2008) and Liu and Chuang (2009) considered further the concept of AR and developed a FDEA/AR model based on the Zadeh's extension principle and α-cut approach, which was applied to the selection of flexible manufacturing systems and assessment of university libraries, respectively. However, in their researches, the constraints of DMU under assessment were canceled. Jahanshahloo et al. (2009a) attached the constraints and reformed the proof for finding the lower and upper bounds of the efficiency at different levels. Z. Zhou et al. (2010) also corrected proof of *Proposition 1* in the study of Jahanshahloo et al. (2009a). Z. Zhou et al. (2012a) corrected the models and proof of *Proposition 1* in the study of Liu and Chuang (2009) and also proposed a generalized FDEA (GFDEA) model with AR, whose lower and upper bounds at given α-levels could be obtained similarly. Liu (2014) proposed a methodology for a fuzzy two-stage DEA model, where the AR approach was utilized to restrict weight flexibility. Liu (2016) utilized the AR approach to reduce the weight flexibility using a relational network model to take the operations of individual periods into account in measuring efficiencies under fuzzy environment.

3.4.4.1 Mathematical Formulation of GFDEA/AR Model

The GFDEA/AR model proposed by Z. Zhou, Zhao, Lui, and Ma (2012b), which is one of the adapted models within in the scope of the thesis, is explained as the following paragraphs.

Let inputs $\tilde{X}_{ij}$ and outputs $\tilde{Y}_{rj}$ be fuzzy numbers with membership functions $\mu_{\tilde{X}_{ij}}$ and $\mu_{\tilde{Y}_{rj}}$, respectively, where *j=1, ..., n*, *i=1, ..., m* and *r=1, ..., s*. Suppose the relative importance obtained from the experts range from $L_{O_1}$to $U_{O_1}$for output 1 and from $L_{O_2}$to $U_{O_2}$for output 2. The associated constraints are $L_{O_1}/U_{O_2} \leq u_1/u_2 \leq L_{O_1}/U_{O_2}$. Generalizing to all outputs and inputs, respectively, gives

$$\begin{aligned} & L_{O_p}\big/U_{O_q} \leq u_p\big/u_q \leq U_{O_p}\big/L_{O_q}, \quad p<q=2,\ldots,\mathrm{m} \\ & L_{I_p}\big/U_{I_q} \leq v_p\big/v_q \leq U_{I_p}\big/L_{I_q}, \quad p<q=2,\ldots,\mathrm{s} \end{aligned} \tag{3.80}$$

To simplify the notation, let $C_{pq}^L = L_{I_p}/U_{I_q}$, $C_{pq}^U = U_{I_p}/L_{I_q}$, $D_{pq}^L = L_{O_p}/U_{O_q}$ and $D_{pq}^U = U_{O_p}/L_{O_q}$. The GFDEA/AR model can be represented as the following fuzzy programming:

$$\begin{aligned} & \tilde{E}_{j_0} = \max \sum_{r=1}^{s} u_r \tilde{Y}_{rj_0} - \delta_1 u_0 \\ & s.t. \quad \sum_{i=1}^{m} v_i \tilde{X}_{ij_0} = 1 \\ & \qquad \sum_{r=1}^{s} u_r \tilde{Y}_{rj} - \sum_{i=1}^{m} v_i \tilde{X}_{ij} - \delta_1 u_0 \leq 0, \quad j=1,\ldots,n \\ & \qquad C_{pq}^L \leq \frac{v_p}{v_q} \leq C_{pq}^U, \quad 1 \leq p < q = 2,\ldots,\mathrm{m} \\ & \qquad D_{pq}^L \leq \frac{u_p}{u_q} \leq D_{pq}^U, \quad 1 \leq p < q = 2,\ldots,\mathrm{s} \\ & \qquad v_i \geq \varepsilon, \quad i=1,\ldots,m; \; u_r \geq \varepsilon, \quad r=1,\ldots,s \\ & \qquad \delta_1 \delta_2 (-1)^{\delta_3} u_0 \geq 0. \end{aligned} \tag{3.81}$$

where parameters δ_1, δ_2 and δ_3 are binary ones assuming only values 0 and 1. If $\delta_1 = 0$, the GFDEA/AR model reduces to the fuzzy CCR/AR model. If $\delta_1 = 1$ and $\delta_2 = 1$, the GFDEA/AR model reduces to the fuzzy BCC/AR model. If $\delta_1 = 1$, $\delta_1 = 1$ and $\delta_3 = 0$, the GFDEA/AR model reduces to the fuzzy FG/AR model. If $\delta_1 = 1$, $\delta_1 = 1$ and $\delta_3 = 1$, the GFDEA/AR model reduces to the fuzzy ST/AR model.

Model (3.81) introduces a fuzzy efficiency score that has lower and upper bounds at a specific α level. The linear programming forms of the lower and upper bounds of Model (3.81) are given as follows:

$$\begin{aligned}
&(\mathrm{E}_{j_0})_\alpha^L = \max \sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^L - \delta_1 u_0 \\
&s.t. \quad \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^U = 1 \\
&\qquad \sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^L - \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^U - \delta_1 u_0 \le 0, \\
&\qquad \sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^U - \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^L - \delta_1 u_0 \le 0, j = 1,\ldots,n. j \ne j_0 \\
&\qquad C_{pq}^L \le \frac{v_p}{v_q} \le C_{pq}^U, \quad 1 \le p < q = 2,\ldots,\mathrm{m} \\
&\qquad D_{pq}^L \le \frac{u_p}{u_q} \le D_{pq}^U, \quad 1 \le p < q = 2,\ldots,\mathrm{s} \\
&\qquad v_i \ge \varepsilon, \quad i = 1,\ldots,m;\ u_r \ge \varepsilon, \quad r = 1,\ldots,s \\
&\qquad \delta_1 \delta_2 (-1)^{\delta_3} u_0 \ge 0.
\end{aligned} \tag{3.82}$$

$$\begin{aligned}
&(\mathrm{E}_{j_0})_\alpha^U = \max \sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^U - \delta_1 u_0 \\
&s.t. \quad \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^L = 1 \\
&\qquad \sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^U - \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^L - \delta_1 u_0 \le 0, \\
&\qquad \sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^L - \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^U - \delta_1 u_0 \le 0, j = 1,\ldots,n. j \ne j_0 \\
&\qquad C_{pq}^L \le \frac{v_p}{v_q} \le C_{pq}^U, \quad 1 \le p < q = 2,\ldots,\mathrm{m} \\
&\qquad D_{pq}^L \le \frac{u_p}{u_q} \le D_{pq}^U, \quad 1 \le p < q = 2,\ldots,\mathrm{s} \\
&\qquad v_i \ge \varepsilon, \quad i = 1,\ldots,m;\ u_r \ge \varepsilon, \quad r = 1,\ldots,s \\
&\qquad \delta_1 \delta_2 (-1)^{\delta_3} u_0 \ge 0.
\end{aligned} \tag{3.83}$$

For a given value of α, Models (3.82) and (3.83) can be easily solved by any linear programming solvers.

3.4.5 Undesirable Inputs and Outputs in FDEA

DEA measures the relative efficiency of DMUs with multiple performance factors that are categorized into outputs and inputs. Once the efficient frontier is determined, inefficient DMUs can improve their performance to reach the efficient frontier by either increasing their current output levels or decreasing their current input levels (Saen, 2010). The standard DEA models were initially formulated only for desirable inputs and outputs, and are usually based on the assumption that inputs have to be minimized and outputs have to be maximized (Seiford & Zhu, 2002). However, in real life problems, some inputs need to be increased and some outputs need to be decreased to improve the performance of a DMU (Puri and Yadav, 2014a). In these situations, undesirable inputs and/or outputs are emerged which also need to be minimized (Jahanshahloo et al., 2005). There are many desirable factors (inputs/outputs) and undesirable ones in real production processes, such as the pollutant emissions in producing electricity, smoke pollution, waste treatment process, complications of medical operations in health care and so on (Hadi Vencheh, Kazemi Matin, and Tavassoli Kajani, 2005; Liu, Zhou, Ma, Liu, & Shen, 2015).

In DEA literature, there already existed much research concerning applications with undesirable inputs and/or outputs. Wu, Xiong, An, Zhu, and Liang (2015) categorized them into two groups, *direct and indirect approaches*. *Direct approaches* avoid data transformation and incorporate the undesirable inputs and/or outputs directly into the DEA model (Liu & Sharp, 1999). These approaches are mainly based on the study of Fare, Grosskopf, Lovell, and Pasurka (1989), which replaced *strong disposability assumption* of outputs by *weakly disposability assumption*. This study is extended by some researchers (Fare, Grosskopf, Lovell, & Yaiswarng, 1993; Fare, Grosskopf, Noh, & Weber, 2005; P. Zhou, Ang, & Poh, 2008; P. Zhou, Poh, & Ang, 2007; Seiford & Zhu, 2005; Tone, 2004). An important branch employs *directional distance function* for addressing the undesirable outputs (Chung, Fare, & Grosskopf, 1997; Fare & Grosskopf, 2004; Silva Portela, Thanassoulis, & Simpson, 2004; Yu, 2004).

On the other hand, *indirect approaches* are categorized into three groups. *The first one* may regard undesirable inputs as desirable outputs, or undesirable outputs as desirable inputs. Liu and Sharp (1999) initially attempted to formulate this method (Dyckhoff & Allen, 2001; Hailu & Veeman, 2001; Oggioni, Riccardi, & Toninelli 2011). This approach only needs the information on whether the data has to be minimized or maximized (Liu et al., 2010). *The second one* includes an intuitive reaction to apply some transformations. For this propose, various transformation techniques were proposed by some researchers (Amirteimoori, Kordrostami, & Sarparast, 2006; Golany & Roll 1989; Grubesic & Wei, 2012; Iqbal Ali & Koopmans, 1951; Korhonen & Luptacik, 2004; Lovell, Pastor, & Turner, 1995; Oggioni et al., 2011; Pastor, 1996; Seiford, 1990; Scheel, 2001(non-linear monotonic decreasing transformation approach); Seiford and Zhu, 2002 (linear monotonic decreasing transformation approach); Wu, An, Xiong, & Chen, 2013). *The last one* is slack based measurement approach, which takes care of the undesirable outputs through the slacks of undesirable outputs (Tone, 2004).

Some of the existing approaches have been briefly summarized by Khalili-Damghania, Tavana, and Santos-Arteagad (2016) as follows. The first is just simply to ignore the undesirable factors. The second is to treat the undesirable outputs as inputs and the undesirable inputs as outputs. The third is to treat the undesirable outputs in the non-linear DEA model (Fare et al., 1989). The last is either to treat the undesirable outputs as inputs or to apply a monotone decreasing transformation. For example, Lovell et al. (1995) proposed a monotone decreasing function that is denoted $1/y^b$ where y^b represents the undesirable outputs. Ramli and Munisamy (2013) presented a detailed review for modeling undesirable factors in DEA.

The recent applications of DEA models with desirable and undesirable factors in various industries can be found in (Anvari, Zulkifli, Sorooshian, & Boyerhassani, 2014; Barros, Managi, & Matousek, 2012; Charles, Kumar, & Irene Kavitha, 2012; Hu, Qi, & Yang, 2012; Jahanshahloo et al., 2012; Kumar Mandal & Madheswaran, 2010; Leleu, 2013; Liang et al., 2009; Liu et al., 2010; Lozano & Gutierrez, 2011; Ramli & Munisamy, 2013; Riccardi, Oggioni, & Toninelli, 2012; Sueyoshi & Goto, 2012; Yang & Pollitt, 2009; You & Yan, 2011).

As stated in previously, there are many approaches and studies for modeling DEA with desirable and undesirable inputs and/or outputs. However, in the literature, there are a few studies for modeling FDEA with desirable and undesirable inputs and/or outputs as explained in the following paragraph.

Saen (2010) proposed a DEA methodology that considers both undesirable outputs and imprecise data simultaneously for the supplier selection problem. Puri and Yadav (2014a) proposed an FDEA model in which all inputs, desirable outputs and undesirable outputs are taken as fuzzy numbers, in particular TFNs. Khalili-Damghani et al. (2016) have developed a comprehensive FDEA model with desirable inputs and/or undesirable outputs for emerging market assessment and selection decisions. Finally, Ignatius et al. (2016) have proposed a DEA-based framework for evaluating the carbon efficiency in which the input-output data are described by the symmetrical and asymmetrical fuzzy numbers. The proposed model also includes the undesirable outputs.

Since the proposed TPM PMS have the desirable and undesirable inputs and outputs, in the implementation phase of proposed TPM PMS, there different approaches are used for modeling FDEA in the presence of undesirability. *The first approach* is the ignorance of the undesirable performance measures (inputs and outputs). *The second approac*h is to treat the undesirable outputs as inputs and the desirable inputs as outputs (Liu & Sharp, 1999). *The third approach* is to apply both the second approach and the FDEA model proposed by Puri and Yadav (2014a), which is one of the adapted models in this thesis, and explained as the following paragraphs. These three different approaches are incorporated into the FDEA/AR models which are shown in Equations (3.82) and (3.83).

In this section, only general formulation of the FDEA model proposed by Puri and Yadav (2014a) is given.

Puri and Yadav (2014a) assume that the performance of a homogeneous set of n DMUs ($DMU_j; j = 1, \dots, n$) is to be measured. The performance of a DMU is characterized by a production process of m fuzzy inputs to yield s fuzzy outputs in which s_1 fuzzy outputs are desirable (good) and s_2 fuzzy outputs are undesirable (bad) such that $s = s_1 + s_2$. Let $\tilde{Y}$ be the fuzzy output matrix consisting of positive fuzzy elements. Then the fuzzy output matrix $\tilde{Y}$ can be decomposed as $\tilde{Y} = [\tilde{Y}^g \quad \tilde{Y}^b]^T$, where $\tilde{Y}^g$ and $\tilde{Y}^b$ are the matrices for desirable fuzzy outputs and undesirable fuzzy outputs respectively. Let $\tilde{X}$ be the fuzzy input matrix consisting of positive fuzzy elements. Further, let $\tilde{x}_{ik}$ ($i = 1, \dots, m$) be the m fuzzy inputs used by the kth DMU, and $\tilde{y}_{rk}^g$ ($r = 1, \dots, s_1$) and $\tilde{y}_{rk}^b$ ($p = 1, \dots, s_2$) be the s_1 desirable and s_2 undesirable fuzzy outputs produced by the kth DMU respectively. The fuzzy efficiency of the kth DMU with the undesirable fuzzy outputs can be evaluated from the following FDEA model with undesirable fuzzy outputs:

$$\begin{aligned}
&\max\ \tilde{E}_k = \frac{\sum_{r=1}^{s_1} u_{rk}^g \tilde{y}_{rk}^g - \sum_{p=1}^{s_2} u_{pk}^g \tilde{y}_{pk}^g}{\sum_{i=1}^{m} v_{ik} \tilde{x}_{ik}} \\
&s.t. \quad 0 \le \tilde{E}_j = \frac{\sum_{r=1}^{s_1} u_{rk}^g \tilde{y}_{rj}^g - \sum_{p=1}^{s_2} u_{pk}^g \tilde{y}_{pj}^g}{\sum_{i=1}^{m} v_{ik} \tilde{x}_{ij}} \le 1 \quad \forall j = 1, 2, \dots, n, \\
&\qquad u_{rk}^g \ge \varepsilon\ \forall r, \quad u_{pk}^b \ge \varepsilon\ \forall p, \quad v_{ik} \ge \varepsilon\ \forall i, \quad \varepsilon > 0.
\end{aligned} \tag{3.84}$$

By using Charnes–Cooper transformation (Cooper et al., 2007), Model (3.84) can be transformed into the linear programming problem given by

$$
\begin{aligned}
\max\ \tilde{E}_k &= \sum_{r=1}^{s_1} u_{rk}^{g}\tilde{y}_{rk}^{g} - \sum_{p=1}^{s_2} u_{pk}^{g}\tilde{y}_{pk}^{g} \\
s.t. \quad & \sum_{i=1}^{m} v_{ik}\tilde{x}_{ij} = \tilde{1}, \\
& \sum_{r=1}^{s_1} u_{rk}^{g}\tilde{y}_{rj}^{g} - \sum_{p=1}^{s_2} u_{pk}^{b}\tilde{y}_{pj}^{b} - \sum_{i=1}^{m} v_{ik}\tilde{x}_{ij} \le \tilde{0} \quad \forall j = 1,2,\ldots,n, \\
& \sum_{r=1}^{s_1} u_{rk}^{g}\tilde{y}_{rj}^{g} - \sum_{p=1}^{s_2} u_{pk}^{b}\tilde{y}_{pj}^{b} \ge \tilde{0} \quad \forall j = 1,2,\ldots,n, \\
& u_{rk}^{g} \ge \varepsilon\ \forall r,\quad u_{pk}^{b} \ge \varepsilon\ \forall p,\quad v_{ik} \ge \varepsilon\ \forall i,\quad \varepsilon > 0,
\end{aligned}
\tag{3.85}
$$

where u_{rk}^{g}, u_{pk}^{b} and v_{ik} are the weights for the *rth* desirable fuzzy output, *pth* undesirable fuzzy output and *ith* fuzzy input of the *kth* DMU respectively, and ε is the non-Archimedean infinitesimal. Puri and Yadav (2014a) used the methodology proposed by Saati et al. (2002) (shown as Model (3.75)) to solve the Model (3.85).

Within in the scope of the thesis, the proposed GFDEA/AR models integrated with three different undesirability approaches (as stated previously) are explained in detail in Section 4.4.1.

3.4.6 FDEA Integrated with MCDM Methods

Since an integrated FCOPRAS-FDEA method is conducted within the scope of the thesis, some studies that combine different MCDM methods with FDEA and then develop hybrid methods are examined in this section. In the literature there are few studies that use MCDM methods integrated with FDEA (Table 3.10).

As seen in Table 3.10, AHP and FAHP are the most widely used MCDM methods with FDEA. Additionally, these integrated methods have been mostly used in the areas of “facility layout design” and “supplier evaluation and selection”. There has not been any study in the literature about the application and theory of combined FCOPRAS-FDEA methodology.

Table 3.10 Summary of FDEA integrated with MCDM methods

MCDM Methods	Application Problems	References
AHP	Facility layout design	Ertay, Ruan, and Tuzkaya (2006)
AHP	Personnel selection	Lin (2010)
Delphi technique and AHP	Supplier performance evaluation	Awasthi, Noshad, and Chauan (2014)
FAHP	Supplier selection	Kuo, Lee, and Hu (2010)
FAHP	Evaluation of new product development projects	Chiang and Che (2010)
ANP	Personnel selection	Lin (2010)
FAHP	Evaluation of product research and development projects	Liu (2011)
ANP-Fuzzy DEMATEL	NC machine tools planning	Sarina, Zhang, and Qiu (2012)
Multi-objective fuzzy linear programming	A numerical example	Zerafat Angiz et al. (2012a)
Multi-objective priority assignment	Buffer management	Jolai, Asadzadeh, Ghodsi, and Bagheri-Marani (2013)
Multi-objective fuzzy linear programming	High-technology project selection at NASA	Tavana, Khalili-Damghani, and Sadi-Nezhad (2013c)
FAHP	A numerical example	Alem et al. (2013)
FAHP	Selection of the best tunnel ventilation system	Mirhedayatian et al. (2013a)
TOPSIS	Vendor evaluation for a high-tech investment decision making	Langroudi et al. (2013)
TOPSIS	Welding process selection for repairing nodular cast iron engine block	Mirhedayatian et al. (2013b)
AHP	Supplier performance evaluation	Awasthi et al. (2014)
FAHP	Facility layout design with safety and ergonomic factors	Azadeh and Moradi (2014)
DEMATEL-Fuzzy ANP	Performance measurement of publicly held pharmaceutical companies	Tavana, Khalili-Damghani, and Rahmatian (2014)
AHP	Optimization of human resources and industrial banks	Azadeh, Ghaderi, Mirjalili, Moghaddam, and Haghighi (2015b)
DEMATEL-AHP-Fuzzy Cognitive Map	Leanness assessment and optimization	Azadeh, Zarrin, Abdollahi, Noury, and Farahmand (2015a)
FAHP	Intelligent building assessment	Loron and Loron (2015b)
FAHP-Fuzzy Simulation	Facility layout design	Azadeh, Moghaddam, Nazari, and Sheikhalishahi (2016b)
Grey system theory	A numerical example	Khodabakhshi, Tavana, Abootaleb (2016)

3.4.7 Review on FDEA based Performance Measurement Studies

In this section, another different search related to review on FDEA based performance measurement studies are carried out using “Scopus”. As for the terms used in “article title, abstract, keywords”, Table 3.11 gives the set chosen, along with the different combinations tested between them in this search. As a result, a selected list of FDEA-based studies with regard to performance measurement in a multi-dimensional setting is presented in Table 3.12.

Table 3.11 Keywords used in this search

	And	
Or	Fuzzy Data Envelopment Analysis FDEA	Performance Measurement Performance Evaluation Performance Assessment

Table 3.12 FDEA-based performance measurement studies

Researchers	**Proposed FDEA Models**	**Application Problems**
Girod and Triantis (1999)	FDEA	Newspaper preprint insertion manufacturing processes
Dia (2004)	FDEA	A numerical example
Wu et al. (2005)	FDEA-Game Model	Vendor evaluation
Wu et al. (2006)	FDEA	Performance analysis in the service industry
Soleimani-damaneh (2006)	FDEA	A numerical example
Kuo and Wang (2008)	FDEA	Measurement the efficiency of multinational corporations
Nureize and Watada (2009)	FDEA-Fuzzy Regression Analysis	A numerical example
Y.-M. Wang et al. (2009b)	FDEA	Evaluation of the performance of manufacturing enterprise
Kuo, Lee, and Hu (2010)	FDEA-FAHP	Supplier selection
Azadeh et al. (2011a)	FDEA-Principle Component Analysis	Performance assessment of wireless communication industry
Khoshfetrat and Daneshvar (2011)	FDEA-Weak Efficiency Frontier	A numerical example
Muren et al. (2011)	GFDEA	A numerical example
Guo (2011)	FDEA	Performance evaluation of Airport Construction Energy-saving
Khalili-Damghani and Abtahi (2011)	FDEA	Measuring efficiency of just in time implementation
Wang and Chin (2011)	FDEA-Double Frontier Analysis	Selection of flexible manufacturing system
Azadeh et al. (2012)	FDEA	Performance assessment and optimization of integrated HSE management system
Hedayat, Saghehei, and Khoshjahan (2012)	Two Level FDEA	Project performance evaluation
Sarina et al. (2012)	FDEA-ANP-Fuzzy DEMATEL	NC machine tools planning
Costantino, Dotoli, Epicoco, Falagario, and Sciancalepore (2012)	FDEA	Performance evaluation of supplier
Jafarian-Moghaddam and Ghoseiri (2012)	Fuzzy dynamic DEA	Performance analysis of railway transportation
Azadeh et al. (2013b)	FDEA- Principle Component Analysis	Development of decision support system for performance assessment
Chen et al. (2013)	FDEA	Vendor selection and performance evaluation

Table 3.12 FDEA-based performance measurement studies (cont.)

Researchers	Proposed FDEA Models	Application Problems
Srinivasa Raju and Kumar (2013)	FDEA	Performance evaluation of an irrigation system
Puri and Yadav (2013)	FDEA-Mix Efficiency Measure	Performance evaluation in banking sector
Wang and Yan (2013)	FDEA/AR	Performance evaluation for manufacturing mode
Moon (2013)	FDEA	Evaluation of innovation performance
Awasthi et al. (2014)	FDEA-AHP	Supplier performance evaluation
Azadeh, Madine, Motevali Haghighi, and Mirzaei Rad (2014)	FDEA	Performance assessment of HSE and maintenance systems
Shen et al. (2014)	FDEA	Road safety evaluation
Tavana and Khalili-Damghani (2014)	Two-stage FDEA	Performance evaluation in the banking industry
Tavana et al. (2014)	FDEA-DEMATEL-Fuzzy ANP	Performance measurement of publicly held pharmaceutical companies
Dotoli, Epicoco, Falagario, and Sciancalepore (2015)	FDEA-Cross Efficiency	Performance evaluation of healthcare systems
Azadi, Jafarian, Mirhedayatian, and Saen (2015b)	FDEA-Genetic Algortihm	Measurement of corporate sustainability performance
Ghasemi, Ignatius, Lozano, Emrouznejad, and Hatami-Marbini (2015)	GFDEA-Super Efficiency	A numerical example
Jahed, Amirteimoori, and Azizi (2015)	FDEA with Double Frontier Analysis	Selection of flexible manufacturing system
Khalili-Damghania, Tavana, and Santos-Arteagad (2016)	FDEA	Assessment of emerging markets for international banking
Çakır (2016)	FDEA	Efficiency measurement in the tea industry
Hekmatnia, Allahdadi, and Payan (2016)	FDEA-Slack Based Measure	Project performance evaluation
Azadeh, Gaeini, Motevali Haghighi, and Nasirian (2016c)	FDEA-A Unique Adaptive Neuro Fuzzy Inference System	Performance evaluation in a natural gas transmission unit
Egilmez, Gumus, Kucukvar, and Tatari (2016)	FDEA	Sustainability performance assessment of the food manufacturing sectors

As one can see from Table 3.12, there has not been any study about the performance measurement of TPM using FDEA method in the literature.

3.5 Conclusion

In this chapter, the detailed information and comprehensive survey on methods used in this thesis are presented. As it is stated in the previous chapter, studies about which performance measurement of TPM are very limited. In this respect, a new framework is proposed to measure TPM performance. This framework involves the use of the fuzzy set theory that allows incorporating unquantifiable information, incomplete information, non-obtainable information, and partially ignorant facts into the decision making models. In this context, in the evaluation phase of proposed TPM PMS, the novel performance measures in TPM should be evaluated under the multiple attribute using linguistic variables which are essentially from the insufficient and/or imprecise nature of data as well as the subjective and evaluative preferences of the decision maker. Thus, in this phase, the COPRAS-G and improved FCOPRAS based on fuzzy arithmetic and fuzzy ranking methods are carried out to evaluate novel performance indicators in TPM. In the implementation phase of the proposed TPM PMS, various GFDEA/AR models incorporating FCOPRAS and also including desirable and undesirable inputs and outputs are proposed and then used to measure TPM performance based on novel performance indicators.

According to results of this chapter, AHP and FAHP are the most widely used MADM methods with FDEA. These integrated methods have been mostly used in the application areas of “facility layout design” and “supplier evaluation and selection”. There has not been any study in the literature about the application and theory of combined FCOPRAS-FDEA methodology. Additionally, this is one the first studies for the performance evaluation of TPM using proposed FDEA methods. In the subsequent chapter, the proposed TPM PMS is explained in detail.

CHAPTER FOUR
THE PROPOSED TOTAL PRODUCTIVE MAINTENANCE PERFROMANCE MEASUREMENT SYSTEM

4.1 Introduction

TPM is one of the best techniques (strategies or practices) for making manufacturing organizations competitive and effective in the field of maintenance (Sharma et al., 2012a, 2012b). It has been also widely used maintenance practice for improving manufacturing performance by increasing the effectiveness of production facilities as compared to traditional maintenance practices (Jain et al., 2014). A number of researchers and practitioners have evaluated the needs, contributions, benefits and also critical success factors of an effective TPM implementation program towards improving manufacturing performance as explained in detail in previous sections. Moreover, the measurement of TPM performance is significantly required for continuous improvement of the TPM implementation program.

Although TPM is a commonly used maintenance technique, a few studies have been made related to the performance measurement in TPM implementation (see Section 2.4.4.2). However, more comprehensive systematic research efforts are required aimed at solidifying theoretical constructs and promoting the implementation of more practical approaches by establishing appropriate indicators for performance measurement of TPM. In the literature, it is also emphasized that the human-oriented factors have a greater impact than process-oriented factors on TPM implementation in any organization (Seng et al., 2005; Peach et al., 2016). Thus, this thesis aims to develop a systematic framework for performance measurement of TPM based on novel performance indicators including quantitative and qualitative data. This chapter presents the proposed TPM PMS in detail. The proposed TPM PMS separates into phases of design, evaluation, implementation, and review. Figure 4.1 illustrates the general overview of the proposed TPM PMS.

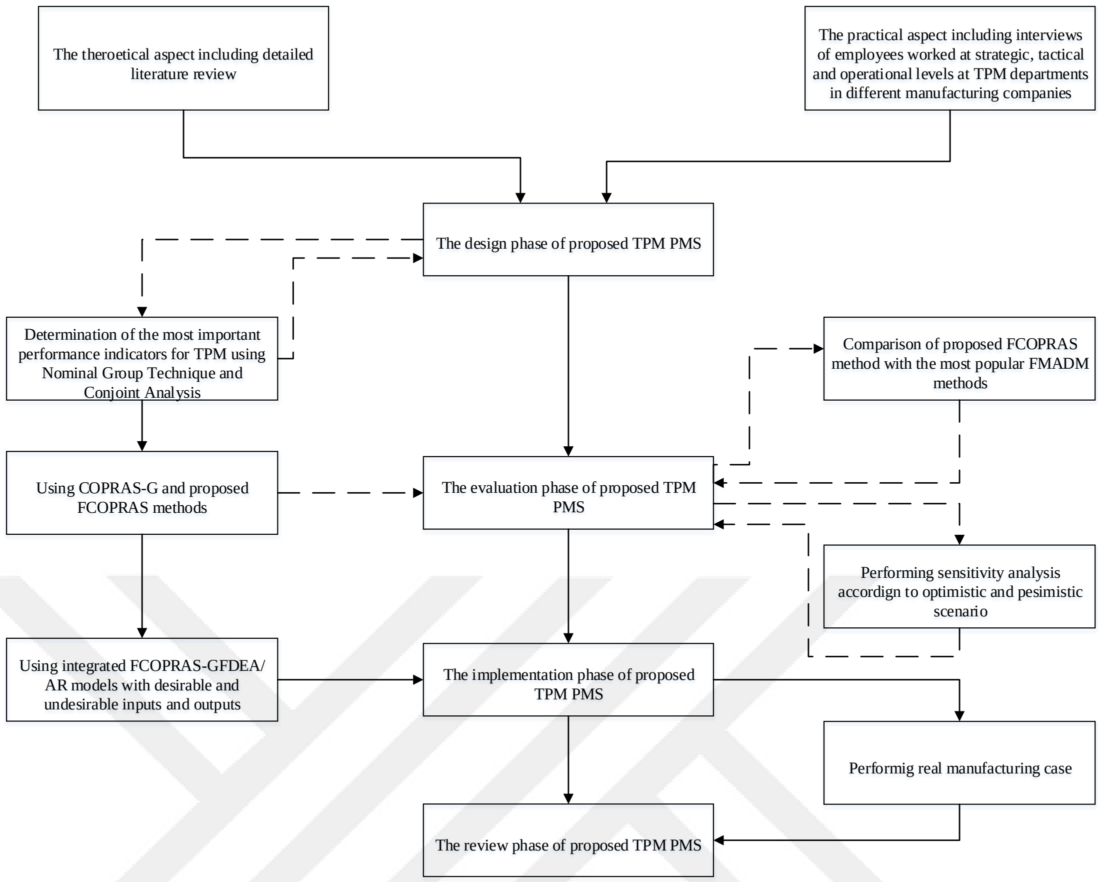

Figure 4.1 The general overview of the proposed TPM PMS

The rest of this chapter is organized as follows. As seen Figure in 4.1, the following section starts with the design phase of the proposed TPM PMS. Section 4.3 gives information about the evaluation phase of the proposed TPM PMS and also the methods used in this phase. In section 4.4, firstly, the detailed information is presented on the implementation phase of TPM PMS. Secondly, proposed mathematical models are formulated and explained in detail. Section 4.5 is completed by providing the review phase of the proposed TPM PMS. Section 4.6 provides the positioning of the proposed TPM PMS in the literature. Finally, concluding remarks about this chapter are provided in Section 4.7.

4.2 The Design Phase of the Proposed TPM PMS

The design phase of proposed TPM PMS is about identifying for the key objectives and designing novel performance indicators for TPM. Identifying and deciding the different performance indicators to measure the TPM performance, a flow diagram is given in Figure 4.2.

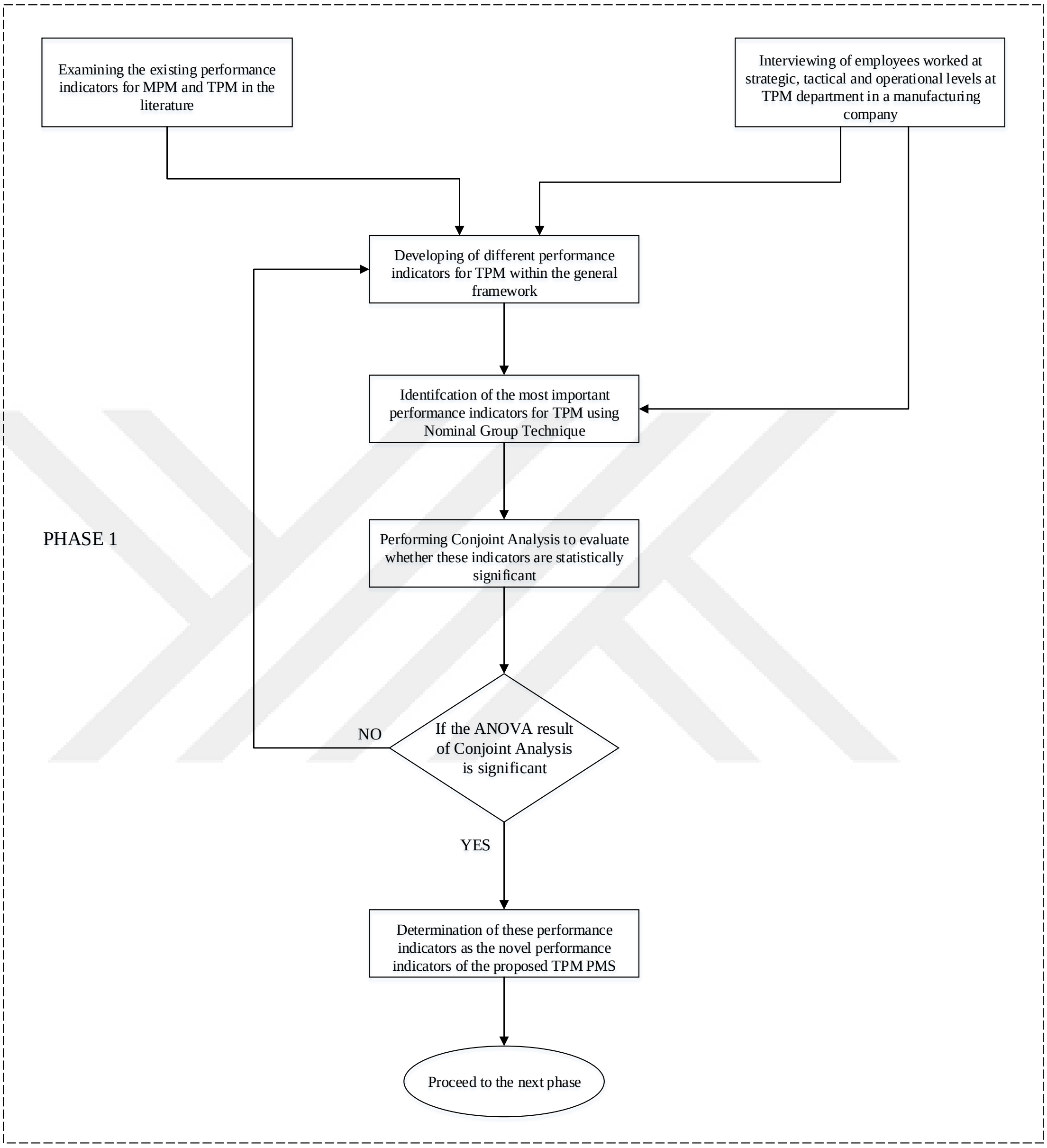

Figure 4.2 The flow diagram of the design phase of the proposed TPM PMS

As seen in Figure 4.2, this phase begins with the theoretical aspect including the detailed literature review on existing performance indicators for MPM and TPM (See Sections 2.3.2 and 2.4.4), and it is supported by practical aspects including the interviews of some employees worked at strategic, tactical and operational levels at the TPM department in a manufacturing company. In this context, the following important and relevant research questions should be answered and the performance indicators for TPM need to be developed based on the answers to these questions.

(1) Why is there a need to develop a reliable and meaningful TPM PMS?

(2) What indicators to be measured?

(3) Are the indicators related to the maintenance strategy/practice/technique and if yes, which one of them?

The first question searches to define the various indicators having impact on TPM performance that need to be monitored by a measurement system in the literature and practice. The second question requires the examination and the development of specific indicators based on maintenance strategy/practice/technique. For example, OEE is the fundamental measure of TPM performance and has limited productivity behavior of only individual equipment (see Section 2.4.4.1). However, TPM strictly emphases on some critical success factors (e.g., human factors, see Section 2.4.3.4) for its effective implementation. In this context, their regular feedback should be incorporated into the performance evaluation of TPM. Accordingly, different types of indicators which tend to impact on TPM performance are determined based on the theoretical and practical aspects and listed in Table 4.1.

According to Table 4.1, "operational-related indicators" are the production losses observed while running the plant. Since these are the most common problems observed in production, they are the ones analyzed regularly. One of the operational-related indicators is "unplanned downtime which can be result of a machine failure". The equipment-failure downtime explains the equipment availability, and this availability means that a machine can continue producing parts during a period of time. The availability rate is defined by three elements such as reliability, maintainability, and maintenance readiness and it is also related to the maintenance effectiveness (Fleischer et al., 2006; Huang, 2002). The reliability means the length of the running time of equipment without any failure, and it is evaluated by "MTBF". The maintainability means the length of the repairing time of equipment which satisfies an operating condition, and it is evaluated by "MTTR". The maintenance readiness is the responsibility of the maintenance function which provides the sustainability of the production equipment at the optimum conditions. Furthermore, one of the most important time losses is arisen from “changeovers and replacement of routine wear parts”. Since the changeover time differs from one process to another, it takes a long time to analyze and reduce. The other main losses are “minor stoppages”, “idling time”, “reduced speed”, and “quality defects” that are discussed in Section 2.4.4.1.

Table 4.1 A general list for proposed TPM Performance Indicators (TPM PIs) (Muchiri & Pintelon, 2008; Turanoglu Bekar & Kahraman, 2016; Turanoglu Bekar et al., 2016)

CATEGORY	TPM PIs
OPERATIONAL RELATED	**Planned Downtime** Number of Preventive Maintenance Preventive Maintenance Time
	Unplanned down time Number of Unplanned Maintenance (Equipment Failures) Mean Time Between Failure (MTBF) Mean Time to Repair (MTTR) (Failure Frequency) Set up (changeovers) and Adjustments Routine Wear Parts Minor Stoppages and Idling Reduced Speed Quality Losses Reduced Yield
BUSINESS RELATED	Stock Control Spare Parts Inventories Internal Logistic Problems (Storage, Shipping) Organization Problems and Labour Unrest HSE Problems Capital Project
EXTERNAL RELATED	**Logistic Problems** Supplier Failure Delivery Time Utility Shortage (Gas, Electricity Or Waters) **Environmental Regulation** Production Quatos **Natural Causes** Weather Conditions
OTHERS	Human-oriented Factors Availability of Maintenance personnel

“Business-related indicators” consist of problems at entire business level. One of them is internal logistics problems; namely, shipping and storage of the finished goods. This may cause production to slow down or shut down for a while (Muchiri & Pintelon, 2008). “Organizational problems or labour unrest” are stated employee satisfaction and also may cause the production to shutdown leading to production loss. “Employee satisfaction indicators” can include morale, teamwork and industrial harmony. Some of these are “employee absentees”, “employee turnover rate”, and “refusal of extended hours or overtimes” (Parida & Chattopadhyay, 2007). “HSE problems” cause production to be slowed down or stopped. Indicator for HSE problems is the number of HSE incidents (Muchiri et al., 2010). “Capital projects within the plant” forces production to be stopped until they are finished (Muchiri & Pintelon, 2008).

“One class of the external-related indicators” is “logistic problems” and includes “third-party failure to supply, transport problems resulting in a delay in raw-material arrival and shortage of utilities like electricity, gas, or water”. Second class is “environmental regulations with regard to production quotas in the cause of environmental degradation”. For example, if the quantity of carbon dioxide emissions can be restricted, the production quantity can also be limited because the plant should use the lower capacity. “Natural causes arise from poor weather conditions or similar natural phenomena” (Muchiri & Pintelon, 2008).

The human factors represented by maintenance technicians and other related staff (e.g., machine operators are in direct contact with the maintenance activities and efforts because of the autonomous maintenance concept in TPM) are the backbone of the maintenance system in any organization (Cabahug, Edwards, & Nicholas, 2004; Ljungberg, 1998). Qualified and well-trained machine operators and maintenance technicians are the driving force behind any effective maintenance measurement system (Simoes et al., 2011). As such, the effectiveness of the different facets of the performance system is very much dependent on the competency, training, and motivation of the human factor in charge of the maintenance system (Peach et al., 2016).

In this thesis, the human-oriented factors are proposed to measure TPM performance. These factors are divided into two groups, direct and indirect human-oriented factors. Proposed indicators for direct human-oriented factors are “Competence of maintenance personnel”, “experience of operators in production line”, “operator reliability”, and “training and continuing education”. Indirect human-oriented factor is addressed from two different points such as motivation management and work environment. Proposed indicators for the motivational management and work environment are “new ideas generated and implemented”, and “5S level”, respectively. Another proposed indicator is “availability of maintenance personnel”. This indicator is very important when the breakdowns occur and urgently should be repaired. Thus, the availability of maintenance personnel needs to be looked into, because otherwise it can act as a performance killer.

After a general list is determined for the proposed TPM PIs (see Table 4.1), these TPM PIs are analyzed by the decision makers to identify the most important ones. These decision makers work at strategic, tactical and operational levels in a manufacturing company. They determine the ranking of TPM PIs using the nominal group technique, which is a structured variation of a small-group discussion to reach consensus, and then the twelve TPM PIs having scored higher than 15 are selected. Table 4.2 gives the results of nominal group technique.

To determine whether these twelve TPM PIs (as specified in bold in Table 4.2) are statistically significant, conjoint analysis is performed that is an MADM technique based on the experimental design. Conjoint analysis is used as a way to map the strategic thinking of respondents because it is one of the most widely used methodologies for analyzing personal preferences (Carroll & Green, 1995). Conjoint analysis requires respondents to rate different scenarios with varying combinations of attribute levels. Conjoint analysis can measure preferences at the individual level and reveal hidden motivations which may not even be apparent to the respondents themselves, as well as providing realistic choices and scenarios for the respondents to consider (Kim, Kim, & Sohn, 2009). A further advantage of conjoint analysis is that it gives a psychological profile of respondents’ preferences and corresponding decision-making processes, because it uses algebraic theory to study cognitive processes and to develop statistical estimations (Bronn & Olson, 1999; Kuhfeld, 2006).

In the conjoint analysis, the full factorial design is generally used to obtain the statistical results. However, in this case, if the full factorial design is used for conjoint analysis, there would be too much combinations (2^{12}) because each TPM

PIs have two possible levels. Hence, the numbers of design should be reduced. In this context, the Taguchi design methodology is used for reducing the number of the designs. Then the conjoint analysis is performed by the Taguchi OA 16 table. Tables 4.3 and 4.4 present the possible levels of each TPM PIs and the experimental design using the Taguchi OA 16 table, respectively.

Part-worth is estimated based on the value placed on each level of the individual TPM PIs. The ANOVA results of conjoint analysis are displayed in Table 4.5. According to Table 4.6, the value of test statistic F is found 12.343. Also significance level α (Sig.) is found 0.031. Then, it is concluded that the proposed multiple regression model for the twelve TPM PIs are statistically significant. Finally the relative weights of these performance measures are calculated and presented in Table 4.6.

Table 4.2 The results of nominal group technique

PROPOSED TPM PIs	MEMBER 1 (OPERATIONAL LEVEL)	MEMBER 2 (TACTICAL LEVEL)	MEMBER 3 (STRATEGIC LEVEL)	TOTAL	AVERAGE	RANK
HSE problems	23	15	24	62	20.6667	1
Organization problems and labour unrest	24	14	23	61	20.3333	2
Human-oriented factors	22	23	10	55	18.3333	3
Availability of maintenance personnel	17	24	9	50	16.6667	4
Number of preventive maintenance	12	22	15	49	16.3333	5=6=7
Preventive maintenance time	14	21	14	49	16.3333	5=6=7
Quality losses	19	9	21	49	16.3333	5=6=7
Reduced speed	20	10	17	47	15.6667	8
MTBF	13	20	13	46	15.3333	9=10
MTTR	15	19	12	46	15.3333	9=10
Number of unplanned maintenance	16	13	16	45	15.0000	11=12
Reduced yield	18	8	19	45	15.0000	11=12
Set up and adjustments	21	12	11	44	14.6667	13
Stock control	6	18	18	42	14.0000	14=15
Spare parts inventories	5	17	20	42	14.0000	14=15
Capital Project	2	7	22	31	10.3333	16
Utility shortage	9	16	5	30	10.0000	17
Delivery time	11	6	7	24	8.0000	18
Internal logistic problems	7	4	8	19	6.3333	19=20
Supplier failure	10	3	6	19	6.3333	19=20
Routine wear parts	4	11	2	17	5.6667	21
Production quatos	8	1	4	13	4.3333	22
Minor stoppages and idling	3	5	1	9	3.0000	23
Weather conditions	1	2	3	6	2.0000	24

Table 4.3 Possible levels of TPM PIs

	TPM PIs	Level 1	Level 2
1	HSE problems	Low	High
2	Organization problems and labour unrest	Low	High
3	Human-oriented factors	Bad	Good
4	Availability of maintenance personnel	Unavailable	Available
5	Number of preventive maintenance	Low	High
6	Preventive maintenance time	Low	High
7	Quality losses	Low	High
8	Reduced speed	Low	High
9	MTBF	Low	High
10	MTTR	Low	High
11	Number of unplanned maintenance	Low	High
12	Reduced yield	Low	High

Table 4.4 Ortogonal Array and result for TPM PIs

Run No	1	2	3	4	5	6	7	8	9	10	11	12	OTHERS			Results (Ranking)
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	12
2	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	3
3	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	11
4	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1
5	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	4
6	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	13
7	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	2
8	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	6
9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	7
10	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	16
11	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	5
12	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	9
13	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	10
14	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	15
15	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	8
16	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	14

Table 4.5 ANOVA results of conjoint analysis

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	333.250	12	27.771	12.343	0.031
Residual	6.750	3	2.250		
Total	340.000	15			

Table 4.6 Relative weights of TPM PIs

TPM PIs	Deviations	Part-Worth Utilities (Relative Weights-%)
HSE problems	$\pm\beta_1$=4.00*2=8.00	8.00/52.50=15.24
Organization problems and labour unrest	$\pm\beta_2$=1.00*2=2.00	2.00/52.50=3.81
Human-oriented factors	$\pm\beta_3$=1.50*2=3.00	3.00/52.50=5.71
Availability of maintenance personnel	$\pm\beta_4$=3.00*2=6.00	6.00/52.50=11.43
Number of preventive maintenance	$\pm\beta_5$=0	0
Preventive maintenance time	$\pm\beta_6$=0	0
Quality losses	$\pm\beta_7$=1.50*2=3.00	3.00/52.50=5.71
Reduced speed	$\pm\beta_8$=2.25*2=4.50	4.50/52.50=8.57
MTBF	$\pm\beta_9$=3.75*2=7.50	7.50/52.50=14.29
MTTR	$\pm\beta_{10}$=3.75*2=7.50	7.50/52.50=14.29
Number of unplanned maintenance	$\pm\beta_{11}$=4.25*2=8.50	8.50/52.50=16.19
Reduced yield	$\pm\beta_{12}$=1.25*2=2.50	2.50/52.50=4.76
	TOTAL= 52.50	**TOTAL=100**

According to Table 4.6, the TPM PIs that are “the number of unplanned maintenance” and “HSE” problems have the highest relative weights with the values 16.19% and 15.24%, respectively. Furthermore, the TPM PIs that are “the number of preventive maintenance” and “preventive maintenance time” have the relative weights with the value 0. That means these TPM PIs do not have statistically significant impacts on the TPM performance. Therefore these two TPM PIs are ignored before proceeding to the evaluation phase of the proposed TPM PMS.

4.3 Evaluation Phase of the Proposed TPM PMS

In this phase, some of the basic questions require deliberation and critical examination while evaluating the proposed TPM PIs. These questions are like:

(1) How to evaluate the proposed TPM PIs under some attributes?

(2) Are the proposed TPM PIs included quantitative and qualitative data? If yes,

(3) How to collect relevant data for them?

The first question needs to implement a proper MADM method. In this context, COPRAS-G method is selected for the evaluation of the proposed TPM PIs (for detail see Section 3.3.3). According to the answer of second and third questions, the proposed TPM PIs include both quantitative and qualitative data, so these data are obtained by the linguistic variables. To evaluate these TPM PIs, FCOPRAS method is also proposed in this phase. The flow diagram of the evaluation phase of the proposed TPM PMS is illustrated in Figure 4.3.

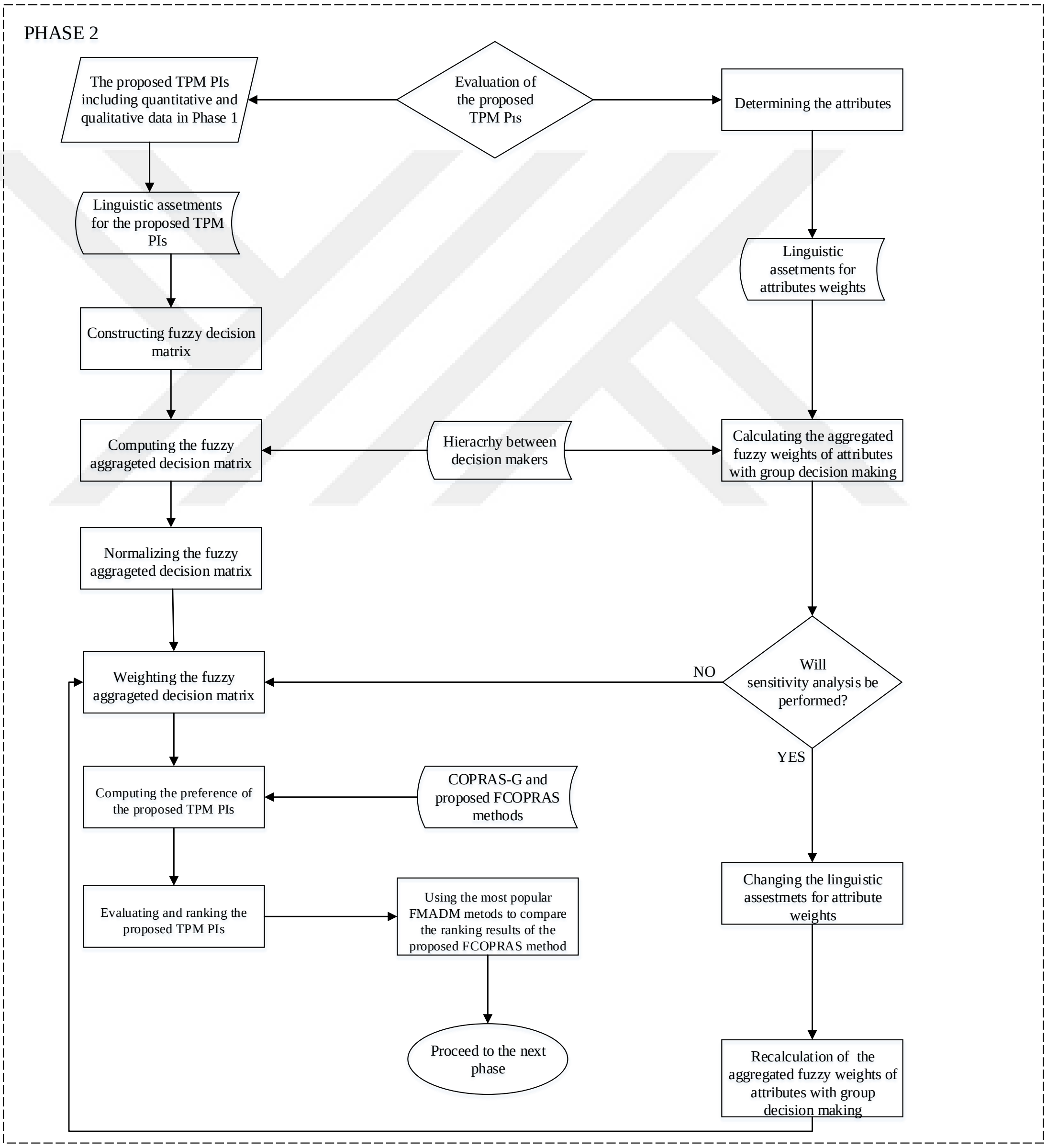

Figure 4.3 The flow diagram of the evaluation phase of the proposed TPM PMS

The set of attributes and initial values of attributes are determined on the basis of expert, normative and calculation methods. According to the literature investigation and expert's opinions, the committee including TPM, production and quality managers determines some attributes. When these attributes are determined, the following questions are criticized by the committee. Are the proposed TPM PIs;

(1) measurable objectively and subjectively?

(2) challenging and yet attainable?

(3) promptly communicated and easily understood?

(4) clear?

(5) practical?

According to the answers of these questions, the SMART test, which is frequently used to provide a quick reference to determine the quality of the performance indicators, is used to assure the compatibility of the proposed TPM PIs. SMART stands for (Parida & Kumar, 2006):

- "S. Specific – clear and focused to avoid misinterpretation. Should include measure assumptions and definitions and be easily interpreted.
- M. Measurable – can be quantified and compared to other data. It should allow meaningful statistical analysis. Avoid yes/no measures except in limited cases, such as start-up or systems-in-place situations.
- A. Attainable – achievable, reasonable, and credible under the conditions expected.
- R. Realistic – fits into the organization's constraints and is cost-effective.
- T. Timely – obtainable within the time frame given."

The main steps for the evaluation phase of the proposed TPM PMS are as follows.

In Step 1, the selected attributes for assessment of the proposed TPM PIs are determined. These are x_1 – *specificity* that is clear and concentrated to keep away misunderstanding and it should contain measure suppositions and descriptions and be simply explained; x_2 – *measurability* that can be quantified and resembled to other data; x_3 – *attainability* that is achievable, rational, and reliable under the conditions expected; x_4 – *practicalness* that conforms to the organization's restrictions and is profitable; x_5 – *timely that* is available within the time frame given; x_6 - *cost of measure*. The first five attributes are *benefit attributes*, while the last attribute is *cost one*. Additionally, the committee provides linguistic assessments for the six attributes and alternatives (the proposed TPM PIs) using rating scales. These scales are also expressed in detail in Chapter 5.

In Step 2, before evaluating the importance of the attributes, hierarchy between the decision makers in the committee is defined and they are ranked in a fuzzy way as $\tilde{1}$, $\tilde{2}$ and $\tilde{3}$. *In Step 2.1*, the relative importance or fuzzy weights of the decision makers are computed by using a subjective method such as "Rank Reciprocal" which is solely based on preference information given by an expert (Malczewski, 1999). After the fuzzy ranks are assigned and the reciprocal fuzzy weights are calculated, these weights are normalized using the geometric fuzzy normalization method proposed by Chang and Lee (1995), which is summarized below (Wang & Elhag, 2006):

$$\hat{w}_i^L = \frac{w_i^L}{\sqrt{\left(\sum_{j=1}^{n} w_j^L\right)\left(\sum_{j=1}^{n} w_j^U\right)}}, \quad i = 1, \ldots, \text{n}, \tag{4.1}$$

$$\hat{w}_i^M = \frac{w_i^M}{\sum_{j=1}^{n} w_j^M}, \quad i = 1, \ldots, \text{n}, \tag{4.2}$$

$$\hat{w}_i^U = \frac{w_i^U}{\sqrt{\left(\sum_{j=1}^{n} w_j^L\right)\left(\sum_{j=1}^{n} w_j^U\right)}}, \quad i = 1, \ldots, \text{n}, \tag{4.3}$$

where $w_i = (w_i^L, w_i^M, w_i^U)$ and $\hat{w}_i = (\hat{w}_i^L, \hat{w}_i^M, \hat{w}_i^U)$ are respectively non-normalized and normalized triangular fuzzy weights. In the above equations, the fuzzy arithmetic operations for TFNs which are given in Equations (3.34-3.45) in Section 3.2.5.3 are used.

In Step 2.2, firstly the linguistic assessments for all of the attributes are obtained from the decision makers and then an acceptable operator is applied to get a group preference from individual preferences for these assessments. The fuzzy aggregation procedure is performed by applying the fuzzy weighted triangular averaging operator, as defined by the following equations (Aydin, Kahraman, & Kaya, 2012; Kaya & Kahraman, 2014):

$$\tilde{a}_{ij} = \left[(\tilde{x}_{ij}^1 \otimes \hat{w}_1) \oplus (\tilde{x}_{ij}^2 \otimes \hat{w}_2) \oplus, \ldots, \oplus (\tilde{x}_{ij}^K \otimes \hat{w}_k)\right], \tag{4.4}$$

where $\tilde{a}_{ij}$ is the aggregated fuzzy weights for the attributes, K is the number of decision makers in the committee, x_{ij}^K is the linguistic assessment of the *k*th decision maker, and $\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_k; k = 1, 2, \ldots, K$ are the normalized fuzzy weights of the decision makers obtained by Equation (4.3). Also, $\otimes$ and $\oplus$ indicates fuzzy multiplication and fuzzy addition operators, respectively. When this equation is calculated, the fuzzy arithmetic based on α-cuts which is given in Equations (3.25-3.29) in Section 3.2.5.1 is utilized.

In Step 3, firstly, the TPM PIs proposed in Phase 1 are specified as the alternatives. Then, the fuzzy decision matrices are constructed for each decision maker. In this context, appropriate fuzzy ratings are assigned by each decision maker to all alternatives with regard to each attribute by using linguistics variables (explained in detail in Chapter 5). The fuzzy decision matrix ($\widetilde{D}_k$) with fuzzy evaluations of decision maker k for the alternatives with regard to the predefined attributes can be constructed as follows:

$$\tilde{D}_k = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_M \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_N \end{array} \\ \begin{bmatrix} \tilde{x}_{11k} & \tilde{x}_{12k} & \cdots & \tilde{x}_{1nk} \\ \tilde{x}_{12k} & \tilde{x}_{22k} & \cdots & \tilde{x}_{2nk} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{1mk} & \tilde{x}_{2mk} & \cdots & \tilde{x}_{nmk} \end{bmatrix} \end{array} \quad (4.5)$$

Fuzzy ratings of the kth decision maker are represented by $\tilde{x}_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk})$ where $i = 1, 2, \dots, M$ for alternatives; $j = 1, 2, \dots, N$ for attributes and $k = 1, 2, \dots, K$ for decision makers.

In Step 4, the fuzzy aggregation procedure expressed in *Step 2.2* is performed to integrate decision makers' evaluations. In this way, the aggregated fuzzy decision matrix is computed.

In Step 5, the aggregated fuzzy decision matrix is normalized. In the normalization process, the linear scale transformation is used to transform the various criteria scales into a comparable scale. In this way, the normalized aggregated fuzzy decision matrix are obtained by the following equations and denoted by $\tilde{R}$:

$$\tilde{R} = [\tilde{r}_{ij}]_{n \times m}, \quad (4.6)$$

where B and C are the set of benefit attribute which must be maximized and cost attribute which must be minimized, respectively, and the TFN $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$,

$$\tilde{r} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), \quad j \in B; \quad (4.7)$$

$$\tilde{r} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), \quad j \in C; \quad (4.8)$$

$$c_j^* = \max_i c_{ij} \quad if \quad j \in B; \quad (4.9)$$

$$a_j^- = \min_i a_{ij} \quad if \quad j \in C; \tag{4.10}$$

The normalization method mentioned above is to preserve the property that the ranges of normalized TFNs belong to [0;1] (Kaya & Kahraman, 2014).

In Step 6, the weighted normalized aggregated fuzzy decision matrix is calculated by using the following equations:

$$\tilde{V} = [\tilde{v}_{ij}]_{n\times m}, \tag{4.11}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{a}_{ij}, \tag{4.12}$$

where $\tilde{a}_{ij}$ is the aggregated fuzzy weights for the attributes obtained by Equation (4.4).

In Step 7, the COPRAS-G method whose steps are explained in the previous chapter is applied to compute the preference of alternatives. The Equations (3.59-3.64) given in Section 3.3.2.2 are used to determine the ranking orders of all alternatives.

In Step 8, the FCOPRAS method is proposed to obtain fuzzy utility degrees of alternatives. In the proposed FCOPRAS method, all fuzzy judgments and numbers are not converted to crisp values (or real numbers) and all calculations are performed in accordance with the fuzzy arithmetic operations and fuzzy ranking method. Thus, it can be said that *in this method the information loss is not included because of non-existence of defuzzification step*. This is the innovative side of the proposed FCOPRAS method. It is summarized as the following steps.

In Step 8.1, the sums of the fuzzy $\tilde{P}_i$ values whose larger values are more preferable are calculated by the formula given below:

$$\tilde{P}_i = \sum_{j=1}^{n} \tilde{v}_{ij} \quad if \quad j \in B, \; and \;\; \forall i, \tag{4.13}$$

where $\tilde{v}_{ij}$ is the TFN in the weighted normalized aggregated fuzzy decision matrix. The related calculations to the fuzzy arithmetic based on α-cuts are given in Equations (3.25) and (3.39) in Section 3.2.5.1.

In Step 8.2, the sums of the fuzzy $\tilde{R}_i$ values whose smaller values are more preferable are calculated by the formula given below:

$$\tilde{R}_i = \sum_{j=1}^{n} \tilde{v}_{ij} \quad if \quad j \in C, \; and \;\; \forall i, \tag{4.14}$$

where $\tilde{v}_{ij}$ is the TFN in the weighted normalized aggregated fuzzy decision matrix. For this equation, the related calculations to the fuzzy arithmetic based on α-cuts are given in Equations (3.25) and (3.39) in Section 3.2.5.1.

In Step 8.3, the fuzzy $\tilde{Q}_i$ values that are relative significance of each alternative are calculated by the formula given below:

$$\tilde{Q}_i = \tilde{P}_i \oplus \frac{\sum_{i=1}^{m} \tilde{R}_i}{\tilde{R}_i \otimes \sum_{i=1}^{m} \frac{1}{\tilde{R}_i}}. \tag{4.15}$$

In the above equation, the related calculations to the fuzzy arithmetic based on α-cuts are given in Equations (3.25-3.29) in Section 3.2.5.1.

In Step 8.4, the optimally criterion *K* is determined by the formula given below:

$$K = \max_i \tilde{Q}_i. \tag{4.16}$$

When the maximum fuzzy $\tilde{Q}_i$ value is determined, the fuzzy ranking method based on α-cut proposed by Basirzadeh &Abbasi (2008) is used, which is explained in detail in Section 3.2.7. In this context, the fuzzy $\tilde{Q}_i$ values are ranked using Equation (3.49) according to different α-levels.

In Step 8.5, the fuzzy $\tilde{N}_i$ values of each alternative are calculated as follows:

$$\tilde{N}_i = \frac{\tilde{Q}_i}{K} \times 100. \tag{4.17}$$

In the above equation, the related calculations to the fuzzy arithmetic based on α-cuts are given in Equations (3.28) and (3.29) in Section 3.2.5.1.

In Step 9, the proposed FCOPRAS method is compared with the most popular FMADM methods using the Spearman rank correlation coefficient. This step is also expressed in detail in Chapter 5.

In Step 10, the sensitivity analysis is performed to the effects of the optimistic and pessimistic changes in the aggregated fuzzy weights of the attributes. This step is also expressed in detail in Chapter 5.

4.4 Implementation Phase of the Proposed TPM PMS

In this phase, measurement should be made using the proposed TPM PIs to assess whether operations are efficient and effective, and the strategy is successfully implemented in TPM. The issues related to this phase are determined by answering the question like:

(1) How to measure? That is,

(2) How do the proposed TPM PIs evaluate the efficiency and effectiveness of TPM?

These questions need to implement a proper performance measurement method. In this context, FDEA method is selected for the evaluation of TPM performance (for detailed information see Section 3.4). The flow diagram of the implementation phase of the proposed TPM PMS is illustrated in Figure 4.4.

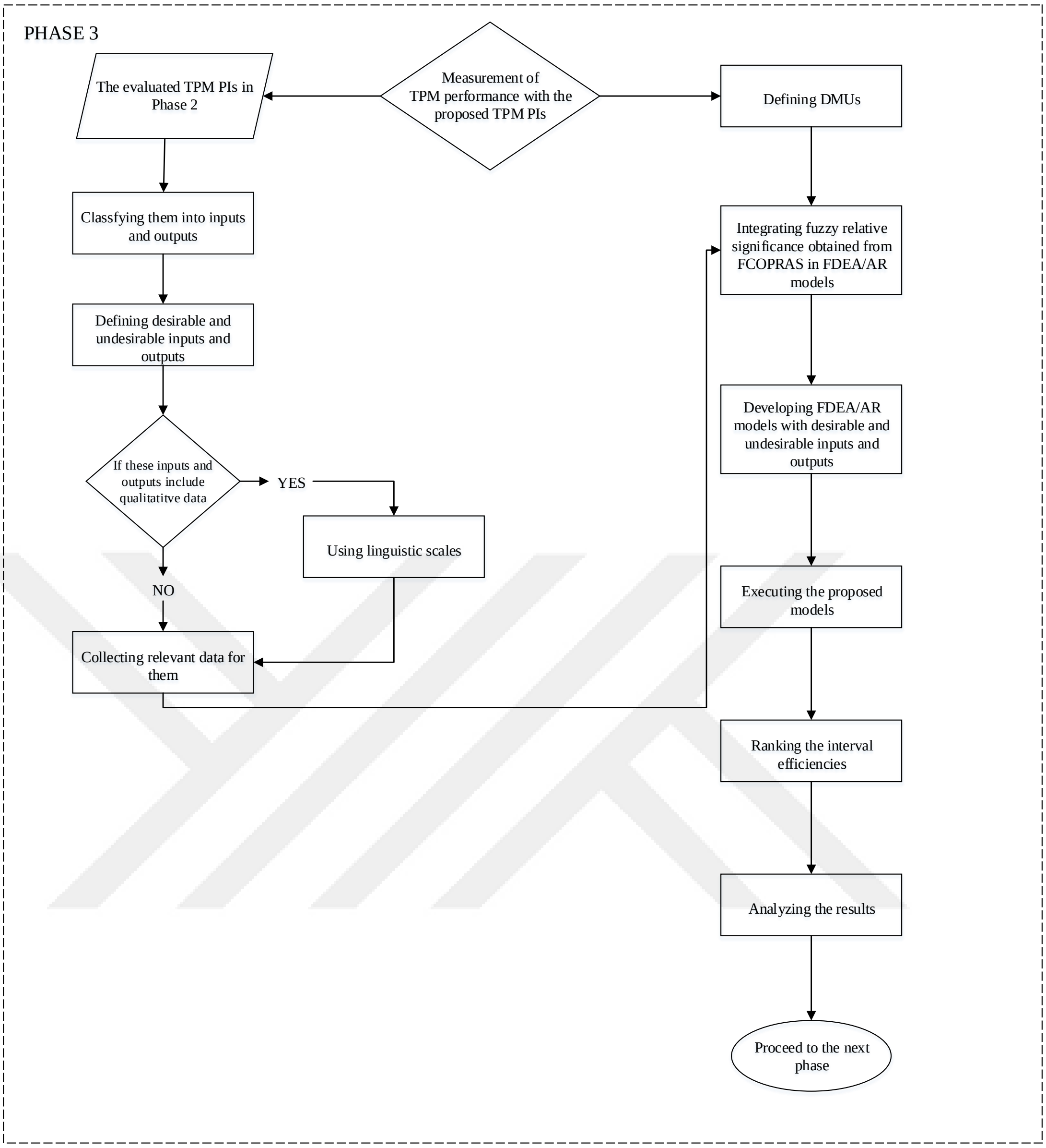

Figure 4.4 The flow diagram of the implementation phase of the proposed TPM PMS

According to Figure 4.4, the main steps for the implementation phase of the proposed TPM PMS as follows.

In Step 1, the DMUs (e.g., production lines in a plant) are defined in detail to measure TPM performance.

When TPM PIs is developed, it is considered to relate them to both the process inputs and the process outputs**.** Thus**,** ***In Step 2***, the evaluated TPM PIs in Phase 2 are classified as *inputs* which are required for the system to sustain its existence, and *outputs* that are the results of the process in this system.

In Step 3, desirable and undesirable inputs and outputs are determined. The detailed information for this context is given in the previous chapter in Section 3.4.5.

In Step 4, the relevant data is collected for the inputs and outputs which are determined in the previous step with regard to each DMU identified in ***Step 1***. When the data are collected, if these inputs and outputs include qualitative data, linguistic scale is used to evaluate these data. Additionally, in order to rectify the problems due to the significant differences in the magnitude of these inputs and outputs, the linear scale transformation (given in Equations (4.7-4.9)) is used to transform these various inputs and outputs scales into a comparable scale.

In Step 5, fuzzy relative significance (fuzzy $\tilde{Q}_i$ values) of the alternatives (proposed TPM PIs are called as inputs and outputs) obtained from FCOPRAS in Phase 2 are integrated with the GFDEA/AR models. Then, these models are extended by adding to some approaches in the presence of desirable and undesirable inputs and outputs. In this context, the mathematical descriptions of the proposed models are explained in Section 4.4.1.

In Step 6, the proposed models are solved to obtain the fuzzy efficiencies of the DMUs by using ***General Algebraic Modeling System (GAMS) 23.5***.

In Step 7, the fuzzy efficiencies of the DMUs are ranked by using the area measurement method of Chen and Klein (1997). It is a proper method for ranking of these efficiencies because it does not need the exact membership functions of the fuzzy numbers to be ranked. Chen and Klein (1997) proposed the following index for ranking fuzzy numbers (Liu, 2008):

$$I(\tilde{\mathrm{E}}_j) = \sum_{i=0}^{n}((\mathrm{E}_j)_{\alpha_i}^{U}) - c) \Big/ \left[\sum_{i=0}^{n}((\mathrm{E}_j)_{\alpha_i}^{U}) - c) - \sum_{i=0}^{n}((\mathrm{E}_j)_{\alpha_i}^{L}) - d)\right], n \to \infty \tag{4.18}$$

where $c = \underset{i,j}{min}\left\{\left(E_j\right)_{\alpha_i}^{L}\right\}$ and $d = \underset{i,j}{max}\left\{\left(E_j\right)_{\alpha_i}^{U}\right\}$. The larger the value of the ranking index the more preferred the number is.

In Step 8, TPM performance values of the DMUs are analyzed according to ranking results in ***Step 7***.

4.4.1 Mathematical Descriptions of the Proposed Models

In this section, firstly the fuzzy $\tilde{Q}_i$ values of inputs and outputs obtained from FCOPRAS are incorporated into the GFDEA/AR models which are explained in Section 3.4.4.1. In this context, the models given in Equation (3.82) and (3.83) are rearranged as follows:

Model (1)

$$(\mathrm{E}_{j_0})_\alpha^L = \max \sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^L - \delta_1 u_0 \qquad (4.19)$$

Subject to;

$$\sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^L - \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^U - \delta_1 u_0 \le 0, \qquad (4.20)$$

$$\sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^U - \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^L - \delta_1 u_0 \le 0, j = 1, \ldots, n. j \neq j_0 \qquad (4.21)$$

$$\sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^U = 1, \qquad (4.22)$$

$$QI_{pq}^L \le \frac{v_p}{v_q} \le QI_{pq}^U, \quad 1 \le p < q = 2, \ldots, \mathrm{m} \qquad (4.23)$$

$$QO_{pq}^L \le \frac{u_p}{u_q} \le QO_{pq}^U, \quad 1 \le p < q = 2, \ldots, \mathrm{s} \qquad (4.24)$$

$$v_i \ge \varepsilon, \quad i = 1, \ldots, m; \; u_r \ge \varepsilon, \quad r = 1, \ldots, s \qquad (4.25)$$

$$v_i \ge \varepsilon, \quad i = 1, \ldots, m; \; u_r \ge \varepsilon, \quad r = 1, \ldots, s \qquad (4.26)$$

where v_i is the weight for the ith input, u_r is the weight for the rth output for $i = 1, \dots, m,\ r = 1, \dots, s,$ and ε is a positive number less than any positive real number. QI_{pq}^L, QI_{pq}^U, QO_{pq}^L and QO_{pq}^U are the lower and upper bounds of the fuzzy relative significance of inputs and outputs respectively obtained from the FCOPRAS method. The parameters δ_1, δ_2 and δ_3 are binary ones assuming only values zero and one. In the above model, the values of these parameters are taken zero. So, the GFDEA/AR model reduces to the fuzzy CCR/AR model.

In Model (1), the objective function in Equation (4.19) calculates the lower bound of efficiency at any given α- cut level for the DMU_{j_0}. The constraint in Equation (4.20) is shown as $\frac{\sum_{r=1}^{s} u_r (\tilde{Y}_{rp})_\alpha^L}{\sum_{r=1}^{m} v_i (\tilde{X}_{ip})_\alpha^U} \leq 1$ meaning that the ratio of the maximum value of the output data to the minimum value of the input data is less and equal than one for the DMU_p at the given α- cut level. The constraint in Equation (4.21) is also shown as $\frac{\sum_{r=1}^{s} u_r (\tilde{Y}_{rj})_\alpha^U}{\sum_{r=1}^{m} v_i (\tilde{X}_{ij})_\alpha^L} \leq 1$ meaning that the ratio of the maximum value of the output data to the minimum value of the input data is less and equal than one for the other DMUs at the given α- cut level. The constraint in Equation (4.22) demonstrates that the sum of the maximum value of the weighted input data for the DMU_{j_0} is equal to one at the given α-cut level. This constraint also provides converting the fractional linear programming model to a conventional linear programming model. The constraints in Equations (4.23) and (4.24) give the assurance regions for the inputs and outputs data, respectively. Additionally, Equation (4.25) provides the sign constraints for the decision variables. Finally, Equation (4.26) gives the binary constraint for the parameters δ_1, δ_2 and δ_3.

In Model (2), the objective function in Equation (4.27) calculates the upper bound of the efficiency at any given α-cut level for the DMU_{j_0}. The constraint in Equation (4.28) gives that the ratio of the maximum value of the output data to the minimum value of the input data is less and equal than one for the DMU_{j_0} at the given α-cut level. The constraint in Equation (4.29) also presents that the ratio of the minimum value of the output data to the maximum value of the input data is less and equal than one for the other DMUs at the given α-cut level. The constraint in Equation (4.30) provides that the sum of the minimum value of the weighted input data for the DMU_{j_0} is equal to one at the given α-cut level. The constraints in Equations (4.31) and (4.32) give the assurance regions for the inputs and outputs data, respectively. Additionally, Equation (4.33) provides the sign constraints for the decision variables. Finally, Equation (4.34) gives the binary constraint for the parameters δ_1, δ_2 and δ_3.

Model (2)

$$(\mathrm{E}_{j_0})_\alpha^U = \max \sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^U - \delta_1 u_0 \tag{4.27}$$

Subject to;

$$\sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^U - \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^L - \delta_1 u_0 \leq 0, \tag{4.28}$$

$$\sum_{r=1}^{s} u_r (Y_{rj_0})_\alpha^L - \sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^U - \delta_1 u_0 \leq 0, j = 1, \ldots, n. j \neq j_0 \tag{4.29}$$

$$\sum_{i=1}^{m} v_i (X_{ij_0})_\alpha^L = 1, \tag{4.30}$$

$$QI_{pq}^L \leq \frac{v_p}{v_q} \leq QI_{pq}^U, \quad 1 \leq p < q = 2, \ldots, \mathrm{m} \tag{4.31}$$

$$QO_{pq}^L \leq \frac{u_p}{u_q} \leq QO_{pq}^U, \quad 1 \leq p < q = 2, \ldots, \mathrm{s} \tag{4.32}$$

$$v_i \geq \varepsilon, \quad i = 1, \ldots, m; \; u_r \geq \varepsilon, \quad r = 1, \ldots, s \tag{4.33}$$

$$\delta_1 \delta_2 (-1)^{\delta_3} u_0 \geq 0. \tag{4.34}$$

Secondly, Models (1) and (2) are extended by adding three different undesirability approaches. ***First approach*** is the ignorance of the undesirable outputs and desirable inputs. Thus, Models (1) and (2) are solved without any modifications.

Second approach is to treat the undesirable outputs as inputs and the desirable inputs as outputs. In this way, Models (1) and (2) are solved without any modifications. Therefore, in these models, the number of inputs and outputs are only changed. Then these models are called "Models (3) and (4)".

Third approach is to apply the FDEA model proposed by Puri and Yadav (2014a) with ignorance of the desirable inputs. In this context, Models (1) and (2) are integrated with the FDEA model which is given in Equation (3.85) in Section 3.4.5. Consequently, Models (5) and (6) are obtained as follows.

Puri and Yadav (2014a) used a method developed by Saati et al. (2002) to solve the FDEA model. However, Models (5) and (6) are proposed based on the approach developed by Kao and Liu (2000a).

In Models (5) and (6), it is assumed that the performance of a homogeneous set of n DMUs ($DMU_j; j = 1, \dots, n$) is to be measured. The performance of a DMU is characterized by a production process of m fuzzy inputs to yield s fuzzy outputs in which s_1 fuzzy outputs are desirable (good) and s_2 fuzzy outputs are undesirable (bad) such that $s = s_1 + s_2$. Let $\tilde{Y}$ be the fuzzy output matrix consisting of positive fuzzy elements. Then the fuzzy output matrix $\tilde{Y}$ can be decomposed as $\tilde{Y} = [\tilde{Y}^g \quad \tilde{Y}^b]^T$, where $\tilde{Y}^g$ and $\tilde{Y}^b$ are the matrices for desirable fuzzy outputs and undesirable fuzzy outputs respectively. Let $\tilde{X}$ be the fuzzy input matrix consisting of positive fuzzy elements. Further, let $\tilde{X}_{ij_0} = \left[\left(\tilde{X}_{ij_0}\right)_\alpha^L, \left(\tilde{X}_{ij_0}\right)_\alpha^U\right]$ $(i = 1, \dots, m)$ be the m fuzzy inputs used by the j_0th DMU, $\tilde{Y}_{rj_0}^g = \left[\left(\tilde{Y}_{rj_0}^g\right)_\alpha^L, \left(\tilde{Y}_{rj_0}^g\right)_\alpha^U\right]$ $(r = 1, \dots, s_1)$ be the α-level form of the s_1 desirable fuzzy outputs, and $\tilde{Y}_{pj_0}^b = \left[\left(\tilde{Y}_{pj_0}^b\right)_\alpha^L, \left(\tilde{Y}_{pj_0}^b\right)_\alpha^U\right]$ $(p = 1, \dots, s_2)$ be the α-level form of the s_2 desirable fuzzy outputs produced by the j_0th DMU respectively. The lower bound $(E_{j_0})_\alpha^L$ and the upper bound $(E_{j_0})_\alpha^U$ of the fuzzy efficiency score of the j_0th DMU with the undesirable fuzzy outputs can be evaluated from the Models (5) and (6).

In Model (5), the objective function in Equation (4.35) calculates the lower bound of the efficiency at any given α-cut level for the DMU_{j_0}. The constraint in Equation (4.37) gives that the ratio of the lower bound of the desirable output data to the lower bound of the undesirable output data and the upper bound of the input data is less and equal than 1 for the DMU_{j_0} at the given α-cut level. The constraint in Equation (4.38) also presents that the ratio of the upper bound of the desirable output data to the upper bound of the undesirable output data and the lower bound of the input data is less and equal than 1 for the other DMUs at the given α-cut level. The constraint in Equation (4.38) prevents taking negative efficiency score of the lower bound for the DMU_{j_0} at the given α-cut level. The constraint in Equation (4.39) provides that the sum of the upper bounds of the weighted input data for the DMU_{j_0} is equal to 1 at the given α-cut level. The constraints in Equations (4.40), (4.41), and (4.42) give the assurance regions for the inputs and desirable and undesirable outputs data, respectively. The last constraint in Equation (4.43) provides the sign constraints for the decision variables.

In Model (6), the objective function in Equation (4.44) calculates the upper bound of the efficiency at any given α-cut level for the DMU_{j_0}. The constraint in Equation (4.45) gives that the ratio of the upper bound of the desirable output data to the upper bound of the undesirable output data and the lower bound of the input data is less and equal than 1 for the DMU_{j_0} at the given α-cut level. The constraint in Equation (4.46) also presents that the ratio of the lower bound of the desirable output data to the lower bound of the undesirable output data and the upper bound of the input data is less and equal than 1 for the other DMUs at the given α-cut level. The constraint in Equation (4.47) prevents taking negative efficiency score of the upper bound for the DMU_{j_0} at the given α-cut level. The constraint in Equation (4.48) provides that the sum of the lower bounds of the weighted input data for the DMU_{j_0} is equal to 1 at the given α-cut level. The constraints in Equations (4.49), (4.50), and (4.51) give the assurance regions for the inputs and desirable and undesirable outputs data, respectively. The last constraint in Equation (4.52) provides the sign constraints for the decision variables.

Model (5)

$$(\mathrm{E}_{j_0})^L_\alpha = \max \sum_{r=1}^{s_1} u_r^g (Y^g_{rj_0})^L_\alpha - \sum_{p=1}^{s_2} u_p^b (Y^b_{rj_0})^L_\alpha \tag{4.35}$$

Subject to;

$$\sum_{r=1}^{s_1} u_r^g (Y^g_{rj_0})^L_\alpha - \sum_{p=1}^{s_2} u_p^b (Y^b_{rj_0})^L_\alpha - \sum_{i=1}^{m} v_i (X_{ij_0})^U_\alpha \le 0, \tag{4.36}$$

$$\sum_{r=1}^{s_1} u_r^g (Y^g_{rj_0})^U_\alpha - \sum_{p=1}^{s_2} u_p^b (Y^b_{rj_0})^U_\alpha - \sum_{i=1}^{m} v_i (X_{ij_0})^L_\alpha \le 0, \ \ j = 1,\dots,n, \ \ j \ne j_0 \tag{4.37}$$

$$\sum_{r=1}^{s_1} u_r^g (Y^g_{rj_0})^L_\alpha - \sum_{p=1}^{s_2} u_p^b (Y^b_{rj_0})^L_\alpha \ge 0, \tag{4.38}$$

$$\sum_{i=1}^{m} v_i (X_{ij_0})^U_\alpha = 1, \tag{4.39}$$

$$QI^L_{pq} \le \frac{v_p}{v_q} \le QI^U_{pq}, \quad 1 \le p < q = 2,\dots,\mathrm{m} \tag{4.40}$$

$$QO^L_{pq} \le \frac{u_p^g}{u_q^g} \le QO^U_{pq}, \quad 1 \le p < q = 2,\dots,\mathrm{s}_1 \tag{4.41}$$

$$QO^L_{pq} \le \frac{u_p^b}{u_q^b} \le QO^U_{pq}, \quad 1 \le p < q = 2,\dots,\mathrm{s}_2 \tag{4.42}$$

$$v_i \ge \varepsilon, \ i = 1,\dots,m; u_r^g \ge \varepsilon, \ r = 1,\dots,s_1; u_p^b \ge \varepsilon, \ p = 1,\dots,s_2, \tag{4.43}$$

where u_r^g, u_p^b, and v_i are the weights for the rth desirable fuzzy output, pth undesirable fuzzy output and ith fuzzy input of the j_0th DMU respectively, and ε is the non-Archimedean infinitesimal.

Model (6)

$$(\mathrm{E}_{j_0})^U_\alpha = \max \sum_{r=1}^{s_1} u_r^g (Y^g_{rj_0})^U_\alpha - \sum_{p=1}^{s_2} u_p^b (Y^b_{rj_0})^U_\alpha \tag{4.44}$$

Subject to;

$$\sum_{r=1}^{s_1} u_r^g (Y^g_{rj_0})^U_\alpha - \sum_{p=1}^{s_2} u_p^b (Y^b_{rj_0})^U_\alpha - \sum_{i=1}^{m} v_i (X_{ij_0})^L_\alpha \le 0, \tag{4.45}$$

$$\sum_{r=1}^{s_1} u_r^g (Y^g_{rj_0})^L_\alpha - \sum_{p=1}^{s_2} u_p^b (Y^b_{rj_0})^L_\alpha - \sum_{i=1}^{m} v_i (X_{ij_0})^U_\alpha \le 0, \;\; j = 1,\ldots,n, \;\; j \ne j_0 \tag{4.46}$$

$$\sum_{r=1}^{s_1} u_r^g (Y^g_{rj_0})^U_\alpha - \sum_{p=1}^{s_2} u_p^b (Y^b_{rj_0})^U_\alpha \ge 0, \tag{4.47}$$

$$\sum_{i=1}^{m} v_i (X_{ij_0})^L_\alpha = 1, \tag{4.48}$$

$$QI^L_{pq} \le \frac{v_p}{v_q} \le QI^U_{pq}, \quad 1 \le p < q = 2,\ldots,\mathrm{m} \tag{4.49}$$

$$QO^L_{pq} \le \frac{u_p^g}{u_q^g} \le QO^U_{pq}, \quad 1 \le p < q = 2,\ldots,\mathrm{s}_1 \tag{4.50}$$

$$QO^L_{pq} \le \frac{u_p^b}{u_q^b} \le QO^U_{pq}, \quad 1 \le p < q = 2,\ldots,\mathrm{s}_2 \tag{4.51}$$

$$v_i \ge \varepsilon, \; i = 1,\ldots,m; u_r^g \ge \varepsilon, \; r = 1,\ldots,s_1; u_p^b \ge \varepsilon, \; p = 1,\ldots,s_2, \tag{4.52}$$

where u_r^g, u_p^b, and v_i are the weights for the *r*th desirable fuzzy output, *p*th undesirable fuzzy output and *i*th fuzzy input of the j_0th DMU respectively, and ε is the non-Archimedean infinit esimal.

4.5 Review Phase of the Proposed TPM PMS

The main purpose of this phase is to periodically monitor and review the appropriateness of the proposed TPM PMS in view of the current competitive environment. The issues related to this phase are determined by answering the question like:

(1) How to use TPM performance results for preventive and predictive decisions and actions?

(2) How to review and modify the TPM strategy and system at regular intervals?

(3) When and how does one update the proposed TPM PIs?

For the answers of the first and second questions, the measured TPM performance is recorded and assessed against the target for each measurement unit. It can also be compared with already existing and previously measured indicator for TPM (e.g., OEE value). For the answer of the third question, a measure may be deleted or replaced, the target may change, and the definition of measures may change in the proposed TPM PMS. The flow diagram of the review phase of the proposed TPM PMS is illustrated in Figure 4.5.

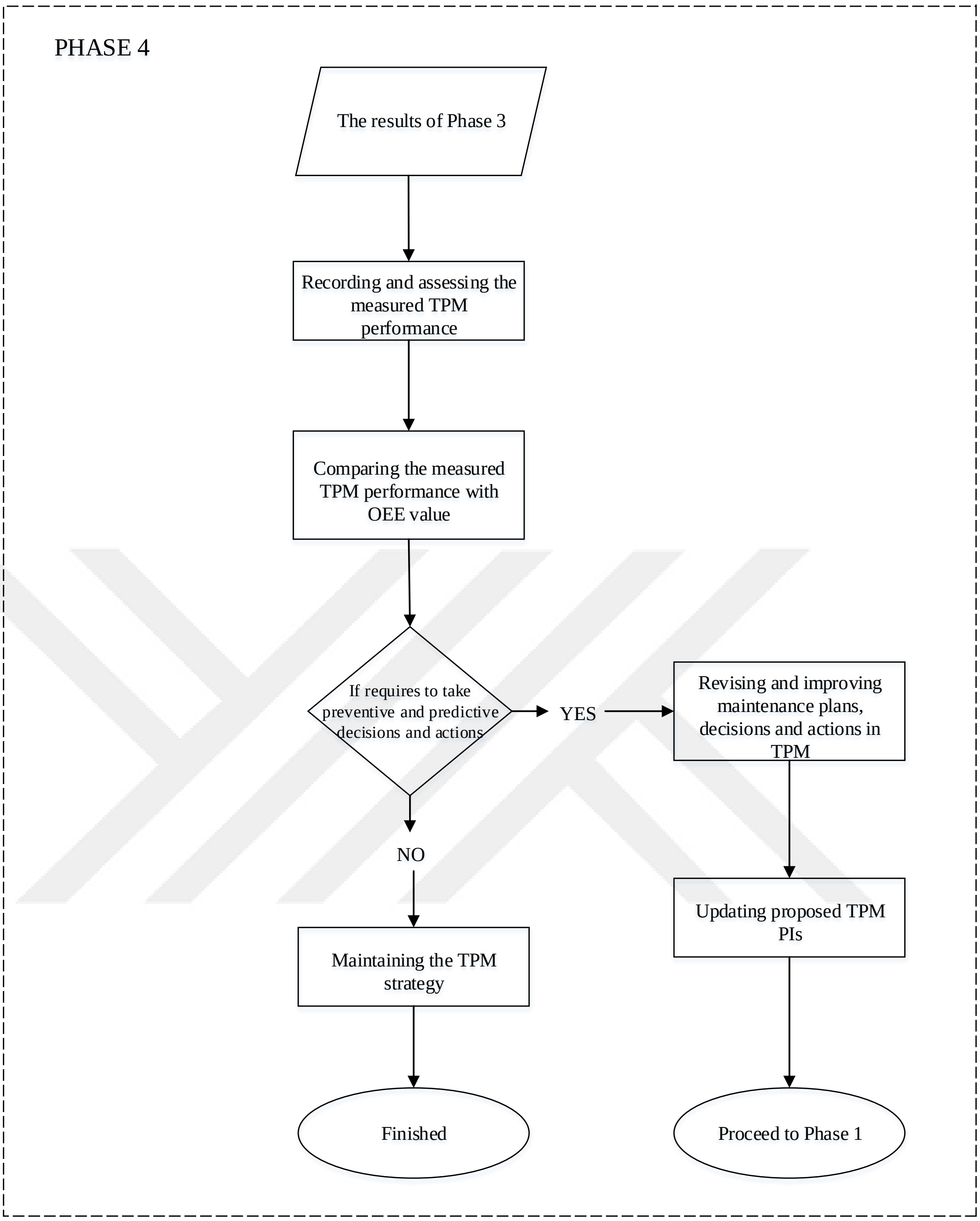

Figure 4.5 The flow diagram of the review phase of the proposed TPM PMS

4.6 Positioning of the proposed TPM PMS in the literature

Based on the results of the literature review, there are a few studies related to the efficiency measurement in TPM implementation (See Section 2.4.4.2). This study proposes a new framework that evaluates performance of TPM implementation based on novel PIs in TPM using Models (1-6). These models have some computational and practical implications such as:

- They consider AR for inputs and outputs and perform together with a FMADM method for increasing their computational effort and reliability;
- They handle both desirable and undesirable inputs and outputs that are very suitable for analyzing complicated real-life problems;
- They account for the uncertainties inherent to real life data using fuzzy sets to provide more flexibility for dealing with real-life cases;
- Solving these models leads to a fuzzy efficiency score (i.e., optimistic and pessimistic efficiency values according to different α-cut levels) for each DMU. This provides a practical and broader approach for the decision makers.

The positioning of the proposed TPM PMS is also presented in Table 4.7.

Table 4.7 Positioning of the proposed TPM PMS

	Park (2002)	**Wang (2006)**	**Jeon et al. (2011)**	**Proposed TPM PMS**
Efficiency measurement in TPM		√	√	√
PIs in TPM	√			√
Novel PIs in TPM				√
Multiple inputs and outputs		√	√	√
Desirable and undesirable inputs and outputs				√
MADM				√
FMADM				√
GDM				√
Fuzzy GDM				√
Fuzzy attribute weights				√
Fuzzy relative significance				√
Fuzzy group hierarchy				√
Fuzzy aggregation				√
Fuzzy arithmetic				√
Fuzzy ranking				√
Linguistic variables				√
Optimization		√	√	
Fuzzy optimization				√
Sensitivity analysis				√
Real-word manufacturing case		√	√	√

4.7 Conclusion

In this chapter, the proposed TPM PMS is presented. The proposed TPM PMS consists of design, evaluation, implementation and review phases.

In the design phase, a general list is provided for the proposed TPM PIs and then these TPM PIs are explained in detail. Afterwards, nominal group technique and conjoint analysis are used to determine the most important TPM PIs.

In the evaluation phase, the TPM PIs determined in Phase 1 are assessed through COPRAS-G and proposed FCOPRAS methods to achieve the fuzzy relative significance and ranking orders of these TPM PIs.

In the implementation phase, four GFDEA/AR models in the presence of desirable and undesirable inputs and outputs are proposed to measure TPM performance.

In the review phase, the appropriateness of the proposed TPM PMS is periodically monitored and re-evaluated to take necessary decisions and actions. In addition, modification and improvement of TPM strategy and system can be made regularly.

In the subsequent chapter, the proposed TPM PMS is implemented to a real-world in an automotive manufacturing company.

CHAPTER FIVE
IMPLEMENTATION OF THE PROPOSED TOTAL PRODUCTIVE MAINTENANCE PERFORMANCE MEASUREMENT SYSTEM USING A REAL MANUFACTURING CASE

5.1 Chapter Introduction

This chapter presents a case study to implement the proposed TPM PMS in a manufacturing company which is operating in automotive industry. Firstly, the proposed TPM PIs is evaluated by using COPRAS-G method. Next, the proposed FCOPRAS is utilized to achieve the fuzzy relative significance (fuzzy $\tilde{Q}_i$ values) of the proposed TPM PIs. Additionally, it is compared with the most popular FMADM methods and its reliability also represented by the sensitivity analysis. Secondly, these TPM PIs are classified as desirable and undesirable inputs and outputs, and then their fuzzy $\tilde{Q}_i$ values obtained from FCOPRAS are integrated with the GFDEA/AR models in the presence of desirable and undesirable inputs and outputs. As stated in the previous chapter, the GFDEA/AR models are modified based on the three different undesirability approaches. In this regard, Models (1) and (2) based on the first approach, Models (3) and (4) based on the second approach, and Models (3) and (4) based on the third approach are solved to obtain fuzzy efficiencies of DMUs which represents production lines of the company. Then, these fuzzy efficiencies are ranked using a proper ranking method. According to the ranking results, the DMUs which have the best and the worst TPM performance values are determined. Consequently, the performance values of each production line are compared to its corresponding OEE values which have previously measured by the company.

The rest of this chapter is organized as follows. In Section 5.2, the proposed TPM PIs are defined briefly. In Section 5.3, evaluation of the proposed TPM PIs using COPRAS-G and proposed FCOPRAS methods is demonstrated. In Section 5.4, performance evaluation of TPM using the proposed TPM PIs is presented. Finally, in Section 5.5, results and discussion about the implementation of the proposed TPM PMS are provided.

5.2 Proposed TPM PIs in the Design Phase

As stated in Section 4.2, the proposed TPM PIs are given in depth in Table 5.1.

Table 5.1 A detailed list for the proposed TPM PIs

Category	Sub -Category		Proposed TPM PIs
Operational-related	**Unplanned down-time**		Number of unplanned maintenance
			MTTR
			MTBF
			Reduced speed
			Reduced yield
			Quality losses
Business-related	**HSE problems**		Number of HSE incidents
	Organization problems and labour unrest (Employee satisfaction)		Employee absentees
			Employee turn-over rate
			Refusal of extended hours or overtimes
Human-oriented	**Direct human-oriented**		Competence of maintenance personnel
			Experience of operators in production line
			Operator reliability
			Training and continuing education
	Indirect human-oriented	**Motivational management**	New ideas generated and implemented
		Work environment	Level of 5S
Other	-		Availability of maintenance personnel

The proposed TPM PIs presented in the third column of Table 5.1 are evaluated under previously determined attributes (see Section 4.3) using COPRAS-G and proposed FCOPRAS methods in the next section.

5.3 Evaluation of the Proposed TPM PIs Using COPRAS-G and FCOPRAS Methods

5.3.1 Determination of the Attribute Weights Using Fuzzy GDM

The committee provides linguistic assessments for the six attribute (determined in Step 1 in Section 4.3) and alternatives (proposed TPM PIs given in Table 5.1) using the linguistic terms proposed by Jamalnia and Soukhakian (2009). These terms are presented in Table 5.2.

Table 5.2 Linguistic terms for the ratings of alternatives and importance weights of attributes

Linguistic Terms for Attributes	Scores (%)	Linguistic Terms for Alternatives
Very Low Important (VLI)	(0, 0, 10)	Very Poor (VP)
Low Important (LI)	(5, 15, 25)	Poor (P)
Somewhat Low Important (SLI)	(20, 32.5, 45)	Somewhat Poor (SP)
Medium Important (M)	(40, 50, 60)	Fair (F)
Somewhat High Important (SHI)	(55, 67.5, 80)	Somewhat Good (SG)
High Important (HI)	(75, 85, 95)	Good (G)
Very High Important (VHI)	(90, 100, 100)	Very Good (VG)

Since the hierarchy between the decision makers in the committee is defined, they are ranked in a fuzzy way as $\tilde{1}$, $\tilde{2}$ and $\tilde{3}$. Then, the fuzzy weights of the decision makers are calculated by using the Rank Reciprocal method. After the fuzzy ranks are assigned and the reciprocal fuzzy weights are calculated, these weights are normalized using Equations (4.1-4.3) which are given in Step 2.1 in Section 4.3. The normalized fuzzy weights of decision makers are given in Table 5.3.

Table 5.3 Assessing decision makers' importance weights by the rank reciprocal

	TPM Manager (TPM M.)	Production Manager (P.M.)	Quality Manager (Q.M.)
Fuzzy Rank	around 1 = (0.5, 1, 1.5)	around 2=(1.25, 2, 2.75)	around 3=(2.5, 3, 3.5)
Reciprocal Fuzzy Weights	(0.6667, 1, 2)	(0.3636, 0.5, 0.8)	(0.2857, 0.3333, 0.4)
Normalized Fuzzy Weights	(0.3249 0.5455 0.9746)	(0.1772 0.2727 0.3898)	(0.1392 0.1818 0.1949)

The linguistic assessments for all of attributes are obtained from the decision makers as given in Table 5.4. Then, the aggregated fuzzy weights of these attributes are acquired using Equation (4.4) which is explained in Step 2.2 in Section 4.3 and also given in Table 5.4.

Table 5.4 Linguistic assessments for all of the criteria and their aggregated fuzzy weights

Attributes	**TPM M.**	**P.M.**	**Q.M.**	**Aggregated Fuzzy Weights**		
Specifity	VHI	VHI	VHI	0.3701	0.6413	1.0000
Measurability	HI	VHI	HI	0.3255	0.5714	0.9625
Attainability	SHI	HI	HI	0.2668	0.4839	0.8562
Practicalness	MI	HI	HI	0.2355	0.4227	0.7312
Timely	SLI	VHI	HI	0.2109	0.3877	0.6500
Cost of Measure	SHI	HI	SHI	0.2489	0.4635	0.8375

5.3.2 Construction of the Fuzzy Decision Matrix

As stated in Step 3 in Section 4.3, the fuzzy decision matrices are constructed for each decision maker. In this context, appropriate fuzzy ratings are assigned by each decision maker to all alternatives with regard to each attribute by using linguistics terms (presented in Table 5.2) and the fuzzy decision matrix is constructed in Table 5.5. Afterwards, the aggregated fuzzy decision matrix is computed as mentioned in Step 4 in Section 4.3 and the results are presented in Table 5.6. After the fuzzy aggregation, the aggregated fuzzy decision matrix is normalized using Equations (4.6-4.10) which are given in Step 5 in Section 4.3. The normalized aggregated fuzzy decision matrix is given in Table 5.7. Finally, the weighted normalized aggregated fuzzy decision matrix is calculated using Equations (4.11-4.12) which are given in Step 6 in Section 4.3. Table 5.8 provides the weighted normalized aggregated fuzzy decision matrix.

5.3.3 Implementation of the COPRAS-G Method

As stated in Step 7 in Section 4.3, the COPRAS-G method is performed using the weighted normalized aggregated decision matrix which is given in Table 5.8. When calculating the sums P_j and R_j of the attribute values, Equations (3.59) and (3.60) are used, respectively. The values of $\hat{w}_{j1}$ and $\hat{b}_{j1}$ in these equations represent respectively the lower and upper bounds of the corresponding attribute in the weighted normalized aggregated fuzzy decision matrix. As a conclusion, the P_j, R_j, Q_j, and N_j values are calculated by Equations (3.59-3.64) which are given in Section 3.3.3.2, and these values and the ranking orders of alternatives are presented in Table 5.9.

Table 5.5 Fuzzy decision matrix provided by the decision makers

Alternatives	ATTRIBUTES																	
	Specifity			**Measurability**			**Attainability**			**Practicalness**			**Timely**			**Cost of Measure**		
	TPM M.	**P.M.**	**Q.M.**	**TPM M.**	**P.M.**	**Q.M.**	**TPM M.**	**P.M.**	**Q.M.**	**TPM M.**	**P.M.**	**Q.M.**	**TPM M.**	**P.M.**	**Q.M.**	**TPM M.**	**P.M.**	**Q.M.**
MTTR	VG	VG	VG	VG	VG	VG	VG	VG	VG	VG	VG	VG	G	VG	VG	SP	SP	G
MTBF	VG	VG	VG	VG	VG	VG	VG	VG	VG	VG	VG	VG	G	VG	VG	SP	SP	G
Number of unplanned maintenance	VG	VG	VG	VG	VG	VG	VG	VG	VG	VG	VG	VG	G	VG	VG	G	VP	SG
Number of HSE incidents	SG	G	SP	SG	VG	G	G	G	G	G	G	VG	SG	G	VG	G	P	G
Reduced speed	SG	G	SG	G	G	G	G	SG	G	G	SG	G	SG	G	G	G	SP	SG
Reduced yield	G	G	SG	G	G	G	SG	SG	G	G	SG	G	SG	G	G	G	SP	SG
Quality defects	SG	SG	SG	G	G	G	VG	SG	VG	VG	SG	G	G	G	G	G	SP	SG
Availability of maintenance personnel	SG	SG	F	VG	G	SG	G	F	SG	G	SG	SP	VG	SG	SP	VG	SP	F
Competence of maintenance personnel	SG	SG	F	G	F	SP	G	SP	SP	G	SP	P	SG	P	P	SG	SG	SP
Experience of operators in production line	SG	F	F	G	F	SP	G	SP	P	SG	F	VP	G	SG	P	G	G	VP
Operator reliability	SG	F	SP	SG	P	P	G	VP	SP	SG	P	SP	SG	P	P	G	VG	VP
Training and continuing education	SG	F	F	G	SP	P	SG	SP	SP	SG	SP	SP	SG	P	SP	P	G	SP
New ideas generated and implemented	F	F	F	G	SG	SP	G	SP	F	SG	SP	SP	SG	SG	P	P	F	P
Level of 5S	SG	SP	SP	SG	SG	P	SG	SP	SP	SG	SP	G	G	SG	SP	SP	F	F
Employee absentees	F	P	SG	SG	SG	G	SG	SP	VG	G	SP	G	SG	SG	SG	VP	SP	SG
Employee turn-over rate	SG	P	SP	SG	SG	G	SG	SP	VG	SG	SP	SP	SG	SG	SG	VP	SP	SG
Refusal of extended hours or overtimes	SP	VP	F	G	SP	SG	G	VP	SP	SG	P	SP	SG	SP	F	P	G	SP

Table 5.6 The aggregated fuzzy decision matrix

Alternatives	ATTRIBUTES																	
	Specifity			**Measurability**			**Attainability**			**Practicalness**			**Timely**			**Cost of Measure**		
MTTR	0.5772	1.0000	1.5593	0.5772	1.0000	1.5593	0.5772	1.0000	1.5593	0.5772	1.0000	1.5593	0.5284	0.9182	1.5106	0.2048	0.4205	0.7991
MTBF	0.5772	1.0000	1.5593	0.5772	1.0000	1.5593	0.5772	1.0000	1.5593	0.5772	1.0000	1.5593	0.5284	0.9182	1.5106	0.2048	0.4205	0.7991
Number of unplanned maintenance	0.5772	1.0000	1.5593	0.5772	1.0000	1.5593	0.5772	1.0000	1.5593	0.5772	1.0000	1.5593	0.5284	0.9182	1.5106	0.3202	0.5864	1.1208
Number of HSE incidents	0.3394	0.6591	1.2377	0.4426	0.7954	1.3546	0.4810	0.8500	1.4813	0.5019	0.8773	1.4911	0.4369	0.7818	1.3449	0.3569	0.6591	1.2085
Reduced speed	0.3882	0.7227	1.3059	0.4810	0.8500	1.4813	0.4455	0.8023	1.4229	0.4455	0.8023	1.4229	0.4160	0.7545	1.3351	0.3557	0.6750	1.2572
Reduced yield	0.4531	0.8182	1.4521	0.4810	0.8500	1.4813	0.3806	0.7068	1.2767	0.4455	0.8023	1.4229	0.4160	0.7545	1.3351	0.3557	0.6750	1.2572
Quality defects	0.3527	0.6750	1.2474	0.4810	0.8500	1.4813	0.5152	0.9114	1.4813	0.4943	0.8841	1.4716	0.4810	0.8500	1.4813	0.3557	0.6750	1.2572
Availability of maintenance personnel	0.3318	0.6432	1.2085	0.5019	0.9000	1.5008	0.3911	0.7227	1.3157	0.3690	0.7068	1.3254	0.4177	0.7887	1.3741	0.3835	0.7250	1.2670
Competence of maintenance personnel	0.3318	0.6432	1.2085	0.3424	0.6591	1.2475	0.3070	0.6114	1.1890	0.2861	0.5796	1.1500	0.1945	0.4364	0.9259	0.3040	0.6114	1.1792
Experience of operators in production line	0.3053	0.5955	1.1305	0.3424	0.6591	1.2475	0.2861	0.5796	1.1500	0.2496	0.5046	1.0331	0.3481	0.6750	1.2864	0.3766	0.6955	1.3157
Operator reliability	0.2774	0.5637	1.1013	0.1945	0.4364	0.9259	0.2715	0.5228	1.0526	0.2154	0.4682	0.9648	0.1945	0.4364	0.9259	0.4032	0.7364	1.3352
Training and continuing education	0.3053	0.5955	1.1305	0.2861	0.5796	1.1500	0.2420	0.5159	1.0428	0.2420	0.5159	1.0428	0.2154	0.4682	0.9648	0.1770	0.3727	0.7017
New ideas generated and implemented	0.2565	0.5000	0.9356	0.3690	0.7068	1.3254	0.3348	0.6432	1.2182	0.2420	0.5159	1.0428	0.2831	0.5796	1.1402	0.0941	0.2455	0.5263
Level of 5S	0.2420	0.5159	1.0428	0.2831	0.5796	1.1402	0.2420	0.5159	1.0428	0.3185	0.6114	1.1402	0.3690	0.7068	1.3254	0.1915	0.4045	0.7894
Employee absentees	0.2154	0.4364	0.8381	0.3806	0.7068	1.2767	0.3394	0.6386	1.1500	0.3835	0.7068	1.2864	0.3527	0.6750	1.2474	0.1120	0.2113	0.4288
Employee turn-over rate	0.2154	0.4682	0.9648	0.3806	0.7068	1.2767	0.3394	0.6386	1.1500	0.2420	0.5159	1.0428	0.3527	0.6750	1.2474	0.1120	0.2113	0.4288
Refusal of extended hours or overtimes	0.1207	0.2682	0.5945	0.3557	0.6750	1.2572	0.2715	0.5228	1.0526	0.2154	0.4682	0.9648	0.2698	0.5477	1.0720	0.1770	0.3727	0.7017

Table 5.7 The normalized aggregated fuzzy decision matrix

Alternatives	ATTRIBUTES																	
	Specifity			Measurability			Attainability			Practicalness			Timely			Cost of Measure		
MTTR	0.3702	0.6413	1.0000	0.3702	0.6413	1.0000	0.3702	0.6413	1.0000	0.3702	0.6413	1.0000	0.3498	0.6078	1.0000	0.1177	0.2238	0.4594
MTBF	0.3702	0.6413	1.0000	0.3702	0.6413	1.0000	0.3702	0.6413	1.0000	0.3702	0.6413	1.0000	0.3498	0.6078	1.0000	0.1177	0.2238	0.4594
Number of unplanned maintenance	0.3702	0.6413	1.0000	0.3702	0.6413	1.0000	0.3702	0.6413	1.0000	0.3702	0.6413	1.0000	0.3498	0.6078	1.0000	0.0839	0.1605	0.2938
Number of HSE incidents	0.2177	0.4227	0.7938	0.2838	0.5101	0.8688	0.3085	0.5451	0.9500	0.3219	0.5626	0.9563	0.2892	0.5176	0.8903	0.0779	0.1428	0.2636
Reduced speed	0.2489	0.4635	0.8375	0.3085	0.5451	0.9500	0.2857	0.5145	0.9125	0.2857	0.5145	0.9125	0.2754	0.4995	0.8839	0.0748	0.1394	0.2645
Reduced yield	0.2906	0.5247	0.9313	0.3085	0.5451	0.9500	0.2441	0.4533	0.8188	0.2857	0.5145	0.9125	0.2754	0.4995	0.8839	0.0748	0.1394	0.2645
Quality defects	0.2262	0.4329	0.8000	0.3085	0.5451	0.9500	0.3304	0.5845	0.9500	0.3170	0.5670	0.9438	0.3184	0.5627	0.9807	0.0748	0.1394	0.2645
Availability of maintenance personnel	0.2128	0.4125	0.7750	0.3219	0.5772	0.9625	0.2508	0.4635	0.8438	0.2366	0.4533	0.8500	0.2765	0.5221	0.9097	0.0743	0.1298	0.2453
Competence of maintenance personnel	0.2128	0.4125	0.7750	0.2196	0.4227	0.8000	0.1969	0.3921	0.7625	0.1835	0.3717	0.7375	0.1288	0.2889	0.6129	0.0798	0.1539	0.3095
Experience of operators in production line	0.1958	0.3819	0.7250	0.2196	0.4227	0.8000	0.1835	0.3717	0.7375	0.1601	0.3236	0.6625	0.2304	0.4469	0.8516	0.0715	0.1353	0.2498
Operator reliability	0.1779	0.3615	0.7063	0.1248	0.2799	0.5938	0.1741	0.3353	0.6750	0.1381	0.3003	0.6188	0.1288	0.2889	0.6129	0.0705	0.1278	0.2334
Training and continuing education	0.1958	0.3819	0.7250	0.1835	0.3717	0.7375	0.1552	0.3309	0.6688	0.1552	0.3309	0.6688	0.1426	0.3100	0.6387	0.1341	0.2524	0.5316
New ideas generated and implemented	0.1645	0.3207	0.6000	0.2366	0.4533	0.8500	0.2147	0.4125	0.7813	0.1552	0.3309	0.6688	0.1874	0.3837	0.7548	0.1788	0.3833	1.0000
Level of 5S	0.1552	0.3309	0.6688	0.1816	0.3717	0.7313	0.1552	0.3309	0.6688	0.2043	0.3921	0.7313	0.2443	0.4679	0.8774	0.1192	0.2326	0.4912
Employee absentees	0.1381	0.2799	0.5375	0.2441	0.4533	0.8188	0.2177	0.4096	0.7375	0.2460	0.4533	0.8250	0.2335	0.4469	0.8258	0.2194	0.4452	0.8400
Employee turn-over rate	0.1381	0.3003	0.6188	0.2441	0.4533	0.8188	0.2177	0.4096	0.7375	0.1552	0.3309	0.6688	0.2335	0.4469	0.8258	0.2194	0.4452	0.8400
Refusal of extended hours or overtimes	0.0774	0.1720	0.3813	0.2281	0.4329	0.8063	0.1741	0.3353	0.6750	0.1381	0.3003	0.6188	0.1786	0.3626	0.7097	0.1341	0.2524	0.5316

Table 5.8 The weighted normalized aggregated fuzzy decision matrix

Alternatives	ATTRIBUTES																	
	Specifity			Measurability			Attainability			Practicalness			Timely			Cost of Measure		
MTTR	0.1370	0.4113	1.0000	0.1205	0.3664	0.9625	0.0987	0.3103	0.8563	0.0872	0.2711	0.7312	0.0738	0.2357	0.6500	0.0293	0.1037	0.3847
MTBF	0.1370	0.4113	1.0000	0.1205	0.3664	0.9625	0.0987	0.3103	0.8563	0.0872	0.2711	0.7312	0.0738	0.2357	0.6500	0.0293	0.1037	0.3847
Number of unplanned maintenance	0.1370	0.4113	1.0000	0.1205	0.3664	0.9625	0.0987	0.3103	0.8563	0.0872	0.2711	0.7312	0.0738	0.2357	0.6500	0.0209	0.0744	0.2461
Number of HSE incidents	0.0806	0.2711	0.7938	0.0924	0.2915	0.8362	0.0823	0.2638	0.8134	0.0758	0.2378	0.6993	0.0610	0.2007	0.5787	0.0194	0.0662	0.2208
Reduced speed	0.0921	0.2972	0.8375	0.1004	0.3115	0.9144	0.0762	0.2490	0.7813	0.0673	0.2175	0.6673	0.0581	0.1937	0.5745	0.0186	0.0646	0.2215
Reduced yield	0.1076	0.3365	0.9313	0.1004	0.3115	0.9144	0.0651	0.2193	0.7011	0.0673	0.2175	0.6673	0.0581	0.1937	0.5745	0.0186	0.0646	0.2215
Quality defects	0.0837	0.2776	0.8000	0.1004	0.3115	0.9144	0.0881	0.2828	0.8134	0.0747	0.2397	0.6901	0.0672	0.2182	0.6374	0.0186	0.0646	0.2215
Availability of maintenance personnel	0.0788	0.2645	0.7750	0.1048	0.3298	0.9264	0.0669	0.2243	0.7225	0.0557	0.1916	0.6216	0.0583	0.2024	0.5913	0.0185	0.0601	0.2055
Competence of maintenance personnel	0.0788	0.2645	0.7750	0.0715	0.2415	0.7700	0.0525	0.1897	0.6529	0.0432	0.1571	0.5393	0.0272	0.1120	0.3984	0.0199	0.0713	0.2592
Experience of operators in production line	0.0725	0.2449	0.7250	0.0715	0.2415	0.7700	0.0489	0.1799	0.6315	0.0377	0.1368	0.4845	0.0486	0.1732	0.5535	0.0178	0.0627	0.2092
Operator reliability	0.0659	0.2318	0.7063	0.0406	0.1599	0.5715	0.0465	0.1622	0.5780	0.0325	0.1269	0.4525	0.0272	0.1120	0.3984	0.0175	0.0592	0.1955
Training and continuing education	0.0725	0.2449	0.7250	0.0597	0.2124	0.7099	0.0414	0.1601	0.5726	0.0366	0.1399	0.4890	0.0301	0.1202	0.4152	0.0334	0.1170	0.4452
New ideas generated and implemented	0.0609	0.2056	0.6000	0.0770	0.2590	0.8181	0.0573	0.1996	0.6690	0.0366	0.1399	0.4890	0.0395	0.1487	0.4906	0.0445	0.1777	0.8375
Level of 5S	0.0574	0.2122	0.6688	0.0591	0.2124	0.7038	0.0414	0.1601	0.5726	0.0481	0.1657	0.5347	0.0515	0.1814	0.5703	0.0297	0.1078	0.4114
Employee absentees	0.0511	0.1795	0.5375	0.0794	0.2590	0.7881	0.0581	0.1982	0.6315	0.0579	0.1916	0.6033	0.0492	0.1732	0.5368	0.0546	0.2063	0.7035
Employee turn-over rate	0.0511	0.1926	0.6188	0.0794	0.2590	0.7881	0.0581	0.1982	0.6315	0.0366	0.1399	0.4890	0.0492	0.1732	0.5368	0.0546	0.2063	0.7035
Refusal of extended hours or overtimes	0.0286	0.1103	0.3813	0.0742	0.2473	0.7760	0.0465	0.1622	0.5780	0.0325	0.1269	0.4525	0.0377	0.1406	0.4613	0.0334	0.1170	0.4452

Table 5.9 Solution results of COPRAS-G method

Alternatives			Alternative's weight	Alternative's utility degree	Rank
	P_j	R_j	Q_j	N_j	
MTTR	3.4152	0.2885	3.6347	96.9117	3
MTBF	3.4152	0.2885	3.6347	96.9117	2
Number of unplanned maintenance	3.4152	0.1889	3.7505	100.0000	1
Number of HSE incidents	2.9401	0.1707	3.3110	88.2815	7
Reduced speed	2.9503	0.1697	3.3235	88.6154	6
Reduced yield	2.9503	0.1697	3.3235	88.6154	5
Quality defects	3.0624	0.1697	3.4357	91.6045	4
Availability of maintenance personnel	2.8198	0.1598	3.2162	85.7524	8
Competence of maintenance personnel	2.3147	0.1946	2.6401	70.3925	10
Experience of operators in production line	2.3830	0.1607	2.7771	74.0467	9
Operator reliability	1.9752	0.1519	2.3921	63.7803	15
Training and continuing education	2.1355	0.3328	2.3257	62.0109	16
New ideas generated and implemented	2.3067	0.5894	2.4141	64.3673	14
Level of 5S	2.3090	0.3052	2.5165	67.0966	12
Employee absentees	2.4119	0.5297	2.5315	67.4970	11
Employee turn-over rate	2.3291	0.5297	2.4486	65.2873	13
Refusal of extended hours or overtimes	1.9937	0.3328	2.1840	58.2305	17

According to Table 5.9, the best three alternatives (proposed TPM PIs) are "the number of unplanned maintenance (equipment failures)", "MTTR", and "MTBF", respectively. Additionally, "refusal of extended hours or overtimes" is the worst alternative.

5.3.4 Implementation of the Proposed FCOPRAS Method

As stated in subsequent steps of Step 8 in Section 4.3, the proposed FCOPRAS method is implemented to achieve fuzzy $\tilde{P}_i$, $\tilde{R}_i$, and $\tilde{Q}_i$ values using Equations (4.13-4.15). These values are presented in Table 5.10 and their membership functions are also illustrated in Figures 5.1-5.3. Afterwards, the fuzzy $\tilde{Q}_i$ values are ranked as explained in Step 8.4 in Section 4.3 and the rankings of the alternatives according to different α-cut levels are given in Table 5.11.

Table 5.10 Fuzzy $\tilde{P}_i$, $\tilde{R}_i$, and $\tilde{Q}_i$ values of alternatives

Alternatives	$\tilde{P}_i$			$\tilde{R}_i$			$\tilde{Q}_i$		
MTTR	0.5172	1.5947	4.2000	0.0293	0.1037	0.3847	0.5190	1.6782	7.9868
MTBF	0.5172	1.5947	4.2000	0.0293	0.1037	0.3847	0.5190	1.6782	7.9868
Number of unplanned maintenance	0.5172	1.5947	4.2000	0.0209	0.0744	0.2461	0.5200	1.7112	9.5109
Number of HSE incidents	0.3921	1.2648	3.7213	0.0194	0.0662	0.2208	0.3952	1.3957	9.4479
Reduced speed	0.3942	1.2688	3.7750	0.0186	0.0646	0.2215	0.3972	1.4028	9.7324
Reduced yield	0.3985	1.2784	3.7884	0.0186	0.0646	0.2215	0.4016	1.4125	9.7459
Quality defects	0.4141	1.3297	3.8553	0.0186	0.0646	0.2215	0.4172	1.4637	9.8128
Availability of maintenance personnel	0.3645	1.2126	3.6367	0.0185	0.0601	0.2055	0.3678	1.3566	9.6404
Competence of maintenance personnel	0.2731	0.9649	3.1356	0.0199	0.0713	0.2592	0.2758	1.0863	8.7236
Experience of operators in production line	0.2792	0.9763	3.1645	0.0178	0.0627	0.2092	0.2825	1.1144	9.3990
Operator reliability	0.2126	0.7929	2.7066	0.0175	0.0592	0.1955	0.2161	0.9391	9.0335
Training and continuing education	0.2402	0.8774	2.9117	0.0334	0.1170	0.4452	0.2417	0.9514	6.2366
New ideas generated and implemented	0.2713	0.9528	3.0667	0.0445	0.1777	0.8375	0.2721	1.0016	5.5605
Level of 5S	0.2576	0.9318	3.0503	0.0297	0.1078	0.4114	0.2592	1.0121	6.7909
Employee absentees	0.2958	1.0015	3.0971	0.0546	0.2063	0.7035	0.2968	1.0435	5.1290
Employee turn-over rate	0.2744	0.9628	3.0641	0.0546	0.2063	0.7035	0.2754	1.0048	5.0960
Refusal of extended hours or overtimes	0.2196	0.7874	2.6490	0.0334	0.1170	0.4452	0.2211	0.8614	5.9740

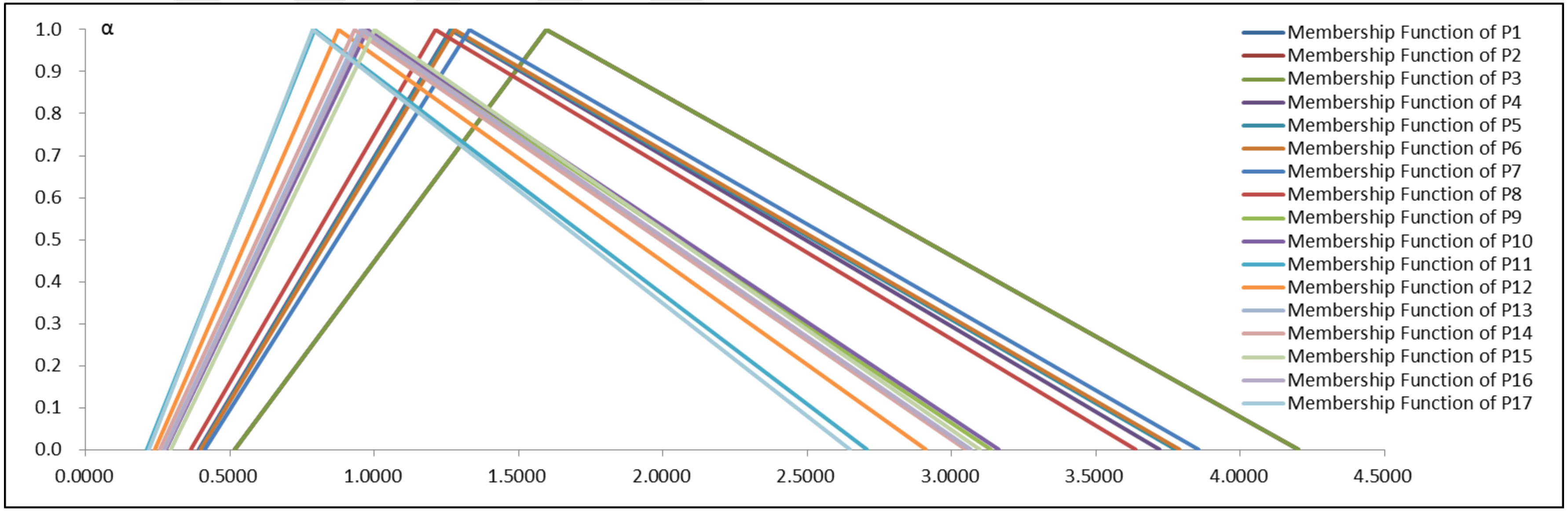

Figure 5.1 Membership functions of the fuzzy $\tilde{P}_i$ values

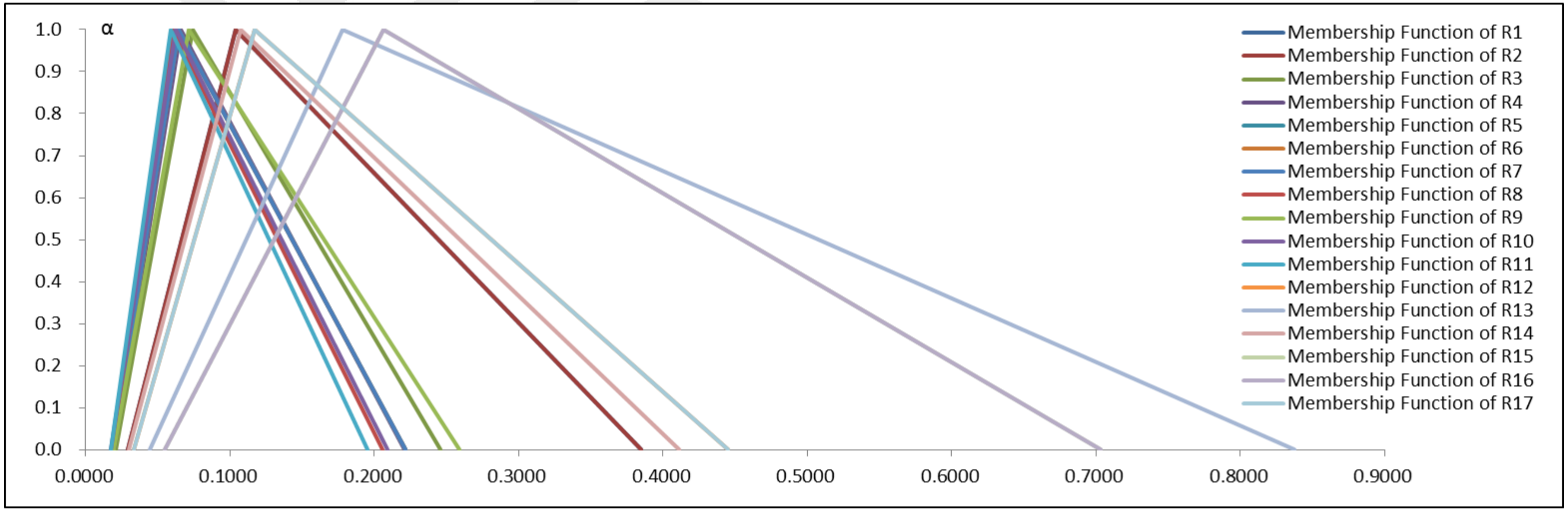

Figure 5.2 Membership functions of the fuzzy $\tilde{R}_i$ values

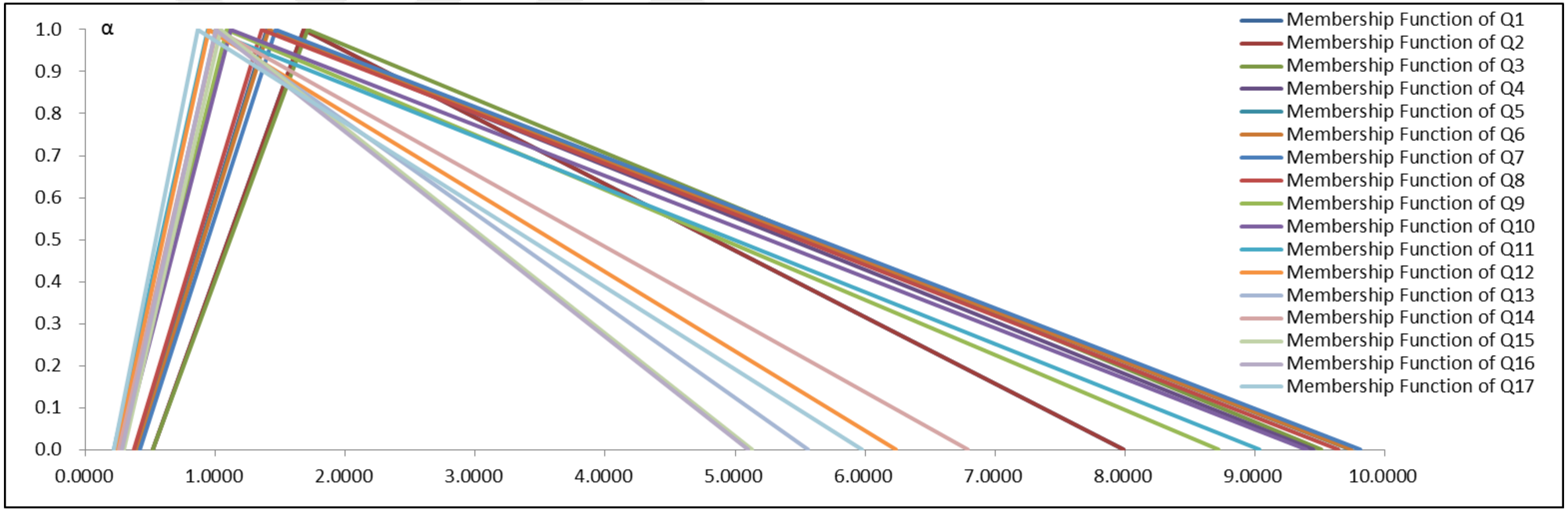

Figure 5.3 Membership functions of the fuzzy $\tilde{Q}_i$ values

Table 5.11 The ranking of fuzzy $\tilde{Q}_i$ values of alternatives according to different α-cut levels

$\alpha = 0$		$\alpha = 0.1$		$\alpha = 0.2$		$\alpha = 0.3$		$\alpha = 0.4$	
Ranking	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$	**Ranking**	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$	**Ranking**	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$	**Ranking**	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$	**Ranking**	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$
$\tilde{Q}_3$	7.9179	$\tilde{Q}_3$	6.7215	$\tilde{Q}_3$	5.6150	$\tilde{Q}_3$	4.5985	$\tilde{Q}_3$	3.6718
$\tilde{Q}_7$	7.6253	$\tilde{Q}_7$	6.4400	$\tilde{Q}_7$	5.3486	$\tilde{Q}_7$	4.3512	$\tilde{Q}_7$	3.4477
$\tilde{Q}_6$	7.4971	$\tilde{Q}_6$	6.3269	$\tilde{Q}_6$	5.2502	$\tilde{Q}_6$	4.2668	$\tilde{Q}_6$	3.3770
$\tilde{Q}_5$	7.4733	$\tilde{Q}_5$	6.3059	$\tilde{Q}_5$	5.2318	$\tilde{Q}_5$	4.2511	$\tilde{Q}_5$	3.3637
$\tilde{Q}_8$	7.3494	$\tilde{Q}_8$	6.1972	$\tilde{Q}_8$	5.1378	$\tilde{Q}_1$	4.1792	$\tilde{Q}_1$	3.3581
$\tilde{Q}_4$	7.3177	$\tilde{Q}_4$	6.1785	$\tilde{Q}_4$	5.1299	$\tilde{Q}_2$	4.1792	$\tilde{Q}_2$	3.3581
$\tilde{Q}_1$	7.0904	$\tilde{Q}_1$	6.0453	$\tilde{Q}_1$	5.0749	$\tilde{Q}_4$	4.1718	$\tilde{Q}_4$	3.3043
$\tilde{Q}_2$	7.0904	$\tilde{Q}_2$	6.0453	$\tilde{Q}_2$	5.0749	$\tilde{Q}_8$	4.1710	$\tilde{Q}_8$	3.2970
$\tilde{Q}_{10}$	6.7871	$\tilde{Q}_{10}$	5.6981	$\tilde{Q}_{10}$	4.7003	$\tilde{Q}_{10}$	3.7937	$\tilde{Q}_{10}$	2.9783
$\tilde{Q}_9$	6.3965	$\tilde{Q}_9$	5.3767	$\tilde{Q}_9$	4.4413	$\tilde{Q}_9$	3.5905	$\tilde{Q}_9$	2.8241
$\tilde{Q}_{11}$	6.2869	$\tilde{Q}_{11}$	5.2614	$\tilde{Q}_{11}$	4.3241	$\tilde{Q}_{11}$	3.4750	$\tilde{Q}_{11}$	2.7140
$\tilde{Q}_{14}$	5.2901	$\tilde{Q}_{14}$	4.4672	$\tilde{Q}_{14}$	3.7095	$\tilde{Q}_{14}$	3.0172	$\tilde{Q}_{14}$	2.3902
$\tilde{Q}_{12}$	4.9003	$\tilde{Q}_{12}$	4.1405	$\tilde{Q}_{12}$	3.4406	$\tilde{Q}_{12}$	2.8007	$\tilde{Q}_{12}$	2.2208
$\tilde{Q}_{13}$	4.6474	$\tilde{Q}_{13}$	3.9446	$\tilde{Q}_{13}$	3.2948	$\tilde{Q}_{13}$	2.6979	$\tilde{Q}_{13}$	2.1538
$\tilde{Q}_{17}$	4.5992	$\tilde{Q}_{17}$	3.8804	$\tilde{Q}_{17}$	3.2191	$\tilde{Q}_{15}$	2.6447	$\tilde{Q}_{15}$	2.1219
$\tilde{Q}_{15}$	4.5030	$\tilde{Q}_{15}$	3.8353	$\tilde{Q}_{15}$	3.2158	$\tilde{Q}_{17}$	2.6154	$\tilde{Q}_{16}$	2.0735
$\tilde{Q}_{16}$	4.4199	$\tilde{Q}_{16}$	3.7610	$\tilde{Q}_{16}$	3.1503	$\tilde{Q}_{16}$	2.5878	$\tilde{Q}_{17}$	2.0692

Table 5.11 The ranking of fuzzy $\tilde{Q}_i$ values of alternatives according to different α-cut levels (con.)

$\alpha = 0.5$		$\alpha = 0.6$		$\alpha = 0.7$		$\alpha = 0.8$		$\alpha = 0.9$	
Ranking	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$	**Ranking**	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$	**Ranking**	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$	**Ranking**	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$	**Ranking**	$Q^{Tri}(\tilde{Q}_1 \dots \tilde{Q}_{17})$
$\tilde{Q}_3$	2.8351	$\tilde{Q}_3$	2.0882	$\tilde{Q}_3$	1.4313	$\tilde{Q}_3$	0.8643	$\tilde{Q}_3$	0.3872
$\tilde{Q}_7$	2.6382	$\tilde{Q}_1$	1.9400	$\tilde{Q}_1$	1.3430	$\tilde{Q}_1$	0.8207	$\tilde{Q}_1$	0.3730
$\tilde{Q}_1$	2.6117	$\tilde{Q}_2$	1.9400	$\tilde{Q}_2$	1.3430	$\tilde{Q}_2$	0.8207	$\tilde{Q}_2$	0.3730
$\tilde{Q}_2$	2.6117	$\tilde{Q}_7$	1.9226	$\tilde{Q}_7$	1.3011	$\tilde{Q}_7$	0.7734	$\tilde{Q}_7$	0.3397
$\tilde{Q}_6$	2.5805	$\tilde{Q}_6$	1.8775	$\tilde{Q}_6$	1.2680	$\tilde{Q}_6$	0.7519	$\tilde{Q}_6$	0.3292
$\tilde{Q}_5$	2.5697	$\tilde{Q}_5$	1.8691	$\tilde{Q}_5$	1.2618	$\tilde{Q}_5$	0.7478	$\tilde{Q}_5$	0.3272
$\tilde{Q}_4$	2.5272	$\tilde{Q}_4$	1.8407	$\tilde{Q}_4$	1.2448	$\tilde{Q}_4$	0.7393	$\tilde{Q}_4$	0.3244
$\tilde{Q}_8$	2.5157	$\tilde{Q}_8$	1.8271	$\tilde{Q}_8$	1.2312	$\tilde{Q}_8$	0.7281	$\tilde{Q}_8$	0.3177
$\tilde{Q}_{10}$	2.2540	$\tilde{Q}_{10}$	1.6208	$\tilde{Q}_{10}$	1.0789	$\tilde{Q}_{10}$	0.6281	$\tilde{Q}_{10}$	0.2685
$\tilde{Q}_9$	2.1423	$\tilde{Q}_9$	1.5448	$\tilde{Q}_9$	1.0319	$\tilde{Q}_9$	0.6035	$\tilde{Q}_9$	0.2595
$\tilde{Q}_{11}$	2.0413	$\tilde{Q}_{11}$	1.4567	$\tilde{Q}_{11}$	0.9602	$\tilde{Q}_{11}$	0.5520	$\tilde{Q}_{14}$	0.2351
$\tilde{Q}_{14}$	1.8286	$\tilde{Q}_{14}$	1.3322	$\tilde{Q}_{14}$	0.9012	$\tilde{Q}_{14}$	0.5355	$\tilde{Q}_{15}$	0.2329
$\tilde{Q}_{12}$	1.7008	$\tilde{Q}_{12}$	1.2407	$\tilde{Q}_{15}$	0.8435	$\tilde{Q}_{15}$	0.5140	$\tilde{Q}_{11}$	0.2319
$\tilde{Q}_{13}$	1.6626	$\tilde{Q}_{13}$	1.2243	$\tilde{Q}_{12}$	0.8406	$\tilde{Q}_{12}$	0.5064	$\tilde{Q}_{13}$	0.2268
$\tilde{Q}_{15}$	1.6475	$\tilde{Q}_{15}$	1.2213	$\tilde{Q}_{13}$	0.8389	$\tilde{Q}_{13}$	0.5005	$\tilde{Q}_{16}$	0.2251
$\tilde{Q}_{16}$	1.6074	$\tilde{Q}_{16}$	1.1895	$\tilde{Q}_{16}$	0.8198	$\tilde{Q}_{16}$	0.4983	$\tilde{Q}_{12}$	0.2203
$\tilde{Q}_{17}$	1.5805	$\tilde{Q}_{17}$	1.1493	$\tilde{Q}_{17}$	0.7757	$\tilde{Q}_{17}$	0.4596	$\tilde{Q}_{17}$	0.2010

According to Table 5.11, the best alternative for all levels of α-cut is “the number of unplanned maintenance”. When transitioning from nondeterministic conditions (e.g., levels of α-cut being 0, 0.1, 0.2, and 0.3) to deterministic conditions (levels of α-cut approaching to 1), the ranking orders of the alternatives change. For example, at the deterministic conditions (e.g., levels of α-cut equal 0.6, 0.7, 0.8, and 0.9), while the best three alternatives are “the number of unplanned maintenance”, “MTTR”, and “MTBF”, the worst alternative is “refusal of extended hours or overtimes” for these α-cut levels. Furthermore, at the nondeterministic conditions (e.g., levels of α-cut equal 0, 0.1, 0.2, 0.3 and 0.4), while the best three alternatives are “the number of unplanned maintenance”, “quality defects”, and “reduced yield”, the worst alternative is “employee turn-over rate” for these α-cut levels. As a conclusion, the other alternatives have almost the same rankings for the different levels of α-cut. According to this table, the optimally criterion K (as explained in Step 8.4 in Section 4.3) is calculated as below:

$$K = \max_j \tilde{Q}_j = \tilde{Q}_3 = TFN(0.5200, 1.7112, 9.5109) \tag{5.1}$$

Finally, the fuzzy $\widetilde{N}_i$ values of alternatives are calculated by division of the optimality criterion K to the fuzzy $\tilde{Q}_i$ values of each alternative. In this context, these values are obtained using Equation (4.17) which is given in Section 4.3 and they are, respectively, $\widetilde{98.07}$, $\widetilde{98.07}$, $\widetilde{100}$, $\widetilde{81.56}$, $\widetilde{81.98}$, $\widetilde{82.54}$, $\widetilde{85.54}$, $\widetilde{79.28}$ $\widetilde{63.48}$, $\widetilde{65.12}$, $\widetilde{54.88}$, $\widetilde{55.60}$, $\widetilde{58.53}$, $\widetilde{59.15}$, $\widetilde{60.98}$, $\widetilde{58.71}$ and $\widetilde{50.34}$.

If the pessimistic values (only lower bounds), optimistic (only upper bounds) values, interval values (both lower and upper bounds) and fuzzy values given in Table 5.8 are employed individually in COPRAS, then the solution results are obtained as in Table 5.12. Moreover, Figure 5.4 shows the comparisons among the methods pessimistic COPRAS, optimistic COPRAS, COPRAS-G and proposed FCOPRAS according to the ranking orders of alternatives. As it can be seen in Table 5.12, the best alternative is the “number of unplanned maintenance” which has same ranking orders in all methods. The worst alternative is the “refusal of extended hours or overtimes” which has same ranking orders in all methods except the proposed

FCOPRAS method for α=0. In this method, the “employee turn-over rate” is the worst alternative. Additionally, the “MTTR” and “MTBF” have the same N_j and fuzzy $\widetilde{N}_i$ values in all methods. Thus, these alternatives are selected as the best alternatives after the “number of unplanned maintenance” in all methods except the proposed FCOPRAS method for α=0 and 0.5. In the proposed FCOPRAS method for α=0 and 0.5, the best alternative is the “quality defects” after the alternative “the number of unplanned maintenance”. Furthermore, the “competence of maintenance personnel” is always the *10*th ranked alternative with respect to all methods. The ranking orders of the alternatives such as “number of HSE incidents”, “reduced speed”, “reduced yield”, “availability of maintenance personnel” and “new ideas generated and implemented” generally change a bottom or a top order from the current order in all methods. As a conclusion, it is seen that proposed FCOPRAS method presents similar but not the same results of other COPRAS methods.

Table 5.12 Solution results of pessimistic COPRAS, optimistic COPRAS, COPRAS-G and fuzzy COPRAS

Alternatives	**Pessimistic COPRAS**		**Optimistic COPRAS**		**COPRAS-G**		**Proposed FCOPRAS**			
								Ranking		
	N_j	**Ranking**	N_j	**Ranking**	N_j	**Ranking**	$\widetilde{N}_i$	**α=0**	**α=0.5**	**α=0.9**
MTTR	98.0750	3	96.4955	3	96.9117	3	$\widetilde{98.0741}$	7	3	3
MTBF	98.0750	2	96.4955	2	96.9117	2	$\widetilde{98.0741}$	8	4	2
Number of unplanned maintenance	100.0000	1	100.0000	1	100.0000	1	$\widetilde{100}$	1	1	1
Number of HSE incidents	79.6595	7	91.3478	7	88.2815	7	$\widetilde{81.5604}$	6	7	7
Reduced speed	79.0954	4	91.9828	6	88.6154	6	$\widetilde{81.9802}$	4	6	6
Reduced yield	79.0954	6	91.9828	5	88.6154	5	$\widetilde{82.5434}$	3	5	5
Quality defects	83.9974	5	94.2944	4	91.6045	4	$\widetilde{85.5396}$	2	2	4
Availability of maintenance personnel	73.7721	8	90.0230	8	85.7524	8	$\widetilde{79.2772}$	5	8	8
Competence of maintenance personnel	55.0425	10	75.8174	10	70.3925	10	$\widetilde{63.4811}$	10	10	10
Experience of operators in production line	58.2970	15	79.6231	9	74.0467	9	$\widetilde{65.1239}$	9	9	9
Operator reliability	45.8961	9	70.1398	14	63.7803	15	$\widetilde{54.8796}$	11	11	13
Training and continuing education	46.6133	16	67.4615	15	62.0109	16	$\widetilde{55.5988}$	13	13	16
New ideas generated and implemented	51.9996	14	68.8464	11	64.3673	14	$\widetilde{58.5308}$	14	14	14
Level of 5S	52.6580	13	72.2133	16	67.0966	12	$\widetilde{59.1472}$	12	12	11
Employee absentees	57.5761	12	71.0100	13	67.4970	11	$\widetilde{60.9782}$	16	15	12
Employee turn-over rate	52.9503	11	69.6560	12	65.2873	13	$\widetilde{58.7191}$	17	16	15
Refusal of extended hours or overtimes	44.7887	17	62.9880	17	58.2305	17	$\widetilde{50.3375}$	15	17	17

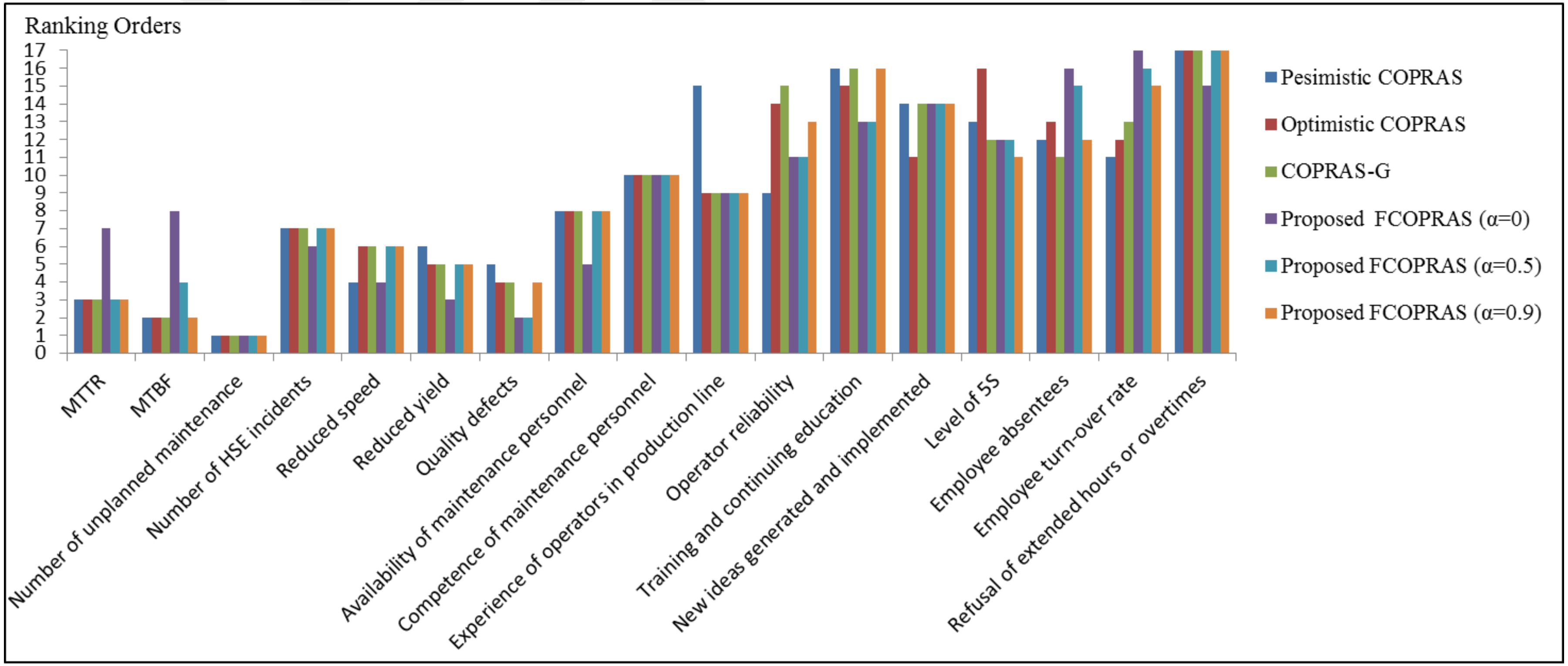

Figure 5.4 The comparison of the proposed FCOPRAS and other COPRAS methods

5.3.5 Comparison of the Proposed FCOPRAS Method with the Most Popular FMADM Methods

In this section, the proposed FCOPRAS method is compared to five recently proposed FMADM methods, i.e., fuzzy TOPSIS, fuzzy ARAS, fuzzy VIKOR, fuzzy MULTIMOORA and fuzzy ELECTRE I based on Hamming distance (Awasthi, Chauhan, & Goyal, 2011; Balazentis, Balazentis, & Brauers, 2012; Hatami-Marbini, Tavana, Moradi, & Kangi, 2013; Kahraman, Suder, & Turanoglu Bekar, 2016; Turskis & Zavadskas, 2010; Kaya & Kahraman, 2010). During the comparison process, the normalized aggregated fuzzy decision matrix given in Table 5.7 is utilized as the final decision matrix into the computational procedure of the benchmarked methods. The comparison of the ranking orders for different FMADM methods is given in Table 5.13. In order to measure the similarity between the ranks by the proposed FCOPRAS method and benchmarked FMADM methods, the Spearman rank correlation coefficient is calculated. The Spearman rank correlation coefficient (ρ) formulated by Equation (5.2), is utilized (Gibbons, 1971).

$$\rho = 1 - \frac{6\sum_{a=1}^{A} D_a^2}{A(A^2-1)} \tag{5.2}$$

where A represents the total number of alternatives and D_a is the difference between the ranks obtained by the different FMADM methods for the same alternative a. Spearman's rank correlation coefficients of the proposed FCOPRAS method with other FMADM are given in Table 5.14. A pictorial representation is also given in Figure 5.5 for comparison of the Spearman's rank correlation coefficients.

5.3.6 Sensitivity Analysis

In order to see the effects of the optimistic and pessimistic changes in the weights of the criteria, a sensitivity analysis is realized. The new aggregated fuzzy weights of attributes are determined using the randomly generated linguistic assessment values for ten different cases as given in Table 5.15.

Table 5.13 Comparative results of the proposed FCOPRAS method with other FMADM methods for alternatives

Alternatives	**The proposed FCOPRAS method**			**Fuzzy TOPSIS**	**Fuzzy ARAS**	**Fuzzy VIKOR**	**Fuzzy MULTIMOORA**			**Fuzzy ELECTRE I**
	α=0	**α=0.5**	**α=0.9**				**Fuzzy Ratio System (1)**	**Fuzzy Reference Point (2)**	**Fuzzy Full Multiplicative (3)**	
	Ranking	**Ranking**	**Ranking**	**Ranking**	**Ranking**	**Ranking**	**Ranking**	**Ranking**	**Ranking**	**Ranking**
MTTR	7	3	3	1	3	1	3	8	5	3
MTBF	8	4	2	2	2	2	2	9	6	2
Number of unplanned maintenance	1	1	1	3	1	3	1	1	1	1
Number of HSE incidents	6	7	7	7	7	5	7	5	7	7
Reduced speed	4	6	6	6	6	6	6	3	3	6
Reduced yield	3	5	5	5	5	7	5	2	4	5
Quality defects	2	2	4	4	4	4	4	4	2	4
Availability of maintenance personnel	5	8	8	8	8	8	8	6	8	8
Competence of maintenance personnel	10	10	10	13	10	12	10	7	10	10
Experience of operators in production line	9	9	9	14	9	13	9	10	9	9
Operator reliability	11	11	13	17	11	16	12	12	11	17
Training and continuing education	13	13	16	15	17	15	13	13	13	14
New ideas generated and implemented	14	14	14	9	16	9	17	17	16	13
Level of 5S	12	12	11	12	15	14	11	11	12	12
Employee absentees	16	15	12	10	12	11	14	15	14	11
Employee turn-over rate	17	16	15	11	13	10	15	16	15	15
Refusal of extended hours or overtimes	15	17	17	16	14	17	16	14	17	16

Table 5.14 Results of the Spearman test

	Proposed and other FMADM Methods		Proposed Fuzzy COPRAS (α=0)	Proposed Fuzzy COPRAS (α=0.5)	Proposed Fuzzy COPRAS (α=0.9)	Fuzzy TOPSIS	Fuzzy ARAS	Fuzzy VIKOR	Fuzzy MULTIMOORA-1	Fuzzy MULTIMOORA-2	Fuzzy MULTIMOORA-3	Fuzzy ELECTRE I
Spearman's rho	**Proposed Fuzzy COPRAS (α=0)**	**CC**	1.000	.931**	.863**	.669**	.833**	.674**	.885**	.958**	.956**	.826**
		Sig.	.	.000	.000	.003	.000	.003	.000	.000	.000	.000
	Proposed Fuzzy COPRAS (α=0.5)	**CC**		1.000	.961**	.797**	.922**	.811**	.973**	.865**	.971**	.922**
		Sig.		.	.000	.000	.000	.000	.000	.000	.000	.000
	Proposed Fuzzy COPRAS (α=0.9)	**CC**			1.000	.870**	.953**	.870**	.971**	.819**	.931**	.971**
		Sig.			.	.000	.000	.000	.000	.000	.000	.000
	Fuzzy TOPSIS	**CC**				1.000	.814**	.978**	.794**	.598*	.748**	.907**
		Sig.				.	.000	.000	.000	.011	.001	.000
	Fuzzy ARAS	**CC**					1.000	.836**	.944**	.801**	.907**	.912**
		Sig.					.	.000	.000	.000	.000	.000
	Fuzzy VIKOR	**CC**						1.000	.799**	.598*	.757**	.897**
		Sig.						.	.000	.011	.000	.000
	Fuzzy MULTIMOORA-1	**CC**							1.000	.858**	.953**	.936**
		Sig.							.	.000	.000	.000
	Fuzzy MULTIMOORA-2	**CC**								1.000	.929**	.787**
		Sig.								.	.000	.000
	Fuzzy MULTIMOORA-3	**CC**									1.000	.890**
		Sig.									.	.000
	Fuzzy ELECTRE I	**CC**										1.000
		Sig.										.

Correlation Coefficient is denoted by "CC"
Significant (2-tailed) is denoted by "Sig."
**Correlation is significant at the 0.01 level (2-tailed)
*Correlation is significant at the 0.05 level (2-tailed)

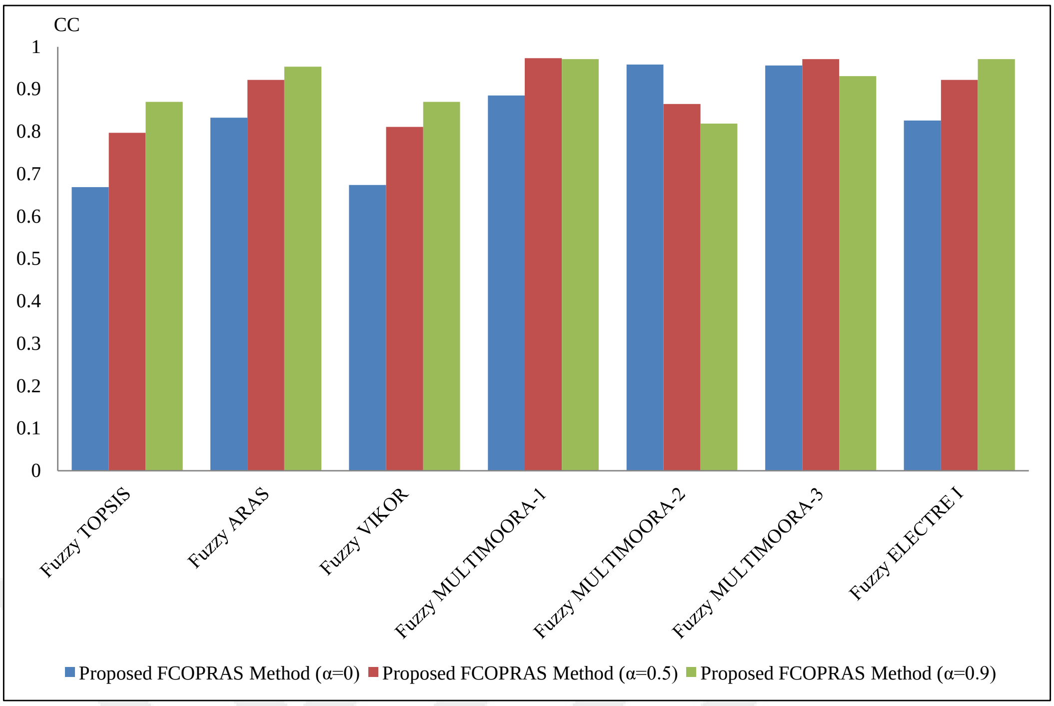

Figure 5.5 Comparison of Spearman's rank correlation coefficients of the proposed FCOPRAS method with other FMADM methods

According to Table 5.14, when the proposed FCOPRAS method is compared to other FMADM methods independently, the minimum and maximum correlation coefficient values are provided as 0.669 (fuzzy TOPSIS) and 0.958 (fuzzy MULTIMOORA-2 that is fuzzy reference point) for α=0, respectively. Furthermore, the maximum and minimum correlation coefficient values are provided as 0.797 (fuzzy TOPSIS) and 0.973 (fuzzy MULTIMOORA-1 that is fuzzy ratio system) for α=0.5. Finally, these values are yielded as 0.870 (fuzzy TOPSIS and fuzzy VIKOR) and 0.971 (fuzzy ELECTRE I and fuzzy MULTIMOORA-1) in case of α=0.9. These values support the similarity of the results and indicate that the proposed method has high correlation or substantial relationship with the other FMADM methods. Additionally, the correlations between fuzzy ARAS and the proposed FCOPRAS methods for α=0, α=0.5 and α=0.9 are high (0.833, 0.922 and 0.953, respectively). This means that these methods produce rankings that are statistically similar since there is not enough evidence to accept the null hypothesis in accordance with significant values 0.000, 0.000 and 0.000, respectively. As a conclusion, the maximal correlation values can be provided by the calculation of the proposed FCOPRAS with α = 0.5 and α = 0.9.

Table 5.15 Aggregated fuzzy weights of attributes for ten different cases

CASES	Attributes	TPM M.	P.M.	Q.M.	Aggregated Fuzzy Weights		
CURRENT CASE	Specifity	VHI	VHI	VHI	0.3701	0.6413	1.0000
	Measurability	HI	VHI	HI	0.3255	0.5714	0.9625
	Attainability	SHI	HI	HI	0.2668	0.4839	0.8562
	Practicalness	MI	HI	HI	0.2355	0.4227	0.7312
	Timely	SLI	VHI	HI	0.2109	0.3877	0.6500
	Cost of Measure	SHI	HI	SHI	0.2489	0.4635	0.8375
CASE 1	Specifity	SLI	VLI	HI	0.1151	0.2255	0.4503
	Measurability	LI	LI	VLI	0.0171	0.0834	0.2450
	Attainability	SLI	VLI	SHI	0.0962	0.2039	0.4305
	Practicalness	VHI	SHI	HI	0.3359	0.6008	1.0000
	Timely	MI	VHI	LI	0.2014	0.3892	0.6954
	Cost of Measure	VHI	HI	VLI	0.2890	0.5282	0.9272
CASE 2	Specifity	HI	VHI	VHI	0.3498	0.6078	1.0000
	Measurability	VHI	SLI	SLI	0.2355	0.4589	0.8194
	Attainability	LI	SHI	VHI	0.1582	0.2964	0.4968
	Practicalness	VLI	VLI	HI	0.0691	0.1023	0.2129
	Timely	VLI	SHI	HI	0.1336	0.2242	0.3935
	Cost of Measure	HI	SHI	VLI	0.2258	0.4288	0.8323
CASE 3	Specifity	HI	HI	LI	0.2852	0.5374	1.0000
	Measurability	SLI	SHI	SLI	0.1415	0.3126	0.6232
	Attainability	SHI	HI	HI	0.3093	0.5610	0.9927
	Practicalness	SLI	LI	SHI	0.1118	0.2535	0.5145
	Timely	VLI	VHI	LI	0.1238	0.2230	0.3985
	Cost of Measure	VHI	VLI	MI	0.2588	0.4732	0.8406
CASE 4	Specifity	VHI	VHI	VHI	0.3701	0.6413	1.0000
	Measurability	LI	VLI	VLI	0.0104	0.0525	0.1938
	Attainability	VLI	SHI	MI	0.0982	0.1763	0.3375
	Practicalness	VHI	SLI	SHI	0.2594	0.4854	0.8375
	Timely	HI	SHI	VHI	0.2991	0.5320	0.9188
	Cost of Measure	VHI	SLI	SLI	0.2281	0.4446	0.7938
CASE 5	Specifity	SLI	VHI	LI	0.2833	0.5485	1.0000
	Measurability	SHI	MI	SHI	0.2677	0.5149	0.9600
	Attainability	LI	SHI	LI	0.0991	0.2407	0.4960
	Practicalness	MI	VLI	MI	0.1524	0.2985	0.6080
	Timely	HI	LI	SLI	0.2302	0.4627	0.9120
	Cost of Measure	VLI	SHI	SLI	0.1029	0.1996	0.4080

Table 5.15 Fuzzy weights of attributes for ten different cases (cont.)

CASES	Attributes	TPM M.	P.M.	Q.M.	Aggregated Fuzzy Weights		
CASE 6	Specifity	HI	SLI	VLI	0.2017	0.3991	0.8099
	Measurability	VLI	HI	HI	0.1715	0.2792	0.4718
	Attainability	LI	LI	MI	0.0584	0.1544	0.3310
	Practicalness	VLI	SLI	VHI	0.1161	0.1954	0.3380
	Timely	SHI	VLI	LI	0.1342	0.2858	0.6268
	Cost of Measure	HI	HI	SLI	0.2922	0.5452	1.0000
CASE 7	Specifity	VHI	SHI	HI	0.3272	0.5853	0.9742
	Measurability	HI	VLI	LI	0.1659	0.3250	0.6710
	Attainability	SLI	SLI	SLI	0.0849	0.2152	0.4645
	Practicalness	HI	MI	VHI	0.2912	0.5176	0.8968
	Timely	HI	VHI	VHI	0.3498	0.6078	1.0000
	Cost of Measure	SLI	VLI	SHI	0.0937	0.1986	0.4194
CASE 8	Specifity	MI	MI	MI	0.1645	0.3207	0.6000
	Measurability	VHI	VHI	VHI	0.3701	0.6413	1.0000
	Attainability	VLI	LI	LI	0.0101	0.0437	0.1562
	Practicalness	HI	VHI	VHI	0.3389	0.5888	0.9687
	Timely	LI	LI	SHI	0.0652	0.1574	0.3187
	Cost of Measure	HI	VHI	HI	0.3255	0.5713	0.9625
CASE 9	Specifity	VHI	VHI	VHI	0.3701	0.6413	1.0000
	Measurability	VHI	VHI	VHI	0.3701	0.6413	1.0000
	Attainability	HI	HI	HI	0.3085	0.5451	0.9500
	Practicalness	HI	HI	HI	0.3085	0.5451	0.9500
	Timely	MI	VHI	VHI	0.2660	0.4664	0.7500
	Cost of Measure	VHI	VHI	VHI	0.3701	0.6413	1.0000
CASE 10	Specifity	MI	MI	SHI	0.1779	0.3411	0.6250
	Measurability	VHI	VHI	VHI	0.3701	0.6413	1.0000
	Attainability	HI	VHI	VHI	0.3389	0.5888	0.9687
	Practicalness	LI	LI	SLI	0.0340	0.1166	0.2750
	Timely	SHI	SHI	SLI	0.1950	0.3921	0.7563
	Cost of Measure	MI	SLI	MI	0.1418	0.2901	0.5625

When ten different cases are examined and compared to the current case, in Case 1, the aggregated fuzzy weights of the attributes “specifity”, “measurability”, “attainability” and “timely” are significantly decreased while the aggregated fuzzy weights of the attributes “practicalness” and “cost of measure” are increased. In case 2, the aggregated fuzzy weights of all attributes except the attribute “specifity” are decreased. In case 3, the aggregated fuzzy weights of the attributes “measurability”, "practicalness" and "timely" are decreased while the aggregated fuzzy weight of the attribute "attainability" and "cost of measure" are increased. In case 4, the aggregated fuzzy weights of the attributes "measurability", "attainability" and "cost of measure" are decreased while the aggregated fuzzy weights of the attributes "practicalness" and "timely" are increased. In case 5, the aggregated fuzzy weights of the attributes "measurability", "attainability", "practicalness" and "cost of measure" are decreased while the aggregated fuzzy weights of the attribute "timely" is increased. According to Case 6, the aggregated fuzzy weights of the attributes "specifity", "measurability", "attainability", "practicalness" and "timely" are decreased while the aggregated fuzzy weights of the attribute "cost of measure" is increased. According to Case 7, the aggregated fuzzy weights of the attributes "specifity", "measurability", "attainability" and "cost of measure" are decreased while the aggregated fuzzy weights of the attribute "practicalness" and "timely" are increased. According to Case 8, the aggregated fuzzy weights of the attribute "specifity" and "attainability" and "timely" are decreased while the aggregated fuzzy weights of the attribute "measurability" and "practicalness" and "cost of measure" are increased. In Case 9, the aggregated fuzzy weights of the attributes of five attributes are increased while the aggregated fuzzy weight of the attribute "specifity" is the same. Finally, according to Case 10, the aggregated fuzzy weights of the attributes "specifity", "practicalness" and "cost of measure" are decreased while the aggregated fuzzy weights of the attributes "measurability", "attainability" and "timely" are increased. Afterwards, these weights given in Table 5.15 are used by the proposed FCOPRAS method to obtain the ranking orders of alternatives. The ranking results of alternatives are given in Table 5.16 and also illustrated in Figures 5.6-5.8.

In order to save time, to provide easiness for the sensitivity analysis calculations and to avoid calculation errors, the proposed FCOPRAS and other FMADM methods mentioned in Section 5.4.4 are coded with *MATLAB R2016a.* Some examples of the developed codes for the proposed FCOPRAS and the other FMADM methods using MATLAB 2016a are presented in Appendix A1.

Table 5.16 The ranking results of sensitivity analysis

Alternatives	Ranking Orders of Alternatives for α=0, 0.5 and 0.9																																
	Current Case			**Case 1**			**Case 2**			**Case 3**			**Case 4**			**Case 5**			**Case 6**			**Case 7**			**Case 8**			**Case 9**			**Case 10**		
MTTR	7	3	3	9	7	3	9	7	3	7	5	3	8	5	3	4	3	3	10	8	3	5	3	3	8	7	3	7	3	3	7	3	3
MTBF	8	4	2	10	8	2	10	8	2	8	6	2	9	6	2	5	2	2	11	9	2	6	2	2	9	8	2	8	4	2	8	4	2
Number of unplanned maintenance	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Number of HSE incidents	6	7	7	5	5	5	6	6	8	6	7	7	5	7	6	8	8	7	6	6	8	7	7	6	6	6	7	5	7	7	6	8	6
Reduced speed	4	6	6	4	4	7	4	4	6	3	3	5	4	4	7	6	6	6	4	4	6	4	6	7	4	4	6	4	6	6	3	5	5
Reduced yield	3	5	5	3	3	6	2	3	5	4	4	6	3	3	5	3	5	5	2	3	5	3	5	5	3	3	5	3	5	5	4	6	7
Quality defects	2	2	4	1	2	4	3	2	4	2	2	4	2	2	4	2	4	4	1	2	4	2	4	4	2	2	4	2	2	4	2	2	4
Availability of maintenance personnel	5	8	8	6	6	8	5	5	7	5	8	8	6	8	8	7	7	8	5	5	7	8	8	8	5	5	8	6	8	8	5	7	8
Competence of maintenance personnel	10	10	10	11	11	10	11	10	10	11	10	10	11	11	10	10	10	10	9	11	10	10	10	10	10	10	10	10	10	10	10	10	10
Experience of operators in production line	9	9	9	7	9	9	7	9	9	9	9	9	7	9	9	9	9	9	7	7	9	9	9	9	7	9	9	9	9	9	9	9	9
Operator reliability	11	11	13	8	10	11	8	11	11	10	11	11	10	10	12	11	11	16	8	10	11	11	11	15	11	11	11	11	11	13	11	11	15
Training and continuing education	13	13	16	13	13	14	13	13	13	13	13	15	13	13	14	13	15	15	13	13	13	13	14	16	13	13	14	13	13	16	13	15	16
New ideas generated and implemented	14	14	14	15	16	16	15	14	14	14	14	14	15	15	16	14	14	14	15	15	15	15	15	14	15	16	15	14	15	14	14	13	13
Level of 5S	12	12	11	12	12	12	12	12	12	12	12	12	12	12	11	12	12	11	12	12	12	12	12	11	12	12	12	12	12	11	12	12	14
Employee absentees	16	15	12	16	15	13	17	17	16	16	15	13	16	14	13	15	13	12	16	16	14	14	13	12	16	15	13	16	14	12	16	14	11
Employee turn-over rate	17	16	15	17	17	15	16	16	15	17	17	16	17	16	15	16	16	13	17	17	16	16	16	13	17	17	16	17	16	15	17	16	12
Refusal of extended hours or overtimes	15	17	17	14	14	17	14	15	17	15	16	17	14	17	17	17	17	17	14	14	17	17	17	17	14	14	17	15	17	17	15	17	17

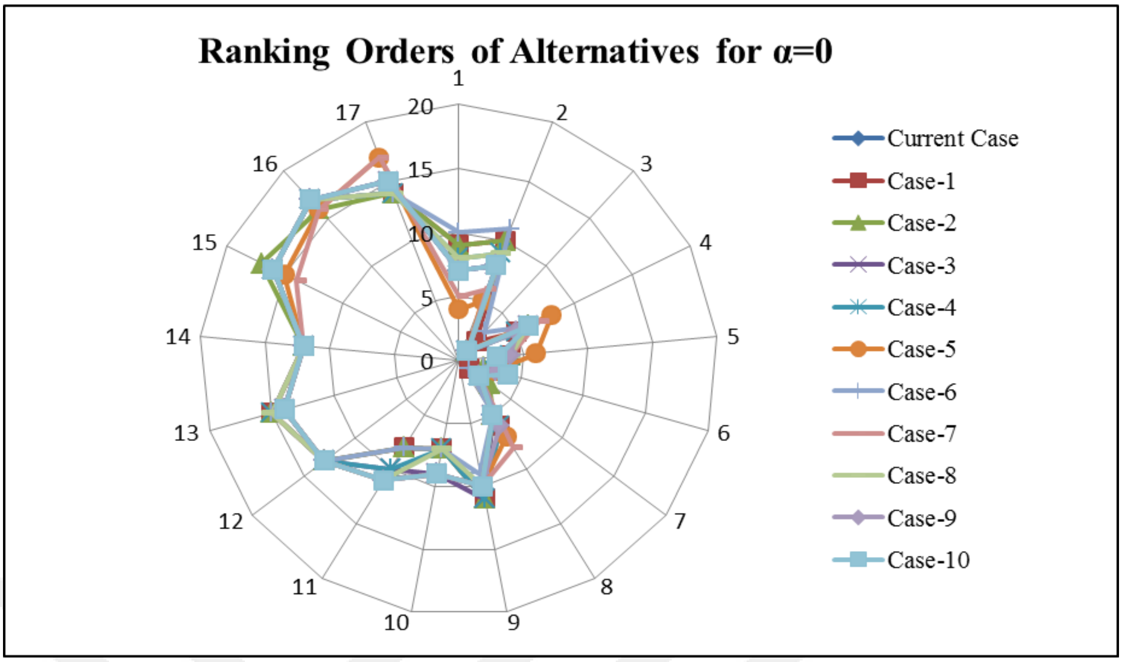

Figure 5.6 Ranking orders of alternatives for α=0 according to ten different cases

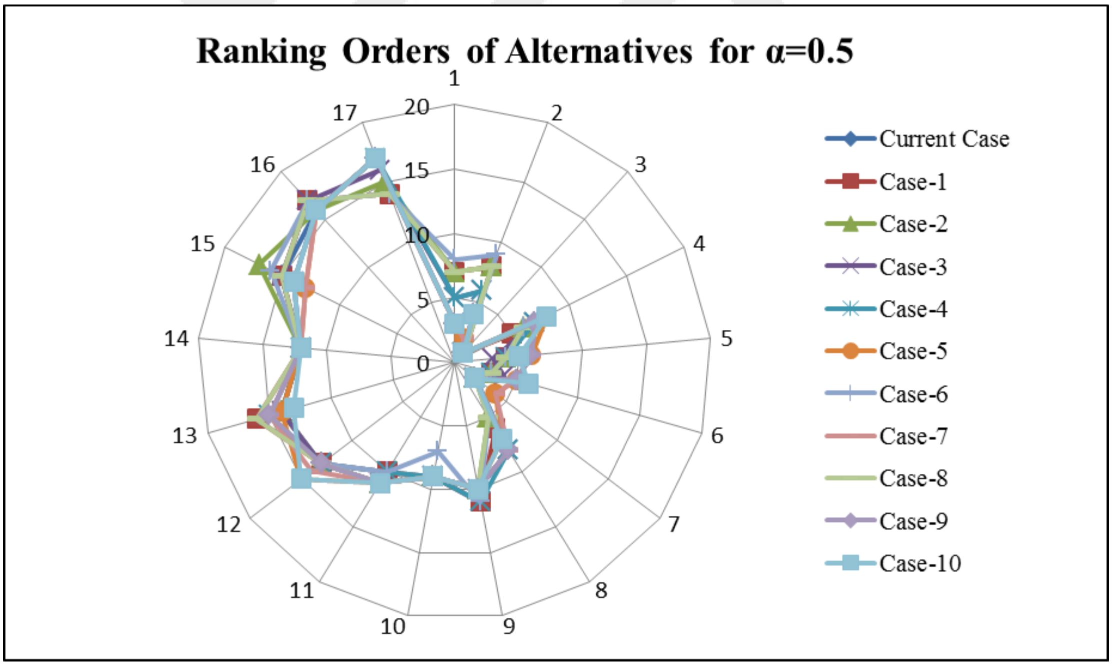

Figure 5.7 Ranking orders of alternatives for α=0.5 according to ten different cases

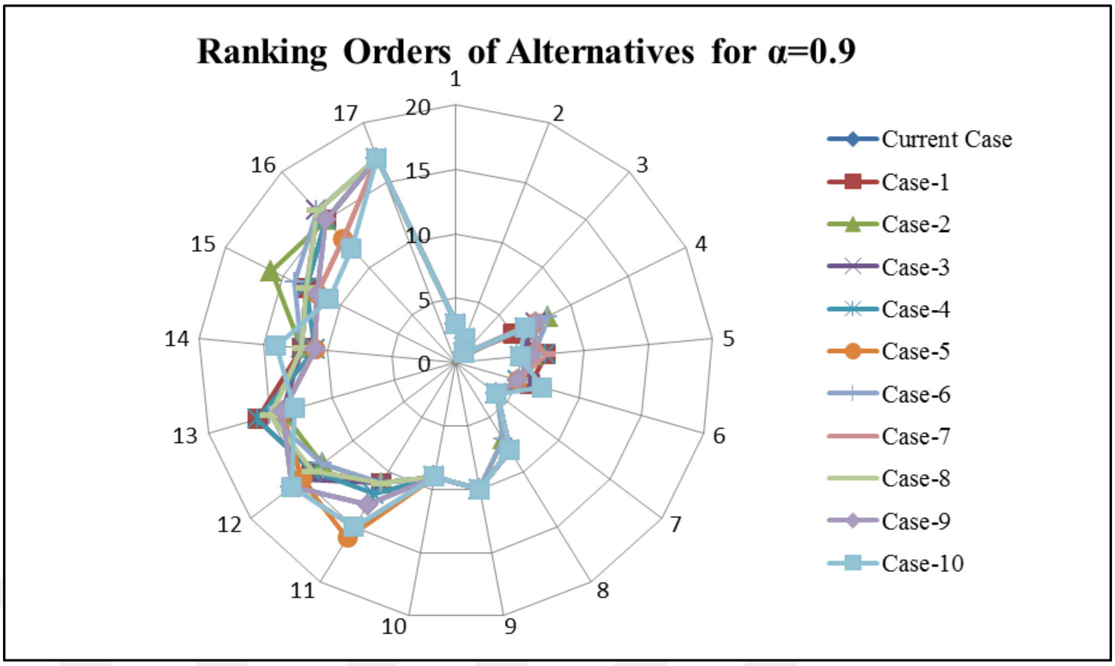

Figure 5.8 Ranking orders of alternatives for α=0.9 according to ten different cases

When the α-cut level is 0, the ranking orders of the alternatives are given in Table 5.16 and Figure 5.6 according to the current and ten different cases. The current case represents the ranking order of the results obtained by the attribute weights originally assigned by the decision makers. The alternative “the number of unplanned maintenance” is the best option in the current and other cases except cases 1 and 6. In case 1, this alternative ranks as the second order and the best alternative is “quality defects”. In case 6, this alternative ranks as the third order and the best alternative is also “quality defects”. Additionally, the alternatives like “refusal of extended hours or overtimes” and “employee turn-over rate” are the worst options in the most cases. Furthermore, the rank orders of the other alternatives generally change the bottom or the top order from the current order in all cases.

When the α-cut levels are 0.5 and 0.9, the ranking orders of the alternatives are given in Table 5.16 and Figures 5.7 and 5.8 according to the current and ten different cases. The alternative “the number of unplanned maintenance” is the best option in all cases for these α-cut levels. The alternatives such as “refusal of extended hours or overtimes” and “employee turn-over rate” are the worst options in most cases except case 2. In this case, the worst alternative is “employee absentees”. The alternatives such as “number of HSE incidents”, “reduced speed”, “reduced yield”, “quality defects”, “availability of maintenance personnel”, “competence of maintenance personnel”, and “experience of operators in production line” take place almost in the same rank order in all cases. The rank orders of the other alternatives generally change the bottom or the top order from the current order in all cases. As a result of the sensitivity analysis, even when weights of the attributes retrieve optimistic and pessimistic values, the rank orders of the alternatives do not change considerably. This indicates that the proposed FCOPRAS method is reliable for the evaluation of novel PIs in TPM. Additionally, it could be used to assess different application problems.

5.4 Performance Evaluation of TPM Using the Proposed TPM PIs

5.4.1 Definition of DMUs

As stated in Step 1 in Section 4.4, the DMUs whose TPM performance should be measured are defined in detail in this section. In this context, this thesis is implemented in a company operating in the automotive industry in Aegean Free Zone since 2002. 860 Direct and 130 indirect employees work in the company. Along with the core operating departments, there are support functions including the TPM department. In the TPM department, there are one lead engineer and four supervisors and 28 maintenance technicians. The overall TPM activities of this company are managed by the TPM-office.

This company produces components of fuel injection systems. These components are tubular rail (CR), high pressure valve (HPV), and nozzle holder body (NHB). CR is manufactured in two segments which are “CR Machining” and “CR & Test (A&T)”. HPV is manufactured in a separate assembly line and being assembled to rail in CR A&T line. NHB is manufactured in two segments as well as those “NHB Beginning of Line (BOL)” and “NHB End of Line (EOL)”. In this context, the proposed GFDEA/AR models with desirable and undesirable inputs and outputs are used to evaluate TPM performance of four production lines (DMUs) such as “Rail

Machining (DMU_1)", "Rail Assembly and HPV (DMU_2)", "NHB BOL (DMU_3)"and "NHB EOL (DMU_4)".

5.4.2 Determination of Desirable and Undesirable Inputs and Outputs

As stated in Steps 2 and 3 in Section 4.4, the proposed TPM PIs (alternatives) given in Table 5.1 are classified as inputs and outputs. Afterwards, these inputs and outputs are determined as desirable and undesirable inputs and outputs. Table 5.17 presents a list for the desirable and undesirable inputs and outputs and their corresponding fuzzy $\tilde{Q}_i$ values (fuzzy relative significance) which are determined in Section 5.3.4 (see Table 5.10).

Table 5.17 A list for desirable and undesirable inputs and outputs and their fuzzy $\tilde{Q}_i$ values

The proposed TPM PIs	Inputs		Outputs		Fuzzy $\tilde{Q}_i$ values		
	Desirable	Undesirable	Desirable	Undesirable			
MTTR			√		0.5190	1.6782	7.9868
MTBF			√		0.5190	1.6782	7.9868
Number of unplanned maintenance				√	0.5200	1.7112	9.5109
Number of HSE incidents				√	0.3952	1.3957	9.4479
Reduced speed				√	0.3972	1.4028	9.7324
Reduced yield				√	0.4016	1.4125	9.7459
Quality defects				√	0.4172	1.4637	9.8128
Availability of maintenance personnel	√				0.3678	1.3566	9.6404
Competence of maintenance personnel	√				0.2758	1.0863	8.7236
Experience of operators in production line	√				0.2825	1.1144	9.3990
Operator reliability	√				0.2161	0.9391	9.0335
Training and continuing education	√				0.2417	0.9514	6.2366
New ideas generated and implemented	√				0.2721	1.0016	5.5605
Level of 5S	√				0.2592	1.0121	6.7909
Employee absentees		√			0.2968	1.0435	5.1290
Employee turn-over rate		√			0.2754	1.0048	5.0960
Refusal of extended hours or overtimes		√			0.2211	0.8614	5.9740

As stated in Step 4 in Section 4.4, the relevant data of "MTRR", "MTBF", "the number of unplanned maintenance", "quality defects", "the number of HSE incidents", and "reduced yield" are crisp values, which can be treated as degenerated

TFNs. “Reduced speed” which cannot be assessed by exact data, are represented as TFNs. In these inputs, “new ideas generated and implemented”, “level of 5S” and “employee absentees” are crisp, which can be treated as degenerated TFNs. In addition, “employee turn-over rate” and “training and continuing education” are scored by approximate value according to production lines. Hence, they are represented as TFNs. The inputs “availability of maintenance personnel”, “operator reliability” and “refusal of extended hours or overtimes” are evaluated from the observations of the production line supervisor and team leader using fuzzy linguistic scale such as “very low”, “low”, “medium”, “high” and “very high”. The membership functions of these inputs are shown in Figure 5.9, which can be regarded as degenerated TFNs. The relevant data of “competence of maintenance personnel” is a crisp value, which can be treated as degenerated TFN and it is obtained from the table of ability for maintenance personnel in the company. Finally, the relevant data of the input “experience of operators in production line” is assessed according to years of relevant work experience on a specific machine and operation and also working time in the company, which is a crisp value, and can be treated as a degenerated TFN.

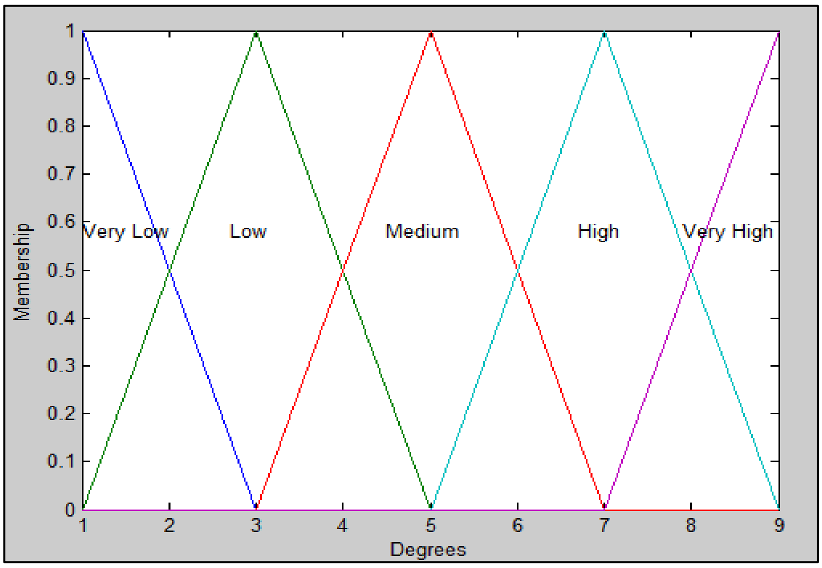

Figure 5.9 The membership functions of the inputs “availability of maintenance personnel”, “operator reliability” and “refusal of extended hours or overtimes”

5.4.3 Data Description and Normalization

The relevant data for all inputs and outputs regarding the four production lines (DMUs) are collected and listed in Table 5.18. Then, the inputs and outputs data determined by approximate values in Table 5.18 are transformed TFNs. For example, the data of the input “competence of maintenance personnel” is around 82 for the Rail Machining production line. The value approximate 82 is transformed to a TFN as (80, 82, 84) in the proposed GFDEA/AR models with desirable and undesirable inputs and outputs. The inputs data determined by linguistic scale in Table 5.18 also are transformed to TFNs. For example, the input “operator reliability” is expressed “high” for the Rail Machining production line. According to the membership functions of “operator reliability”, high is represented by TFN as (5, 7, 9) in the proposed GFDEA/AR models with desirable and undesirable inputs and outputs. For the crisp data in inputs and outputs, the mean and standard deviation of the crisp value are used to degenerate symmetric TFNs. For example, the mean and standard deviation of the data of the output “MTTR” for the Rail Machining production line is 1.59 and 0.83. This crisp data is transformed to a TFN as (0.76, 1.59, 2.42) in the proposed GFDEA/AR models with desirable and undesirable inputs and outputs. If the mean and standard deviation of crisp data is not known, the spread value is used to transform crisp data to TFN. Table 5.19 lists fuzzy values for all inputs and outputs.

In order to rectify the problems due to the significant differences in the magnitude of inputs and outputs, the linear scale transformation is used to the various inputs and outputs scales into a comparable scale. In this context, the fuzzy normalized values of all inputs and outputs are listed in Table 5.20.

5.4.4 Solving the Proposed GFDEA/AR Models in the Presence of Desirable and Undesirable Inputs and Outputs

As stated in Step 5 in Section 4.4, the proposed GFDEA/AR models in the presence of desirable and undesirable inputs and outputs which are explained in detail in Section 4.4.1 are constructed to evaluate TPM performance for DMUs. In this context, firstly the α-cut sets of inputs and outputs for each DMU are obtained using the fuzzy normalized values given in Table 5.20. These α-cut sets of inputs and outputs are given in Table 5.21. Afterwards, the proposed Models (1-6) based on *the first*, *second third approaches* (explained in Section 4.4.1) are performed according to the concept of α-cut for the lower and upper bounds of each DMU. Each model includes eighty-eight different mathematical models (for the lower and upper bounds of each DMU at eleven different α-cut levels) and these are solved by using *General Algebraic Modeling System (GAMS) 23.5*. The mathematical formulation of each model in the open form is not given since each of the mathematical models includes one objective function, 17 decision variables (total number of the inputs and outputs) and 154 constraints. An example of the developed codes of Model (1) iGAMS 23.5 is presented in Appendix A2.

Table 5.18 The relevant data for inputs and outputs for four production lines

DESIRABLE INPUTS	PRODUCTION LINES (DMUs)				UNITS
	RAIL MACHINING (DMU_1)	**RAIL ASSEMBLY AND HPV (DMU_2)**	**NHB BOL (DMU_3)**	**NHB EOL (DMU_4)**	
Availability of maintenance personnel	MEDIUM	LOW	MEDIUM	HIGH	Linguistics Scale
Competence of maintenance personnel	approximate 82	approximate 85	approximate 67	approximate 78	Point Scoring System (0 To 100)
Experience of operators in production line	7.2	6.4	4.5	4.0	Years
Operator reliability	HIGH	LOW	MEDIUM	HIGH	Linguistics Scale
Training and continuing education	approximate 14	approximate 17	approximate 15	approximate 16	Hours per Year
New ideas generated and implemented	18	10	6	8	Avg. Points Gained/Employee)
Level of 5S	3.71	3.83	4.00	3.83	Point Scoring System (1 To 5)
UNDESIRABLE INPUTS	**DMU_1**	**DMU_2**	**DMU_3**	**DMU_4**	
Employee absentees	1.39	1.8	2.09	1.37	%
Employee turn-over rate	approximate 0.3	approximate 0.6	approximate 1.2	approximate 0.7	%
Refusal of extended hours or overtimes	LOW	MEDIUM	HIGH	MEDIUM	Linguistics Scale
DESIRABLE OUTPUTS	**DMU_1**	**DMU_2**	**DMU_3**	**DMU_4**	
MTTR	1.59	1.24	1.80	1.11	Minute (Mean-Standard Deviation)
	0.83	0.25	1.31	0.68	
MTBF	120.99	78.66	134.46	63.43	Minute (Mean-Standard Deviation)
	35.32	22.72	29.25	35.91	
UNDESIRABLE OUTPUTS	**DMU_1**	**DMU_2**	**DMU_3**	**DMU_4**	
Reduced speed	approximate 2473	approximate 1756	approximate 2070	approximate 1834	Minute
Reduced yield	99	93	97	95	%
Quality defects	1	7	3	5	%
Number of unplanned maintenance	76.19 16.88	104.51 24.06	178.68 40.99	114.11 72.48	Number (Mean-Standard Deviation)
Number of HSE incidents	0.77	1.80	1.03	1.55	Incident per Man Hour

Table 5.19 Fuzzy values of the relevant data for inputs and outputs

DESIRABLE INPUTS	**DMU_1**	**DMU_2**	**DMU_3**	**DMU_4**
Availability of maintenance personnel	(3, 5, 7)	(1, 3, 5)	(3 ,5, 7)	(5, 7, 9)
Competence of maintenance personnel	(80, 82, 84)	(83, 85, 87)	(65, 67, 69)	(76, 78, 80)
Experience of operators in production line	(7.0, 7.2, 7.4)	(6.2, 6.4, 6.6)	(4.3, 4.5, 4.7)	(3.8, 4.0, 4.2)
Operator reliability	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)
Training and continuing education	(10, 14, 18)	(13, 17, 21)	(11, 15, 19)	(12, 16, 20)
New ideas generated and implemented	(16, 18, 20)	(8, 10, 12)	(4, 6, 8)	(6, 8, 10)
Level of 5S	(3.21, 3.71, 4.21)	(3.33, 3.83, 4.33)	(3.50, 4.00, 4.50)	(3.33, 3.83, 4.33)
UNDESIRABLE INPUTS	**DMU_1**	**DMU_2**	**DMU_3**	**DMU_4**
Employee absentees	(1.09, 1.39, 1.69)	(1.50, 1.80, 2.10)	(1.79, 2.09, 2.39)	(1.07, 1.37, 1.67)
Employee turn-over rate	(0.1, 0.3, 0.5)	(0.4, 0.6, 0.8)	(1.0, 1.2, 1.4)	(0.5, 0.7, 0.9)
Refusal of extended hours or overtimes	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)
DESIRABLE OUTPUTS	**DMU_1**	**DMU_2**	**DMU_3**	**DMU_4**
MTTR	(0.76, 1.59, 2.42)	(0.99, 1.24, 1.49)	(0.49, 1.80, 3.11)	(0.68, 1.11, 1.79)
MTBF	(85.67, 120.99, 156.31)	(55.94, 78.66, 101.38)	(105.21, 134.46, 163.71)	(27.52, 63.43, 99.34)
UNDESIRABLE OUTPUTS	**DMU_1**	**DMU_2**	**DMU_3**	**DMU_4**
Reduced speed	(2413, 2473, 2533)	(1696, 1756, 1816)	(2010, 2070, 2130)	(1774, 1834, 1894)
Reduced yield	(98.00, 99.00, 100.00)	(88.35, 93.00, 97.65)	(92.15, 97.00, 101.85)	(90.25, 95.00, 99.75)
Quality defects	(0.95, 1.00, 1.05)	(6.65, 7.00, 7.35)	(2.85, 3.00, 3.15)	(4.75, 5.00, 5.25)
Number of unplanned maintenance	(59.31, 76.19, 93.07)	(80.45, 104.51, 128.57)	(137.69, 178.68, 219.67)	(41.63, 114.11, 186.59)
Number of HSE incidents	(0.75, 0.77, 0.79)	(1.78, 1.80, 1.82)	(1.01, 1.03, 1.05)	(1.53, 1.55, 1.57)

Table 5.20 Fuzzy normalized values of the relevant data for inputs and outputs

DESIRABLE INPUTS (BAD-V_i^B)		**DMU_1**			**DMU_2**			**DMU_3**			**DMU_4**	
Availability of maintenance personnel (v_1^B)	0.3333	0.5556	0.7778	0.1111	0.3333	0.5556	0.3333	0.5556	0.7778	0.5556	0.7778	1.0000
Competence of maintenance personnel (v_2^B)	0.9195	0.9425	0.9655	0.9540	0.9770	1.0000	0.7471	0.7701	0.7931	0.8736	0.8966	0.9195
Experience of operators in production line (v_3^B)	0.9459	0.9730	1.000	0.8378	0.8649	0.8919	0.5811	0.6081	0.6351	0.5135	0.5405	0.5676
Operator reliability (v_4^B)	0.5556	0.7778	1.0000	0.1111	0.3333	0.5556	0.3333	0.5556	0.7778	0.4444	0.7778	1.0000
Training and continuing education (v_5^B)	0.4762	0.6667	0.8571	0.6190	0.8095	1.0000	0.5238	0.7143	0.9048	0.5714	0.7619	0.9524
New ideas generated and implemented (v_6^B)	0.8000	0.9000	1.0000	0.4000	0.5000	0.6000	0.2000	0.3000	0.4000	0.3000	0.4000	0.5000
Level of 5S (v_7^B)	0.7133	0.8244	0.9356	0.7400	0.8511	0.9622	0.7778	0.8889	1.0000	0.7400	0.8511	0.9622
UNDESIRABLE INPUTS (GOOD-V_i^G)		**DMU_1**			**DMU_2**			**DMU_3**			**DMU_4**	
Employee absentees (v_1^G)	0.6331	0.7698	0.9817	0.5095	0.5944	0.7133	0.4477	0.5120	0.5978	0.6407	0.7810	1.0000
Employee turn-over rate (v_2^G)	0.2000	0.3333	1.0000	0.1250	0.1667	0.2500	0.0714	0.0833	0.1000	0.1111	0.1429	0.2000
Refusal of extended hours or overtimes (v_3^G)	0.2000	0.3333	1.0000	0.1429	0.2000	0.3333	0.1111	0.1429	0.2000	0.1429	0.2000	0.3333
DESIRABLE OUTPUTS (GOOD-U_i^G)		**DMU_1**			**DMU_2**			**DMU_3**			**DMU_4**	
MTTR (u_1^G)	0.2025	0.3082	0.6447	0.3289	0.3952	0.4949	0.1576	0.2722	1.0000	0.2737	0.4414	0.7206
MTBF (u_2^G)	0.5233	0.7391	0.9548	0.3417	0.4805	0.6193	0.6427	0.8210	1.0000	0.1681	0.3875	0.6068
UNDESIRABLE OUTPUTS (BAD-U_i^B)		**DMU_1**			**DMU_2**			**DMU_3**			**DMU_4**	
Reduced speed (u_1^B)	0.6696	0.6858	0.7029	0.9339	0.9658	1.0000	0.7962	0.8193	0.8438	0.8955	0.9248	0.9560
Reduced yield (u_2^B)	0.8499	0.8924	0.9394	0.9048	0.9500	1.0000	0.8675	0.9108	0.9588	0.8857	0.9300	0.9789
Quality defects (u_3^B)	0.9048	0.9500	1.0000	0.1293	0.1357	0.1429	0.3016	0.3167	0.3333	0.1810	0.1900	0.2000
Number of unplanned maintenance (u_4^B)	0.4473	0.5464	0.7019	0.3238	0.3983	0.5175	0.1895	0.2330	0.3023	0.2231	0.3648	1.0000
Number of HSE incidents (u_5^B)	0.9494	0.9740	1.0000	0.4121	0.4167	0.4213	0.7143	0.7282	0.7426	0.4777	0.4839	0.4902

Table 5.21 The α-cut sets of inputs and outputs

$\mathbf{V_i^B}$	**DMU$_1$**	**DMU$_2$**	**DMU$_3$**	**DMU$_4$**
v_1^B	$(0.3333 + 0.2223\alpha, 0.7778 - 0.2223\alpha)$	$(0.1111 + 0.2222\alpha, 0.5556 - 0.2222\alpha)$	$(0.3333 + 0.2223\alpha, 0.7778 - 0.2223\alpha)$	$(0.5556 + 0.2222\alpha, 1.000 - 0.2222\alpha)$
v_2^B	$(0.9195 + 0.0270\alpha, 0.9655 - 0.0270\alpha)$	$(0.9540 + 0.0230\alpha, 1.000 - 0.0230\alpha)$	$(0.7471 + 0.0230\alpha, 0.7931 - 0.0230\alpha)$	$(0.8736 + 0.0230\alpha, 0.9195 - 0.0230\alpha)$
v_3^B	$(0.9459 + 0.0271\alpha, 1.0000 - 0.0271\alpha)$	$(0.8378 + 0.0271\alpha, 0.8919 - 0.0271\alpha)$	$(0.5811 + 0.0270\alpha, 0.6351 - 0.0270\alpha)$	$(0.5135 + 0.0270\alpha, 0.5676 - 0.0270\alpha)$
v_4^B	$(0.5556 + 0.2222\alpha, 1.0000 - 0.2222\alpha)$	$(0.1111 + 0.2222\alpha, 0.5556 - 0.2222\alpha)$	$(0.3333 + 02223\alpha, 0.7778 - 0.2223\alpha)$	$(0.4444 + 0.2222\alpha, 1.000 - 0.2223\alpha)$
v_5^B	$(0.4762 + 0.1908\alpha, 0.8571 - 0.1908\alpha)$	$(0.6190 + 0.1905\alpha, 1.000 - 0.1905\alpha)$	$(0.5238 + 0.1905\alpha, 0.9048 - 0.1905\alpha)$	$(0.5714 + 0.1905\alpha, 0.9524 - 0.1905\alpha)$
v_6^B	$(0.8000 + 0.1000\alpha, 1.0000 - 0.1000\alpha)$	$(0.4000 + 0.1000\alpha, 0.6000 - 0.1000\alpha)$	$(0.2000 + 0.1000\alpha, 0.4000 - 0.1000\alpha)$	$(0.3000 + 0.1000\alpha, 0.5000 - 0.1000\alpha)$
v_7	$(0.7133 + 0.1111\alpha, 0.9356 - 0.1111\alpha)$	$(0.7400 + 0.1111\alpha, 0.9622 - 0.1111\alpha)$	$(0.7778 + 0.1111\alpha, 1.000 - 0.1111\alpha)$	$(0.7400 + 0.1111\alpha, 0.9622 - 0.1111\alpha)$
$\mathbf{V_i^G}$	**DMU$_1$**	**DMU$_2$**	**DMU$_3$**	**DMU$_4$**
v_1^G	$(0.6331 + 0.1367\alpha, 0.9817 - 0.2119\alpha)$	$(0.5095 + 0.0849\alpha, 0.7133 - 0.1189\alpha)$	$(0.4477 + 0.0643\alpha, 0.5978 - 0.0858\alpha)$	$(0.6407 + 0.1403\alpha, 1.0000 - 0.2190\alpha)$
v_2^G	$(0.2000 + 0.1333\alpha, 1.0000 - 0.6667\alpha)$	$(0.1250 + 0.0417\alpha, 0.2500 - 0.0833\alpha)$	$(0.0714 + 0.0119\alpha, 0.1000 - 0.0167\alpha)$	$(0.1111 + 0.0318\alpha, 0.2000 - 0.0571\alpha)$
v_3^G	$(0.2000 + 0.1333\alpha, 1.000 - 0.6667\alpha)$	$(0.1429 + 0.0571\alpha, 0.3333 - 0.1333\alpha)$	$(0.1111 + 0.0318\alpha, 0.2000 - 0.0571\alpha)$	$(0.1429 + 0.0571\alpha, 0.3333 - 0.1333\alpha)$
$\mathbf{U_i^G}$	**DMU$_1$**	**DMU$_2$**	**DMU$_3$**	**DMU$_4$**
u_1^G	$(0.2025 + 0.1057\alpha, 0.6447 - 0.3365\alpha)$	$(0.3289 + 0.0663\alpha, 0.4949 - 0.0997\alpha)$	$(0.1576 + 0.1146\alpha, 1.000 - 0.7278\alpha)$	$(0.2737 + 0.1677\alpha, 0.7206 - 0.2792\alpha)$
u_2^G	$(0.5233 + 0.2158\alpha, 0.9548 - 0.2157\alpha)$	$(0.3417 + 0.1388\alpha, 0.6193 - 0.1388\alpha)$	$(0.6427 + 0.1783\alpha, 1.000 - 0.1783\alpha)$	$(0.1681 + 0.2194\alpha, 0.6068 - 0.2194\alpha)$
$\mathbf{U_i^B}$	**DMU$_1$**	**DMU$_2$**	**DMU$_3$**	**DMU$_4$**
u_1^B	$(0.6696 + 0.0162\alpha, 0.7029 - 0.0171\alpha)$	$(0.9339 + 0.0319\alpha, 1.0000 - 0.0342\alpha)$	$(0.7962 + 0.0245\alpha, 0.8438 - 0.0517\alpha)$	$(0.8995 + 0.0293\alpha, 0.9560 - 0.0312\alpha)$
u_2^B	$(0.8499 + 0.0425\alpha, 0.9394 - 0.0470\alpha)$	$(0.9048 + 0.0452\alpha, 1.0000 - 0.0500\alpha)$	$(0.8675 + 0.0433\alpha, 0.9588 - 0.0480\alpha)$	$(0.8857 + 0.0443\alpha, 0.9789 - 0.0489\alpha)$
u_3^B	$(0.9048 + 0.0452\alpha, 1.000 - 0.0500\alpha)$	$(0.1293 + 0.0006\alpha, 0.1429 - 0.0007\alpha)$	$(0.3016 + 00151\alpha, 0.3333 - 0.0166\alpha)$	$(0.1810 + 0.0009\alpha, 0.2000 - 0.0100\alpha)$
u_4^B	$(0.4473 + 0.0991\alpha, 0.7019 - 0.1555\alpha)$	$(0.3238 + 0.0745\alpha, 0.5175 - 0.1192\alpha)$	$(0.1895 + 0.0435\alpha, 0.3023 - 0.0693\alpha)$	$(0.2231 + 0.1417\alpha, 1.000 - 0.6352\alpha)$
u_5^B	$(0.9494 + 0.0246\alpha, 1.000 - 0.0260\alpha)$	$(0.4141 + 0.0004\alpha, 0.4213 - 0.0005\alpha)$	$(0.7143 + 0.0144\alpha, 0.7426 - 0.0144\alpha)$	$(0.4777 + 0.0006\alpha, 0.4902 - 0.0006\alpha)$

By solving Models (1) and (2) based on the first approach for each DMU, respectively, the fuzzy efficiencies are obtained under the α-cut levels as 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1.0, as given in Table 5.22. Models (3) and (4) based on the second approach are solved for each DMU and the fuzzy efficiencies of these models are obtained in Table 5.23. Finally, Models (5) and (6) based on the third approach are also solved for each DMU and the fuzzy efficiencies of these models are presented in Table 5.24.

Table 5.22 The fuzzy efficiencies obtained by solving Models (1) and (2) based on the first approach

DMUs	α	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
1	L	0.8182	0.8641	0.9198	0.9842	1	1	1	1	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1
2	L	0.6263	0.6544	0.6908	0.7448	0.8057	0.8716	0.9443	1	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1
3	L	0.8802	0.9296	0.9812	1	1	1	1	1	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1
4	L	0.6240	0.6499	0.6781	0.7105	0.7445	0.7820	0.8243	0.8690	0.9161	0.9801	1
	U	1	1	1	1	1	1	1	1	1	1	1

Table 5.23 The fuzzy efficiencies obtained by solving Models (3) and (4) based on the second approach

DMUs	α	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
1	L	0.8316	0.8705	0.9117	0.9567	1	1	1	1	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1
2	L	0.8801	0.9135	0.9483	0.9856	1	1	1	1	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1
3	L	0.7558	0.8014	0.8580	0.9213	0.9999	1	1	1	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1
4	L	0.6705	0.7089	0.7491	0.7930	0.8435	0.8991	0.9653	1	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1

Table 5.24 The fuzzy efficiencies obtained by solving Models (5) and (6) based on the third approach

DMUs	α	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
1	L	0.2958	0.3264	0.3611	0.3999	0.4427	0.4899	0.5420	0.59998	0.6726	0.7618	0.9396
	U	1	1	1	1	1	1	1	1	1	1	1
2	L	0.2425	0.2650	0.2977	0.3452	0.4054	0.4792	0.5711	0.7417	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1
3	L	0.8504	0.9896	1	1	1	1	1	1	1	1	1
	U	1	1	1	1	1	1	1	1	1	1	1
4	L	0.1925	0.2202	0.2526	0.2907	0.3360	0.3915	0.4608	0.5474	0.6576	0.8540	1
	U	1	1	1	1	1	1	1	1	1	1	1

The fuzzy efficiency scores of the four production lines at eleven distinctive α-values are listed in Tables 5.22-5.24. As stated in Step 7 in Section 4.4, the ranking method which is denoted by Equation (4.18) is used to compare the fuzzy efficiency scores of DMUs. In this context, the ranking indices of the four fuzzy efficiency scores for each models are calculated using Equation (4.18) and given in the first row of Table 5.25. Based on the ranking indices, the TPM performances of the four production lines are ranked accordingly.

Table 5.25 The ranking results of DMUs according to the models

Models (1) and (2) based on the first approach				
DMUs	**1**	**2**	**3**	**4**
I	0.8994	0.5957	0.9492	0.4629
Ranking	2	3	1	4
Models (3) and (4) based on the second approach				
DMUs	**1**	**2**	**3**	**4**
I	0.8401	0.8986	0.7530	0.6219
Ranking	2	1	3	4
Models (5) and (6) based on the third approach				
DMUs	**1**	**2**	**3**	**4**
I	0.3798	0.4417	0.9808	0.3474
Ranking	3	2	1	4

Table 5.25 reveals that DMU_3 (NHB BOL) has the highest TPM performance value while DMU_4 (NHB EOL) has the lowest TPM performance value according to the ranking results of Models (1) and (2) based on the first approach. However, in Models (3) and (4) based on the second approach, the best TPM performance value is obtained by DMU2 (Rail assembly and HPV) and DMU_4 again has the worst TPM performance value. Furthermore, DMU_1 (Rail machining) has the same ranking order in Models (1-4) based on the first and second approaches. In this table, according to the ranking results of Models (5) and (6) based on the third approach, the DMU_3 is the most efficient production line with respect to TPM performance. DMU_4 has also the lowest TPM performance value.

As a conclusion, it is observed that the production lines DMU_2 and DMU_3 together define an efficient frontier and DMU_1 is the production line with the best performance followed by these production lines according to TPM performance.

5.5 Results and Discussion

In this section, a real manufacturing case study is presented to demonstrate the applicability of the proposed TPM PMS. After defining the proposed TPM PIs in the design phase, COPRAS-G and the proposed FCOPRAS methods are applied for evaluation of the proposed TPM PIs in the evaluation phase. When the proposed FCOPRAS is developed, all calculations are made based on the fuzzy arithmetic operations and fuzzy ranking method. Therefore, no fuzzy value is converted to a crisp value. According to the comparisons based on the ranking orders among the conventional COPRAS methods and the proposed FCOPRAS method for α=0, 0.5 and 0.9, the proposed FCOPRAS method gives similar but not the same results of other COPRAS methods. Thereby, it is preferred over the COPRAS-G method since it is not using the conversion method which cannot guarantee one-to-one correspondence between fuzzy numbers and real numbers.

The proposed FCOPRAS method is also compared to the most popular FMADM methods using the Spearman's rank correlation coefficient in the evaluation phase. In this sense, fuzzy MULTIMOORA-2 has the highest correlation coefficient with the proposed FCOPRAS methods for α=0. Additionally, fuzzy ELECTRE I based on hamming distance and fuzzy MULTIMOORA-1 have the highest correlation coefficient for 0.5 and 0.9. It is concluded that the proposed FCOPRAS method produce statistically similar rankings with the other FMADM methods in the literature. Finally, the validity and the robustness of the proposed FCOPRAS method are tested by using sensitivity analysis according to optimistic and pessimistic changes in the linguistic assessments of attributes.

According to the fuzzy efficiencies of the GFDEA/AR models with coexisting of desirable and undesirable inputs and outputs proposed in the implementation phase, *Model (3) and (4) based on the second approach* give the best fuzzy efficiencies while *Models (5) and (6) based on the third approach* presents the worst fuzzy efficiencies for each DMU at any given α-cut level. However, *Models (1) and (2) based on the first approach* calculates the intermediate fuzzy efficiencies for each

DMU at any given α-cut level among the proposed models. Accordingly, *Models (3) and (4)* provide an optimistic efficiency values while *Model (5) and (6)* give a pessimistic efficiency values. *Models (1) and (2)* find the efficiencies between the optimistic and pessimistic values. Consequently, the proposed models give an opportunity to see the different approaches for the performance evaluation of TPM.

In the review phase, the comparisons are made between the TPM performance values obtained by the proposed models (I indexes as seen in Table 5.25) and the OEE values (the average values of thirty-six weeks) which have been measured by the company with respect to each DMU. Figure 5.10 illustrates these comparisons.

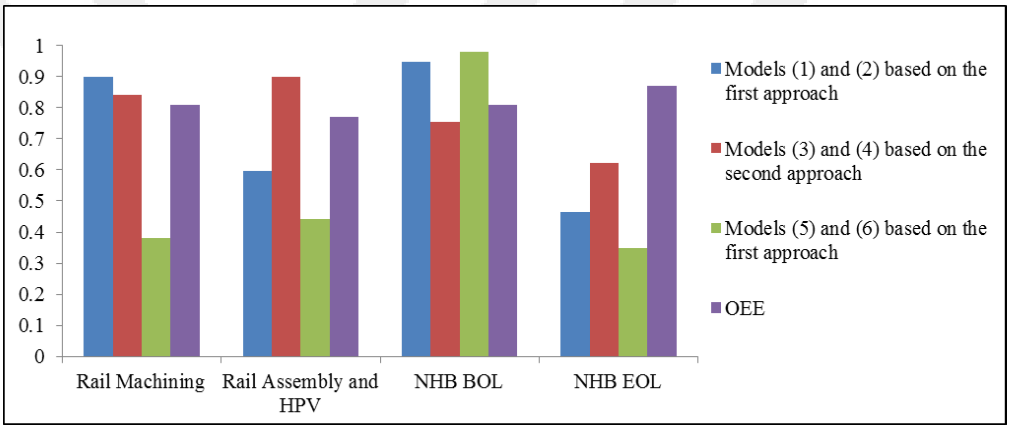

Figure 5.10 The comparisons of TPM performance values with the OEE values with respect to each DMU

As seen in Figure 5.10, the production lines such as “Rail Machining” and “NHB BOL” have the highest OEE values after the production line “NHB EOL” while the production line “Rail Assembly and HPV” has the lowest OEE value. However, “NHB EOL” has the lowest TPM performance value according to Models (1-6). It can be concluded that other indicators (e.g., “operator reliability”, “competence of maintenance personnel”, “level of 5S, etc.) have a greater impact than the operational related indicators (e.g., “reduced speed”, “reduced yield”, “quality defects”, MTTR and MTBF) in this production line. Furthermore, the ranking orders of the production lines namely “Rail Machining”, “NHB BOL” and “Rail Assembly and HPV” according to OEE values are similar to the ranking orders of these lines according to TPM performance values obtained by Models (1-4).

CHAPTER SIX
CONCLUSIONS

6.1 Summary of the Thesis

TPM has been widely implemented as a lean production tool for improving manufacturing performance in many organizations in today's competitive environment. The performance of TPM should be measured by some factors since it can make a great contribution to companies in advancing their manufacturing operations. In most organizations, the performance of TPM is measured by OEE metric which gives information about the only equipment-related performance. However, different factors such as business-related factors, external-related factors and especially human-related factors (e.g., operators who are most familiar with the daily operation of the equipment and maintenance personnel who are most familiar with the technical specifications and long run performance of the equipment) have a great impact on successful implementation of TPM.

According to the literature, although several critical success factors for TPM implementation have been defined in various studies, a few studies have been made related to the performance measurement in TPM implementation. However, these studies have the lack of methodological approach to determine which one of these critical success factors has the most important effect on TPM performance. Furthermore, these studies have not a systematic way to show how these factors are evaluated under some conflicting attributes and how they are used for the measurement of TPM performance. The main goal of this thesis is to fulfill this gap in the literature and develop a new framework in order to measure TPM performance based on novel performance indicators. This framework is called TPM PMS and composed of four phases. After these phases were explained in detail, the proposed TPM PMS was implemented using a real manufacturing case study.

Within this context, in the design phase of the proposed TPM PMS, novel performance indicators having impact on TPM performance have been determined according to the theoretical aspect including detailed literature reviews and the practical aspect including interviews of employees worked at TPM department in the manufacturing company. In this phase, firstly nominal group technique has been used to obtain most important indicators and secondly conjoint analysis has been performed whether these indicators are statistically significant.

In the evaluation phase, since the proposed TPM PIs include qualitative data, these data have been represented by linguistic variables. Thereby, an improved FMADM model (that is the proposed FCOPRAS model) has been employed based upon COPRAS method for the evaluation of these indicators. The proposed FCOPRAS method has been compared with the conventional COPRAS methods such as pessimistic COPRAS, optimistic COPRAS and COPRAS-G and the most popular FMADM methods in the literature namely fuzzy TOPSIS, fuzzy ARAS, fuzzy VIKOR, fuzzy MULTIMOORA and fuzzy ELECTRE I based on hamming distance. Finally, sensitivity analysis has been carried out to determine the robustness of the proposed FCOPRAS method. In this phase, the proposed FCOPRAS and the other FMADM methods have been coded in MATLAB R2016a to provide easiness for the sensitivity analysis calculations and to reduce calculation errors arising from the complexity of the calculation processes of these methods.

In the implementation phase, the proposed TPM PIs have been classified as desirable and undesirable inputs and outputs. Afterwards, these inputs and outputs have been used to measure TPM performance of the pre-determined DMUs. In this sense, the different GFDEA/AR models in the presence of desirable and undesirable inputs and outputs have been improved. Afterwards, these models have been solved by using GAMS 23.5. The results demonstrate the applicability and superiority of the proposed models in performance measurement for TPM.

Finally, in the review phase, the obtained TPM performance values for each DMU have been compared to the OEE values which were evaluated previously in the company. Through the results provided by the proposed TPM PMS, the company can make some adjustments for its production lines (especially ineffective production line) and TPM plans in order to obtain more attractive outcomes and increase competitiveness.

6.2 Contributions of the Thesis

Within the scope of this thesis, the contributions are discussed in detail with respect to each phase of the proposed TPM PMS as follows.

In the design phase, novel performance indicators for TPM have been designed. These indicators provide a different perspective exclusive of OEE, which is commonly used and well-accepted metric, for successful TPM implementation in many manufacturing industries. In addition, the most important ones of these indicators were determined using conjoint analysis in this phase. Thus, it is concluded that the proposed models based on these indicators provide statistically significant and meaningful results.

In the evaluation phase, the question “Do novel performance indicators in TPM have the same relative importance?” is investigated. According to this, COPRAS-G and proposed FCOPRAS methods have been applied to assess of these indicators. The proposed FCOPRAS method possesses some advantages as follows.

- It uses uncertain information about the alternatives’ criterion values stated in terms of linguistic variables.
- It is more appropriate in real life applications.
- It uses group decision making including fuzzy group hierarchy.
- All fuzzy judgments are not converted to real numbers and they are represented by fuzzy numbers. Thus, all calculations are performed in accordance with the fuzzy arithmetic and fuzzy ranking method. Thus, it can be said that in this method the information loss is not included;
- Its calculations are coded and performed in a parametric and fuzzy way

using ***MATLAB 2016a***. Thus, if the number and linguistic assessments of the attributes and the alternatives and also the linguistic terms are changed, the program can be easily adapted according to these changes. For that reason, the proposed FCOPRAS method can be employed to assess different application problems.

In the implementation phase, TPM performance has been firstly measured with novel performance indicators exclusive of OEE. In this context, the GFDEA/AR models have been firstly integrated with the proposed FCOPRAS method. Additionally, these models have been extended in the presence of desirable and undesirable inputs and outputs. Thus, the proposed models make a significant contribution into the TPM literature.

Managers responsible for the TPM program implementation in the companies are invited to fill out a form with their judgments, regarding to their expertise and experiences in a successful TPM implementation. In this sense, in the review phase by monitoring the performance of TPM, it is validated by the managers (e.g., TPM, Production and Quality) in order to control TPM plans, compare the TPM performances of production lines and so prioritize the most important preventive and predictive decisions and actions according to production lines, especially the ineffective ones in TPM program implementation.

As a conclusion, the proposed TPM PMS has the following contributions and benefits.

- It standardizes the performance of TPM.
- It allows to measure TPM performance with different indicators especially soft indicators. Thus, it uses both quantitative and qualitative data.
- It supports a true picture of the current state of the production processes in terms of TPM performance.
- It offers a powerful control tool and reliable evidence in order to make effective decisions and actions.

- It provides a holistic and systematic approach, saving time, money, effort and making the TPM implementation process more effective.
- It provides important information for the annual meeting in the company.
- It is also applicable to all industries.

6.3 Recommendations for Future Research

During this thesis possible research directions have emerged as a result of the detailed literature survey.

In future researches, firstly the proposed FCOPRAS method might be extended by using other other extensions of fuzzy sets like type-2, intuitionistic, hesitant fuzzy multisets, nonstationary, and neutrosophic sets to evaluate novel performance indicators in TPM. Additionally, the proposed FCOPRAS method might be used to assess different application problems.

The proposed GFDEA/AR models might be extended by using other extensions of fuzzy sets which have not been used to model FDEA, different undesirability approaches and models. Besides, different undesirability approaches can be adapted to the proposed models in the proposed GFDEA/AR models.

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The proposed TPM PMS can be performed using with different real case studies for various industries.

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APPENDICES

APPENDIX A - EXAMPLES OF DEVELOPED MATLAB 2016a AND GAMS 23.5 CODES

Appendix A1: An example of developed MATLAB 2016a Codes for the evaluation phase of the porposed TPM PMS

```
%initialize linguistic terms for Attributes
clc;clear;
import java.util.*
keySet =   {'VLI', 'LI', 'SLI', 'MI','SHI','HI','VHI'};
valueSet = [[0,0,10];
            [5,15,25];
            [20,32.5,45];
            [40,50,60];
            [55,67.5,80];
            [75,85,95];
            [90,100,100]];
keySet2 = {'VP','P','SP','F','SG','G','VG'};
valueSet2 = [0.0000 0.0000  0.1000
             0.0500 0.1500  0.2500
             0.2000 0.3250  0.4500
             0.4000 0.5000  0.6000
             0.5500 0.6750  0.8000
             0.7500  0.8500  0.9500
             0.9000  1.0000  1.0000];

scale_constant = 100;
lm = HashMap;
lm2 = HashMap;
for y=1:size(keySet,2)
    lm.put(keySet{y},valueSet2(y,:));
    lm2.put(keySet2{y},valueSet2(y,:));
end
DD={'VHI' 'VHI' 'VHI'
    'HI' 'VHI' 'HI'
    'SHI' 'HI' 'HI'
    'MI' 'HI' 'HI'
    'SLI' 'VHI' 'HI'
    'SHI' 'HI' 'SHI'
    };
DD2 ={ 'VG' 'VG' 'VG' 'VG' 'VG' 'VG' 'VG' 'VG' 'VG'  'VG' 'VG' 'VG'  'G' 'VG' 'VG'   'SP' 'SP'G'
    'VG' 'VG' 'VG'  'VG' 'VG' 'VG'  'VG' 'VG' 'VG'  'VG' 'VG' 'VG'  'G' 'VG' 'VG'   'SP' 'SP''G'
    'VG' 'VG' 'VG'  'VG' 'VG' 'VG'  'VG' 'VG' 'VG'  'VG' 'VG' 'VG'  'G' 'VG' 'VG'   'G' 'VP''SG'
    'SG' 'G' 'SP'   'SG' 'VG' 'G'   'G' 'G' 'G'     'G' 'G' 'VG'    'SG' 'G' 'VG'   'G' 'P' 'G'
    'SG' 'G' 'SG'   'G' 'G' 'G'     'G' 'SG' 'G'    'G' 'SG' 'G'    'SG' 'G' 'G'    'G' 'SP''SG'
    'G' 'G' 'SG'    'G' 'G' 'G'     'SG' 'SG' 'G'   'G' 'SG' 'G'    'SG' 'G' 'G'    'G' 'SP''SG'
    'SG' 'SG' 'SG'  'G' 'G' 'G'     'VG' 'SG' 'VG'  'VG' 'SG' 'G'   'G' 'G' 'G'     'G' 'SP''SG'
    'SG' 'SG' 'F'   'VG' 'G' 'SG'   'G' 'F' 'SG'    'G' 'SG' 'SP'   'VG' 'SG' 'SP'  'VG' 'SP''F'
    'SG' 'SG' 'F'   'G' 'F' 'SP'    'G' 'SP' 'SP'   'G' 'SP' 'P'    'SG' 'P' 'P'    'SG' 'SG'SP'
    'SG' 'F' 'F'    'G' 'F' 'SP'    'G' 'SP' 'P'    'SG' 'F' 'VP'   'G' 'SG' 'P'    'G' 'G' 'VP'
    'SG' 'F' 'SP'   'SG' 'P' 'P'    'G' 'VP' 'SP'   'SG' 'P' 'SP'   'SG' 'P' 'P'    'G' 'VG''VP'
    'SG' 'F' 'F'    'G' 'SP' 'P'    'SG' 'SP' 'SP'  'SG' 'SP' 'SP'  'SG' 'P' 'SP'   'P' 'G' 'SP'
    'F' 'F' 'F'     'G' 'SG' 'SP'   'G' 'SP' 'F'    'SG' 'SP' 'SP'  'SG' 'SG' 'P'   'P' 'F' 'P'
    'SG' 'SP' 'SP'  'SG' 'SG' 'P'   'SG' 'SP' 'SP'  'SG' 'SP' 'G'   'G' 'SG' 'SP'   'SP' 'F' 'F'
    'F' 'P' 'SG'    'SG' 'SG' 'G'   'SG' 'SP' 'VG'  'G' 'SP' 'G'    'SG' 'SG' 'SG'  'VP' 'SP'SG'
    'SG' 'P' 'SP'   'SG' 'SG' 'G'   'SG' 'SP' 'VG'  'SG' 'SP' 'SP'  'SG' 'SG' 'SG'  'VP''SP''SG'
    'SP' 'VP' 'F'   'G' 'SP' 'SG'   'G' 'VP' 'SP'   'SG' 'P' 'SP'   'SG' 'SP' 'F'   'P' 'G' 'SP'
    };
DM_Maximizing_Criterias = 5;
DM_Minimizing_Criterias = 1;
nfw = [0.3249, 0.5455, 0.9746;      %DM1 ->TPM Manager
      0.1772, 0.2727, 0.3898;      %DM2 -> Production Manager
      0.1392, 0.1818, 0.1949];     %DM3 -> Quality Manager

AFW = FIND_W(nfw,lm,DD);
NAFW = FIND_NAFW(AFW);
AFDM = FIND_AFDM(nfw,lm2,DD2);
NAFDM = FIND_NAFDM(DM_Maximizing_Criterias,DM_Minimizing_Criterias,AFDM);
WNAFDM = FIND_WNAFDM(NAFW,NAFDM);
   [G,Boolean_matrix_E,Boolean_matrix_F,D_levl,C_levl,concordance,discordance]=FIND_ELECTRE(WNAF
DM,NAFW)
```

Appendix A1: An example of developed MATLAB 2016a Codes for the evaluation phase of the porposed TPM PMS (Cont.)

```
    [WNAFDM_MM,BNP_sorted_Y,Y_I,D_max_sorted,D_max_I,BNP_sorted_U,U_I]=FIND_MULTIMOORA(NAFW,AFDM)
;
    P_values = FIND_P(WNAFDM);
    R_values = FIND_R(WNAFDM);
    Q = FIND_Q(P_values,R_values);

    [N,BASIR_RANKING] = BASIRZADEH(Q);

    [CC,FNIS,FPIS,DN,DP,TOPSIS_RANKING] = FIND_TOPSIS(WNAFDM);

    [CRISP_Q_VALUES,VIKOR_RANKING]=FIND_VIKOR(NAFW,WNAFDM);

    [K_SORTED,ARAS_RANKING,S_Values,S_Crisp]=FIND_ARAS(AFDM,NAFW,DM_Minimizing_Criterias,DM_Maxim
izing_Criterias);


    clearvars -except AFW NAFW AFDM NAFDM WNAFDM R_values P_values Q  ...
                N N_CV_p N_CV_u CC FNIS FPIS DN DP CRISP_Q_VALUES ...
                VIKOR_RANKING BASIR_RANKING CV_u_RANKING CV_p_RANKING ...
                K_SORTED ARAS_RANKING S_Values S_Crisp ...
                WNAFDM_MM BNP_sorted_Y Y_I D_max_sorted D_max_I ...
                BNP_sorted_U U_I G Boolean_matrix_E ...
                Boolean_matrix_F D_levl C_levl concordance discordance

    javaaddpath('jxl.jar');
    javaaddpath('MXL.jar');
    import mymxl.*;
    import jxl.*;

    filename=['results_',datestr(now, 'dd_HH_MM_SS'),'.xls'];
    xlwrite(filename,AFW,'AFW')
    xlwrite(filename,NAFW,'NAFW')
    xlwrite(filename,AFDM,'AFDM')
    xlwrite(filename,NAFDM,'NAFDM')
    xlwrite(filename,WNAFDM,'WNAFDM')
    xlwrite(filename,P_values,'P_values')
    xlwrite(filename,R_values,'R_values')
    xlwrite(filename,Q,'Q')
    xlwrite(filename,N,'N')
    xlwrite(filename,BASIR_RANKING,'RANKING_BASIRZADEH')
    xlwrite(filename,N_CV_u,'N_CV_u')
    xlwrite(filename,CV_u_RANKING,'RANKING_CVU')
    xlwrite(filename,N_CV_p,'N_CV_p')
    xlwrite(filename,CV_p_RANKING,'RANKING_CVP')
    xlwrite(filename,CC,'CC')
    xlwrite(filename,FNIS,'FNIS')
    xlwrite(filename,FPIS,'FPIS')
    xlwrite(filename,DN,'DN')
    xlwrite(filename,DP,'DP')
    xlwrite(filename,CRISP_Q_VALUES,'CRISP_Q_VALUES_VIKOR')
    xlwrite(filename,VIKOR_RANKING,'VIKOR_RANKING')
    xlwrite(filename,K_SORTED,'ARAS_K_SORTED');
    xlwrite(filename,ARAS_RANKING,'ARAS_RANKING')
    xlwrite(filename,S_Values,'S_Values')
    xlwrite(filename,S_Crisp,'S_Crisp')
    xlwrite(filename,WNAFDM_MM,'WNAFDM_MM')
    xlwrite(filename,BNP_sorted_Y,'BNP_sorted_Y')
    xlwrite(filename,Y_I,'Y_I')
    xlwrite(filename,D_max_sorted,'D_max_sorted')
    xlwrite(filename,D_max_I,'D_max_I')
    xlwrite(filename,BNP_sorted_U,'BNP_sorted_U')
    xlwrite(filename,U_I,'U_I')
    xlwrite(filename,G,'G')
    xlwrite(filename,double(Boolean_matrix_E),'Boolean_matrix_E')
    xlwrite(filename,double(Boolean_matrix_F),'Boolean_matrix_F')
    xlwrite(filename,D_levl,'D_levl')
    xlwrite(filename,C_levl,'C_levl')
    xlwrite(filename,concordance,'concordance')
    xlwrite(filename,discordance,'discordance')

    clc
```

Appendix A2: An example of developed GAMS 23.5 Codes for the implementation phase of the porposed TPM PMS

The Codes for the lower bound of fuzzy efficiency for DMU$_1$ at α=0 (Model-1)

```
sets
i inputs/1*10/
j outputs/1*7/
s DMUs/1*4/
k coasrinpleft1/1*9/
l coasrinpleft2/1*8/
n coasrinpleft3/1*7/
o coasrinpleft4/1*6/
p coasrinpleft5/1*5/
r coasrinpleft6/1*4/
y coasrinpleft7/1*3/
a coasrinpleft8/1*2/
b coasrinpleft9/1*1/
ain coasrinpright1/1*9/
bin coasrinpright2/1*8/
c coasrinpright3/1*7/
d coasrinpright4/1*6/
e coasrinpright5/1*5/
f coasrinpright6/1*4/
g coasrinpright7/1*3/
kin coasrinpright8/1*2/
lin coasrinpright9/1*1/
kout coasroutleft1/1*6/
lout coasroutleft2/1*5/
nout coasroutleft3/1*4/
out coasroutleft4/1*3/
pout coasroutleft5/1*2/
rout coasroutleft6/1*1/
aout coasroutright1/1*6/
bout coasroutright2/1*5/
cout coasroutright3/1*4/
dout coasroutright4/1*3/
eout coasroutright5/1*2/
fout coasroutright6/1*1/
alias (i,ip)
alias (j,jp);

table xl(s,i) left amaount of input i used by DMU s
   1      2      3      4      5      6      7      8      9      10
1 0.3333 0.9195 0.9459 0.5556 0.4762 0.8000 0.7133 0.6331 0.2000 0.2000

2 0.1111 0.9540 0.8378 0.1111 0.6190 0.4000 0.7400 0.5095 0.1250 0.1429

3 0.3333 0.7471 0.5811 0.3333 0.5238 0.2000 0.7778 0.4477 0.0714 0.1111

4 0.5556 0.8736 0.5135 0.4444 0.5714 0.3000 0.7400 0.6407 0.1111 0.1429;

table xr(s,i) right amaount of input i used by DMU s
   1      2      3      4      5      6      7      8      9      10
1 0.7778 0.9655 1.0000 1.0000 0.8571 1.0000 0.9356 0.9817 1.0000 1.0000

2 0.5556 1.0000 0.8919 0.5556 1.0000 0.6000 0.9622 0.7133 0.2500 0.3333

3 0.7778 0.7931 0.6351 0.7778 0.9048 0.4000 1.0000 0.5978 0.1000 0.2000

4 1.0000 0.9195 0.5676 1.0000 0.9524 0.5000 0.9622 1.0000 0.2000 0.3333;

table yl(s,j) left amaount of output j produced by DMU s
   1      2      3      4      5      6      7
1 0.2025 0.5233 0.4473 0.9494 0.6696 0.8499 0.9048

2 0.3289 0.3417 0.3238 0.4121 0.9339 0.9048 0.1293

3 0.1576 0.6427 0.1895 0.7143 0.7962 0.8675 0.3016

4 0.2737 0.1681 0.2231 0.4777 0.8955 0.8857 0.1810;

table yr(s,j) right amaount of output j produced by DMU s
   1      2      3      4      5      6      7
1 0.6447 0.9548 0.7019 1.0000 0.7029 0.9394 1.0000

2 0.4949 0.6193 0.5175 0.4213 1.0000 1.0000 0.1429

3 1.0000 1.0000 0.3023 0.7426 0.8438 0.9588 0.3333

4 0.7206 0.6068 1.0000 0.4902 0.9560 0.9789 0.2000;
```

Appendix A2: An example of developed GAMS 23.5 Codes for the implementation phase of the porposed TPM PMS (Cont.)

The Codes for the lower bound of fuzzy efficiency for DMU_1 at α=0 (Model-1)

```
parameter coasrinpleft1(i) left coefficent of inputs
/
1 0.1754
2 0.1776
3 0.1952
4 0.2001
5 0.2156
6 0.1891
7 0.1745
8 0.1822
9 0.2068
/;
parameter coasrinpleft2(i) left coefficent of inputs
/
1 0.1231
2 0.1353
3 0.1386
4 0.1494
5 0.1310
6 0.1209
7 0.1262
8 0.1433
/;
...
parameter coasrinpright1(i) right coefficent of inputs
/
1 9.4918
2 9.2228
3 12.8060
4 10.8317
5 9.1780
6 9.6734
7 6.3813
8 7.0626
9 11.3986
/;
parameter coasrinpright2(i) right coefficent of inputs
/
1 7.9925
2 11.0977
3 9.3868
4 7.9536
5 8.3830
6 5.5301
7 6.1205
8 9.8780
/;
...
scalar t "alpha level" /0.1/;
scalar m "epsilon"/0.000001/;
positive variables u(j),v(i);
variables
u(j)
v(i)
z
uo
;
equations
objfunct
cons1
cons2
cons3
cons4
cons5
cons6
cons7
cons8
cons9
cons10
cons11
cons12
cons13
cons14
...
```

Appendix A2: An example of developed GAMS 23.5 Codes for the implementation phase of the porposed TPM PMS (Cont.)

The Codes for the lower bound of fuzzy efficiency for DMU$_1$ at α=0 (Model-1)

```
objfunct..z=e=sum((s,j)$(ord (s)=1),u(j)*(yl(s,j)+bl(s,j)*t))-uo;
cons1(s)$(ord (s)=1)..sum((i),v(i)*(xr(s,i)-ar(s,i)*t))-uo=e=1;
cons2(s)$(ord    (s)=1)..sum((j),u(j)*(yl(s,j)+bl(s,j)*t))-sum((i),v(i)*(xr(s,i)-ar(s,i)*t))-
uo=l=0;
cons3(s)$(ord    (s)=2)..sum((j),u(j)*(yr(s,j)-br(s,j)*t))-sum((i),v(i)*(xl(s,i)+al(s,i)*t))-
uo=l=0;
cons4(s)$(ord    (s)=3)..sum((j),u(j)*(yr(s,j)-br(s,j)*t))-sum((i),v(i)*(xl(s,i)+al(s,i)*t))-
uo=l=0;
cons5(s)$(ord    (s)=4)..sum((j),u(j)*(yr(s,j)-br(s,j)*t))-sum((i),v(i)*(xl(s,i)+al(s,i)*t))-
uo=l=0;
cons6(i,ip)$(ord(i)>=2 and ord(i)-ord(ip)eq 1)..v(i)*coasrinpleft1(ip)-v('1')=l=0;
cons7(i,ip)$(ord(i)>=3 and ord(i)-ord(ip)eq 2)..v(i)*coasrinpleft2(ip)-v('2')=l=0;
cons8(i,ip)$(ord(i)>=4 and ord(i)-ord(ip)eq 3)..v(i)*coasrinpleft3(ip)-v('3')=l=0;
cons9(i,ip)$(ord(i)>=5 and ord(i)-ord(ip)eq 4)..v(i)*coasrinpleft4(ip)-v('4')=l=0;
cons10(i,ip)$(ord(i)>=6 and ord(i)-ord(ip)eq 5)..v(i)*coasrinpleft5(ip)-v('5')=l=0;
cons11(i,ip)$(ord(i)>=7 and ord(i)-ord(ip)eq 6)..v(i)*coasrinpleft6(ip)-v('6')=l=0;
cons12(i,ip)$(ord(i)>=8 and ord(i)-ord(ip)eq 7)..v(i)*coasrinpleft7(ip)-v('7')=l=0;
cons13(i,ip)$(ord(i)>=9 and ord(i)-ord(ip)eq 8)..v(i)*coasrinpleft8(ip)-v('8')=l=0;
cons14(i,ip)$(ord(i)=10 and ord(i)-ord(ip)eq 9)..v(i)*coasrinpleft9(ip)-v('9')=l=0;
cons15(i,ip)$(ord(i)>=2 and ord(i)-ord(ip)eq 1)..v(i)*coasrinpright1(ip)-v('1')=g=0;
cons16(i,ip)$(ord(i)>=3 and ord(i)-ord(ip)eq 2)..v(i)*coasrinpright2(ip)-v('2')=g=0;
cons17(i,ip)$(ord(i)>=4 and ord(i)-ord(ip)eq 3)..v(i)*coasrinpright3(ip)-v('3')=g=0;
cons18(i,ip)$(ord(i)>=5 and ord(i)-ord(ip)eq 4)..v(i)*coasrinpright4(ip)-v('4')=g=0;
cons19(i,ip)$(ord(i)>=6 and ord(i)-ord(ip)eq 5)..v(i)*coasrinpright5(ip)-v('5')=g=0;
cons20(i,ip)$(ord(i)>=7 and ord(i)-ord(ip)eq 6)..v(i)*coasrinpright6(ip)-v('6')=g=0;
cons21(i,ip)$(ord(i)>=8 and ord(i)-ord(ip)eq 7)..v(i)*coasrinpright7(ip)-v('7')=g=0;
cons22(i,ip)$(ord(i)>=9 and ord(i)-ord(ip)eq 8)..v(i)*coasrinpright8(ip)-v('8')=g=0;
cons23(i,ip)$(ord(i)=10 and ord(i)-ord(ip)eq 9)..v(i)*coasrinpright9(ip)-v('9')=g=0;
cons24(j,jp)$(ord(j)>=2 and ord(j)-ord(jp)eq 1)..u(j)*coasroutleft1(jp)-u('1')=l=0;
cons25(j,jp)$(ord(j)>=3 and ord(j)-ord(jp)eq 2)..u(j)*coasroutleft2(jp)-u('2')=l=0;
cons26(j,jp)$(ord(j)>=4 and ord(j)-ord(jp)eq 3)..u(j)*coasroutleft3(jp)-u('3')=l=0;
cons27(j,jp)$(ord(j)>=5 and ord(j)-ord(jp)eq 4)..u(j)*coasroutleft4(jp)-u('4')=l=0;
cons28(j,jp)$(ord(j)>=6 and ord(j)-ord(jp)eq 5)..u(j)*coasroutleft5(jp)-u('5')=l=0;
cons29(j,jp)$(ord(j)=7 and ord(j)-ord(jp)eq 6)..u(j)*coasroutleft6(jp)-u('6')=l=0;
cons30(j,jp)$(ord(j)>=2 and ord(j)-ord(jp)eq 1)..u(j)*coasroutright1(jp)-u('1')=g=0;
cons31(j,jp)$(ord(j)>=3 and ord(j)-ord(jp)eq 2)..u(j)*coasroutright2(jp)-u('2')=g=0;
cons32(j,jp)$(ord(j)>=4 and ord(j)-ord(jp)eq 3)..u(j)*coasroutright3(jp)-u('3')=g=0;
cons33(j,jp)$(ord(j)>=5 and ord(j)-ord(jp)eq 4)..u(j)*coasroutright4(jp)-u('4')=g=0;
cons34(j,jp)$(ord(j)>=6 and ord(j)-ord(jp)eq 5)..u(j)*coasroutright5(jp)-u('5')=g=0;
cons35(j,jp)$(ord(j)=7 and ord(j)-ord(jp)eq 6)..u(j)*coasroutright6(jp)-u('6')=g=0;
cons36(j)..u(j)=g=m;
cons37(i)..v(i)=g=m;
cons38..uo=g=0;
cons39..uo=l=1;


model FDEAARDMU1L/all/;
solve FDEAARDMU1L using mip maximizing z;
Option Limrow=100000;
Option Limcol=100000;
FDEAARDMU1L.optcr=0;
FDEAARDMU1L.reslim=3600;
FDEAARDMU1L.iterlim=1e9;
display z.l,u.l,v.l,uo.l;
```