# FEATURE WEIGHTING ALGORITHM
## FOR
## DECISION SUPPORT SYSTEM OF INNOVATION POLICIES

by

Caner Hamarat

Submitted to the Graduate School of Engineering and Natural Sciences

in partial fulfillment of

the requirements for the degree of Master of Science

in

SABANCI UNIVERSITY

Spring 2009

# FEATURE WEIGHTING ALGORITHM

# FOR

# DECISION SUPPORT SYSTEM OF INNOVATION POLICIES

APPROVED BY:

Assist. Prof. Dr. Kemal Kılıç                      ………………………….

(Thesis Supervisor)

Assist. Prof. Dr. Gürdal Ertek                      ………………………….

Assist. Prof. Dr. Tonguç Ünlüyurt              ………………………….

Assoc. Prof. Dr. Erhan Budak                    ………………………….

Assoc. Prof. Dr. Uğur Sezerman                ………………………….

DATE OF APPROVAL: **11.08.2009**

# FEATURE WEIGHTING ALGORITHM
## FOR
# DECISION SUPPORT SYSTEM OF INNOVATION POLICIES


Caner HAMARAT


Industrial Engineering, M.Sc. Thesis, 2009


Thesis Supervisor: Assist. Prof. Dr. Kemal KILIÇ

**Keywords**: Feature Subset Selection, Feature Weighting, Innovation, Decision Support Systems, Simulated Annealing, Genetic Algorithm.

**Abstract**


The main aim of this thesis is to develop a Decision Support System (DSS) framework for innovation management. Determinants of innovation are the features that determine the innovation performance. For this reason, feature subset selection problem becomes an important issue. In order to construct the core of the DSS, we proposed two algorithms, which are Simulated Annealing and Genetic Algorithm.

Determination of relevant features and prediction accuracy are the main objectives. Our proposed algorithms have been checked on two different data sets, Iris and Concrete Compressive Strength. After validation, algorithms have been implemented on innovation performance data. Feature weights that are obtained and prediction accuracies are presented for comparing and interpreting our algorithms.

# İNOVASYON POLİTİKALARI KARAR DESTEK SİSTEMİ İÇİN ÖZNİTELİK AĞIRLIKLANDIRILMASI

Caner HAMARAT

## Özet

Bu tezin temel amacı inovasyon yönetimi için Karar Destek Sistemi çerçevesi geliştirmektir. İnovasyon belirleyicileri inovasyon performansını belirleyen özniteliklerdir. Bu nedenle, öznitelik altkümesi seçimi önemli bir konu olmaktadır. Karar Destek Sistemi'nin çekirdeğini oluşturmak için Benzetimsel Tavlama ve Genetik Algoritması olmak üzere iki algoritma önerilmiştir.

Temel amaçlar ilgili özniteliklerin belirlenmesini sağlamak ve tahmin doğruluğunu arttırmaktır. Önerilen algoritmalarımız İris ve Concrete Compressive Strength referans dataları üzerinde kontrol edilmiştir. Bundan sonra, önerilen algoritmalar inovasyon datasına uygulanmıştır. Önerilen algoritmaların karşılaştırılması ve yorumlanması için elde edilen öznitelik ağırlıkları ve tahmin doğruluk seviyeleri sunulmuştur.

**Acknowledgements**

*To my Family,*

**Table of Contents**

**List of figures**

**List of Tables**

# CHAPTER 1

## 1. INTRODUCTION

### 1.1. What is Innovation?

Innovation has always been an important phenomenon, especially in recent years. Effects of globalization have been experienced more intensively, causing a more competitive market for firms. Firms are relentlessly in search for various strategies that will to improve their competitiveness. Due to the globalization, geographical boundaries have been less important and production costs have decreased considerably and virtually there is a company somewhere around the world that can beat your prices. Therefore, price competition seems not to be a sufficient strategy by itself for ensuring the firms' competitiveness. Innovativeness is being considered to be among the strategies that can lead to long term performance. Consequently, firms have been obliged to consider innovation policies in order to create new markets by making innovations.

Oxford Handbook of Innovation defines innovation as, putting an idea for a *new* product or process *into practice* (Fagerberg et al, 2004). Beside this general definition, there are various other definitions, which are fundamentally similar with subtle differences, in the literature.

Schumpeter is among the pioneers in the field of innovation and proposes the definition of innovation as one or more of the following events (Sundbo, 1998):

- Introduction of a new product or a new product quality.

- Introduction of a new production method. This need not be a new scientific invention. It might consist of a new way of treating a product commercially.

- The opening up of a new market.

- The opening up of a new source for raw materials or semimanufactures regardless of whether the source has existed before.

- The creation of a new organizational structure in industry, for example by creating or breaking down a monopoly situation.

His definition of innovation has influenced many researchers such as Luecke and Katz who define innovation in their book as follows;

*Innovation is the embodiment, combination, or synthesis of knowledge in original, relevant, valued new products, processes, or services* (Luecke, 2003)**.**

Another milestone definition of innovation has been provided by the latest edition of the Oslo Manual. It is defined as the implementation of a new or significantly improved *product* (good or service), or *process*, a new *marketing* method, or a new *organizational* method in business practices, workplace organization or external relations (Oslo Manual, 2005).

Substantial research in order to determine the factors that influence the innovativeness of the firms exists in literature. These factors are referred to as the *determinants of innovation*, which will be explained in further detail in the following chapter. Although each determinant is shown to have an influence on innovation performance of the firm level, there is no research that comprehensively handles these determinants and established their relative significance with respect to each other. Such an analysis is essential in order to develop a decision support system that can develop innovation management policies for the upper management.

## 1.2. Motivation of the Thesis

The thesis is part of a TUBITAK supported research project that aims to develop decision support system for innovation management. Our focus is particularly the *development of the DSS framework* and proposing alternative solutions to the *feature weighting problem* which will be utilized at the core of the DSS. The *feature weighting problem* is closely related to the feature subset selection problem where there is an extensive research available and continuous to grow.

Generally speaking, the *feature subset selection* is to choose the feature subsets that will provide the best classification accuracy amongst the features that are thought necessary for clarification of interrelationships throughout data, namely unraveling the hidden relationships. Consider a data set composing of ten features and according to the values attained for each feature, each sample has a corresponding score. The main goal of feature subset selection is to specify which feature has an impact on the sample score. In other words, which ones among the feature subset should be utilized in order to achieve the most accurate prediction can be made, regarding to a new sample score.

Instead of using all of the features, reducing the feature subset size by selecting only a certain proportion would help to reduce the learning costs. Note that, this procedure will not only speed up the whole process, but also increase the model accuracy by preventing information pollution that is caused by too much data, *i.e., uncertainty due to the abundance of information*. In brief, by an appropriate choice of necessary feature subset selection, there can be a significant increase of efficiency in speed and accuracy of data mining.

The *feature subset selection* problem plays a crucial role in various applications where there are data sets that are composed of too many variables. Some examples of these applications, can be listed as; Customer Relationship Management (Yong, 2006), the advisory systems used in the Internet websites (Schwab, 2000), image analysis (Law, 2004) to Gene Expression Analysis (Guyon et al, 2002).

Note that in the *feature subset selection problem* the features are classified as relevant or not, that is to say a dichotomous relation is assumed. However, *degree of relevance* is a better representation of the reality rather than the 0-1 representation of the feature subset selection problem. In this thesis we will adopt a feature weighting approach and propose two algorithms that are based on well-known metaheuristics, namely, the Simulated Annealing and the Genetic Algorithms. The developed algorithms are *generic* and can be applied to any other context that requires feature weighting.

## 1.3. The Major Contributions of the Thesis

- A Decision Support Systems framework for innovation management.

- Simulated Annealing based feature weighting algorithm.

- Genetic Algorithms based feature weighting algorithm.

- Determination of significance levels of innovation determinants.

In the following section we will discuss the relevant literature on innovation determinants, feature subset selection. Next we will present the proposed algorithms, Simulated Annealing and Genetic Algorithm. In chapter 4 we will introduce the results of the algorithms for benchmark data, Iris and Concrete Compressive Strength data. Chapter 5 will be where we will discuss the results. The thesis will be finalized with our concluding remarks and presentation of further research problems.

# C H A P T E R   2

## 2. LITERATURE REVIEW

In this chapter we will provide the relevant literature regarding to the issues discussed in this thesis. We will first present the available research on determinants of innovations. Next we will briefly discuss decision supports systems and present some examples from the literature regarding to the decision support systems that are developed particularly for upper management. We will conclude the chapter with a survey on feature subset selection. Note that the relevant literature on simulated annealing and genetic algorithms will be presented in Chapter 3 where we will introduce the proposed algorithms.

### 2.1. INNOVATION DETERMINANTS

In order to develop a DSS that can be utilized to generate innovation policies, first step is the determination of the features that affect the innovation performance, which are referred to in the literature as the *innovation determinants*. According to the literature - innovation performance of firms is influenced by various factors (*determinants of innovation*) which can be classified as; *general firm characteristics* such as age, size of firm, ownership status, *intellectual capital* that consists of human, social and organizational capital, *organizational culture* that includes centralization, formalization, communication, reward system, etc.; *collaborations*, *innovation outlay*, *business strategies* such as the manufacturing, marketing and technology strategies, and *sectoral conditions* such as market dynamism, public incentives, internal and external barriers to innovations, and tax rebates. We will present the literature regarding to each one of these factors in detail next.

### 2.1.1. General Firm Characteristics

In the literature, four of the general firm characteristics are shown to be influential on firm's innovativeness, namely, *firm size, firm age, ownership status* and *foreign capital*. In the literature there is an ongoing debate on the influence of firm age on innovativeness. Note that it is quite possible that as a firm gets older, the gathered knowledge and the resources that can be used for innovations improve the firm's chance to be innovative, on the other hand the very same years also results in increase in bureaucracy and resistance against new ideas. Similarly, there is evidence in the literature which supports that innovativeness and firm age is negatively related with each other (Balasubramanian, 2008), or positively related with each other (Sorensen, 2000). Furthermore, there is also empirical evidence that there is not significant relation with the age of the firma and its innovativeness (Roger, 2004; Gunday et al, 2008).

Ownership status is shown to be another important determinant of innovation since it influences the R&D activities and consequently has an effect on innovation performance. Bishop et al (1999) have claimed that foreign capital has a negative impact on innovative success. Similarly Rogers (2004) also demonstrates that the foreign ownership results in lower innovations. On the contrary, Love and Ashcroft have rejected this claim by proposing that firm size, foreign capital and having R&D department are all positively related with innovativeness (Love, 1999).

Avermaete et al (2003) have tried to determine the impact level of firm size, age and regional economic performance on innovative performance. Their research indicates that young firms consider the impact on firm's turnover more while introducing innovations and bigger firms prefer to introduce new products to the market. Gunday et al (2008) provide empirical support that the firm size is positively correlated with innovativeness. According to Bhattacharya and Bloch (2004), firm size is significantly correlated with innovation particularly for low technology firms. However, they claim that for high technology firms, innovation performance is also increasing with firm size but with a decreasing rate.

### 2.1.2. Firm Structure

Firm structure can be analyzed under two main topics, namely, *organization culture* and *intellectual capital*. Gunday et al (2008) have proposed the sub-elements of organization culture as communication, formalization, centralization, management support, work discretion, time availability and reward system. Management support and managing staff's enthusiasm about innovation have favorable effects on firm's innovation performance (Montalvo, 2004). Time availability is also an important factor for innovativeness (Fry, 1987). Since time can be considered as crucial resource in a firm, time availability of employees during the working hours for new ideas, projects and research can be seen as an important innovation determinant. Granting employees extra time for their duties and being flexible about deadlines provide a more open-minded atmosphere and more efficient solutions (Hornsby et al, 2002). Eisenberger and Armeli (1997) claimed that rewards increase creativity. However, reward system should be fair and satisfactory and proportional with individual performance in order to be efficient (Lawler, 1967; Cissell, 1987). Moenaert et al (1994) mention that formalization, centralization and employees that can use initiative increase the communication between R&D and marketing departments so provide a positive impact on innovativeness.

Intellectual capital can be divided into three groups of human, social and organizational capital (Edvinson, 1997). Subramaniam ve Youndth claim that organizational and social capital together affect innovation activities in small scales, but human and social capital together trigger radical innovation activities (Subramaniam, 2005). Specialization is considered as an important component of human capital (Walker, 1987) and Cohen and Levinthal mentioned in their research that human capital is a crucial determinant for innovation performance (Cohen, 1989).

### *2.1.3. Firm Strategies*

The innovative performance of the firms is directly related with their strategies. Loch et al state the important role of internal and external growing strategies of the firms in their innovation performances (Loch et al, 1996). The statistical effects of management strategies on innovation performances were investigated by Belderbos (2001). Although there appear to be no linear interaction between the firm scale and innovation, the innovation performance of the firms are shown to be apparently in interaction with their production intensity, R&D intensity, export intensity and operation auditing. François et al (2002) showed the financial and control strategies of the firms as business practices which must be managed carefully for the firm's innovation performance and market success. The relation between the export performance and the firm scale innovation performance was analyzed by Roper and Love (2002). Their conclusion was mentioning the strong effect of product innovation on the export probability and trend of the firms. In another study, Geroski (1995) mentioned the bigger innovative trend of exporting firms compared to their non-international rivals.

Diversification, differentiation and cost reducing strategies are also innovation related factors (Ahuja, 2001). Galende et al (2003) observed the positive effect of differentiation strategies on the innovative capacity of the firms. Hitt et al (1997) showed also globalization as a beneficial strategy for the firms. However, the strategy mentioned to be meaningful if the firm also implements diversification strategies in its market space. In this research, globalization concept was handled as considering global market spaces as first cause and employing people from different nationalities.

Effective information management is presented as a method for enhancing innovation and performance in the literature. Information management term covers the concepts of reaching new information, storing the present information in firm, re-arranging the information and distributing them. Liao and Chuang (2006) mentioned the effect of information management on innovation speed as well as the positive effects of

innovation policies on the performance of the firms. Especially, distribution of information and information answering are mentioned to be the elements that have the greatest influence on factors that provide competitive advantages, like innovation (Hall, 2006).

Innovation capabilities of firms were classified according to their management strategies by Soutaris (2002). The innovative studies were mentioned to be faster in firms working with specialized suppliers compared to the supplier dominant firms. In the same study, competitive environment, information reaching, technological strategy, risk assessment and internal coordination are shown as factors directly related with the innovative capabilities for supplier dominant firms. On the other hand, innovative capability is much more related with the high grow and export rates for the firms working with specialized suppliers. Love et al remarked the positive effects of getting involved in global markets, technological approaches, R&D collaborations and presence of R&D department on the innovation capacity of the firms (Love et al, 1996). Sáez et al (2002) mentioned innovation as an occasionally occurring result of collaborations between complementary sources like rivals, suppliers, customers, research centers and universities. According to Tehter, many firms develop new processes, products and services without collaborating other organizations in the aim of innovation. However, the firms innovating for the market, not only for themselves show tendency for collaborations and partnerships (Tehter, 2002).

### 2.1.4. Sectoral Conditions and Relations

Structures and strategies of the successful firms must be in an adequate relation with the sectoral conditions and the market they are involved in. Firms must observe the atmosphere around them in order to develop a stable innovation culture. Barringer and Bludorn (1999) have stated that the firms become more innovative and practical under the pressure of high competition. The effects of market conditions on firm success and their effect on innovative performance of the firms were investigated by Terwiesch et al (1996). They mentioned that the innovative performance was more important in

technologically stable and mature industries. Geroski (1995) also mentioned that the firms in competitive markets are more innovative.

Periodical consultations with the customers, use of market surveys and observation of rival products and processes are directly related with the innovation of the firms. Especially the relations with the suppliers who are closer to technical information are beneficial. Soutaris (2001) suggests enhancement of international relations by collaborations with buying license and joint-ventures/partnerships to the firms. Kappel and Rubenstein (1999) mentioned that the partnerships can reduce the risks of innovation in ambiguous markets as well as they provide a more stable position in the market.

Public arrangements and incentives are also mentioned as factors affecting innovation. Public arrangements and incentives are important in encouraging firms for innovative activities. Jaumotte and Pain (2005) indicated the positive relation between the public funds and the innovative states of the firms according to the EU Innovation Survey.

## 2.2. A GENERAL REVIEW OF DECISION SUPPORT SYSTEMS AND DSS FOR INNOVATION

Decision support system can be defined as a model or knowledge based system developed for supporting and enhancing decision making process. Its aim is to help user to give more accurate decisions. DSS can be made in several forms such as using Excel and VBA codes, Java applications or other programming languages. According to the Hanna et al (2003), most important advantages of a DSS can be given as follows:

- Combining human judgment and computerized information for semi-structured decision situations.

- Designed to be used easily. GUI stage becomes important in order to be as user-friendly as possible.

- Using models to analyze decision making situations and may include background information pertinent to the situation analyzed.

- Aiming to improve the decision-making efficiency instead of its own effectiveness.

- Providing support for various managerial levels. A DSS can be PC-based or web-based.

There are certain components that a DSS should include and these are database, model or knowledge base, GUI (Graphical User Interface) and user (Figure 2.1). Database is used for storing data, model base as an archive of models for data analysis, knowledge base contains the background information about the data, and GUI is the interface between model base, knowledge base, database and user.
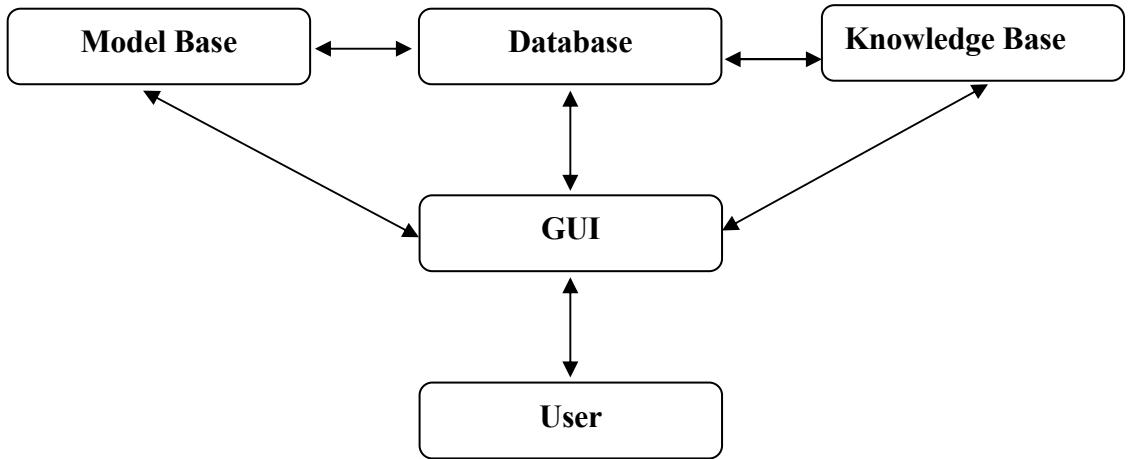
Figure 2.1: General scheme of a Decision Support System.

Application areas of DSS are very wide that any situation that needs decision-making process can be an application field. To give examples; logistics, portfolio management, health care, hospital management, reliability analysis and scheduling are fields that use DSS commonly.

Innovation, which is a very hot topic for industry, has not been utilized by the usage of DSS. There are few examples of innovation DSS in the literature. *Innovation Tool* developed by i10 (2009) provides a 14 questions test and according to the answers, it gives an innovation score ranging from 0 to 100. Additionally, it gives general suggestions about developing innovation. It is a user-friendly application but it has a limited questionnaire. Another similar example is a Leonardo da Vinci Project, *Innovation Company Model* (2007). Its main aim is to develop an innovation management tool in wood processing industry. There is a database composed of articles, book chapters and useful links and there is a 21 questions survey to fill. After submitting survey, it suggests the user book chapters, articles and web links to check. *HypeIMT* is an idea management software for new product development (2009). It collects the new ideas in a firm via a portal page and these ideas are rated according to pre- specified criteria. It is a useful software for a firm that aims to develop successful ideas.

When these examples are considered, it can be said that there is a lack of a well-developed DSS in the field of innovation. For this reason, innovation is a good candidate for developing a DSS. Since the knowledge base is one of the most crucial components of a DSS, we have proposed a Feature Subset Selection (FSS) algorithm to be used in DSS. This algorithm can be applied on several fields but for the reasons that are mentioned above, we have chosen to apply it for innovation policies. The details of the proposed algorithms are provided in Chapter 3. Before getting into the FSS algorithm, it will be more appropriate to present a literature review about feature subset selection and its methods.

## 2.3. FEATURE SUBSET SELECTION

Data analysis module, which will construct the engine of the DSS that is developed in the context of the project, will constitute of fuzzy logic based rules. These rules will be determined from the collected data by data mining techniques. One of the most important steps of data mining is to assure that the features used in the model are relevant to enlighten the secret relationships throughout data.
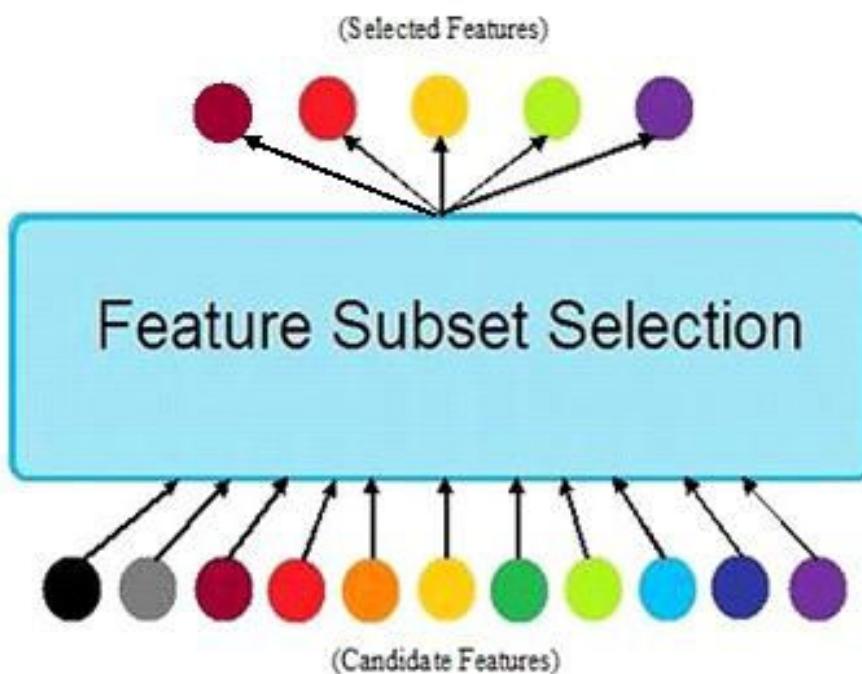


Figure 2.2: Feature selection procedure.

If there are missing features, then determining the relationships would be impossible. On the other hand, if the number of features utilized is too much and include irrelevant features, there will be an ambiguous situation caused by unnecessary data and relationship determination would be hard if not impossible. Therefore, feature selection step is the most crucial step in data mining, regardless of which data mining methodology is utilized.

The fuzzy logic based system modeling technique that will be used in this thesis, aims to determine the significance of the feature. That is to say, rather than classifying a feature dichotomously as relevant or irrelevant, a weight would be assigned to each one of the individual features that will represent its relative significance. Initially, suggested method will search and find the unnecessary features. Then, by analyzing the feature subset that is eliminated from unnecessary features, remaining ones will be given their corresponding importance weights. The features that are explained in Section 2.1 are the ones chosen after elimination among a large set of determinants. This elimination is done in Gunday's Master of Science thesis (2007). Our aim is to develop a Simulated Annealing and Genetic Algorithm based feature subset selection (actually feature weighting) method, which is an important module of Fuzzy Inference Engine of DSS. Although this method can be applied on various fields, we will apply it to identify the relative significance of the determinants for innovation. We will now present a short literature review of the feature subset selection methods.

There are several algorithms in the literature proposed for the feature subset selection problem. These methods can be classified under three main categories, namely, the *filter methods,* the *wrappers methods* and the *embedded methods*. Briefly speaking, the filter methods determine the feature subsets based on an a priori criteria such as correlation, entropy or information acquisition directly from the sample data instead of using learning algorithms. On the other hand, the wrappers methods utilize various learning algorithms. The fundamental motivation of the wrapper methods is the fact that the feature subset chosen by the filtering step is the *best* subset selection in terms of the objective function of the particular filtering technique. However, recall that the main aim of feature subset selection is to obtain the features that will provide the *best classification accuracy*. Hence, although wrappers method is more costly than filter method in terms of the computational time, it can yield more efficient results in practice. In Embedded method, classification process is computed synchronously with feature subset selection. Each method will be explained in more detail in later sections.

Whichever method is used for feature subset selection, there are some common structural elements that should be considered. These are the starting point, searching strategy, feature subset evaluation, and the termination criterion. The major issue while determining the starting point is to decide the methodology that will be used. That is to say, depending on whether the backward elimination or the forward insertion will be used the starting point changes. In the backward elimination, all features are selected initially and at each iteration specified features (*with respect to a criterion*) are eliminated. On the other hand, the forward insertion is just the opposite of backward elimination and starts with an empty subset, and at each iteration specified features are inserted to the subset. Note that, apart from starting with an empty subset or full subset, backward elimination or forward insertion can also be applied on a subset composed of a random number of features chosen as starting point. Searching strategy is a major step in feature subset selection. Evaluation of all possible feature subsets can be extremely costly and misleading. For example, in a data set of *n* features, computational time for searching all possible $2^n$ feature subsets would be too costly. Computational complexity has triggered the need for more efficient searching strategies. The classification of these strategies can be done by using three different methods that are filter methods, wrappers methods and embedded methods. These methods will be explained in detail in Section 2.3.1, 2.3.2 and 2.3.3. Another important element is the subset evaluation. After generating a candidate feature subsets, a pre-determined subset evaluation method should be applied in order to decide which subset to use. Evaluating feature subsets with learning algorithm itself in wrappers method or measuring the data classification performance of features with metric functions can be given as examples of subset evaluation. Finally, one should also define a termination criterion. It should be specified when or according to what criterion the applied method should be terminated. There are several options for determining the termination criterion. Terminating the algorithm when feature subset size reaches a pre-specified number or when candidate feature subsets starts to make no difference in terms of the classification accuracy are some examples of possible termination criteria.

There are various application areas of feature subset selection. Text categorization is one of the most common fields where feature subset selection is used (Yang, 1997; Forman, 2003). With the widespread usage of the Internet, written media mediums such

as newspapers or magazines are published via the Internet. Besides, expanding usage of e-mails results in growing written document traffic via the Internet. For this reason, feature subset selection has a major importance in terms of easy access to the information stored in databases and of proper classification of these documents. Each term mentioned in these written documents can be considered as distinct features and with an appropriate feature subset selection algorithm, required classification can be achieved. As well as classification of written documents, gene expression analysis is another field where feature subset selection is used extensively (Guyon et al, 2002). If each gene in DNA sequence is considered as a feature, it can be possible to determine which genes have significant effect on certain diseases or genetic characteristics. Thus, any disease can be cured by finding the problematic gene(s) that causes it.

Let's now discuss the above mentioned three different feature subset selection methodologies in more detail. Note that, due to the wide range of the literature on feature subset selection, a comprehensive literature review is not possible. Therefore, we will only cover the most significant and relevant papers for the research in the next subsections.

### 2.3.1. Filter Methods

Recall that feature subset selection is widely used especially for classification problems where it is possible to make inference about samples whose several features are unknown (*dependent variable)* based on their known features (*independent variable)*. Hence, feature subset selection and learning method used for classification are the two fundamental steps of inference problems. The feature subset selection method that determines the significant features directly from the data based on a pre-specified function that indirectly measures the relation between the feature and the *independent variable* is referred to as the *filter methods.* Filter methods are independent from the learning algorithm that will be used for the inference problem. Its distinctive characteristic is to filter the features directly in the feature subset generation stage and not to use the learning algorithm inside evaluation function. Learning algorithm is applied as a second step, after

feature subsets are generated. There are several widely used filter methods for determining feature subsets. Most of these methods are based on statistical metrics. Among these metrics; correlation, distance between means, impurity, entropy and mutual information acquisition can be listed as examples.

Correlation based metrics are widely used for feature subset generation. It will be helpful to investigate the correlation between two features in order to analyze their linear relationship. If their correlation is high, it means that these two features (or a feature and an output score, i.e., the independent variable) are interdependent on each other. There is a crucial point to take into consideration while generating feature subsets using correlation method.

Hall (2000) claims that feature subsets that are composed of features, which have minimum correlation among themselves and maximum correlation with the output score, give better results. It is possible to develop distinct solution strategies using correlation metrics. As mentioned earlier by modifying the searching strategy, the feature subset evaluation and the termination criterion; different filter methods can be obtained. For example; one possible method is to use forward insertion in order to add a specific number of features to subset based on their correlation with output score by using nearest neighborhood algorithm. Another method can be choosing the feature having the highest correlation with output score and eliminating specific number of features having the highest correlation with the chosen feature. Next, among the remaining features, those that have the highest correlation values with output score is selected by forward insertion.

Beside correlation metric, feature subset selection by using entropy metric is another common filter method. Entropy metric measures the statistical distributional randomness of features. Entropy of each feature is calculated based on the function that is presented as follows where $c$ denotes the class number.

$$Entropy(x_i) = -\sum_{i=0}^{c-1} p(x_i) \log_2 p(x_i),$$

First step to use entropy metric is to apply clustering analysis for each feature and prototype scores are computed. Next; probabilities of class belongings of each cluster are calculated. Then; by determining the features according to low entropy scores, feature subset is formed by deciding which feature to include. To have clear understanding and detailed presentation of this method's usage in genetic field, Liu et al (2002) article can be a good reference.

Another common filter method is to use mutual information metric (Guyon et al, 2002)**.** The base function of this method is given as follows:

$$Mutual\_Information(i) = \sum_{x_i} \sum_{y} p(X = x_i, Y = y) \log \frac{p(X = x_i, Y = y)}{p(X = x_i)p(Y = y)}$$

In this method, mutual information between a feature and a class is defined as the relevance and mutual information between two features is defined as the redundancy. The main aim is to find the feature subsets that have minimum redundancy and maximum relevance. Minimum redundancy-maximum relevance strategy of mutual information method utilizes similar steps to the strategy used in correlation method as discussed earlier. RELIEF is an example of filter method using mutual information.

RELIEF, which is the most quoted algorithm by researchers and in this sense it can be regarded as a groundwork filter algorithm, is a feature subset selection method that filters by using the means of the differences between the distance of sample's closest point in its own class and the distance of sample's closest point in other classes except from its own class. Kenji and Rendell (1992) have introduced this method into the literature and it has drawn attention of other researchers that there have been many publications in the literature with moderate modifications and different techniques. The basic reason for mutual information method being more popular than other filter methods is that it aims to optimize a direct indicator of classification instead of optimizing some statistical metrics which can be indirect indicators of accurate classification. According to this method; for each feature, *m* samples are selected randomly. The objective of selecting only *m* random samples is to increase the speed of the algorithm. For each *m* samples, scores will be

computed for each feature of each sample. Calculation of scores is done in this manner: For each sample, closest sample which is from a different class is found and their distance is calculated. Then, closest sample which is from the same class is found for the sample chosen at the first step. Their distance is calculated again and difference between the second distance and first distance is computed. This procedure is repeated for each $m$ samples and the mean of the distance differences is computed. By this method, a mean is calculated for each feature. The features that have the highest means are chosen as the features that will be used for best feature subset selection. The point that should be observed is the meaning of the two distances computed for each sample. If a feature is a good classifier, $m$ random samples selected for that feature are distant to the samples that are from different classes in terms of that feature and are close to the samples that are from the same class. Therefore, larger the means of the differences of the two distances (in other words, maximum first distance and minimum second distance is preferred), better classifier that feature is.

RELIEF algorithm has considered as milestone and has been improved by several researchers. Among these improvements, Kononenko (1994) has introduced RELIEF-F. The main difference between RELIEF and RELIEF-F is, instead of computing distances of the sample from the same and different classes based on one sample which is the closest, to compute *k-neighbor distances* from the same and different classes for a sample and computing the means of $k$ differences of distances.

### 2.3.2. *Wrappers Methods*

Wrappers methods have been introduced as an alternative for filter methods. In filter methods, feature subset selection is done by using several statistical metrics independent of the technique used in classification. However, wrappers methods base feature subset selection on directly classification score.

Wrappers methods are more costly than the filter methods because feature subsets are evaluated by the learning algorithm itself. The loss of time due to the complexity is usually covered by more efficient feature selection. In wrappers method, learning algorithm is repeated for each candidate feature subset and model evaluation is

performed. On the other hand, in filter methods, learning algorithm is conducted only once after the feature selection stage. Hence, the wrappers method can be highly costly and time consuming for data sets that includes too many features or samples. Since the model is evaluated from scratch for each candidate feature subset, there can be extreme loss of time or computational support can be insufficient. For example, in the literature the classification of written documents is performed mostly based on the filter methods, which are more simple and practical than wrappers methods, because there are too many samples and features together in the text recognition problem (Mladeni'c, 2006).

Wrappers methods should answer three basic questions, namely, the strategy that will be used for searching the feature space, the performance metric that will guide the searching strategy and the classification method that will be used. In the literature, different suggestions have been proposed for each one of these questions and distinct combinations of these propositions have resulted in various methods. A detailed comparative analysis of these methods has been done by Kohavi and John (1997).

In wrappers methods, candidate feature subsets are tried to be constructed by applying different techniques during the procedure of searching feature space. Step-by-step backwards elimination, step-by-step forward insertion or genetic algorithms can be given as examples of these different techniques. In step-by-step backwards elimination method, it is possible to start with a full feature subset or with a specific sized feature subset. According to this method, until a pre-determined number of features are obtained, candidate feature subsets are generated by eliminating one feature at each step. Each candidate feature subset is given a score by applying the learning algorithm and when the termination criterion is reached, feature subset selection is completed. Step-by-step forward insertion is very similar to step-by-step backwards elimination. As a starting point, an empty feature subset or a specific sized feature subset is used and features are added iteratively until the termination criterion is satisfied.

There are considerably many Genetic Algorithm applications as wrappers methods. Genetic Algorithm (GA) is used as a meta-heuristic optimization tool in various fields. Its basic principle is based on the natural selection method that is observed in biological

systems. Briefly speaking, in GA's, a pool of genes that are composed of chromosomes where each chromosome represents a candidate solution is generated and new generations are created by using methods that imitate biological concepts such as mutation, crossover or regeneration. It is assumed that the new gene pools will be generated including better solutions where weak and unfavorable solutions will be eliminated at each generation in the same manner of biological systems. In the context of feature selection, for the appropriate usage of chromosome structure, each feature is placed in the chromosome, so each chromosome will represent a candidate solution. In the subsequent generations, different chromosomes are generated as many as the parameter that represents the *size of the gene pool*. In the first generation, each different chromosome in the *initial population* consists of 0s and 1s which are assigned randomly or according to a pre-determined criterion (There are several different techniques are available). Note that, a *0* in the chromosome sequence indicates that the corresponding feature is not a member of that feature subset, and a *1* represents that the corresponding feature is included in that feature subset. After the reproduction, the reproduction, the mutation and the crossover steps, the initial population is updated and a new generation is obtained. Throughout all these steps, the classification score of the solution that is coded by the corresponding chromosome structure is used as the *fitness score, which* affects the chance of heritance for that solution to next generation. Higher the classification score a solution has, higher the probability that it will be transferred to the next generation (either as a whole, in the case of reproduction, or partially after the crossover). Consequently the feature subset that gives the best score can be obtained. Vafaie and De Jong (1992), Yang and Honavar (1998), Handels and Ross (1999) and Liu et al (2005) are among the examples of genetic algorithm based feature subset selection methods in the literature. Note that we will later discuss GA's in more detail in Chapter 3 where we will present the proposed algorithms for the feature subset selection problems.

### *2.3.3. Embedded Methods*

Embedded methods are third type of the feature subset selection methods apart from filter methods and wrappers methods, although they are not used as common as the other two methods. In embedded methods, classification and feature subset selection is

performed simultaneously. By not splitting the training data into a training and validation set, faster solutions are achieved. Embedded methods incorporate feature selection as a part of training process. Decision trees can be given as examples of embedded methods.

The main advantage of the embedded methods is to use data in a more efficient way. In wrappers method, learning algorithm has to be repeated for each candidate feature subset. However, in the embedded methods, it is not needed to separate data into verification and training sets since evaluation is performed simultaneously with feature subset selection. Thus, it is not required to construct new training data from scratch for each candidate feature subset. There is another important difference of embedded methods from wrappers methods, that it is not possible to use independent methods for classification and feature subset selection since they are performed simultaneously. In other words; contrary to wrappers methods, in embedded methods, it is not applicable to replace a classification method with another classification method.

That is to say, embedded methods are combination of filters and wrappers methods. Since classification and feature subset selection is implemented simultaneously, they give efficient results in terms of time complexity. CART method, which is developed by Breiman et al (1984), is one of the first examples of embedded methods.

# C H A P T E R  3

## 3. ALGORITHMS

### 3.1. THE FRAMEWORK OF THE DSS AND THE PROPOSED ALGORITHMS

The Decision Support System will enhance the upper managers' ability to establish sound policies to improve the innovativeness of the firms. It will identify the shortcoming factors in the firm based on the web based questionnaire that they will reply and generate a report regarding to these shortcoming factors and make suggestions. In order to identify the shortcoming factors, first thing that is required is to identify the *relevant factors*, i.e. the determinants of innovation and their relative significance with respect to each other. We will utilize two algorithms that are proposed in this thesis for this purpose. After the significance of the innovation determinants (i.e., *the features*) are identified, by benchmarking the firm (based on the questionnaire that they fill and the data that was collected earlier) (Gunday, 2007), it will be possible to suggest policies to improve the innovation capability of the company.

Therefore, the determination of the significance of the features constitutes the essence of the rule base that will be used to develop. As a result of a detailed literature review, innovation determinants (features) that are directly related with the innovativeness at the firm level were presented earlier. Note that, there is no research in the literature that we are aware of regarding to the significance degrees of these features relative to each other with respect to their influence on the innovativeness at the firm level innovation.

An improved Fuzzy Logic Based System Modeling (FLBSM) algorithm based method is used within the project. The most distinctive character of the proposed method

from the other techniques mentioned in the literature is that it seeks answer for how important the features are, instead of classifying the features by using a binary logic whether they are important or not.

## 3.2. FLOW CHART OF THE DECISION SUPPORT SYSTEM

The proposed Decision Support System consists of two phases. First phase is named as Model Determination and the second is named Fuzzy Inference phase. Model Determination phase includes the construction of the rule base from the data retrieved from the database, while Fuzzy Inference phase comprises prediction of firm's innovation level based on these rules and defining the most appropriate policies for the firms. That is to say; in the first phase, instead of the user data (their response to the questionnaire), data retrieved from the other firms and stored in the database will be used in order to build the rule base and identify the significance of the factors (*features*). On the other hand; in the second phase, innovation policy suggestions for the user will be determined by using the user data.

FLOWCHART OF THE DECISION SUPPORT SYSTEM

1. Model Determination (MD)
   a. Determination of the importance weights of features
      i. Choosing starting points for feature weights (Equal weighted, correlation, entropy, mutual information, i.e.)
      ii. FLBSM based feature weighting optimization (Simulated Annealing, Genetic Algorithm, i.e.)
   b. Fuzzy clustering of innovation scores and construction of the rule base.
2. Fuzzy Inference (FI)
   a. Fuzzy innovation inference based upon user data.
   b. Determination of the shortcoming features which are suitable for improvement.
   c. Reporting.

On the other hand; FLBSM algorithm, which is proposed to be used in the step 1.a.ii within the determination of importance weights of features, also includes the usage of the methods in the Model Determination and Fuzzy Inference phases step by step. So that, the rule base that is the most appropriate for the training data (namely, the one that has the least inference error) will be obtained. For this reason, details of the algorithm are given below in order to prevent repetition.


## 3.3. ARCHITECTURE OF THE DECISION SUPPORT SYSTEM


The Decision Support System that is developed will be a web-based tool that is used by the firms for determining their innovation policies, that will give them opportunity to compare themselves with the firms in the same sector and that give innovation policy suggestions in order to be more innovative. In this framework, firms will fill out a survey that includes innovation determinants and a report will be presented to the firms according to the answers given in the survey. In this context, a three-layered architecture is anticipated for the DSS (Figure 3.1).
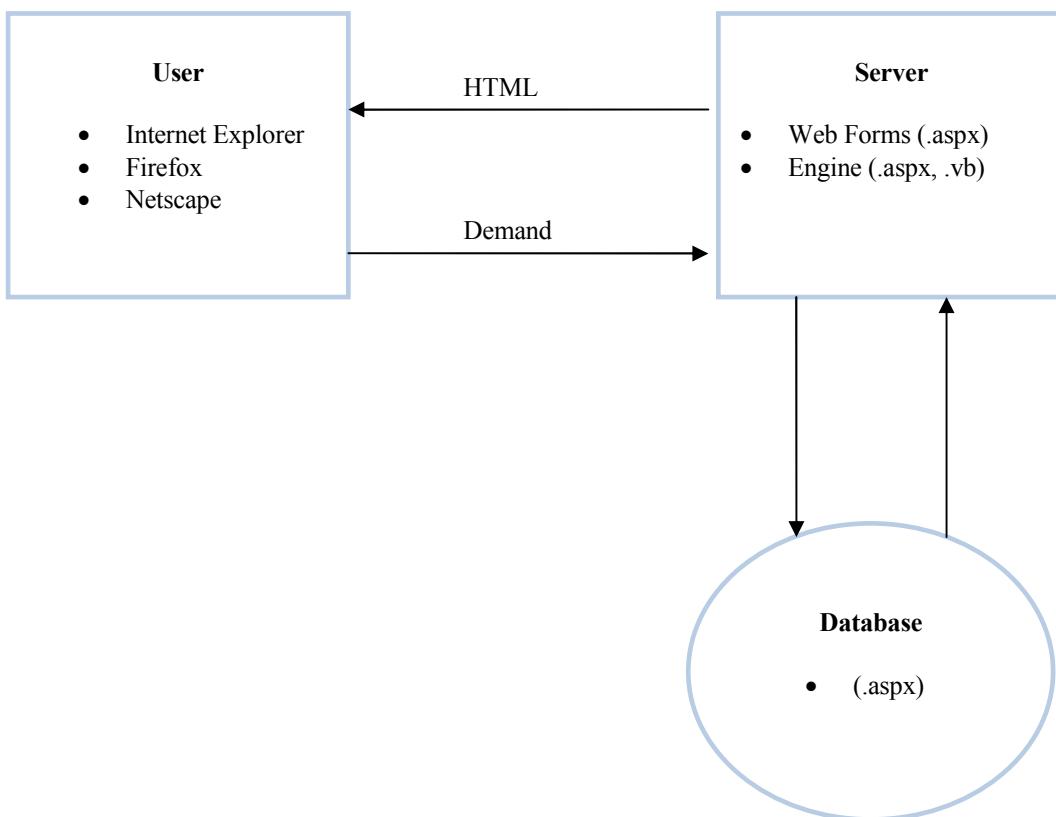
Figure 3.1: Architecture of the Decision Support System

In the first layer, the user will fill out the survey from his/her personal computer via a web browser (Internet Explorer, Firefox, Netscape, i.e.) and answers of the user will be sent to the second layer, which is the server. The server will constitute the rule base using the data retrieved from the database (third layer) and the reports will be prepared by using the rule base. The proposed algorithms in this thesis will constitute *the engine,* which are coded in Visual Basic (.vb). The reports that will be prepared after the constitution of the rule base will be completely based on the historical data with the help of fuzzy logic based system modeling algorithm. ASP .Net, where .aspx codes are used, will provide the connection between *the database* and *the server.*

## 3.4. THE FRAMEWORK OF THE FUZZY SYSTEM MODELING ALGORITHM

Flowchart of the fuzzy system modeling methodology that will be utilized as the engine of the decision support system is depicted below in figure 3.2. System modeling and inference modules that are on the left side of the flowchart will be used for determining feature weights of the DSS. These feature weights will be optimized according to a performance metric based on inference errors.
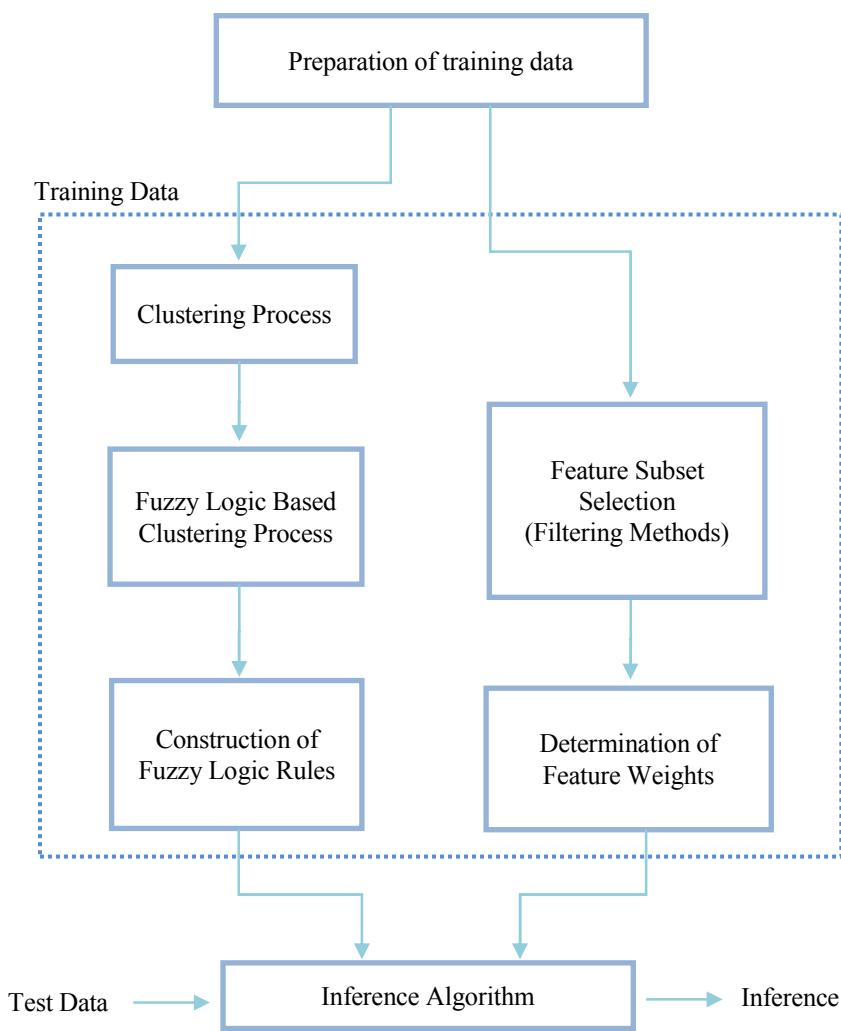


Figure 3.2: Flowchart of the Fuzzy Logic Based System Modeling Module

Note that as depicted in Figure 3.2 we adopted a *filtering stage* before the determination of the significance degrees of the features. Since the proposed algorithms

are metaheuristics based (particularly the *simulated annealing*) it is beneficial to begin with a reasonable starting point for the relative significance degreed of each one of the features. At this stage, approaches such as correlation based, entropy, mutual information and equal importance weighting are used.

## 3.5. DETERMINATION OF THE SIGNIFICANCE DEGREES OF THE FEATURES (SIMULATED ANNEALING)

Simulated Annealing is an algorithm that aims to achieve at least a local optimum by step-by-step improvements starting from a starting point that is determined at the filtering stage. Within this process, it tries to avoid local optimum traps as much as possible. The algorithm, which is developed by Kirkpatrick (1983), is named as Simulated Annealing because it imitates the annealing process in real life. At each step, all the possible solutions in the neighborhood of the temporary solution are analyzed. For the next step; not only the solutions that improves the temporary solution are given chance to be chosen, but also the solutions that worsen the temporary solution are chosen with a pre-determined probability. This technique is thought to avoid falling into the local optimum trap. This pre-determined probability depends on the temperature as it is also valid for the annealing process in real life. Since the temperature is cooled down gradually, meaning that probability is decreased, it provides the diversification strategy at the beginning and intensification strategy throughout the time.

Before getting into the details of the algorithm that is developed for determining the importance weights of the features, the terminology used is presented below.

*n*: The number of the innovation determinants used in the Model (number of features)

*m:* The number of the firms in the database that will be used in the Model

*i=1,2,...,n (index)*

*k=1,2,...,n (index)*

*j=1,2,...,m (index)*

*l=1,2,...,m (index)*

$X_{i,j}$: *The score of the $j^{th}$ firm in terms of $i^{th}$ firm*

$X_j = [X_{i,j}]$ : Vector including the feature values of $j^{th}$ firm

$Y_j$: *Innovation score of the $j^{th}$ firm*

$X_{i,t}$: *The score of the test firm in terms of $i^{th}$ feature*

$X_t = [X_{i,t}]$ : Vector including the feature values of the test firm

$Y_t^*$: *Inferred innovation score of the test firm*

$Y_t^g$: *Real innovation score of the test firm*

$w_i$: *Importance weight of the $i^{th}$ feature*

$c$: Number of clusters used for constructing the rule base

$o=1,2,...,c$ *(index)*

$A_o$ : *Fuzzy clusters resulting from fuzzy clustering of $Y_j$'s*

$\mu_{Ao}(Y_j)$ : Membership degree of $j^{th}$ firm's innovation score to the $A_o$ fuzzy cluster

$k$: Parameter for determining the number of nearest neighbors used in k-nn classification algorithm


FEATURE WEIGHTING ALGORITHM (SA)

**1.** Assign the starting values of importance weights of features ( *Ex*: for equal weighted starting values: $w = [w_i=1/n]$ )

**2.** Pick up a big number M for the initial value of the temporary minimum average error

*TMAE = M*

**3.** Assign the parameters $\varepsilon$ (stepwise increase of importance weight), $\varepsilon_T$ (Temperature decrease parameter of Simulated Annealing), $T$ (Initial temperature of Simulated Annealing), $T^*$ (Final Temperature of Simulated Annealing)

**4.** Temporary importance weight vector $w_G = w$

**5.** Repeat the following steps until ending criteria $(T<T^*)$ is not satisfied

***5.1.*** *Repeat the following steps from i=1 to n*

    ***5.1.1*** *Increase the importance weight of $i^{th}$ firm stepwise by ε,*

    $(w_i := w_i + \varepsilon)$

    ***5.1.2*** Update the importance weights of other features as the sum of the weights is equal to 1

    $(\forall k \neq i \ (k=1,..n) \ w_k = w_k - \varepsilon/(n-1))$

    ***5.1.3***    $w_G = [w_1 = w_1 - \varepsilon/(n-1), \ldots, w_i := w_i + \varepsilon, \ldots, w_n = w_n - \varepsilon/(n-1)]$

    ***5.1.4***    Equalize Temporary Total Error to zero. TTE = 0

    ***5.1.5***    *Repeat the following steps from l=1 to m*

        ***5.1.5.1*** one-leave-out (using *m*-1 data by leaving $l^{th}$ firm data vector out), Construct the sub-training data

        ***5.1.5.2*** Estimate the lth firm's innovation score by using Fuzzy Inference method and calculate its difference (error) between the real score.

        ***5.1.5.3***   $TTE = TTE + error^2$

    ***5.1.6***    Average Error $(AE_i) = TTE/m$

***5.2.*** *Done : = False*

***5.3.*** *Loop until Done = True*

    ***5.3.1***    Pick a random number, *r*, from set of integer numbers {1,…,n}

    ***5.3.2***    *If $AE_r <$ TMAE*

        ***5.3.2.1*** $TMAE = AE_r$

        ***5.3.2.2*** $w_r := w_r + \varepsilon$

        ***5.3.2.3*** $\forall k \neq r \ (k=1,..n) \ w_k = w_k - \varepsilon/(n-1)$

        ***5.3.2.4*** $T := T * \varepsilon_T$

**5.3.2.5** $w^* = [w_1 = w_1 - \varepsilon/(n-1), \ldots, w_r := w_r + \varepsilon, \ldots, w_n = w_n - \varepsilon/(n-1)]$

**5.3.2.6** *Done : = True*

**5.3.3** *If $AE_r \geq TMAE$*

**5.3.3.1** $\Delta = AE_r - TMAE$

**5.3.3.2** Pick a random number, $\rho$, from the interval of $[0,1]$

**5.3.3.3** If $\rho > e^{\Delta/T}$

**5.3.3.3.1** $w_r := w_r + \varepsilon$

**5.3.3.3.2** $\forall k \neq r \ (k=1,..n) \ w_k = w_k - \varepsilon/(n-1)$

**5.3.3.3.3** $T := T * \varepsilon_T$

**5.3.3.3.4** *Done: = True*

**6.** Take $w^*$ as the feature importance weight giving the minimum average error to use in the Model Determination phase.

Fuzzy Inference algorithm used in the step 5.1.5.2 of the above algorithm is explained in detail below.

FUZZY INFERENCE ALGORITHM

1. Fuzzy clustering of innovation scores of firms (FCM, Bezdek, 1973; Bezdek, 1981)) and determination of membership degrees of training data belonging to fuzzy clusters

$\forall o=1,\ldots,c \ ; \ \mu_{Ao}(Y_j)$

2. Transferring innovation scores to the feature space by using Zadeh's Extension Principle (1975).

38

$\forall j,\ \mu_{Ao}(X_j) = \mu_{Ao}(Y_j)$

3. Determination of firms that have the closest k-neighbor feature vector to the test firm's feature vector among the (sub) training data by using the temporary feature weights

    3.1. Repeat the following steps from *j=1 to (m-1)*

        3.1.1 Temporary Distance(TD) = 0

        3.2.1 *Repeat the following steps from i=1 to n*

$$TD = TD + w_T[i] * (X_{i,j} - X_{i,t})^2$$

        3.3.1 Calculate the distance between the test firm's feature vector and $j^{th}$ firm's feature vector (Note: Weighted Euclidian metric is used for distance calculation in step 3.2.1. Feature importance weights that are obtained are used for calculation.)

$$M_j = TD$$

    3.2. Obtain the neighborhood set which is composed of *k* firms with the minimum distance; {*K*}

4. Infer the test firm's innovation score by using the innovation scores of the firms in set {*K*}

## 3.6. DETERMINATION OF THE SIGNIFICANCE OF THE FEATURE WEIGHTS (GENETIC ALGORITHM)

Genetic Algorithms (GA) is another global optimization tool, proposed by Holland (1975), used in many applications successively. Fundamental inspiration source of GA is the biological evolution process. Although there are several GA application methods in the literature that differentiate in many different details, basically there is a common dominant approach among all applications.

First of all, this approach requires constructing an initial gene pool composed of chromosomes, where each chromosome is a solution or represents a solution. The fundamental issue is to decide on the chromosome structure in accordance with the problem structure. It is anticipated that the chromosome structure that will be used within the project will be a vector consisting of feature importance weights, where the summation of weights is equal to 1.

After the construction of initial gene pool, the process of stepwise creation of new generations starts. At each step, next generation is obtained by using current gene pool. The methods for creating next generation are crossover and mutation operators, which are essential part of natural biological life. After crossover and mutation operations; with different GA methods, it is ensured that more competitive and strong chromosomes in the gene pool that constructs the next generation are preserved for the next generations and weaker and less competitive ones are eliminated. At this point, the fundamental decision is how to determine which chromosome is stronger and which one is weaker. This is done by using a *fitness function*, where each chromosome has a *score* according to the *fitness function*. In the project, the average prediction error that reflects the difference between the real scores of the training data and inferred scores that are obtained by using the Fuzzy Inference algorithm will be used as *score* of each chromosome.

Process of creating new generations continues until a pre-determined ending criteria is satisfied and after all these steps, most appropriate chromosome, which has the least average prediction error, will be chosen as the final solution. As well as defining a suitable chromosome structure that is appropriate for the problem and the *fitness function score* that determines whether a chromosome is strong or not; crossover, replication, mutation and migration methods will be significant factors that define the performance of GA.

FEATURE WEIGHTING ALGORITHM (GA)

1. Initialize the first population.

    **1.1** Create a weight array as the population size ($w_i$).

    **1.2** Assign random numbers for the weight array elements.

    **1.3** Normalize the array values as the summation of the values will be equal to 1 ( $\sum w_i = 1$).

2. Pick up a big number M for the initial value of the temporary minimum average error.

*TMAE = M*

3. Calculate the fitness score of each individual of the population.

    **3.1** *Fitness_Array( i ) for all i.*

    **3.2** Assign the average of fitness scores as the fitness level; *Fitness_Level.*

4. Repeat the followings until the best solution found or number of generations reaches the pre-determined level.

    *Best_Solution_Found = True* or *NumberOfGenerations = 50*

    **4.1** Best_Solution_Until = maximum value of *Fitness_Array().*

    **4.2** NumberOfGenerations = NumberOfGenerations + 1

    **4.3** Apply the selection procedure.

        **4.3.1** Choose the parents according to the chosen selection method.

        **4.3.2** Pick up a random number between 0 and 1; $r_1$.

        **4.3.3** If $r_1$ > Crossover_Rate, then apply crossover method on the chosen parents. Otherwise, do nothing.

        **4.3.4** Pick up a random number between 0 and 1; $r_2$.

        **4.3.5** If $r_2$ > Mutation_Rate, then apply mutation method on the chosen parents. Otherwise, do nothing.

    **4.4** Calculate the fitness scores of each candidate individual.

        **4.4.1** If the fitness scores of candidates < Fitness_Level, then eliminate those candidates.

        **4.4.2** Otherwise, insert those candidates to the new generation.

41

**4.5** Check if the best solution is found.

       **4.5.1** If MaxValOfArray( Fitness_Array) > Best_Solution_Until then Best_Solution_Found = True. So, terminate the algorithm.

       **4.5.2** If not, go back to step 4.

## 3.7. SELECTION METHODS OF GENETIC ALGORITHM

**Roulette Wheel Method**

In roulette wheel method, parents that will be used for reproducing new children are selected according to their fitness scores. Fitter the individual is, more chance that individual has to be chosen. Fitness score of an individual determines its portion in the roulette wheel. This is provided by assigning portions for each individual by dividing its fitness score to the summation of fitness score of whole population. Afterwards, the fitness array is sorted in descending order. These portions are considered as the probability of being chosen so that a cumulative probability is calculated. Then, a random number is picked up and it is investigated which portion is targeted for the candidate.

**Crossover and Mutation**

Crossover and mutation are crucial operators that affect the performance of the Genetic Algorithm. As crossover aims to transfer the properties of fitter individuals to the next generations, mutation provides randomness to the algorithm not getting trapped in local optimums. There are several methods used for crossover and mutation operations. For example, uniform crossover, single point crossover, two point crossover or multiple point crossover methods can be given as different methods of crossover (Genetic Server/Library)**.** Mutation is generally applied by altering a single point in the chromosome. There are different methods for altering such as randomness, uniform, Gaussian, boundary or flip, which is used in binary expressions that all 0s become 1 and vice versa. In this thesis, single point crossover and random single point mutation is used, where there are pre-determined probabilities for applying crossover and mutation operators.

# C H A P T E R  4

## 4. BENCHMARK DATA

In this chapter we will evaluate the performance of the proposed algorithm with two benchmark data that is publicly available in University of California at Irvine Machine Learning Repository (Blake, 1998). There are two issues that we should evaluate. First of all we have to assess if the proposed feature weighting algorithms are capable of identifying the relevant and irrelevant features. Second issue is the predictive performance of the proposed algorithms and the fuzzy inference methodology. We will utilize the Iris Data and the Concrete Compressive Strength Data for these purposes. In order to determine the performance of the feature weighting algorithms we modified the existing data sets by adding dummy features that are generated randomly.

### 4.1. IRIS DATA

IRIS data is among the most commonly utilized benchmark data sets in pattern recognition and machine learning literature considering the number of papers that cite it (*UCI Machine Learning Repository: Iris data set*). The data includes a total of 150 instances (i.e., number of data points) with 50 instances from each one of the three iris classes, namely, Iris Setosa, Iris Versicolor and Iris Virginica. There are 4 attributes that determine the class of Iris plant which are the sepal length, the sepal width, the petal length and the petal width, where all of them are provided in centimeters. Statistical information about Iris data can be found in Table 4.1.

Table 4.1: Statistics of IRIS data.

| Attribute | Minimum | Maximum | Mean | Std. Dev. | Class Correlation |
|---|---|---|---|---|---|
| Sepal Length: | 4.30 | 7.90 | 5.84 | 0.83 | 0.78 |
| Sepal Width: | 2.00 | 4.40 | 3.05 | 0.43 | -0.42 |
| Petal Length: | 1.00 | 6.90 | 3.76 | 1.76 | 0.95 |
| Petal Width: | 0.10 | 2.50 | 1.20 | 0.76 | 0.96 |

Recall that the data set is utilized in order to evaluate the proposed algorithms in terms of two concerns; identification power of relevant features and predictive performance. Hence, we created four additional dummy attributes (i.e., features). Each dummy variable is generated so that it corresponds to one of the actual features. That is to say, each one of the dummy variables has values chosen randomly between upper and lower limits of the original attributes. Note that the fuzzy inference algorithm presented in Chapter 3 is designed to make real valued inferences based on a *k-nn* algorithm. Therefore it had to be modified slightly in order to handle a classification problem such as the Iris data. Since the output classes in the iris data are nominal (i.e. no preferential ordering exists) only appropriate approach was making inferences based on the *counts* of the classes and the inference algorithm is modified accordingly.

We tested the performance of both the algorithm based on the simulated annealing and the algorithm based on the genetic algorithms. Next we will present the results of the analysis.

### 4.1.1. Simulated Annealing Results

In the analysis, the first point of interest was to check if the dummy features are identified properly, that is to say assigned lower feature weights. We have tested the algorithm under for different values of *epsilon*, i.e., weight increment value, number of

neighbors, *k*, and temperature decrease factor, *random direction*. The resulting feature weights (i.e., the significance degrees of the features) that are assigned is tabulated in Table 4.2.

Table 4.2: Feature weights for Iris data computed by Simulated Annealing.

| | | Weights | real sepalLeng | real sepal width | real petal leng | real petal width | dummy1 | dummy2 | dummy3 | dummy4 |
|---|---|---|---|---|---|---|---|---|---|---|
| randomdirection=0.85 | knn=2 | epsilon=0.01 | 0.24 | 0.13 | 0.28 | 0.28 | 0.04 | 0.01 | 0.02 | 0.01 |
| randomdirection=0.85 | knn=2 | epsilon=0.02 | 0.22 | 0.14 | 0.32 | 0.27 | 0.01 | 0.01 | 0.01 | 0.02 |
| randomdirection=0.85 | knn=2 | epsilon=0.03 | 0.08 | 0.18 | 0.37 | 0.11 | 0.09 | 0.07 | 0.06 | 0.05 |
| randomdirection=0.85 | knn=2 | epsilon=0.04 | 0.21 | 0.11 | 0.26 | 0.31 | 0.02 | 0.02 | 0.03 | 0.03 |
| randomdirection=0.85 | knn=2 | epsilon=0.05 | 0.24 | 0.13 | 0.29 | 0.30 | 0.01 | 0.01 | 0.01 | 0.01 |
| randomdirection=0.85 | knn=4 | epsilon=0.01 | 0.22 | 0.16 | 0.27 | 0.27 | 0.05 | 0.01 | 0.01 | 0.02 |
| randomdirection=0.85 | knn=4 | epsilon=0.02 | 0.15 | 0.22 | 0.32 | 0.23 | 0.01 | 0.02 | 0.02 | 0.03 |
| randomdirection=0.85 | knn=4 | epsilon=0.03 | 0.03 | 0.11 | 0.19 | 0.35 | 0.07 | 0.11 | 0.10 | 0.03 |
| randomdirection=0.85 | knn=4 | epsilon=0.04 | 0.24 | 0.13 | 0.29 | 0.30 | 0.01 | 0.00 | 0.01 | 0.02 |
| randomdirection=0.85 | knn=4 | epsilon=0.05 | 0.23 | 0.12 | 0.28 | 0.29 | 0.01 | 0.01 | 0.04 | 0.02 |
| randomdirection=0.85 | knn=6 | epsilon=0.01 | 0.18 | 0.11 | 0.26 | 0.33 | 0.02 | 0.02 | 0.02 | 0.06 |
| randomdirection=0.85 | knn=6 | epsilon=0.02 | 0.05 | 0.10 | 0.17 | 0.54 | 0.02 | 0.02 | 0.03 | 0.06 |
| randomdirection=0.85 | knn=6 | epsilon=0.03 | 0.24 | 0.13 | 0.29 | 0.29 | 0.01 | 0.01 | 0.01 | 0.02 |
| randomdirection=0.85 | knn=6 | epsilon=0.04 | 0.23 | 0.17 | 0.27 | 0.28 | 0.01 | 0.01 | 0.02 | 0.02 |
| randomdirection=0.85 | knn=6 | epsilon=0.05 | 0.22 | 0.12 | 0.27 | 0.31 | 0.01 | 0.02 | 0.02 | 0.03 |
| randomdirection=0.85 | knn=8 | epsilon=0.01 | 0.19 | 0.18 | 0.28 | 0.24 | 0.02 | 0.02 | 0.03 | 0.03 |
| randomdirection=0.85 | knn=8 | epsilon=0.02 | 0.20 | 0.11 | 0.25 | 0.31 | 0.02 | 0.03 | 0.04 | 0.04 |
| randomdirection=0.90 | knn=2 | epsilon=0.01 | 0.25 | 0.13 | 0.29 | 0.29 | 0.00 | 0.02 | 0.01 | 0.01 |
| randomdirection=0.90 | knn=2 | epsilon=0.02 | 0.18 | 0.10 | 0.29 | 0.34 | 0.01 | 0.05 | 0.01 | 0.02 |
| randomdirection=0.90 | knn=2 | epsilon=0.03 | 0.20 | 0.10 | 0.25 | 0.32 | 0.03 | 0.05 | 0.04 | 0.03 |
| randomdirection=0.90 | knn=2 | epsilon=0.04 | 0.21 | 0.16 | 0.26 | 0.27 | 0.02 | 0.02 | 0.03 | 0.03 |
| randomdirection=0.90 | knn=2 | epsilon=0.05 | 0.22 | 0.14 | 0.28 | 0.31 | 0.00 | 0.01 | 0.01 | 0.03 |
| randomdirection=0.90 | knn=4 | epsilon=0.01 | 0.20 | 0.10 | 0.36 | 0.24 | 0.01 | 0.01 | 0.03 | 0.04 |
| randomdirection=0.90 | knn=4 | epsilon=0.02 | 0.20 | 0.10 | 0.32 | 0.26 | 0.01 | 0.04 | 0.02 | 0.05 |
| randomdirection=0.90 | knn=4 | epsilon=0.03 | 0.05 | 0.01 | 0.34 | 0.25 | 0.07 | 0.18 | 0.06 | 0.03 |
| randomdirection=0.90 | knn=4 | epsilon=0.04 | 0.22 | 0.12 | 0.29 | 0.32 | 0.01 | 0.02 | 0.02 | 0.01 |
| randomdirection=0.90 | knn=4 | epsilon=0.05 | 0.25 | 0.12 | 0.28 | 0.31 | 0.01 | 0.01 | 0.01 | 0.01 |
| randomdirection=0.90 | knn=6 | epsilon=0.01 | 0.21 | 0.14 | 0.29 | 0.26 | 0.04 | 0.02 | 0.02 | 0.03 |
| randomdirection=0.90 | knn=6 | epsilon=0.02 | 0.21 | 0.15 | 0.26 | 0.26 | 0.01 | 0.02 | 0.07 | 0.03 |
| randomdirection=0.90 | knn=6 | epsilon=0.03 | 0.22 | 0.12 | 0.29 | 0.33 | 0.01 | 0.01 | 0.01 | 0.01 |
| randomdirection=0.90 | knn=6 | epsilon=0.04 | 0.22 | 0.09 | 0.34 | 0.27 | 0.01 | 0.01 | 0.04 | 0.02 |
| randomdirection=0.90 | knn=6 | epsilon=0.05 | 0.10 | 0.06 | 0.33 | 0.30 | 0.05 | 0.04 | 0.06 | 0.07 |
| randomdirection=0.90 | knn=8 | epsilon=0.01 | 0.17 | 0.12 | 0.22 | 0.27 | 0.01 | 0.06 | 0.06 | 0.09 |
| randomdirection=0.90 | knn=8 | epsilon=0.02 | 0.19 | 0.09 | 0.24 | 0.30 | 0.01 | 0.07 | 0.08 | 0.03 |
| randomdirection=0.95 | knn=2 | epsilon=0.01 | 0.23 | 0.12 | 0.30 | 0.30 | 0.02 | 0.01 | 0.01 | 0.02 |
| randomdirection=0.95 | knn=2 | epsilon=0.02 | 0.22 | 0.11 | 0.29 | 0.29 | 0.03 | 0.02 | 0.04 | 0.02 |
| randomdirection=0.95 | knn=2 | epsilon=0.03 | 0.16 | 0.13 | 0.20 | 0.27 | 0.01 | 0.10 | 0.09 | 0.03 |
| randomdirection=0.95 | knn=2 | epsilon=0.04 | 0.27 | 0.09 | 0.23 | 0.28 | 0.01 | 0.06 | 0.02 | 0.03 |
| randomdirection=0.95 | knn=2 | epsilon=0.05 | 0.23 | 0.13 | 0.28 | 0.32 | 0.01 | 0.01 | 0.02 | 0.01 |
| randomdirection=0.95 | knn=4 | epsilon=0.01 | 0.04 | 0.20 | 0.20 | 0.30 | 0.07 | 0.09 | 0.08 | 0.02 |
| randomdirection=0.95 | knn=4 | epsilon=0.02 | 0.05 | 0.23 | 0.22 | 0.28 | 0.11 | 0.02 | 0.07 | 0.03 |
| randomdirection=0.95 | knn=4 | epsilon=0.03 | 0.16 | 0.07 | 0.21 | 0.30 | 0.14 | 0.03 | 0.06 | 0.03 |
| randomdirection=0.95 | knn=4 | epsilon=0.04 | 0.24 | 0.14 | 0.31 | 0.29 | 0.01 | 0.01 | 0.01 | 0.01 |
| randomdirection=0.95 | knn=4 | epsilon=0.05 | 0.23 | 0.14 | 0.27 | 0.25 | 0.01 | 0.01 | 0.06 | 0.02 |
| randomdirection=0.95 | knn=6 | epsilon=0.01 | 0.15 | 0.17 | 0.32 | 0.27 | 0.01 | 0.02 | 0.02 | 0.03 |
| randomdirection=0.95 | knn=6 | epsilon=0.02 | 0.15 | 0.02 | 0.32 | 0.40 | 0.02 | 0.02 | 0.03 | 0.03 |
| randomdirection=0.95 | knn=6 | epsilon=0.03 | 0.23 | 0.13 | 0.29 | 0.31 | 0.02 | 0.01 | 0.01 | 0.01 |
| randomdirection=0.95 | knn=6 | epsilon=0.04 | 0.24 | 0.14 | 0.29 | 0.29 | 0.01 | 0.01 | 0.02 | 0.02 |
| randomdirection=0.95 | knn=6 | epsilon=0.05 | 0.15 | 0.19 | 0.29 | 0.29 | 0.01 | 0.02 | 0.02 | 0.03 |
| randomdirection=0.95 | knn=8 | epsilon=0.01 | 0.21 | 0.20 | 0.26 | 0.21 | 0.02 | 0.02 | 0.03 | 0.05 |
| randomdirection=0.95 | knn=8 | epsilon=0.02 | 0.18 | 0.14 | 0.33 | 0.23 | 0.02 | 0.03 | 0.04 | 0.04 |

Results indicate that dummy features are given insignificant weights and original features are assigned higher weights indicating that the proposed algorithm is capable of identifying the irrelevant features.

We also evaluated the prediction accuracy of the proposed simulated annealing based algorithm. The class of 150 instances of the Iris plant is inferred by using the modified fuzzy inference algorithm based on the calculated feature weights. The average of classification accuracy was 96.67%. A comparison with some classification algorithms from literature is given in Table 4.3.

Table 4.3: Comparison of Proposed SA algorithm's performance with respect to existing results.

| Method | Proposed SA algorithm | Proposed GA algorithm | Hu's Learning Algorithm | Simple-fuzzy-grid | Multi-rule-table | Pruning | GA-based |
|---|---|---|---|---|---|---|---|
| Classification Rate (%) | 96.67 | 96.25 | 96.00 | 96.67 | 94.67 | 93.33 | 94.67 |

### 4.1.2. Genetic Algorithm Results

We conducted similar analysis for the proposed GA based algorithm. We first introduced the dummy variables and determined the significance degrees of the features. We have conducted the tests for *crossover rate* = 0.95 and 0.99, number of neighbors, $k$=4 and 8, *mutation rate*= 0.07 and 0.06. Population size is taken constant as 50. The table below illustrates the feature weights assigned by GA on Iris data.

Table 4.4: Feature weights for Iris data computed by Genetic Algorithm.

| | | Feature Weights | real sepalLeng | real sepal width | real petal leng | real petal width | dummy1 | dummy2 | dummy3 | dummy4 |
|---|---|---|---|---|---|---|---|---|---|---|
| CrossoverRate=0.95 | knn=2 | MutationRate=0,06 | 0.06 | 0.07 | 0.12 | 0.21 | 0.13 | 0.17 | 0.16 | 0.09 |
| CrossoverRate=0.95 | knn=2 | MutationRate=0,08 | 0.02 | 0.17 | 0.23 | 0.24 | 0.02 | 0.11 | 0.19 | 0.02 |
| CrossoverRate=0.95 | knn=8 | MutationRate=0,06 | 0.23 | 0.21 | 0.16 | 0.23 | 0.02 | 0.07 | 0.00 | 0.07 |
| CrossoverRate=0.95 | knn=8 | MutationRate=0,08 | 0.23 | 0.21 | 0.16 | 0.23 | 0.02 | 0.07 | 0.00 | 0.07 |
| CrossoverRate=0.99 | knn=2 | MutationRate=0,06 | 0.17 | 0.29 | 0.15 | 0.09 | 0.04 | 0.02 | 0.19 | 0.04 |
| CrossoverRate=0.99 | knn=2 | MutationRate=0,08 | 0.16 | 0.21 | 0.10 | 0.16 | 0.04 | 0.12 | 0.22 | 0.01 |
| CrossoverRate=0.99 | knn=8 | MutationRate=0,06 | 0.23 | 0.18 | 0.16 | 0.25 | 0.05 | 0.05 | 0.03 | 0.06 |
| CrossoverRate=0.99 | knn=8 | MutationRate=0,08 | 0.05 | 0.29 | 0.30 | 0.08 | 0.08 | 0.06 | 0.14 | 0.01 |

Other issue that is to be checked is the prediction accuracy of the algorithm. We have checked for the corresponding values of *crossover, k-nn* and *mutation rate*. It can be said that there is an increase in the prediction accuracy compared to SA results. The results can be seen in Table 4.5.

Table 4.5: Prediction accuracies of Iris Data computed by Genetic Algorithm.

| | | Feature Weights | Number of Instances Predicted Correctly | Accuracy (%) |
|---|---|---|---|---|
| CrossoverRate=0.95 | knn=2 | MutationRate=0,06 | 144 | 0.96 |
| CrossoverRate=0.95 | knn=2 | MutationRate=0,08 | 145 | 0.97 |
| CrossoverRate=0.95 | knn=8 | MutationRate=0,06 | 145 | 0.97 |
| CrossoverRate=0.95 | knn=8 | MutationRate=0,08 | 144 | 0.96 |
| CrossoverRate=0.99 | knn=2 | MutationRate=0,06 | 143 | 0.95 |
| CrossoverRate=0.99 | knn=2 | MutationRate=0,08 | 145 | 0.97 |
| CrossoverRate=0.99 | knn=8 | MutationRate=0,06 | 145 | 0.97 |
| CrossoverRate=0.99 | knn=8 | MutationRate=0,08 | 144 | 0.96 |

## 4.2. CONCRETE COMPRESSIVE STRENGTH DATA

The second benchmark data used was the concrete compressive strength data from the UCI Machine Learning Repository since it is not a classification data set but a regression data set like the determinants of innovation data. In this data set, there are 1030 instances and nine attributes, where one of them is the real valued output of concrete compressive strength in megapascals. Concrete data includes eight input attributes, which consist of the weights of seven different components of the concrete in kilograms in an $m^3$ mixture and age of the concrete in days ranging from 1 to 365. The aforementioned seven components are cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate and fine aggregate. Similar to the Iris data, we again created four dummy variables for components. The dummy variables were generated according to the correlation coefficients of attributes so that they resemble three of the components, namely, cement, superplasticizer, blast furnace slag and the age. These attributes are the ones with the highest correlation. More detailed information about the properties of data can be found on Table 4.6 (UCI Mach. Lrn. Repo.).

Table 4.6: Properties of Concrete Compressive Strength data.

| Attribute | Minimum | Maximum | Mean | Std. Dev. | Class Correlation |
|---|---|---|---|---|---|
| Cement: | 10.00 | 540.00 | 281.17 | 104.51 | 0.50 |
| Blast Furnace Slag: | 0.00 | 359.40 | 73.90 | 86.28 | 0.14 |
| Fly Ash: | 0.00 | 200.10 | 54.19 | 64.00 | -0.11 |
| Water: | 121.75 | 247.10 | 181.57 | 21.36 | -0.29 |
| Superplasticizer: | 0.00 | 32.20 | 6.20 | 5.97 | 0.37 |
| Coarse Aggregate: | 801.00 | 1145.00 | 972.92 | 77.75 | -0.17 |
| Fine Aggregate: | 594.00 | 992.60 | 773.58 | 80.18 | -0.17 |
| Age: | 1.00 | 365.00 | 45.66 | 63.17 | 0.33 |

We conducted the same analysis as we did for the iris data. First we will present the results of the analysis corresponding to the proposed simulated annealing based algorithm and later we will discuss the results of the GA based algorithm.

### 4.2.1. Simulated Annealing Results

Table 4.7: Feature weights of Concrete data computed by SA.

| | | Weights | Cement | Blast Furnace Slag | Fly Ash | Water | Superplasti cizer | Coarse Aggregate | Fine Aggregate | Age (day) | Dummy 1 superplast icizer | Dummy 2 coarse aggregate | Dummy 3 Fine aggregate | Dummy 4 age-day |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| knn=2 | Eps=0,01 | RndDrct=0,75 | 0.22 | 0.05 | 0.04 | 0.12 | 0.17 | 0.08 | 0.08 | 0.22 | 0.01 | 0.01 | 0.01 | 0.01 |
| knn=2 | Eps=0,01 | RndDrct=0,85 | 0.22 | 0.05 | 0.04 | 0.12 | 0.16 | 0.08 | 0.08 | 0.23 | 0.01 | 0.01 | 0.01 | 0.01 |
| knn=2 | Eps=0,02 | RndDrct=0,75 | 0.21 | 0.04 | 0.07 | 0.13 | 0.15 | 0.08 | 0.08 | 0.15 | 0.01 | 0.02 | 0.02 | 0.02 |
| knn=2 | Eps=0,02 | RndDrct=0,85 | 0.22 | 0.06 | 0.04 | 0.13 | 0.16 | 0.09 | 0.07 | 0.17 | 0.01 | 0.01 | 0.01 | 0.04 |
| knn=8 | Eps=0,01 | RndDrct=0,75 | 0.23 | 0.05 | 0.04 | 0.13 | 0.17 | 0.08 | 0.08 | 0.18 | 0.01 | 0.02 | 0.01 | 0.01 |
| knn=8 | Eps=0,01 | RndDrct=0,85 | 0.23 | 0.06 | 0.04 | 0.13 | 0.17 | 0.08 | 0.08 | 0.18 | 0.01 | 0.01 | 0.01 | 0.01 |
| knn=8 | Eps=0,02 | RndDrct=0,75 | 0.22 | 0.06 | 0.04 | 0.13 | 0.18 | 0.09 | 0.07 | 0.14 | 0.03 | 0.01 | 0.01 | 0.01 |
| knn=8 | Eps=0,02 | RndDrct=0,85 | 0.21 | 0.05 | 0.04 | 0.12 | 0.15 | 0.07 | 0.09 | 0.20 | 0.01 | 0.01 | 0.02 | 0.02 |

For different values of k-nn =2 and 8, epsilon=0,01 and 0,02 and randomdirection =0,75 and 0,85, SA is implemented on Concrete data. Feature weights obtained can be seen in Table 4.7. These results show that determination of dummy variables is successful. Last 4 features have been assigned lower weights mostly and original features are weighted higher. As mentioned before, instead of classification method used for Iris data, real value prediction is made for Concrete data and Root Mean Square Error is calculated. Results can be seen below for different values of k-nn.

Table 4.8: RMSEs for Concrete data resulted by SA.

| | | Weights | RMSE |
|---|---|---|---|
| knn=2 | Eps=0,01 | RndDrct=0,75 | 14.39 |
| knn=2 | Eps=0,01 | RndDrct=0,85 | 12.95 |
| knn=2 | Eps=0,02 | RndDrct=0,75 | 13.63 |
| knn=2 | Eps=0,02 | RndDrct=0,85 | 13.57 |
| knn=8 | Eps=0,01 | RndDrct=0,75 | 12.79 |
| knn=8 | Eps=0,01 | RndDrct=0,85 | 15.29 |
| knn=8 | Eps=0,02 | RndDrct=0,75 | 12.64 |
| knn=8 | Eps=0,02 | RndDrct=0,85 | 14.12 |

### 4.2.2. Genetic Algorithm Results

Table 4.9: Feature weights of Concrete data computed by GA.

| Weights | Cement | Blast Furnace Slag | Fly Ash | Water | Superplasticizer | Coarse Aggregate | Fine Aggregate | Age (day) | Dummy 1 superplasticizer | Dummy 2 coarse aggregate | Dummy 3 Fine aggregate | Dummy 4 age |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| knn = 2 | 0,1682 | 0,1240 | 0,0629 | 0,0952 | 0,0595 | 0,1410 | 0,0119 | 0,1342 | 0,0612 | 0,0296 | 0,0374 | 0,0748 |
| knn = 3 | 0,1073 | 0,0761 | 0,1073 | 0,1522 | 0,1021 | 0,0294 | 0,1349 | 0,1003 | 0,0398 | 0,0675 | 0,0035 | 0,0796 |
| knn = 4 | 0,1045 | 0,2217 | 0,0229 | 0,1341 | 0,0102 | 0,0740 | 0,0671 | 0,1318 | 0,1535 | 0,0115 | 0,0536 | 0,0153 |
| knn = 5 | 0,1157 | 0,1253 | 0,0988 | 0,1060 | 0,0964 | 0,0651 | 0,0651 | 0,1976 | 0,0627 | 0,0313 | 0,0193 | 0,0167 |
| knn = 6 | 0,1878 | 0,0084 | 0,0042 | 0,1751 | 0,0759 | 0,0591 | 0,1477 | 0,1730 | 0,0907 | 0,0338 | 0,0084 | 0,0359 |
| knn = 7 | 0,0917 | 0,0746 | 0,1085 | 0,1040 | 0,0901 | 0,0450 | 0,0657 | 0,0657 | 0,1096 | 0,1050 | 0,0978 | 0,0423 |
| knn = 8 | 0,0958 | 0,0639 | 0,0286 | 0,1445 | 0,0958 | 0,0504 | 0,1681 | 0,1513 | 0,0168 | 0,0050 | 0,0168 | 0,1630 |
| knn = 9 | 0,0880 | 0,0198 | 0,0651 | 0,1686 | 0,1475 | 0,0268 | 0,0061 | 0,1667 | 0,1209 | 0,0185 | 0,1337 | 0,0384 |
| knn = 10 | 0,1138 | 0,1124 | 0,0112 | 0,1161 | 0,1153 | 0,0583 | 0,0127 | 0,1356 | 0,0289 | 0,1363 | 0,0184 | 0,1411 |
| knn = 11 | 0,1235 | 0,0400 | 0,0400 | 0,1305 | 0,1145 | 0,0797 | 0,1151 | 0,0987 | 0,0607 | 0,0569 | 0,0541 | 0,0862 |
| knn = 12 | 0,1696 | 0,0356 | 0,0082 | 0,0074 | 0,0405 | 0,1105 | 0,0479 | 0,2173 | 0,1842 | 0,1105 | 0,0660 | 0,0023 |
| knn = 13 | 0,1409 | 0,0309 | 0,1513 | 0,0975 | 0,1019 | 0,1464 | 0,0318 | 0,0239 | 0,0255 | 0,1194 | 0,0446 | 0,0860 |
| knn = 14 | 0,1213 | 0,0542 | 0,0271 | 0,0800 | 0,0929 | 0,0477 | 0,1006 | 0,1200 | 0,1239 | 0,0452 | 0,1161 | 0,0710 |
| knn = 15 | 0,0534 | 0,0924 | 0,0505 | 0,0130 | 0,1443 | 0,1111 | 0,0058 | 0,1385 | 0,1097 | 0,0779 | 0,1169 | 0,0866 |

Results indicate us that there has to be a better parameter tuning. In general, dummy features are able to be determined but for some values of *knn*, dummy features are assigned high weights, which is an unwanted situation. For this reason, a full factorial analysis will be done. This analysis will include the results for changing values of *crossover rate, mutation rate, knn and population size.*

Prediction accuracy results for RMSEs are shown in Table 4.10. Minimum RMSE is provided by choosing knn as 5.

Table 4.10: RMSEs for Concrete data resulted by GA.

|  | knn = 2 | knn = 3 | knn = 4 | knn = 5 | knn = 6 | knn = 7 | knn = 8 |
|---|---|---|---|---|---|---|---|
| RMSE | 15,3216 | 14,9704 | 13,7273 | 13,2005 | 14,7050 | 14,5387 | 13,9667 |
|  | knn = 9 | knn = 10 | knn = 11 | knn = 12 | knn = 13 | knn = 14 | knn = 15 |
| RMSE | 14,7163 | 14,3023 | 13,5534 | 14,5093 | 14,8516 | 15,0113 | 15,5361 |

# C H A P T E R  5

## 5. THE SIGNIFICANCE DEGREES OF THE DETERMINANTS OF INNOVATION

### 5.1. INNOVATION DATA

In this thesis, data used for computational analysis is provided by the questionnaire done by Gurhan Gunday's Master of Science thesis (2007). A complex and detailed survey has been proposed to several firms and data collected by this questionnaire has been analyzed. By the factor analysis done, determinants of innovation have been selected and their values have been computed. Innovation performance of each firm has been calculated according to these determinants. Number of innovation determinants is originally 32 and turnover of innovation spending and inverse of centralization are also added as determinants. All the features except turnover of innovation spending are collected based on Likert scale that is between 1 and 5. Inverse of centralization is the complimentary of centralization, sum of these determinants equals 5. Original data set consists of data from 184 firms. However, since there are missing values for some of the firms, we have excluded such firms. Consequently, 89 firms have left for analysis.

Calculated innovativeness score of Gurhan Gunday is computed by using seven criteria which are:

- Ability to offer the new product before competitors,
- Percentage of new products in the existing product diversity,
- Number of new products and projects,
- Innovations developed about work processes and methods,
- Quality of new products and services,
- Number of patented or patentable innovations,
- Renewal of managerial structures and mentality due to the environment conditions.

These criteria are on a Likert scale of five points and by the statistical analysis done by SPSS and AMOS, innovativeness score, which is used as the actual score in this thesis, is obtained.

We have divided our data sets into 4 groups according to the determinants of inverse centralization and turnover of innovation spending. First data set includes turnover of innovation spending and excludes inverse of centralization. When the firms that have missing values are excluded, number of firms is reduced to 89. Second data set excludes both of them so number of missing values decreased. Number of firms for the second data set becomes 98. Firm numbers are the same for third and fourth data set correspondingly. Detailed information can be found in Table 5.1.

Table 5.1: Properties of data sets used.

| Data Sets | Properties | # of firms | # of determinants |
|---|---|---|---|
| 1 | With Turnover of innovation spending and Without inverse of centralization | 89 | 33 |
| 2 | Without Turnover of innovation spending and Without inverse of centralization | 98 | 32 |
| 3 | With Turnover of innovation spending and With inverse of centralization | 89 | 34 |
| 4 | Without Turnover of innovation spending and With inverse of centralization | 98 | 33 |

## 5.2. ANALYSIS OF THE INNOVATION DATA

Results have been collected for Simulated Annealing and Genetic Algorithm separately. Computational analysis for Simulated Annealing has been done for changing values of k nearest neighbor (knn) parameter and weight increment (epsilon) parameter. knn range is chosen between 2 and 20 and epsilon range between 0.01 and 0.20 with an increment of 0.01.

For Genetic Algorithm, knn has also been changed from 2 to 20. Besides knn, crossover and mutation rates have been changed in the ranges of 0.85 to 0.99 and 0.05 to 0.15 correspondingly, with a weight increment of 0.01 for both of them.

## 5.2.1. SIMULATED ANNEALING

For Data Set 1, the RMSEs that are obtained can be seen in Table 5.2 in detail.

| | epsilon=0,01 | 0,02 | 0,03 | 0,04 | 0,05 | 0,06 | 0,07 | 0,08 | 0,09 | 0,1 | 0,11 | 0,12 | 0,13 | 0,14 | 0,15 | 0,16 | 0,17 | 0,18 | 0,19 | 0,2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| knn=2 | 0,782 | 0,755 | 0,712 | 0,707 | 0,772 | 0,738 | 0,763 | 0,729 | 0,772 | 0,753 | 0,781 | 0,764 | 0,785 | 0,797 | 0,778 | 0,767 | 0,814 | 0,819 | 0,735 | 0,751 |
| knn=3 | 0,717 | 0,765 | 0,691 | 0,743 | 0,751 | 0,716 | 0,688 | 0,699 | 0,749 | 0,720 | 0,736 | 0,788 | 0,792 | 0,819 | 0,776 | 0,714 | 0,781 | 0,801 | 0,778 | 0,740 |
| knn=4 | 0,690 | 0,739 | 0,700 | 0,667 | 0,644 | 0,734 | 0,726 | 0,715 | 0,718 | 0,737 | 0,732 | 0,709 | 0,756 | 0,730 | 0,723 | 0,739 | 0,741 | 0,781 | 0,814 | 0,758 |
| knn=5 | 0,648 | 0,668 | 0,747 | 0,722 | 0,696 | 0,716 | 0,714 | 0,722 | 0,650 | 0,727 | 0,753 | 0,696 | 0,710 | 0,781 | 0,737 | 0,761 | 0,761 | 0,745 | 0,726 | 0,754 |
| knn=6 | 0,683 | 0,689 | 0,736 | 0,685 | 0,712 | 0,686 | 0,699 | 0,725 | 0,690 | 0,665 | 0,714 | 0,722 | 0,698 | 0,759 | 0,753 | 0,720 | 0,739 | 0,705 | 0,754 | 0,690 |
| knn=7 | 0,651 | 0,666 | 0,720 | 0,713 | 0,703 | 0,688 | 0,698 | 0,703 | 0,720 | 0,680 | 0,719 | 0,701 | 0,719 | 0,724 | 0,736 | 0,726 | 0,693 | 0,707 | 0,739 | 0,738 |
| knn=8 | 0,641 | 0,665 | 0,686 | 0,683 | 0,693 | 0,688 | 0,696 | 0,692 | 0,685 | 0,689 | 0,690 | 0,707 | 0,717 | 0,735 | 0,732 | 0,724 | 0,747 | 0,716 | 0,763 | 0,746 |
| knn=9 | 0,653 | 0,680 | 0,666 | 0,703 | 0,689 | 0,698 | 0,700 | 0,692 | 0,679 | 0,697 | 0,712 | 0,722 | 0,717 | 0,713 | 0,691 | 0,723 | 0,672 | 0,728 | 0,714 | 0,747 |
| knn=10 | 0,674 | 0,663 | 0,678 | 0,723 | 0,696 | 0,690 | 0,689 | 0,697 | 0,686 | 0,689 | 0,703 | 0,710 | 0,724 | 0,684 | 0,732 | 0,625 | 0,742 | 0,742 | 0,730 | 0,735 |
| knn=11 | 0,632 | 0,663 | 0,690 | 0,684 | 0,701 | 0,692 | 0,690 | 0,674 | 0,689 | 0,709 | 0,682 | 0,681 | 0,701 | 0,697 | 0,711 | 0,737 | 0,714 | 0,734 | 0,711 | 0,717 |
| knn=12 | 0,632 | 0,657 | 0,701 | 0,682 | 0,697 | 0,692 | 0,677 | 0,680 | 0,706 | 0,684 | 0,694 | 0,712 | 0,705 | 0,724 | 0,701 | 0,700 | 0,718 | 0,697 | 0,710 | 0,709 |
| knn=13 | 0,662 | 0,634 | 0,645 | 0,693 | 0,678 | 0,676 | 0,687 | 0,688 | 0,686 | 0,678 | 0,695 | 0,696 | 0,738 | 0,726 | 0,718 | 0,712 | 0,711 | 0,727 | 0,732 | 0,724 |
| knn=14 | 0,643 | 0,648 | 0,681 | 0,686 | 0,688 | 0,704 | 0,668 | 0,686 | 0,694 | 0,693 | 0,705 | 0,731 | 0,695 | 0,708 | 0,727 | 0,721 | 0,674 | 0,722 | 0,694 | 0,728 |
| knn=15 | 0,663 | 0,644 | 0,664 | 0,670 | 0,664 | 0,687 | 0,616 | 0,723 | 0,685 | 0,700 | 0,674 | 0,736 | 0,736 | 0,747 | 0,699 | 0,739 | 0,712 | 0,723 | 0,698 | 0,756 |
| knn=16 | 0,646 | 0,676 | 0,674 | 0,668 | 0,666 | 0,631 | 0,693 | 0,691 | 0,726 | 0,683 | 0,700 | 0,713 | 0,708 | 0,701 | 0,759 | 0,735 | 0,717 | 0,678 | 0,696 | 0,723 |
| knn=17 | 0,637 | 0,669 | 0,698 | 0,705 | 0,688 | 0,689 | 0,684 | 0,700 | 0,692 | 0,678 | 0,698 | 0,710 | 0,740 | 0,694 | 0,679 | 0,711 | 0,719 | 0,714 | 0,721 | 0,715 |
| knn=18 | 0,645 | 0,661 | 0,685 | 0,682 | 0,665 | 0,692 | 0,690 | 0,700 | 0,699 | 0,715 | 0,713 | 0,704 | 0,711 | 0,690 | 0,714 | 0,711 | 0,723 | 0,712 | 0,728 | 0,713 |
| knn=19 | 0,649 | 0,609 | 0,662 | 0,678 | 0,672 | 0,682 | 0,683 | 0,689 | 0,690 | 0,695 | 0,708 | 0,712 | 0,717 | 0,721 | 0,710 | 0,717 | 0,706 | 0,716 | 0,718 | 0,714 |
| knn=20 | 0,650 | 0,627 | 0,669 | 0,695 | 0,688 | 0,697 | 0,695 | 0,705 | 0,695 | 0,697 | 0,695 | 0,717 | 0,698 | 0,736 | 0,720 | 0,710 | 0,682 | 0,710 | 0,722 | 0,710 |

Table 5.2: RMSEs for Data Set1 computed by SA.

| | epsilon=0,01 | 0,02 | 0,03 | 0,04 | 0,05 | 0,06 | 0,07 | 0,08 | 0,09 | 0,1 | 0,11 | 0,12 | 0,13 | 0,14 | 0,15 | 0,16 | 0,17 | 0,18 | 0,19 | 0,2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| knn=2 | 0,461 | 0,411 | 0,404 | 0,404 | 0,445 | 0,418 | 0,435 | 0,401 | 0,418 | 0,431 | 0,411 | 0,462 | 0,424 | 0,359 | 0,418 | 0,366 | 0,406 | 0,471 | 0,460 | 0,461 |
| knn=3 | 0,492 | 0,525 | 0,485 | 0,522 | 0,507 | 0,489 | 0,461 | 0,501 | 0,472 | 0,496 | 0,513 | 0,505 | 0,452 | 0,491 | 0,504 | 0,524 | 0,492 | 0,537 | 0,491 | 0,527 |
| knn=4 | 0,532 | 0,504 | 0,536 | 0,506 | 0,548 | 0,555 | 0,523 | 0,542 | 0,551 | 0,529 | 0,537 | 0,580 | 0,570 | 0,547 | 0,570 | 0,567 | 0,572 | 0,569 | 0,594 | 0,565 |
| knn=5 | 0,555 | 0,551 | 0,539 | 0,555 | 0,569 | 0,541 | 0,566 | 0,544 | 0,571 | 0,572 | 0,580 | 0,575 | 0,574 | 0,587 | 0,618 | 0,581 | 0,618 | 0,585 | 0,597 | 0,583 |
| knn=6 | 0,574 | 0,556 | 0,583 | 0,554 | 0,591 | 0,578 | 0,601 | 0,603 | 0,574 | 0,580 | 0,588 | 0,585 | 0,596 | 0,592 | 0,615 | 0,636 | 0,620 | 0,627 | 0,607 | 0,621 |
| knn=7 | 0,596 | 0,621 | 0,618 | 0,635 | 0,611 | 0,601 | 0,617 | 0,545 | 0,601 | 0,596 | 0,593 | 0,585 | 0,546 | 0,617 | 0,593 | 0,606 | 0,634 | 0,631 | 0,627 | 0,629 |
| knn=8 | 0,575 | 0,602 | 0,593 | 0,600 | 0,621 | 0,609 | 0,602 | 0,604 | 0,623 | 0,601 | 0,606 | 0,626 | 0,644 | 0,642 | 0,634 | 0,636 | 0,630 | 0,638 | 0,640 | 0,641 |
| knn=9 | 0,571 | 0,611 | 0,600 | 0,587 | 0,591 | 0,571 | 0,623 | 0,619 | 0,617 | 0,606 | 0,642 | 0,626 | 0,643 | 0,652 | 0,637 | 0,659 | 0,649 | 0,609 | 0,645 | 0,635 |
| knn=10 | 0,572 | 0,584 | 0,611 | 0,614 | 0,623 | 0,628 | 0,617 | 0,607 | 0,615 | 0,619 | 0,620 | 0,622 | 0,625 | 0,644 | 0,569 | 0,645 | 0,646 | 0,650 | 0,668 | 0,634 |
| knn=11 | 0,607 | 0,609 | 0,635 | 0,613 | 0,628 | 0,640 | 0,607 | 0,615 | 0,623 | 0,616 | 0,634 | 0,638 | 0,645 | 0,645 | 0,660 | 0,630 | 0,636 | 0,672 | 0,658 | 0,646 |
| knn=12 | 0,601 | 0,608 | 0,595 | 0,639 | 0,655 | 0,635 | 0,633 | 0,615 | 0,646 | 0,622 | 0,634 | 0,673 | 0,636 | 0,657 | 0,661 | 0,663 | 0,656 | 0,670 | 0,667 | 0,639 |
| knn=13 | 0,603 | 0,613 | 0,656 | 0,626 | 0,638 | 0,654 | 0,636 | 0,631 | 0,635 | 0,633 | 0,646 | 0,584 | 0,666 | 0,630 | 0,672 | 0,667 | 0,648 | 0,642 | 0,647 | 0,664 |
| knn=14 | 0,605 | 0,606 | 0,617 | 0,651 | 0,642 | 0,635 | 0,634 | 0,624 | 0,631 | 0,638 | 0,662 | 0,659 | 0,637 | 0,678 | 0,640 | 0,662 | 0,667 | 0,669 | 0,670 | 0,667 |
| knn=15 | 0,613 | 0,652 | 0,615 | 0,647 | 0,639 | 0,640 | 0,655 | 0,653 | 0,651 | 0,635 | 0,638 | 0,643 | 0,658 | 0,671 | 0,639 | 0,651 | 0,668 | 0,692 | 0,670 | 0,582 |
| knn=16 | 0,614 | 0,625 | 0,663 | 0,654 | 0,645 | 0,644 | 0,632 | 0,611 | 0,648 | 0,645 | 0,647 | 0,663 | 0,600 | 0,672 | 0,664 | 0,668 | 0,664 | 0,648 | 0,658 | 0,676 |
| knn=17 | 0,631 | 0,623 | 0,602 | 0,652 | 0,659 | 0,622 | 0,646 | 0,637 | 0,647 | 0,653 | 0,630 | 0,660 | 0,666 | 0,672 | 0,649 | 0,667 | 0,678 | 0,671 | 0,665 | 0,673 |
| knn=18 | 0,615 | 0,656 | 0,642 | 0,653 | 0,655 | 0,666 | 0,658 | 0,652 | 0,639 | 0,653 | 0,653 | 0,653 | 0,671 | 0,676 | 0,650 | 0,680 | 0,662 | 0,654 | 0,676 | 0,667 |
| knn=19 | 0,633 | 0,638 | 0,666 | 0,630 | 0,647 | 0,643 | 0,643 | 0,664 | 0,677 | 0,652 | 0,662 | 0,649 | 0,606 | 0,680 | 0,704 | 0,662 | 0,678 | 0,711 | 0,677 | 0,684 |
| knn=20 | 0,631 | 0,640 | 0,616 | 0,640 | 0,615 | 0,661 | 0,663 | 0,660 | 0,679 | 0,663 | 0,659 | 0,679 | 0,661 | 0,678 | 0,673 | 0,670 | 0,661 | 0,682 | 0,640 | 0,715 |

Table 5.3: RMSEs for Data Set2 computed by SA.

| | epsilon=0,01 | 0,02 | 0,03 | 0,04 | 0,05 | 0,06 | 0,07 | 0,08 | 0,09 | 0,1 | 0,11 | 0,12 | 0,13 | 0,14 | 0,15 | 0,16 | 0,17 | 0,18 | 0,19 | 0,2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| knn=2 | 0,413 | 0,469 | 0,420 | 0,455 | 0,429 | 0,424 | 0,417 | 0,419 | 0,393 | 0,385 | 0,417 | 0,448 | 0,424 | 0,454 | 0,461 | 0,430 | 0,510 | 0,395 | 0,453 | 0,493 |
| knn=3 | 0,495 | 0,533 | 0,533 | 0,525 | 0,513 | 0,498 | 0,501 | 0,477 | 0,489 | 0,505 | 0,555 | 0,536 | 0,538 | 0,530 | 0,540 | 0,554 | 0,561 | 0,537 | 0,501 | 0,546 |
| knn=4 | 0,507 | 0,546 | 0,580 | 0,592 | 0,562 | 0,542 | 0,536 | 0,534 | 0,545 | 0,578 | 0,562 | 0,554 | 0,580 | 0,616 | 0,594 | 0,563 | 0,634 | 0,583 | 0,622 | 0,615 |
| knn=5 | 0,573 | 0,585 | 0,559 | 0,571 | 0,567 | 0,602 | 0,549 | 0,593 | 0,600 | 0,582 | 0,556 | 0,626 | 0,612 | 0,614 | 0,648 | 0,628 | 0,609 | 0,626 | 0,664 | 0,645 |
| knn=6 | 0,560 | 0,588 | 0,581 | 0,609 | 0,595 | 0,613 | 0,620 | 0,629 | 0,631 | 0,610 | 0,618 | 0,650 | 0,621 | 0,651 | 0,640 | 0,624 | 0,626 | 0,665 | 0,609 | 0,661 |
| knn=7 | 0,563 | 0,594 | 0,560 | 0,576 | 0,574 | 0,600 | 0,607 | 0,591 | 0,632 | 0,621 | 0,612 | 0,654 | 0,635 | 0,626 | 0,612 | 0,679 | 0,611 | 0,647 | 0,662 | 0,533 |
| knn=8 | 0,611 | 0,582 | 0,602 | 0,596 | 0,635 | 0,634 | 0,645 | 0,637 | 0,643 | 0,626 | 0,639 | 0,638 | 0,658 | 0,637 | 0,645 | 0,690 | 0,646 | 0,666 | 0,678 | 0,620 |
| knn=9 | 0,570 | 0,584 | 0,622 | 0,616 | 0,657 | 0,634 | 0,635 | 0,642 | 0,643 | 0,650 | 0,659 | 0,677 | 0,644 | 0,682 | 0,652 | 0,659 | 0,659 | 0,644 | 0,692 | 0,655 |
| knn=10 | 0,587 | 0,569 | 0,637 | 0,624 | 0,636 | 0,659 | 0,647 | 0,651 | 0,652 | 0,655 | 0,662 | 0,675 | 0,649 | 0,660 | 0,678 | 0,680 | 0,674 | 0,682 | 0,652 | 0,669 |
| knn=11 | 0,577 | 0,617 | 0,642 | 0,636 | 0,660 | 0,654 | 0,649 | 0,658 | 0,662 | 0,670 | 0,681 | 0,645 | 0,646 | 0,672 | 0,676 | 0,646 | 0,680 | 0,667 | 0,654 | 0,673 |
| knn=12 | 0,581 | 0,599 | 0,602 | 0,646 | 0,669 | 0,662 | 0,645 | 0,623 | 0,665 | 0,667 | 0,690 | 0,657 | 0,669 | 0,680 | 0,564 | 0,651 | 0,676 | 0,668 | 0,679 | 0,654 |
| knn=13 | 0,589 | 0,571 | 0,624 | 0,659 | 0,661 | 0,660 | 0,653 | 0,647 | 0,688 | 0,670 | 0,670 | 0,675 | 0,668 | 0,698 | 0,684 | 0,663 | 0,691 | 0,678 | 0,660 | 0,676 |
| knn=14 | 0,606 | 0,622 | 0,679 | 0,666 | 0,654 | 0,645 | 0,652 | 0,678 | 0,673 | 0,671 | 0,667 | 0,633 | 0,693 | 0,653 | 0,685 | 0,733 | 0,677 | 0,647 | 0,688 | 0,691 |
| knn=15 | 0,604 | 0,624 | 0,640 | 0,647 | 0,654 | 0,662 | 0,657 | 0,664 | 0,688 | 0,677 | 0,665 | 0,670 | 0,680 | 0,686 | 0,689 | 0,681 | 0,673 | 0,569 | 0,686 | 0,671 |
| knn=16 | 0,601 | 0,603 | 0,649 | 0,641 | 0,653 | 0,671 | 0,589 | 0,681 | 0,712 | 0,693 | 0,700 | 0,685 | 0,697 | 0,687 | 0,687 | 0,700 | 0,690 | 0,690 | 0,702 | 0,705 |
| knn=17 | 0,619 | 0,645 | 0,664 | 0,666 | 0,627 | 0,668 | 0,658 | 0,669 | 0,684 | 0,662 | 0,690 | 0,694 | 0,673 | 0,678 | 0,699 | 0,697 | 0,696 | 0,698 | 0,697 | 0,686 |
| knn=18 | 0,624 | 0,588 | 0,657 | 0,668 | 0,650 | 0,664 | 0,673 | 0,674 | 0,673 | 0,690 | 0,660 | 0,695 | 0,729 | 0,696 | 0,672 | 0,709 | 0,684 | 0,693 | 0,691 | 0,676 |
| knn=19 | 0,608 | 0,616 | 0,649 | 0,671 | 0,667 | 0,682 | 0,680 | 0,676 | 0,675 | 0,678 | 0,690 | 0,687 | 0,692 | 0,710 | 0,697 | 0,688 | 0,709 | 0,697 | 0,700 | 0,698 |
| knn=20 | 0,615 | 0,593 | 0,650 | 0,653 | 0,670 | 0,606 | 0,669 | 0,676 | 0,680 | 0,689 | 0,684 | 0,726 | 0,694 | 0,691 | 0,680 | 0,698 | 0,732 | 0,682 | 0,699 | 0,713 |

Table 5.4: RMSEs for Data Set3 computed by SA.

| | eps=0,01 | 0,02 | 0,03 | 0,04 | 0,05 | 0,06 | 0,07 | 0,08 | 0,09 | 0,1 | 0,11 | 0,12 | 0,13 | 0,14 | 0,15 | 0,16 | 0,17 | 0,18 | 0,19 | 0,2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| knn=2 | 0,707 | 0,677 | 0,758 | 0,751 | 0,756 | 0,711 | 0,751 | 0,721 | 0,744 | 0,745 | 0,770 | 0,827 | 0,802 | 0,783 | 0,826 | 0,801 | 0,848 | 0,837 | 0,832 | 0,873 |
| knn=3 | 0,694 | 0,757 | 0,733 | 0,720 | 0,686 | 0,754 | 0,780 | 0,774 | 0,730 | 0,745 | 0,789 | 0,767 | 0,775 | 0,738 | 0,778 | 0,808 | 0,852 | 0,789 | 0,794 | 0,830 |
| knn=4 | 0,673 | 0,668 | 0,716 | 0,727 | 0,760 | 0,716 | 0,749 | 0,719 | 0,706 | 0,741 | 0,756 | 0,743 | 0,619 | 0,748 | 0,753 | 0,797 | 0,811 | 0,773 | 0,782 | 0,801 |
| knn=5 | 0,668 | 0,668 | 0,648 | 0,653 | 0,717 | 0,714 | 0,727 | 0,737 | 0,755 | 0,690 | 0,699 | 0,706 | 0,739 | 0,722 | 0,754 | 0,723 | 0,783 | 0,790 | 0,767 | 0,783 |
| knn=6 | 0,664 | 0,667 | 0,678 | 0,714 | 0,665 | 0,716 | 0,693 | 0,696 | 0,735 | 0,742 | 0,749 | 0,773 | 0,739 | 0,737 | 0,771 | 0,747 | 0,758 | 0,694 | 0,716 | 0,806 |
| knn=7 | 0,678 | 0,644 | 0,705 | 0,705 | 0,711 | 0,717 | 0,695 | 0,709 | 0,733 | 0,731 | 0,723 | 0,764 | 0,760 | 0,748 | 0,705 | 0,769 | 0,779 | 0,765 | 0,768 | 0,742 |
| knn=8 | 0,652 | 0,633 | 0,709 | 0,676 | 0,716 | 0,697 | 0,721 | 0,712 | 0,726 | 0,725 | 0,705 | 0,719 | 0,743 | 0,752 | 0,747 | 0,733 | 0,758 | 0,719 | 0,753 | 0,731 |
| knn=9 | 0,661 | 0,701 | 0,653 | 0,671 | 0,703 | 0,703 | 0,724 | 0,709 | 0,701 | 0,695 | 0,727 | 0,748 | 0,745 | 0,713 | 0,681 | 0,745 | 0,747 | 0,739 | 0,750 | 0,732 |
| knn=10 | 0,672 | 0,649 | 0,685 | 0,701 | 0,643 | 0,694 | 0,684 | 0,705 | 0,723 | 0,715 | 0,714 | 0,723 | 0,740 | 0,738 | 0,783 | 0,719 | 0,707 | 0,737 | 0,748 | 0,739 |
| knn=11 | 0,676 | 0,680 | 0,667 | 0,704 | 0,703 | 0,701 | 0,698 | 0,707 | 0,726 | 0,717 | 0,712 | 0,717 | 0,714 | 0,714 | 0,740 | 0,735 | 0,744 | 0,743 | 0,738 | 0,707 |
| knn=12 | 0,660 | 0,684 | 0,685 | 0,702 | 0,702 | 0,713 | 0,722 | 0,717 | 0,726 | 0,717 | 0,724 | 0,719 | 0,747 | 0,701 | 0,705 | 0,775 | 0,733 | 0,738 | 0,734 | 0,739 |
| knn=13 | 0,634 | 0,672 | 0,682 | 0,687 | 0,700 | 0,712 | 0,691 | 0,724 | 0,704 | 0,722 | 0,747 | 0,732 | 0,739 | 0,725 | 0,734 | 0,730 | 0,739 | 0,737 | 0,737 | 0,719 |
| knn=14 | 0,648 | 0,650 | 0,681 | 0,671 | 0,705 | 0,691 | 0,703 | 0,706 | 0,700 | 0,711 | 0,712 | 0,729 | 0,710 | 0,723 | 0,730 | 0,738 | 0,726 | 0,735 | 0,737 | 0,704 |
| knn=15 | 0,645 | 0,675 | 0,698 | 0,704 | 0,714 | 0,701 | 0,696 | 0,690 | 0,695 | 0,705 | 0,732 | 0,763 | 0,738 | 0,726 | 0,732 | 0,740 | 0,726 | 0,701 | 0,741 | 0,730 |
| knn=16 | 0,670 | 0,665 | 0,686 | 0,690 | 0,688 | 0,717 | 0,695 | 0,707 | 0,719 | 0,722 | 0,729 | 0,735 | 0,731 | 0,729 | 0,759 | 0,735 | 0,719 | 0,724 | 0,744 | 0,733 |
| knn=17 | 0,654 | 0,681 | 0,678 | 0,693 | 0,707 | 0,698 | 0,688 | 0,694 | 0,692 | 0,702 | 0,694 | 0,724 | 0,730 | 0,704 | 0,739 | 0,723 | 0,733 | 0,735 | 0,705 | 0,734 |
| knn=18 | 0,659 | 0,676 | 0,702 | 0,670 | 0,671 | 0,700 | 0,702 | 0,711 | 0,717 | 0,752 | 0,726 | 0,728 | 0,728 | 0,740 | 0,734 | 0,729 | 0,726 | 0,732 | 0,727 | 0,732 |
| knn=19 | 0,666 | 0,700 | 0,672 | 0,676 | 0,717 | 0,713 | 0,711 | 0,716 | 0,722 | 0,728 | 0,698 | 0,728 | 0,724 | 0,732 | 0,737 | 0,745 | 0,733 | 0,736 | 0,730 | 0,721 |
| knn=20 | 0,650 | 0,668 | 0,675 | 0,695 | 0,673 | 0,677 | 0,706 | 0,691 | 0,710 | 0,723 | 0,722 | 0,720 | 0,737 | 0,744 | 0,699 | 0,731 | 0,734 | 0,732 | 0,736 | 0,730 |

Table 5.5: RMSEs for Data Set 4 computed by SA.

As it can be seen from the RMSEs, data set that gives the minimum RMSE is the Set 3, where InnoHarCiro_Ratio and InvKult_Cen features are included in the data set. For Data Set 3, best RMSE is achieved with *knn=2* and *epsilon*=0.1 the feature weights computed for knn=2 and epsilon=0.1, are shown on Table 5.6. Note that there are only 21 features shown on table because the remaining 14 features' weights have been assigned as 0. For this reason, they are not included in the table.

Table 5.6: Feature weights of Data Set 3 obtained by SA.

| Attribute | 20 | 3 | 10 | 9 | 34 | 33 | 32 | 31 | 30 | 29 | 28 | 27 | 26 | 25 | 24 | 23 | 22 | 21 | 19 | 18 | 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | 0,102 | 0,096 | 0,090 | 0,083 | 0,072 | 0,066 | 0,061 | 0,057 | 0,052 | 0,049 | 0,045 | 0,041 | 0,038 | 0,034 | 0,030 | 0,026 | 0,022 | 0,018 | 0,010 | 0,006 | 0,002 |

According to the results, three most important determinants of innovation are quality in manufacturing strategies, organizational capital and reward system in organization culture.

### 5.2.2. GENETIC ALGORITHM

Similar to SA, we have also chosen Data Set 3 for Genetic Algorithm analysis. The results show that for *crossover rate* equals 0.86 and *mutation rate* equals to 0.13 and when *knn* is 2, best RSME, which is 0.360, is achieved. Table 5.7 illustrates the further details of the run.

Table 5.7: RSMEs for Data Set 3 by GA.

| Crossover = 0,86 | Mutation = 0.05 | 0,06 | 0,07 | 0,08 | 0,09 | 0,1 | 0,11 | 0,12 | 0,13 | 0,14 | 0,15 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| knn=2 | 0,373 | 0,370 | 0,392 | 0,371 | 0,388 | 0,401 | 0,371 | 0,378 | 0,360 | 0,373 | 0,389 |
| knn=3 | 0,449 | 0,450 | 0,424 | 0,449 | 0,454 | 0,461 | 0,435 | 0,454 | 0,442 | 0,457 | 0,455 |
| knn=4 | 0,505 | 0,494 | 0,505 | 0,481 | 0,485 | 0,504 | 0,496 | 0,507 | 0,505 | 0,494 | 0,505 |
| knn=5 | 0,516 | 0,528 | 0,526 | 0,532 | 0,519 | 0,525 | 0,516 | 0,528 | 0,526 | 0,532 | 0,519 |
| knn=6 | 0,542 | 0,518 | 0,547 | 0,531 | 0,542 | 0,549 | 0,525 | 0,545 | 0,534 | 0,539 | 0,549 |
| knn=7 | 0,554 | 0,554 | 0,546 | 0,558 | 0,543 | 0,552 | 0,557 | 0,555 | 0,545 | 0,550 | 0,544 |
| knn=8 | 0,565 | 0,560 | 0,564 | 0,556 | 0,563 | 0,552 | 0,559 | 0,560 | 0,557 | 0,552 | 0,551 |
| knn=9 | 0,558 | 0,570 | 0,565 | 0,561 | 0,559 | 0,568 | 0,563 | 0,574 | 0,567 | 0,576 | 0,565 |
| knn=10 | 0,583 | 0,582 | 0,575 | 0,578 | 0,590 | 0,576 | 0,574 | 0,566 | 0,579 | 0,584 | 0,578 |
| knn=11 | 0,567 | 0,586 | 0,583 | 0,583 | 0,569 | 0,579 | 0,579 | 0,587 | 0,578 | 0,585 | 0,581 |
| knn=12 | 0,576 | 0,590 | 0,576 | 0,584 | 0,575 | 0,585 | 0,575 | 0,580 | 0,581 | 0,572 | 0,580 |
| knn=13 | 0,577 | 0,585 | 0,581 | 0,586 | 0,592 | 0,580 | 0,584 | 0,586 | 0,586 | 0,586 | 0,592 |
| knn=14 | 0,596 | 0,583 | 0,589 | 0,588 | 0,591 | 0,591 | 0,588 | 0,591 | 0,591 | 0,588 | 0,591 |
| knn=15 | 0,600 | 0,593 | 0,596 | 0,588 | 0,600 | 0,594 | 0,591 | 0,591 | 0,590 | 0,583 | 0,589 |
| knn=16 | 0,597 | 0,602 | 0,597 | 0,598 | 0,592 | 0,593 | 0,595 | 0,593 | 0,604 | 0,591 | 0,598 |
| knn=17 | 0,604 | 0,596 | 0,592 | 0,596 | 0,597 | 0,604 | 0,596 | 0,592 | 0,596 | 0,597 | 0,604 |
| knn=18 | 0,596 | 0,596 | 0,602 | 0,601 | 0,598 | 0,596 | 0,596 | 0,602 | 0,601 | 0,598 | 0,596 |
| knn=19 | 0,603 | 0,606 | 0,603 | 0,604 | 0,608 | 0,603 | 0,606 | 0,603 | 0,604 | 0,608 | 0,603 |
| knn=20 | 0,612 | 0,602 | 0,614 | 0,602 | 0,607 | 0,601 | 0,612 | 0,602 | 0,614 | 0,602 | 0,607 |

Feature weights that are obtained for the run chosen above have been demonstrated below (Table 5.8). Most significant determinant is reward system in organization culture, which has been determined as third significant determinant by SA.

Table 5.8: Feature weights of Data Set 3 obtained by GA.

| Attribute | 10 | 6 | 13 | 29 | 3 | 34 | 4 | 22 | 31 | 25 | 24 | 33 | 1 | 23 | 21 | 7 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | 0,061 | 0,058 | 0,058 | 0,057 | 0,056 | 0,052 | 0,051 | 0,051 | 0,049 | 0,048 | 0,044 | 0,044 | 0,039 | 0,036 | 0,032 | 0,030 | 0,028 |
| Attribute | 27 | 9 | 30 | 18 | 8 | 2 | 17 | 19 | 12 | 32 | 15 | 28 | 5 | 26 | 11 | 14 | 16 |
| Weight | 0,027 | 0,020 | 0,020 | 0,019 | 0,018 | 0,015 | 0,014 | 0,013 | 0,013 | 0,012 | 0,010 | 0,009 | 0,007 | 0,006 | 0,003 | 0,001 | 0,001 |

## 5.3 REDUCTION of INNOVATION DETERMINANTS

We have conducted a narrowing analysis on the innovation determinants and aimed to determine the most significant features. The complete list of determinants of innovation is given below. Beside the determinants given in the list, ratio of innovation spending to the turnover and trend of innovation spending are also added and 32 innovation determinants are determined.

Table 5.9 List of Innovation Determinants

| INNOVATION DETERMINANTS | |
|---|---|
| Human Capital | Monitoring Outer Milieu |
| Social Capital | Monitoring Inner Milieu |
| Organizational Capital | Monitoring Technical Sources |
| Communication | Production Cost |
| Formalization | Production Flexibility |
| Centralization | Production Quality |
| Management Support | Market Dynamism |
| Work Discretion | Market Focus |
| Time Availability | R&D Collaboration |
| Reward System | Operational Collaboration |
| Internal Resistance | Vertical Collaboration |
| Internal Deficiency | Technology Strategies |
| Internal Limits | Marketing Strategies |
| External Difficulties | Innovation Spending |
| External Limits | Public Incentives |

Simulated Annealing and Genetic Algorithm methods have been applied on these 32 determinants and the number of determinants has been reduced to 9 in two stages. For Genetic Algorithm, in the first stage, 10 determinants which have been weighted 0 have been deleted from the list and in the second stage; GA has been applied on 22 determinants. In the second stage, 13 of 22 determinants have been weighted as zero so the final list has been composed of 9 determinants. These determinants and their corresponding weights are given in Table 5.10. RMSE for the last list is calculated as 0.39.

Table 5.10 Final Innovation Determinants by GA.

| INNOVATION DETERMINANTS | Weights |
|---|---|
| Formalization | 0.15 |
| Organizational Capital | 0.14 |
| Innovation Spending | 0.11 |
| Reward System | 0.11 |
| Organizational Capital | 0.11 |
| Market Dynamism | 0.11 |
| Internal Deficiency | 0.10 |
| Public Incentives | 0.09 |
| Social Capital | 0.08 |

A similar strategy is applied also for Simulated Annealing and the final list of 9 innovation determinants are listed below. RMSE for SA is 0.43.

Table 5.11 Final Innovation Determinants by SA.

| INNOVATION DETERMINANTS | Weights |
|---|---|
| Formalization | 0.27 |
| Market Dynamism | 0.20 |
| Innovation Spending | 0.12 |
| Reward System | 0.10 |
| Organizational Capital | 0.08 |
| Internal Deficiency | 0.08 |
| Operational Collaboration | 0.08 |
| Public Incentives | 0.05 |
| Internal Resistance | 0.02 |

Both GA and SA show that *formalization, innovation spending, organizational capital and reward system* are the most effective determinants of innovation.

There is %10 difference between GA and SA RMSE values and GA is better. In order to have a better understanding, the following graph shows comparison of the predicted and calculated innovation scores.

Figure 5.1: Simulated Annealing Results of 9 Features.
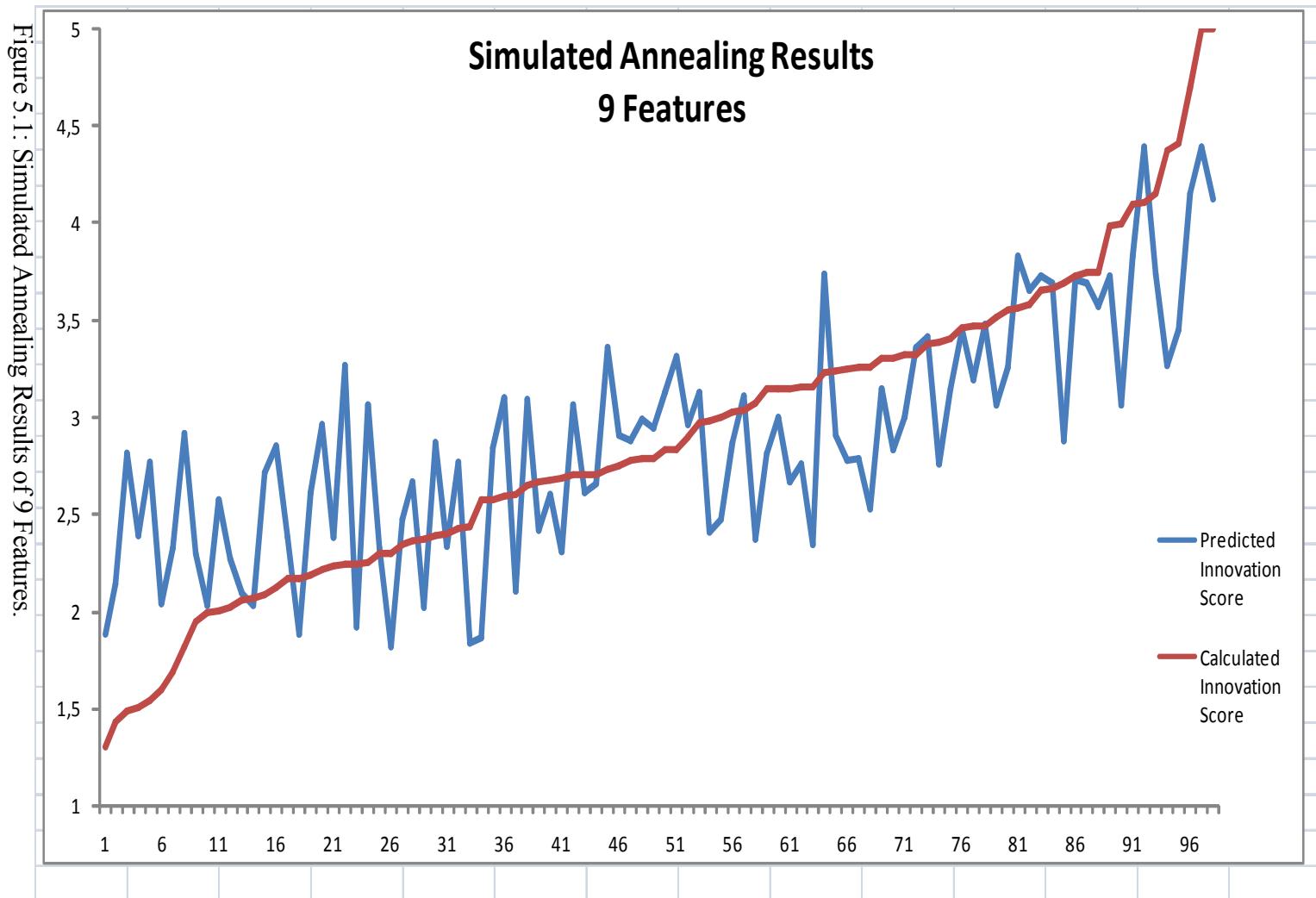
# C H A P T E R   6

## 6.  CONCLUSION & FUTURE WORK

The main aim of this thesis is to develop a DSS framework for innovation management and proposing solutions to the *feature weighting problem* which will be utilized at the core of the DSS. The *feature weighting problem* is a feature subset selection problem where instead of binary choices of features, they are weighted in the range of 1 and 0.

Two main aim of feature weighting problem is to determine relevant features and have good prediction accuracies. We proposed two different algorithms that are Simulated Annealing Algorithm and Genetic Algorithm. In order to check the efficiencies of the algorithms, we have implemented our algorithms on Iris Data and Concrete Compressive Strength Data. The results indicate that our proposed algorithms determine the relevant features accurately and have comparable prediction accuracies.

Innovation data has been analyzed in 4 different sets and Data Set 3 has been chosen as the best set. The results of proposed Simulated Annealing Algorithm and Genetic Algorithm have been demonstrated in Chapter 5.

Main contributions of this thesis have been as the followings:

- A framework for DSS for developing innovation policies.
- Simulated Annealing and Genetic Algorithm based feature weighting algorithms.
- Determination of significance levels of innovation determinants.

A major future work is to develop the entire DSS for innovation management that can suggest policies. This DSS can be put into practice and be a good and efficient innovation tool, by the advantage of lack of innovation tools.

## 7. BIBLIOGRAPHY

**[1]** Ahuja, G., Katila, R., (2001). Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study. Strategic Management Journal, 22: (3), 197–220.

**[2]** Avermaete, T., Viaene, J., Morgan, E.J., Crawford, N., (2003). Determinants of Innovation in Small Food Firms. European Journal of Innovation Management, 6, 8-17.

**[3]** Balasubramanian, N. & Lee, J. (2008) Firm age and innovation, Industrial and Corporate Change, 17(5)

**[4]** Barringer, B. R., Bluedorn, A.C., (1999). The relationship between corporate entrepreneurship and strategic management. Strategic Management Journal, 20, 421–444.

**[5]** Belderbos, R., (2001). Overseas innovations by Japanese firms: an analysis of patent and subsidiary data. Research Policy, 30, 313–332.

**[6]** Bezdek J. C., (1973). Fuzzy mathematics in pattern classification. Ph. D. thesis, Cornell University, Ithaca, NY

**[7]** Bezdek, J. C., (1981). Pattern Recognition with Fuzzy Objective Function Algorithms. Plenum Press.

**[8]** Bhattacharya, M., Bloch, H. (2004). "Determinants of Innovation." Small Business Economics. 22(2), 155-162.

**[9]** Bishop, P., Wiseman, N., (1999). External Ownership and Innovation in the United Kingdom. Applied Economics, 31, 443–450.

**[10]** Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J., (1984), Classification and Regression Trees, Wadsworth and Brooks.

**[11]** C.L. Blake and C.J. Merz (1998). Iris Data Set, UCI repository of machine learning databases. University of California. http://archive.ics.uci.edu/ml/datasets/Iris

**[12]** Cissell, M.J., (1987). Designing Effective Reward Systems. Compensation and Benefits Review, 19: (6), 49-55.

**[13]** Cohen, W.M., Levinthal, D.A., (1989). Innovation and Learning, the Two Faces of R&D. Economic Journal, 99, 569-96.

**[14]** Edvinson, L., (1997). Developing Intellectual Capital at Scandia. Long Range Planning, 30: (3), 366 - 373.

**[15]** Eisenberger, R., Armeli, S., (1997). Can salient reward increase creative performance without reducing intrinsic creative interest? Journal of Personality and Social Psychology, 72(3), 652-63.

**[16]** Fagerberg, J., Mowery, D. C., Nelson, R. R., (2004). The Oxford Handbook of Innovation. Oxford University Press, USA.

**[17]** Forman, G., (2003). An Extensive Empirical Study of Feature Selection Metrics for Text Classification. The Journal of Machine Learning Research, 3, 1289-1305.

**[18]** François, J.P., Favre, F., Negassi, S., (2002). Competence and organization: two drivers of innovation. A micro-econometric study. Economics of Innovation and New Technology, 11: (3), 249–270.

**[19]** Fry, A.S., (1987). The Post It Note: An Intrapreneurial Success. SAM Advanced Management Journal, 52: (3), 4-9.

**[20]** Galende, J., De la Fuente, J.M., (2003). Internal factors determining a firm's innovative behavior. Research Policy, 32, 715–736.

**[21]** Genetic Server/Library, http://www.nd.com/products/genetic/mutation.htm

**[22]** Geroski, P., (1995). Innovation and competitive advantage. OECD Working Paper, 52.

**[23]** Gunday, G., (2007). Innovation Models And Implementations At Firm Level In Manufacturing Industry. Master of Science Thesis, Sabanci University.

**[24]** Gunday, G., Ulusoy, G., Kılıç, K., Alpkan, L., (2008), An Integrated Innovation Model: How Innovations Are Born And What Are Their Impacts On Firm Performance?, Proceedings of 15th International Annual EurOMA Conference in Groningen, June 2008.

**[25]** Gunday, G., Ulusoy, G., Kılıç, K., Alpkan, L., (2008), Modeling Innovation: Determinants of Innovativeness and the Impact of Innovation on Firm Performance. Proceedings of ICMIT2008, Bangkok, Thailand.

**[26]** Guyon, I., Elisseeff, A. (2003), An Introduction to Variable and Feature Selection, Journal of Machine Learning Research, 3, 1157-1182.

**[27]** Guyon, I., Westo, J., Barnhill, S., Vapnik, V., (2002), Gene Selection for Cancer Classification Using Support Vector Machines, Machine Learning, 46(1), 389-422.

**[28]** Hall, B., H., and Mairesse, J., (2006). Empirical studies of innovation in the knowledge driven economy. United Nations University Working Paper, 28.

**[29]** Hall, M.A., (2000), Correlation-Based Feature Selection for Discrete and Numeric Class Machine Learning, Proceedings of the Seventeenth International Conference on Machine Learning, 359-366.

**[30]** Handels, H., Ross, T., (1999), Feature Selection for Optimized Skin Tumor Recognition Using Genetic Algorithms, Artificial Intelligence in Medicine, 16(3), 283-297.

**[31]** Hanna, M. M., Ahuja, R. K. & Winston, W. L. (2003). Developing spreadsheet-based decision support systems using VBA for Excel. Gainesville, USA: Innovation Center.

**[32]** Hitt, M.A., Hoskisson, R. E., Kim, H., (1997). International diversification: effects on innovation and firm performance in product-diversified firms. Academy of Management Journal, 40: (4), 767–798.

**[33]** Holland, J.H., (1975), Adaptation in Natural and Artificial Systems, University of Michigan Press, Ann Arbor.

**[34]** Hornsby, J.S., Kuratko, D.F., Zahra, S.A., (2002). Middle Managers' Perception of the Internal Environment for Corporate Entrepreneurship: Assessing a Measurement Scale. Journal of Business Venturing, 17, 253–273.

**[35]** Hype, make ideas work, http://www.hypeinnovation.com/

**[36]** Innovation Tool Box, http://innovation.si/2007/eng2.asp

**[37]** Innovation Tool, http://www.i10.org.uk/innovation_tool

**[38]** Jaumotte, F. and Pain, N., (2005). Innovation in the business sector. OECD Economics Department Working Papers, no. 459.

**[39]** Kappel T. A., Rubenstein A. H., (1999). Creativity in Design: The Contribution of Information Technology. IEEE Transactions on Engineering Management, 46, 132-143.

**[40]** Kenji, K., Rendell, L. A., (1992), A practical approach to feature selection, Proceedings of the Ninth International Workshop on Machine Learning, 249-256.

**[41]** Kirkpatrick, S., Gelatt, C.D., Vecchi, M.P., (1983). Optimization by Simulated Annealing, Science, 220 (4598), 671-680

**[42]** Koberg, C.S., Uhlenbruck, N., Sarason, Y., (1996). Facilitators of Organizational Innovation: The Role of Life-Cycle Stage. Journal of Business Venturing, 11, 133–149.

**[43]** Kohavi, R., John, G.H., (1997), Wrappers for Feature Subset Selection, Artificial Intelligence, 97(1-2), 273-324.

**[44]** Kononenko, I., (1994), Estimating Attributes: Analysis and Extensions of RELIEF," Machine Learning: ECML-94, 171-197.

**[45]** Law, M.H.C., Figueiredo, M.A.T., Jain, A.K. (2004), Simultaneous Feature Selection and Clustering Using Mixture Models, IEEE Transaction on Pattern Analysis and Machine Intelligence, 26(9), 1154-1166

**[46]** Lawler, E.A., Porter L.W., (1967). The Effect of Performance on Job Satisfaction. Industrial Relations, 7, 20-28.

**[47]** Liao, C., Chuang, S., (2006). Exploring the role of knowledge management for enhancing firm's innovation and performance. Proceedings of the 39th Hawaii International Conference on System Sciences.

**[48]** Liu, H., Jinyang, L., Wong, L., (2002), A Comparative Study On Feature Selection And Classification Methods Using Gene Expression Profiles And Proteomic Patterns, Genome Informatics, 13, 51-60.

**[49]** Liu, J. J., Cutler, G., Li, W., et. al., (2005), Multiclass Cancer Classification and Biomarker Discovery Using GA-Based Algorithms, Genetics and Population Analysis, 21(11), 2691-2697.

**[50]** Loch, C., L. Stein, C. Terwiesch, (1996). Measuring Development Performance in the Electronics Industry. Journal of Product Innovation Management, 13, 3-20.

**[51]** Love, J.H., Ashcroft, B., (1999). Market versus Corporate Structure in Plant-Level Innovation Performance. Small Business Economics, 13:(2), 97-109.

**[52]** Love, J.H., Ashcroft, B., Dunlop, S., (1996). Corporate structure, ownership and the likelihood of innovation. Applied Economics, 28, 737–746.

**[53]** Luecke, R., Katz, R., (2003). Managing creativity and innovation. MA: Harvard Business School Press, Boston.

**[54]** Mladeni´c, D., (2006). Feature Selection for Dimensionality Reduction, SLSFS, LNCS 3940, 84–102.

**[55]** Moenaert, R.K., Souder, W.E., De Meyer, A., Deschoolmeester, D., (1994). R&D-Marketing Integration Mechanisms, Communication Flows, and Innovation Success. Journal of Product Innovation Management, 11, 31-45.

**[56]** Montalvo, C., (2004). What Triggers Change and Innovation? Technovation, 26, 312–323.

**[57]** Oslo Manual, (2005). Proposed Guidelines for Collecting and Interpreting Technological Innovation Data.

**[58]** Rogers, M. (2004). Networks, Firm Size, and Innovation. Small Business Economics 22(2):141–153.

**[59]** Roper, S., Love, J.H., (2002). Innovation and export performance: evidence from the UK and German manufacturing plants. Research Policy, 31: (7), 1087-1102.

**[60]** Sáez, C. B., Marco, T. G., Arribas, E. H., (2002). Collaboration in R&D with universities and research centers: an empirical study of Spanish firms. R&D Management, 32: (4).

**[61]** Schwab, I., Kobsa, A., Koychev, I., (2000), Learning About User from Observation, Adaptive User Interfaces.

**[62]** Sorensen, J. B., T. Stuart. (2000). Aging, obsolescence, and organizational innovation. Admin. Sci. Quart. 45(1) 81-112.

**[63]** Souitaris, V., (2001). External communication determinants of innovation in the context of a newly industrialized country: a comparison of objective and perceptual results from Greece. Technovation, 21, 25–34.

**[64]** Souitaris, V., (2002). Technological trajectories as moderators of firm-level determinants of innovation. Research Policy, 31, 877–898.

**[65]** Subramaniam, M., Youndth, R. A., (2005). The Influence of Intellectual Capital On The Types Of Innovative Capabilities. Academy of Management Journal, 48: (3), 450–463.

**[66]** Sundbo, J. (1998). The Theory of Innovation: Entrepreneurs, Technology and Strategy, Edvard Elgar Publishing.

**[67]** Terwiesch, C., C. Loch, M. Niederkofler, (1996). Does Product Development Make a Difference?. INSEAD Working Paper, June.

**[68]** Tether, B. S., (2002). Who co-operates for innovation, and why: An empirical analysis. Research Policy, 31, 947-967.

**[69]** Vafaie, H., De Jong, K., (1992), Genetic Algorithms as a Tool for Feature Selection in Machine Learning, Proceedings, International Conference on Tools with Artificial Intelligence, 200-203.

**[70]** Walker, O.C., Ruekert R.W., (1987). Marketing's Role in the Implementation of Business Strategies: A Critical Review and Conceptual Framework. Journal of Marketing, 51: (July), 15–33.

**[71]** Yang, J., Honavar, V., (1998), Feature Subset Selection Using a Genetic Algorithm, IEEE Intelligent Systems & Their Applications, 13(2), 44-49.

**[72]** Yang, Y., Pedersen, J.O. (1997), A Comparative Study on Feature Selection in Text Categorization, Proceedings of the Fourteenth International Conference on Machine Learning, 412-420.

**[73]** Yeh, I-Cheng, (2007). Concrete Compressive Strength Data Set, UCI repository of machine learning databases. University of California.
http://archive.ics.uci.edu/ml/datasets/Concrete+Compressive+Strength

**[74]** Yong, S. K., (2006), Toward a Successful CRM: variable selection, sampling and ensemble, Decision Support Systems, 41(2), 542-553.

**[75]** Zadeh, L.A., (1975) The Concept of Linguistic Variable and its Application to Approximate Reasoning, Information Science, 8, 199-249.

## APPENDIX A - Iris Data

```
5.1,3.5,1.4,0.2,Iris-setosa
4.9,3.0,1.4,0.2,Iris-setosa
4.7,3.2,1.3,0.2,Iris-setosa
4.6,3.1,1.5,0.2,Iris-setosa
5.0,3.6,1.4,0.2,Iris-setosa
5.4,3.9,1.7,0.4,Iris-setosa
4.6,3.4,1.4,0.3,Iris-setosa
5.0,3.4,1.5,0.2,Iris-setosa
4.4,2.9,1.4,0.2,Iris-setosa
4.9,3.1,1.5,0.1,Iris-setosa
5.4,3.7,1.5,0.2,Iris-setosa
4.8,3.4,1.6,0.2,Iris-setosa
4.8,3.0,1.4,0.1,Iris-setosa
4.3,3.0,1.1,0.1,Iris-setosa
5.8,4.0,1.2,0.2,Iris-setosa
5.7,4.4,1.5,0.4,Iris-setosa
5.4,3.9,1.3,0.4,Iris-setosa
5.1,3.5,1.4,0.3,Iris-setosa
5.7,3.8,1.7,0.3,Iris-setosa
5.1,3.8,1.5,0.3,Iris-setosa
5.4,3.4,1.7,0.2,Iris-setosa
5.1,3.7,1.5,0.4,Iris-setosa
4.6,3.6,1.0,0.2,Iris-setosa
5.1,3.3,1.7,0.5,Iris-setosa
4.8,3.4,1.9,0.2,Iris-setosa
5.0,3.0,1.6,0.2,Iris-setosa
5.0,3.4,1.6,0.4,Iris-setosa
5.2,3.5,1.5,0.2,Iris-setosa
5.2,3.4,1.4,0.2,Iris-setosa
4.7,3.2,1.6,0.2,Iris-setosa
4.8,3.1,1.6,0.2,Iris-setosa
5.4,3.4,1.5,0.4,Iris-setosa
5.2,4.1,1.5,0.1,Iris-setosa
5.5,4.2,1.4,0.2,Iris-setosa
4.9,3.1,1.5,0.1,Iris-setosa
5.0,3.2,1.2,0.2,Iris-setosa
5.5,3.5,1.3,0.2,Iris-setosa
4.9,3.1,1.5,0.1,Iris-setosa
4.4,3.0,1.3,0.2,Iris-setosa
5.1,3.4,1.5,0.2,Iris-setosa
5.0,3.5,1.3,0.3,Iris-setosa
4.5,2.3,1.3,0.3,Iris-setosa
4.4,3.2,1.3,0.2,Iris-setosa
5.0,3.5,1.6,0.6,Iris-setosa
5.1,3.8,1.9,0.4,Iris-setosa
4.8,3.0,1.4,0.3,Iris-setosa
5.1,3.8,1.6,0.2,Iris-setosa
4.6,3.2,1.4,0.2,Iris-setosa
5.3,3.7,1.5,0.2,Iris-setosa
5.0,3.3,1.4,0.2,Iris-setosa
7.0,3.2,4.7,1.4,Iris-versicolor
6.4,3.2,4.5,1.5,Iris-versicolor
6.9,3.1,4.9,1.5,Iris-versicolor
5.5,2.3,4.0,1.3,Iris-versicolor
6.5,2.8,4.6,1.5,Iris-versicolor
5.7,2.8,4.5,1.3,Iris-versicolor
6.3,3.3,4.7,1.6,Iris-versicolor
```

```
4.9,2.4,3.3,1.0,Iris-versicolor
6.6,2.9,4.6,1.3,Iris-versicolor
5.2,2.7,3.9,1.4,Iris-versicolor
5.0,2.0,3.5,1.0,Iris-versicolor
5.9,3.0,4.2,1.5,Iris-versicolor
6.0,2.2,4.0,1.0,Iris-versicolor
6.1,2.9,4.7,1.4,Iris-versicolor
5.6,2.9,3.6,1.3,Iris-versicolor
6.7,3.1,4.4,1.4,Iris-versicolor
5.6,3.0,4.5,1.5,Iris-versicolor
5.8,2.7,4.1,1.0,Iris-versicolor
6.2,2.2,4.5,1.5,Iris-versicolor
5.6,2.5,3.9,1.1,Iris-versicolor
5.9,3.2,4.8,1.8,Iris-versicolor
6.1,2.8,4.0,1.3,Iris-versicolor
6.3,2.5,4.9,1.5,Iris-versicolor
6.1,2.8,4.7,1.2,Iris-versicolor
6.4,2.9,4.3,1.3,Iris-versicolor
6.6,3.0,4.4,1.4,Iris-versicolor
6.8,2.8,4.8,1.4,Iris-versicolor
6.7,3.0,5.0,1.7,Iris-versicolor
6.0,2.9,4.5,1.5,Iris-versicolor
5.7,2.6,3.5,1.0,Iris-versicolor
5.5,2.4,3.8,1.1,Iris-versicolor
5.5,2.4,3.7,1.0,Iris-versicolor
5.8,2.7,3.9,1.2,Iris-versicolor
6.0,2.7,5.1,1.6,Iris-versicolor
5.4,3.0,4.5,1.5,Iris-versicolor
6.0,3.4,4.5,1.6,Iris-versicolor
6.7,3.1,4.7,1.5,Iris-versicolor
6.3,2.3,4.4,1.3,Iris-versicolor
5.6,3.0,4.1,1.3,Iris-versicolor
5.5,2.5,4.0,1.3,Iris-versicolor
5.5,2.6,4.4,1.2,Iris-versicolor
6.1,3.0,4.6,1.4,Iris-versicolor
5.8,2.6,4.0,1.2,Iris-versicolor
5.0,2.3,3.3,1.0,Iris-versicolor
5.6,2.7,4.2,1.3,Iris-versicolor
5.7,3.0,4.2,1.2,Iris-versicolor
5.7,2.9,4.2,1.3,Iris-versicolor
6.2,2.9,4.3,1.3,Iris-versicolor
5.1,2.5,3.0,1.1,Iris-versicolor
5.7,2.8,4.1,1.3,Iris-versicolor
6.3,3.3,6.0,2.5,Iris-virginica
5.8,2.7,5.1,1.9,Iris-virginica
7.1,3.0,5.9,2.1,Iris-virginica
6.3,2.9,5.6,1.8,Iris-virginica
6.5,3.0,5.8,2.2,Iris-virginica
7.6,3.0,6.6,2.1,Iris-virginica
4.9,2.5,4.5,1.7,Iris-virginica
7.3,2.9,6.3,1.8,Iris-virginica
6.7,2.5,5.8,1.8,Iris-virginica
7.2,3.6,6.1,2.5,Iris-virginica
6.5,3.2,5.1,2.0,Iris-virginica
6.4,2.7,5.3,1.9,Iris-virginica
6.8,3.0,5.5,2.1,Iris-virginica
5.7,2.5,5.0,2.0,Iris-virginica
5.8,2.8,5.1,2.4,Iris-virginica
6.4,3.2,5.3,2.3,Iris-virginica
```

```
6.5,3.0,5.5,1.8,Iris-virginica
7.7,3.8,6.7,2.2,Iris-virginica
7.7,2.6,6.9,2.3,Iris-virginica
6.0,2.2,5.0,1.5,Iris-virginica
6.9,3.2,5.7,2.3,Iris-virginica
5.6,2.8,4.9,2.0,Iris-virginica
7.7,2.8,6.7,2.0,Iris-virginica
6.3,2.7,4.9,1.8,Iris-virginica
6.7,3.3,5.7,2.1,Iris-virginica
7.2,3.2,6.0,1.8,Iris-virginica
6.2,2.8,4.8,1.8,Iris-virginica
6.1,3.0,4.9,1.8,Iris-virginica
6.4,2.8,5.6,2.1,Iris-virginica
7.2,3.0,5.8,1.6,Iris-virginica
7.4,2.8,6.1,1.9,Iris-virginica
7.9,3.8,6.4,2.0,Iris-virginica
6.4,2.8,5.6,2.2,Iris-virginica
6.3,2.8,5.1,1.5,Iris-virginica
6.1,2.6,5.6,1.4,Iris-virginica
7.7,3.0,6.1,2.3,Iris-virginica
6.3,3.4,5.6,2.4,Iris-virginica
6.4,3.1,5.5,1.8,Iris-virginica
6.0,3.0,4.8,1.8,Iris-virginica
6.9,3.1,5.4,2.1,Iris-virginica
6.7,3.1,5.6,2.4,Iris-virginica
6.9,3.1,5.1,2.3,Iris-virginica
5.8,2.7,5.1,1.9,Iris-virginica
6.8,3.2,5.9,2.3,Iris-virginica
6.7,3.3,5.7,2.5,Iris-virginica
6.7,3.0,5.2,2.3,Iris-virginica
6.3,2.5,5.0,1.9,Iris-virginica
6.5,3.0,5.2,2.0,Iris-virginica
6.2,3.4,5.4,2.3,Iris-virginica
5.9,3.0,5.1,1.8,Iris-virginica
```

## APPENDIX B - Concrete Compressive Strength Data

| Cement (component 1)(kg in a m^3 mixture) | Blast Furnace Slag (component 2)(kg in a m^3 mixture) | Fly Ash (component 3)(kg in a m^3 mixture) | Water (component 4)(kg in a m^3 mixture) | Superplasticizer (component 5)(kg in a m^3 mixture) | Coarse Aggregate (component 6)(kg in a m^3 mixture) | Fine Aggregate (component 7)(kg in a m^3 mixture) | Age (day) | Concrete compressive strength(MPa, megapascals) |
|---|---|---|---|---|---|---|---|---|
| 540,0 | 0,0 | 0,0 | 162,0 | 2,5 | 1040,0 | 676,0 | 28 | 79,99 |
| 540,0 | 0,0 | 0,0 | 162,0 | 2,5 | 1055,0 | 676,0 | 28 | 61,89 |
| 332,5 | 142,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 270 | 40,27 |
| 332,5 | 142,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 365 | 41,05 |
| 198,6 | 132,4 | 0,0 | 192,0 | 0,0 | 978,4 | 825,5 | 360 | 44,30 |
| 266,0 | 114,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 90 | 47,03 |
| 380,0 | 95,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 365 | 43,70 |
| 380,0 | 95,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 28 | 36,45 |
| 266,0 | 114,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 28 | 45,85 |
| 475,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 28 | 39,29 |
| 198,6 | 132,4 | 0,0 | 192,0 | 0,0 | 978,4 | 825,5 | 90 | 38,07 |
| 198,6 | 132,4 | 0,0 | 192,0 | 0,0 | 978,4 | 825,5 | 28 | 28,02 |
| 427,5 | 47,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 270 | 43,01 |
| 190,0 | 190,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 90 | 42,33 |
| 304,0 | 76,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 28 | 47,81 |
| 380,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 90 | 52,91 |
| 139,6 | 209,4 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,9 | 90 | 39,36 |
| 342,0 | 38,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 365 | 56,14 |
| 380,0 | 95,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 90 | 40,56 |
| 475,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 180 | 42,62 |
| 427,5 | 47,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 180 | 41,84 |
| 139,6 | 209,4 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,9 | 28 | 28,24 |
| 139,6 | 209,4 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,9 | 3 | 8,06 |
| 139,6 | 209,4 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,9 | 180 | 44,21 |
| 380,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 365 | 52,52 |
| 380,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 270 | 53,30 |
| 380,0 | 95,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 270 | 41,15 |
| 342,0 | 38,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 180 | 52,12 |
| 427,5 | 47,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 28 | 37,43 |
| 475,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 7 | 38,60 |
| 304,0 | 76,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 365 | 55,26 |
| 266,0 | 114,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 365 | 52,91 |
| 198,6 | 132,4 | 0,0 | 192,0 | 0,0 | 978,4 | 825,5 | 180 | 41,72 |
| 475,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 270 | 42,13 |
| 190,0 | 190,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 365 | 53,69 |
| 237,5 | 237,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 270 | 38,41 |
| 237,5 | 237,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 28 | 30,08 |
| 332,5 | 142,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 90 | 37,72 |
| 475,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 90 | 42,23 |
| 237,5 | 237,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 180 | 36,25 |
| 342,0 | 38,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 90 | 50,46 |
| 427,5 | 47,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 365 | 43,70 |
| 237,5 | 237,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 365 | 39,00 |
| 380,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 180 | 53,10 |
| 427,5 | 47,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 90 | 41,54 |
| 427,5 | 47,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 7 | 35,08 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,9 | 3 | 15,05 |
| 380,0 | 95,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 180 | 40,76 |
| 237,5 | 237,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 7 | 26,26 |
| 380,0 | 95,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 7 | 32,82 |
| 332,5 | 142,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 180 | 39,78 |
| 190,0 | 190,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 180 | 46,93 |
| 237,5 | 237,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 90 | 33,12 |
| 304,0 | 76,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 90 | 49,19 |
| 139,6 | 209,4 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,9 | 7 | 14,59 |
| 198,6 | 132,4 | 0,0 | 192,0 | 0,0 | 978,4 | 825,5 | 7 | 14,64 |
| 475,0 | 0,0 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 365 | 41,93 |
| 198,6 | 132,4 | 0,0 | 192,0 | 0,0 | 978,4 | 825,5 | 3 | 9,13 |
| 304,0 | 76,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 180 | 50,95 |
| 332,5 | 142,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 28 | 33,02 |
| 304,0 | 76,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 270 | 54,38 |
| 266,0 | 114,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 270 | 51,73 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 971,0 | 850,6 | 3 | 9,87 |
| 190,0 | 190,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 270 | 50,66 |
| 266,0 | 114,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 180 | 48,70 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 342,0 | 38,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 270 | 55,06 |
| 139,6 | 209,4 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,9 | 360 | 44,70 |
| 332,5 | 142,5 | 0,0 | 228,0 | 0,0 | 932,0 | 594,0 | 7 | 30,28 |
| 190,0 | 190,0 | 0,0 | 228,0 | 0,0 | 932,0 | 670,0 | 28 | 40,86 |
| 485,0 | 0,0 | 0,0 | 146,0 | 0,0 | 1120,0 | 800,0 | 28 | 71,99 |
| 374,0 | 189,2 | 0,0 | 170,1 | 10,1 | 926,1 | 756,7 | 3 | 34,40 |
| 313,3 | 262,2 | 0,0 | 175,5 | 8,6 | 1046,9 | 611,8 | 3 | 28,80 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 3 | 33,40 |
| 425,0 | 106,3 | 0,0 | 151,4 | 18,6 | 936,0 | 803,7 | 3 | 36,30 |
| 375,0 | 93,8 | 0,0 | 126,6 | 23,4 | 852,1 | 992,6 | 3 | 29,00 |
| 475,0 | 118,8 | 0,0 | 181,1 | 8,9 | 852,1 | 781,5 | 3 | 37,80 |
| 469,0 | 117,2 | 0,0 | 137,8 | 32,2 | 852,1 | 840,5 | 3 | 40,20 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 3 | 33,40 |
| 388,6 | 97,1 | 0,0 | 157,9 | 12,1 | 852,1 | 925,7 | 3 | 28,10 |
| 531,3 | 0,0 | 0,0 | 141,8 | 28,2 | 852,1 | 893,7 | 3 | 41,30 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 3 | 33,40 |
| 318,8 | 212,5 | 0,0 | 155,7 | 14,3 | 852,1 | 880,4 | 3 | 25,20 |
| 401,8 | 94,7 | 0,0 | 147,4 | 11,4 | 946,8 | 852,1 | 3 | 41,10 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 3 | 35,30 |
| 323,7 | 282,8 | 0,0 | 183,8 | 10,3 | 942,7 | 659,9 | 3 | 28,30 |
| 379,5 | 151,2 | 0,0 | 153,9 | 15,9 | 1134,3 | 605,0 | 3 | 28,60 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 3 | 35,30 |
| 286,3 | 200,9 | 0,0 | 144,7 | 11,2 | 1004,6 | 803,7 | 3 | 24,40 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 3 | 35,30 |
| 439,0 | 177,0 | 0,0 | 186,0 | 11,1 | 884,9 | 707,9 | 3 | 39,30 |
| 389,9 | 189,0 | 0,0 | 145,9 | 22,0 | 944,7 | 755,8 | 3 | 40,60 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 3 | 35,30 |
| 337,9 | 189,0 | 0,0 | 174,9 | 9,5 | 944,7 | 755,8 | 3 | 24,10 |
| 374,0 | 189,2 | 0,0 | 170,1 | 10,1 | 926,1 | 756,7 | 7 | 46,20 |
| 313,3 | 262,2 | 0,0 | 175,5 | 8,6 | 1046,9 | 611,8 | 7 | 42,80 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 7 | 49,20 |
| 425,0 | 106,3 | 0,0 | 151,4 | 18,6 | 936,0 | 803,7 | 7 | 46,80 |
| 375,0 | 93,8 | 0,0 | 126,6 | 23,4 | 852,1 | 992,6 | 7 | 45,70 |
| 475,0 | 118,8 | 0,0 | 181,1 | 8,9 | 852,1 | 781,5 | 7 | 55,60 |
| 469,0 | 117,2 | 0,0 | 137,8 | 32,2 | 852,1 | 840,5 | 7 | 54,90 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 7 | 49,20 |
| 388,6 | 97,1 | 0,0 | 157,9 | 12,1 | 852,1 | 925,7 | 7 | 34,90 |
| 531,3 | 0,0 | 0,0 | 141,8 | 28,2 | 852,1 | 893,7 | 7 | 46,90 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 7 | 49,20 |
| 318,8 | 212,5 | 0,0 | 155,7 | 14,3 | 852,1 | 880,4 | 7 | 33,40 |
| 401,8 | 94,7 | 0,0 | 147,4 | 11,4 | 946,8 | 852,1 | 7 | 54,10 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 7 | 55,90 |
| 323,7 | 282,8 | 0,0 | 183,8 | 10,3 | 942,7 | 659,9 | 7 | 49,80 |
| 379,5 | 151,2 | 0,0 | 153,9 | 15,9 | 1134,3 | 605,0 | 7 | 47,10 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 7 | 55,90 |
| 286,3 | 200,9 | 0,0 | 144,7 | 11,2 | 1004,6 | 803,7 | 7 | 38,00 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 7 | 55,90 |
| 439,0 | 177,0 | 0,0 | 186,0 | 11,1 | 884,9 | 707,9 | 7 | 56,10 |
| 389,9 | 189,0 | 0,0 | 145,9 | 22,0 | 944,7 | 755,8 | 7 | 59,09 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 7 | 22,90 |
| 337,9 | 189,0 | 0,0 | 174,9 | 9,5 | 944,7 | 755,8 | 7 | 35,10 |
| 374,0 | 189,2 | 0,0 | 170,1 | 10,1 | 926,1 | 756,7 | 28 | 61,09 |
| 313,3 | 262,2 | 0,0 | 175,5 | 8,6 | 1046,9 | 611,8 | 28 | 59,80 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 28 | 60,29 |
| 425,0 | 106,3 | 0,0 | 151,4 | 18,6 | 936,0 | 803,7 | 28 | 61,80 |
| 375,0 | 93,8 | 0,0 | 126,6 | 23,4 | 852,1 | 992,6 | 28 | 56,70 |
| 475,0 | 118,8 | 0,0 | 181,1 | 8,9 | 852,1 | 781,5 | 28 | 68,30 |
| 469,0 | 117,2 | 0,0 | 137,8 | 32,2 | 852,1 | 840,5 | 28 | 66,90 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 28 | 60,29 |
| 388,6 | 97,1 | 0,0 | 157,9 | 12,1 | 852,1 | 925,7 | 28 | 50,70 |
| 531,3 | 0,0 | 0,0 | 141,8 | 28,2 | 852,1 | 893,7 | 28 | 56,40 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 28 | 60,29 |
| 318,8 | 212,5 | 0,0 | 155,7 | 14,3 | 852,1 | 880,4 | 28 | 55,50 |
| 401,8 | 94,7 | 0,0 | 147,4 | 11,4 | 946,8 | 852,1 | 28 | 68,50 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 28 | 71,30 |
| 323,7 | 282,8 | 0,0 | 183,8 | 10,3 | 942,7 | 659,9 | 28 | 74,70 |
| 379,5 | 151,2 | 0,0 | 153,9 | 15,9 | 1134,3 | 605,0 | 28 | 52,20 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 28 | 71,30 |
| 286,3 | 200,9 | 0,0 | 144,7 | 11,2 | 1004,6 | 803,7 | 28 | 67,70 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 28 | 71,30 |
| 439,0 | 177,0 | 0,0 | 186,0 | 11,1 | 884,9 | 707,9 | 28 | 66,00 |
| 389,9 | 189,0 | 0,0 | 145,9 | 22,0 | 944,7 | 755,8 | 28 | 74,50 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 28 | 71,30 |
| 337,9 | 189,0 | 0,0 | 174,9 | 9,5 | 944,7 | 755,8 | 28 | 49,90 |
| 374,0 | 189,2 | 0,0 | 170,1 | 10,1 | 926,1 | 756,7 | 56 | 63,40 |
| 313,3 | 262,2 | 0,0 | 175,5 | 8,6 | 1046,9 | 611,8 | 56 | 64,90 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 56 | 64,30 |
| 425,0 | 106,3 | 0,0 | 151,4 | 18,6 | 936,0 | 803,7 | 56 | 64,90 |
| 375,0 | 93,8 | 0,0 | 126,6 | 23,4 | 852,1 | 992,6 | 56 | 60,20 |
| 475,0 | 118,8 | 0,0 | 181,1 | 8,9 | 852,1 | 781,5 | 56 | 72,30 |
| 469,0 | 117,2 | 0,0 | 137,8 | 32,2 | 852,1 | 840,5 | 56 | 69,30 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 56 | 64,30 |
| 388,6 | 97,1 | 0,0 | 157,9 | 12,1 | 852,1 | 925,7 | 56 | 55,20 |
| 531,3 | 0,0 | 0,0 | 141,8 | 28,2 | 852,1 | 893,7 | 56 | 58,80 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 56 | 64,30 |
| 318,8 | 212,5 | 0,0 | 155,7 | 14,3 | 852,1 | 880,4 | 56 | 66,10 |
| 401,8 | 94,7 | 0,0 | 147,4 | 11,4 | 946,8 | 852,1 | 56 | 73,70 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 56 | 77,30 |
| 323,7 | 282,8 | 0,0 | 183,8 | 10,3 | 942,7 | 659,9 | 56 | 80,20 |
| 379,5 | 151,2 | 0,0 | 153,9 | 15,9 | 1134,3 | 605,0 | 56 | 54,90 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 56 | 77,30 |
| 286,3 | 200,9 | 0,0 | 144,7 | 11,2 | 1004,6 | 803,7 | 56 | 72,99 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 56 | 77,30 |
| 439,0 | 177,0 | 0,0 | 186,0 | 11,1 | 884,9 | 707,9 | 56 | 71,70 |
| 389,9 | 189,0 | 0,0 | 145,9 | 22,0 | 944,7 | 755,8 | 56 | 79,40 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 56 | 77,30 |
| 337,9 | 189,0 | 0,0 | 174,9 | 9,5 | 944,7 | 755,8 | 56 | 59,89 |
| 374,0 | 189,2 | 0,0 | 170,1 | 10,1 | 926,1 | 756,7 | 91 | 64,90 |
| 313,3 | 262,2 | 0,0 | 175,5 | 8,6 | 1046,9 | 611,8 | 91 | 66,60 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 91 | 65,20 |
| 425,0 | 106,3 | 0,0 | 151,4 | 18,6 | 936,0 | 803,7 | 91 | 66,70 |
| 375,0 | 93,8 | 0,0 | 126,6 | 23,4 | 852,1 | 992,6 | 91 | 62,50 |
| 475,0 | 118,8 | 0,0 | 181,1 | 8,9 | 852,1 | 781,5 | 91 | 74,19 |
| 469,0 | 117,2 | 0,0 | 137,8 | 32,2 | 852,1 | 840,5 | 91 | 70,70 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 91 | 65,20 |
| 388,6 | 97,1 | 0,0 | 157,9 | 12,1 | 852,1 | 925,7 | 91 | 57,60 |
| 531,3 | 0,0 | 0,0 | 141,8 | 28,2 | 852,1 | 893,7 | 91 | 59,20 |
| 425,0 | 106,3 | 0,0 | 153,5 | 16,5 | 852,1 | 887,1 | 91 | 65,20 |
| 318,8 | 212,5 | 0,0 | 155,7 | 14,3 | 852,1 | 880,4 | 91 | 68,10 |
| 401,8 | 94,7 | 0,0 | 147,4 | 11,4 | 946,8 | 852,1 | 91 | 75,50 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 91 | 79,30 |
| 379,5 | 151,2 | 0,0 | 153,9 | 15,9 | 1134,3 | 605,0 | 91 | 56,50 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 91 | 79,30 |
| 286,3 | 200,9 | 0,0 | 144,7 | 11,2 | 1004,6 | 803,7 | 91 | 76,80 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 91 | 79,30 |
| 439,0 | 177,0 | 0,0 | 186,0 | 11,1 | 884,9 | 707,9 | 91 | 73,30 |
| 389,9 | 189,0 | 0,0 | 145,9 | 22,0 | 944,7 | 755,8 | 91 | 82,60 |
| 362,6 | 189,0 | 0,0 | 164,9 | 11,6 | 944,7 | 755,8 | 91 | 79,30 |
| 337,9 | 189,0 | 0,0 | 174,9 | 9,5 | 944,7 | 755,8 | 91 | 67,80 |
| 222,4 | 0,0 | 96,7 | 189,3 | 4,5 | 967,1 | 870,3 | 3 | 11,58 |
| 222,4 | 0,0 | 96,7 | 189,3 | 4,5 | 967,1 | 870,3 | 14 | 24,45 |
| 222,4 | 0,0 | 96,7 | 189,3 | 4,5 | 967,1 | 870,3 | 28 | 24,89 |
| 222,4 | 0,0 | 96,7 | 189,3 | 4,5 | 967,1 | 870,3 | 56 | 29,45 |
| 222,4 | 0,0 | 96,7 | 189,3 | 4,5 | 967,1 | 870,3 | 100 | 40,71 |
| 233,8 | 0,0 | 94,6 | 197,9 | 4,6 | 947,0 | 852,2 | 3 | 10,38 |
| 233,8 | 0,0 | 94,6 | 197,9 | 4,6 | 947,0 | 852,2 | 14 | 22,14 |
| 233,8 | 0,0 | 94,6 | 197,9 | 4,6 | 947,0 | 852,2 | 28 | 22,84 |
| 233,8 | 0,0 | 94,6 | 197,9 | 4,6 | 947,0 | 852,2 | 56 | 27,66 |
| 233,8 | 0,0 | 94,6 | 197,9 | 4,6 | 947,0 | 852,2 | 100 | 34,56 |
| 194,7 | 0,0 | 100,5 | 165,6 | 7,5 | 1006,4 | 905,9 | 3 | 12,45 |
| 194,7 | 0,0 | 100,5 | 165,6 | 7,5 | 1006,4 | 905,9 | 14 | 24,99 |
| 194,7 | 0,0 | 100,5 | 165,6 | 7,5 | 1006,4 | 905,9 | 28 | 25,72 |
| 194,7 | 0,0 | 100,5 | 165,6 | 7,5 | 1006,4 | 905,9 | 56 | 33,96 |
| 194,7 | 0,0 | 100,5 | 165,6 | 7,5 | 1006,4 | 905,9 | 100 | 37,34 |
| 190,7 | 0,0 | 125,4 | 162,1 | 7,8 | 1090,0 | 804,0 | 3 | 15,04 |
| 190,7 | 0,0 | 125,4 | 162,1 | 7,8 | 1090,0 | 804,0 | 14 | 21,06 |
| 190,7 | 0,0 | 125,4 | 162,1 | 7,8 | 1090,0 | 804,0 | 28 | 26,40 |
| 190,7 | 0,0 | 125,4 | 162,1 | 7,8 | 1090,0 | 804,0 | 56 | 35,34 |
| 190,7 | 0,0 | 125,4 | 162,1 | 7,8 | 1090,0 | 804,0 | 100 | 40,57 |
| 212,1 | 0,0 | 121,6 | 180,3 | 5,7 | 1057,6 | 779,3 | 3 | 12,47 |
| 212,1 | 0,0 | 121,6 | 180,3 | 5,7 | 1057,6 | 779,3 | 14 | 20,92 |
| 212,1 | 0,0 | 121,6 | 180,3 | 5,7 | 1057,6 | 779,3 | 28 | 24,90 |
| 212,1 | 0,0 | 121,6 | 180,3 | 5,7 | 1057,6 | 779,3 | 56 | 34,20 |
| 212,1 | 0,0 | 121,6 | 180,3 | 5,7 | 1057,6 | 779,3 | 100 | 39,61 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 230,0 | 0,0 | 118,3 | 195,5 | 4,6 | 1029,4 | 758,6 | 3 | 10,03 |
| 230,0 | 0,0 | 118,3 | 195,5 | 4,6 | 1029,4 | 758,6 | 14 | 20,08 |
| 230,0 | 0,0 | 118,3 | 195,5 | 4,6 | 1029,4 | 758,6 | 28 | 24,48 |
| 230,0 | 0,0 | 118,3 | 195,5 | 4,6 | 1029,4 | 758,6 | 56 | 31,54 |
| 230,0 | 0,0 | 118,3 | 195,5 | 4,6 | 1029,4 | 758,6 | 100 | 35,34 |
| 190,3 | 0,0 | 125,2 | 161,9 | 9,9 | 1088,1 | 802,6 | 3 | 9,45 |
| 190,3 | 0,0 | 125,2 | 161,9 | 9,9 | 1088,1 | 802,6 | 14 | 22,72 |
| 190,3 | 0,0 | 125,2 | 161,9 | 9,9 | 1088,1 | 802,6 | 28 | 28,47 |
| 190,3 | 0,0 | 125,2 | 161,9 | 9,9 | 1088,1 | 802,6 | 56 | 38,56 |
| 190,3 | 0,0 | 125,2 | 161,9 | 9,9 | 1088,1 | 802,6 | 100 | 40,39 |
| 166,1 | 0,0 | 163,3 | 176,5 | 4,5 | 1058,6 | 780,1 | 3 | 10,76 |
| 166,1 | 0,0 | 163,3 | 176,5 | 4,5 | 1058,6 | 780,1 | 14 | 25,48 |
| 166,1 | 0,0 | 163,3 | 176,5 | 4,5 | 1058,6 | 780,1 | 28 | 21,54 |
| 166,1 | 0,0 | 163,3 | 176,5 | 4,5 | 1058,6 | 780,1 | 56 | 28,63 |
| 166,1 | 0,0 | 163,3 | 176,5 | 4,5 | 1058,6 | 780,1 | 100 | 33,54 |
| 168,0 | 42,1 | 163,8 | 121,8 | 5,7 | 1058,7 | 780,1 | 3 | 7,75 |
| 168,0 | 42,1 | 163,8 | 121,8 | 5,7 | 1058,7 | 780,1 | 14 | 17,82 |
| 168,0 | 42,1 | 163,8 | 121,8 | 5,7 | 1058,7 | 780,1 | 28 | 24,24 |
| 168,0 | 42,1 | 163,8 | 121,8 | 5,7 | 1058,7 | 780,1 | 56 | 32,85 |
| 168,0 | 42,1 | 163,8 | 121,8 | 5,7 | 1058,7 | 780,1 | 100 | 39,23 |
| 213,7 | 98,1 | 24,5 | 181,7 | 6,9 | 1065,8 | 785,4 | 3 | 18,00 |
| 213,7 | 98,1 | 24,5 | 181,7 | 6,9 | 1065,8 | 785,4 | 14 | 30,39 |
| 213,7 | 98,1 | 24,5 | 181,7 | 6,9 | 1065,8 | 785,4 | 28 | 45,71 |
| 213,7 | 98,1 | 24,5 | 181,7 | 6,9 | 1065,8 | 785,4 | 56 | 50,77 |
| 213,7 | 98,1 | 24,5 | 181,7 | 6,9 | 1065,8 | 785,4 | 100 | 53,90 |
| 213,8 | 98,1 | 24,5 | 181,7 | 6,7 | 1066,0 | 785,5 | 3 | 13,18 |
| 213,8 | 98,1 | 24,5 | 181,7 | 6,7 | 1066,0 | 785,5 | 14 | 17,84 |
| 213,8 | 98,1 | 24,5 | 181,7 | 6,7 | 1066,0 | 785,5 | 28 | 40,23 |
| 213,8 | 98,1 | 24,5 | 181,7 | 6,7 | 1066,0 | 785,5 | 56 | 47,13 |
| 213,8 | 98,1 | 24,5 | 181,7 | 6,7 | 1066,0 | 785,5 | 100 | 49,97 |
| 229,7 | 0,0 | 118,2 | 195,2 | 6,1 | 1028,1 | 757,6 | 3 | 13,36 |
| 229,7 | 0,0 | 118,2 | 195,2 | 6,1 | 1028,1 | 757,6 | 14 | 22,32 |
| 229,7 | 0,0 | 118,2 | 195,2 | 6,1 | 1028,1 | 757,6 | 28 | 24,54 |
| 229,7 | 0,0 | 118,2 | 195,2 | 6,1 | 1028,1 | 757,6 | 56 | 31,35 |
| 229,7 | 0,0 | 118,2 | 195,2 | 6,1 | 1028,1 | 757,6 | 100 | 40,86 |
| 238,1 | 0,0 | 94,1 | 186,7 | 7,0 | 949,9 | 847,0 | 3 | 19,93 |
| 238,1 | 0,0 | 94,1 | 186,7 | 7,0 | 949,9 | 847,0 | 14 | 25,69 |
| 238,1 | 0,0 | 94,1 | 186,7 | 7,0 | 949,9 | 847,0 | 28 | 30,23 |
| 238,1 | 0,0 | 94,1 | 186,7 | 7,0 | 949,9 | 847,0 | 56 | 39,59 |
| 238,1 | 0,0 | 94,1 | 186,7 | 7,0 | 949,9 | 847,0 | 100 | 44,30 |
| 250,0 | 0,0 | 95,7 | 187,4 | 5,5 | 956,9 | 861,2 | 3 | 13,82 |
| 250,0 | 0,0 | 95,7 | 187,4 | 5,5 | 956,9 | 861,2 | 14 | 24,92 |
| 250,0 | 0,0 | 95,7 | 187,4 | 5,5 | 956,9 | 861,2 | 28 | 29,22 |
| 250,0 | 0,0 | 95,7 | 187,4 | 5,5 | 956,9 | 861,2 | 56 | 38,33 |
| 250,0 | 0,0 | 95,7 | 187,4 | 5,5 | 956,9 | 861,2 | 100 | 42,35 |
| 212,5 | 0,0 | 100,4 | 159,3 | 8,7 | 1007,8 | 903,6 | 3 | 13,54 |
| 212,5 | 0,0 | 100,4 | 159,3 | 8,7 | 1007,8 | 903,6 | 14 | 26,31 |
| 212,5 | 0,0 | 100,4 | 159,3 | 8,7 | 1007,8 | 903,6 | 28 | 31,64 |
| 212,5 | 0,0 | 100,4 | 159,3 | 8,7 | 1007,8 | 903,6 | 56 | 42,55 |
| 212,5 | 0,0 | 100,4 | 159,3 | 8,7 | 1007,8 | 903,6 | 100 | 42,92 |
| 212,6 | 0,0 | 100,4 | 159,4 | 10,4 | 1003,8 | 903,8 | 3 | 13,33 |
| 212,6 | 0,0 | 100,4 | 159,4 | 10,4 | 1003,8 | 903,8 | 14 | 25,37 |
| 212,6 | 0,0 | 100,4 | 159,4 | 10,4 | 1003,8 | 903,8 | 28 | 37,40 |
| 212,6 | 0,0 | 100,4 | 159,4 | 10,4 | 1003,8 | 903,8 | 56 | 44,40 |
| 212,6 | 0,0 | 100,4 | 159,4 | 10,4 | 1003,8 | 903,8 | 100 | 47,74 |
| 212,0 | 0,0 | 124,8 | 159,0 | 7,8 | 1085,4 | 799,5 | 3 | 19,52 |
| 212,0 | 0,0 | 124,8 | 159,0 | 7,8 | 1085,4 | 799,5 | 14 | 31,35 |
| 212,0 | 0,0 | 124,8 | 159,0 | 7,8 | 1085,4 | 799,5 | 28 | 38,50 |
| 212,0 | 0,0 | 124,8 | 159,0 | 7,8 | 1085,4 | 799,5 | 56 | 45,08 |
| 212,0 | 0,0 | 124,8 | 159,0 | 7,8 | 1085,4 | 799,5 | 100 | 47,82 |
| 231,8 | 0,0 | 121,6 | 174,0 | 6,7 | 1056,4 | 778,5 | 3 | 15,44 |
| 231,8 | 0,0 | 121,6 | 174,0 | 6,7 | 1056,4 | 778,5 | 14 | 26,77 |
| 231,8 | 0,0 | 121,6 | 174,0 | 6,7 | 1056,4 | 778,5 | 28 | 33,73 |
| 231,8 | 0,0 | 121,6 | 174,0 | 6,7 | 1056,4 | 778,5 | 56 | 42,70 |
| 231,8 | 0,0 | 121,6 | 174,0 | 6,7 | 1056,4 | 778,5 | 100 | 45,84 |
| 251,4 | 0,0 | 118,3 | 188,5 | 5,8 | 1028,4 | 757,7 | 3 | 17,22 |
| 251,4 | 0,0 | 118,3 | 188,5 | 5,8 | 1028,4 | 757,7 | 14 | 29,93 |
| 251,4 | 0,0 | 118,3 | 188,5 | 5,8 | 1028,4 | 757,7 | 28 | 29,65 |
| 251,4 | 0,0 | 118,3 | 188,5 | 5,8 | 1028,4 | 757,7 | 56 | 36,97 |
| 251,4 | 0,0 | 118,3 | 188,5 | 5,8 | 1028,4 | 757,7 | 100 | 43,58 |
| 251,4 | 0,0 | 118,3 | 188,5 | 6,4 | 1028,4 | 757,7 | 3 | 13,12 |
| 251,4 | 0,0 | 118,3 | 188,5 | 6,4 | 1028,4 | 757,7 | 14 | 24,43 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 251,4 | 0,0 | 118,3 | 188,5 | 6,4 | 1028,4 | 757,7 | 28 | 32,66 |
| 251,4 | 0,0 | 118,3 | 188,5 | 6,4 | 1028,4 | 757,7 | 56 | 36,64 |
| 251,4 | 0,0 | 118,3 | 188,5 | 6,4 | 1028,4 | 757,7 | 100 | 44,21 |
| 181,4 | 0,0 | 167,0 | 169,6 | 7,6 | 1055,6 | 777,8 | 3 | 13,62 |
| 181,4 | 0,0 | 167,0 | 169,6 | 7,6 | 1055,6 | 777,8 | 14 | 21,60 |
| 181,4 | 0,0 | 167,0 | 169,6 | 7,6 | 1055,6 | 777,8 | 28 | 27,77 |
| 181,4 | 0,0 | 167,0 | 169,6 | 7,6 | 1055,6 | 777,8 | 56 | 35,57 |
| 181,4 | 0,0 | 167,0 | 169,6 | 7,6 | 1055,6 | 777,8 | 100 | 45,37 |
| 182,0 | 45,2 | 122,0 | 170,2 | 8,2 | 1059,4 | 780,7 | 3 | 7,32 |
| 182,0 | 45,2 | 122,0 | 170,2 | 8,2 | 1059,4 | 780,7 | 14 | 21,50 |
| 182,0 | 45,2 | 122,0 | 170,2 | 8,2 | 1059,4 | 780,7 | 28 | 31,27 |
| 182,0 | 45,2 | 122,0 | 170,2 | 8,2 | 1059,4 | 780,7 | 56 | 43,50 |
| 182,0 | 45,2 | 122,0 | 170,2 | 8,2 | 1059,4 | 780,7 | 100 | 48,67 |
| 168,9 | 42,2 | 124,3 | 158,3 | 10,8 | 1080,8 | 796,2 | 3 | 7,40 |
| 168,9 | 42,2 | 124,3 | 158,3 | 10,8 | 1080,8 | 796,2 | 14 | 23,51 |
| 168,9 | 42,2 | 124,3 | 158,3 | 10,8 | 1080,8 | 796,2 | 28 | 31,12 |
| 168,9 | 42,2 | 124,3 | 158,3 | 10,8 | 1080,8 | 796,2 | 56 | 39,15 |
| 168,9 | 42,2 | 124,3 | 158,3 | 10,8 | 1080,8 | 796,2 | 100 | 48,15 |
| 290,4 | 0,0 | 96,2 | 168,1 | 9,4 | 961,2 | 865,0 | 3 | 22,50 |
| 290,4 | 0,0 | 96,2 | 168,1 | 9,4 | 961,2 | 865,0 | 14 | 34,67 |
| 290,4 | 0,0 | 96,2 | 168,1 | 9,4 | 961,2 | 865,0 | 28 | 34,74 |
| 290,4 | 0,0 | 96,2 | 168,1 | 9,4 | 961,2 | 865,0 | 56 | 45,08 |
| 290,4 | 0,0 | 96,2 | 168,1 | 9,4 | 961,2 | 865,0 | 100 | 48,97 |
| 277,1 | 0,0 | 97,4 | 160,6 | 11,8 | 973,9 | 875,6 | 3 | 23,14 |
| 277,1 | 0,0 | 97,4 | 160,6 | 11,8 | 973,9 | 875,6 | 14 | 41,89 |
| 277,1 | 0,0 | 97,4 | 160,6 | 11,8 | 973,9 | 875,6 | 28 | 48,28 |
| 277,1 | 0,0 | 97,4 | 160,6 | 11,8 | 973,9 | 875,6 | 56 | 51,04 |
| 277,1 | 0,0 | 97,4 | 160,6 | 11,8 | 973,9 | 875,6 | 100 | 55,64 |
| 295,7 | 0,0 | 95,6 | 171,5 | 8,9 | 955,1 | 859,2 | 3 | 22,95 |
| 295,7 | 0,0 | 95,6 | 171,5 | 8,9 | 955,1 | 859,2 | 14 | 35,23 |
| 295,7 | 0,0 | 95,6 | 171,5 | 8,9 | 955,1 | 859,2 | 28 | 39,94 |
| 295,7 | 0,0 | 95,6 | 171,5 | 8,9 | 955,1 | 859,2 | 56 | 48,72 |
| 295,7 | 0,0 | 95,6 | 171,5 | 8,9 | 955,1 | 859,2 | 100 | 52,04 |
| 251,8 | 0,0 | 99,9 | 146,1 | 12,4 | 1006,0 | 899,8 | 3 | 21,02 |
| 251,8 | 0,0 | 99,9 | 146,1 | 12,4 | 1006,0 | 899,8 | 14 | 33,36 |
| 251,8 | 0,0 | 99,9 | 146,1 | 12,4 | 1006,0 | 899,8 | 28 | 33,94 |
| 251,8 | 0,0 | 99,9 | 146,1 | 12,4 | 1006,0 | 899,8 | 56 | 44,14 |
| 251,8 | 0,0 | 99,9 | 146,1 | 12,4 | 1006,0 | 899,8 | 100 | 45,37 |
| 249,1 | 0,0 | 98,8 | 158,1 | 12,8 | 987,8 | 889,0 | 3 | 15,36 |
| 249,1 | 0,0 | 98,8 | 158,1 | 12,8 | 987,8 | 889,0 | 14 | 28,68 |
| 249,1 | 0,0 | 98,8 | 158,1 | 12,8 | 987,8 | 889,0 | 28 | 30,85 |
| 249,1 | 0,0 | 98,8 | 158,1 | 12,8 | 987,8 | 889,0 | 56 | 42,03 |
| 249,1 | 0,0 | 98,8 | 158,1 | 12,8 | 987,8 | 889,0 | 100 | 51,06 |
| 252,3 | 0,0 | 98,8 | 146,3 | 14,2 | 987,8 | 889,0 | 3 | 21,78 |
| 252,3 | 0,0 | 98,8 | 146,3 | 14,2 | 987,8 | 889,0 | 14 | 42,29 |
| 252,3 | 0,0 | 98,8 | 146,3 | 14,2 | 987,8 | 889,0 | 28 | 50,60 |
| 252,3 | 0,0 | 98,8 | 146,3 | 14,2 | 987,8 | 889,0 | 56 | 55,83 |
| 252,3 | 0,0 | 98,8 | 146,3 | 14,2 | 987,8 | 889,0 | 100 | 60,95 |
| 246,8 | 0,0 | 125,1 | 143,3 | 12,0 | 1086,8 | 800,9 | 3 | 23,52 |
| 246,8 | 0,0 | 125,1 | 143,3 | 12,0 | 1086,8 | 800,9 | 14 | 42,22 |
| 246,8 | 0,0 | 125,1 | 143,3 | 12,0 | 1086,8 | 800,9 | 28 | 52,50 |
| 246,8 | 0,0 | 125,1 | 143,3 | 12,0 | 1086,8 | 800,9 | 56 | 60,32 |
| 246,8 | 0,0 | 125,1 | 143,3 | 12,0 | 1086,8 | 800,9 | 100 | 66,42 |
| 275,1 | 0,0 | 121,4 | 159,5 | 9,9 | 1053,6 | 777,5 | 3 | 23,80 |
| 275,1 | 0,0 | 121,4 | 159,5 | 9,9 | 1053,6 | 777,5 | 14 | 38,77 |
| 275,1 | 0,0 | 121,4 | 159,5 | 9,9 | 1053,6 | 777,5 | 28 | 51,33 |
| 275,1 | 0,0 | 121,4 | 159,5 | 9,9 | 1053,6 | 777,5 | 56 | 56,85 |
| 275,1 | 0,0 | 121,4 | 159,5 | 9,9 | 1053,6 | 777,5 | 100 | 58,61 |
| 297,2 | 0,0 | 117,5 | 174,8 | 9,5 | 1022,8 | 753,5 | 3 | 21,91 |
| 297,2 | 0,0 | 117,5 | 174,8 | 9,5 | 1022,8 | 753,5 | 14 | 36,99 |
| 297,2 | 0,0 | 117,5 | 174,8 | 9,5 | 1022,8 | 753,5 | 28 | 47,40 |
| 297,2 | 0,0 | 117,5 | 174,8 | 9,5 | 1022,8 | 753,5 | 56 | 51,96 |
| 297,2 | 0,0 | 117,5 | 174,8 | 9,5 | 1022,8 | 753,5 | 100 | 56,74 |
| 213,7 | 0,0 | 174,7 | 154,8 | 10,2 | 1053,5 | 776,4 | 3 | 17,57 |
| 213,7 | 0,0 | 174,7 | 154,8 | 10,2 | 1053,5 | 776,4 | 14 | 33,73 |
| 213,7 | 0,0 | 174,7 | 154,8 | 10,2 | 1053,5 | 776,4 | 28 | 40,15 |
| 213,7 | 0,0 | 174,7 | 154,8 | 10,2 | 1053,5 | 776,4 | 56 | 46,64 |
| 213,7 | 0,0 | 174,7 | 154,8 | 10,2 | 1053,5 | 776,4 | 100 | 50,08 |
| 213,5 | 0,0 | 174,2 | 154,6 | 11,7 | 1052,3 | 775,5 | 3 | 17,37 |
| 213,5 | 0,0 | 174,2 | 154,6 | 11,7 | 1052,3 | 775,5 | 14 | 33,70 |
| 213,5 | 0,0 | 174,2 | 154,6 | 11,7 | 1052,3 | 775,5 | 28 | 45,94 |
| 213,5 | 0,0 | 174,2 | 154,6 | 11,7 | 1052,3 | 775,5 | 56 | 51,43 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 213,5 | 0,0 | 174,2 | 154,6 | 11,7 | 1052,3 | 775,5 | 100 | 59,30 |
| 277,2 | 97,8 | 24,5 | 160,7 | 11,2 | 1061,7 | 782,5 | 3 | 30,45 |
| 277,2 | 97,8 | 24,5 | 160,7 | 11,2 | 1061,7 | 782,5 | 14 | 47,71 |
| 277,2 | 97,8 | 24,5 | 160,7 | 11,2 | 1061,7 | 782,5 | 28 | 63,14 |
| 277,2 | 97,8 | 24,5 | 160,7 | 11,2 | 1061,7 | 782,5 | 56 | 66,82 |
| 277,2 | 97,8 | 24,5 | 160,7 | 11,2 | 1061,7 | 782,5 | 100 | 66,95 |
| 218,2 | 54,6 | 123,8 | 140,8 | 11,9 | 1075,7 | 792,7 | 3 | 27,42 |
| 218,2 | 54,6 | 123,8 | 140,8 | 11,9 | 1075,7 | 792,7 | 14 | 35,96 |
| 218,2 | 54,6 | 123,8 | 140,8 | 11,9 | 1075,7 | 792,7 | 28 | 55,51 |
| 218,2 | 54,6 | 123,8 | 140,8 | 11,9 | 1075,7 | 792,7 | 56 | 61,99 |
| 218,2 | 54,6 | 123,8 | 140,8 | 11,9 | 1075,7 | 792,7 | 100 | 63,53 |
| 214,9 | 53,8 | 121,9 | 155,6 | 9,6 | 1014,3 | 780,6 | 3 | 18,02 |
| 214,9 | 53,8 | 121,9 | 155,6 | 9,6 | 1014,3 | 780,6 | 14 | 38,60 |
| 214,9 | 53,8 | 121,9 | 155,6 | 9,6 | 1014,3 | 780,6 | 28 | 52,20 |
| 214,9 | 53,8 | 121,9 | 155,6 | 9,6 | 1014,3 | 780,6 | 56 | 53,96 |
| 214,9 | 53,8 | 121,9 | 155,6 | 9,6 | 1014,3 | 780,6 | 100 | 56,63 |
| 218,9 | 0,0 | 124,1 | 158,5 | 11,3 | 1078,7 | 794,9 | 3 | 15,34 |
| 218,9 | 0,0 | 124,1 | 158,5 | 11,3 | 1078,7 | 794,9 | 14 | 26,05 |
| 218,9 | 0,0 | 124,1 | 158,5 | 11,3 | 1078,7 | 794,9 | 28 | 30,22 |
| 218,9 | 0,0 | 124,1 | 158,5 | 11,3 | 1078,7 | 794,9 | 56 | 37,27 |
| 218,9 | 0,0 | 124,1 | 158,5 | 11,3 | 1078,7 | 794,9 | 100 | 46,23 |
| 376,0 | 0,0 | 0,0 | 214,6 | 0,0 | 1003,5 | 762,4 | 3 | 16,28 |
| 376,0 | 0,0 | 0,0 | 214,6 | 0,0 | 1003,5 | 762,4 | 14 | 25,62 |
| 376,0 | 0,0 | 0,0 | 214,6 | 0,0 | 1003,5 | 762,4 | 28 | 31,97 |
| 376,0 | 0,0 | 0,0 | 214,6 | 0,0 | 1003,5 | 762,4 | 56 | 36,30 |
| 376,0 | 0,0 | 0,0 | 214,6 | 0,0 | 1003,5 | 762,4 | 100 | 43,06 |
| 500,0 | 0,0 | 0,0 | 140,0 | 4,0 | 966,0 | 853,0 | 28 | 67,57 |
| 475,0 | 0,0 | 59,0 | 142,0 | 1,9 | 1098,0 | 641,0 | 28 | 57,23 |
| 315,0 | 137,0 | 0,0 | 145,0 | 5,9 | 1130,0 | 745,0 | 28 | 81,75 |
| 505,0 | 0,0 | 60,0 | 195,0 | 0,0 | 1030,0 | 630,0 | 28 | 64,02 |
| 451,0 | 0,0 | 0,0 | 165,0 | 11,3 | 1030,0 | 745,0 | 28 | 78,80 |
| 516,0 | 0,0 | 0,0 | 162,0 | 8,2 | 801,0 | 802,0 | 28 | 41,37 |
| 520,0 | 0,0 | 0,0 | 170,0 | 5,2 | 855,0 | 855,0 | 28 | 60,28 |
| 528,0 | 0,0 | 0,0 | 185,0 | 6,9 | 920,0 | 720,0 | 28 | 56,83 |
| 520,0 | 0,0 | 0,0 | 175,0 | 5,2 | 870,0 | 805,0 | 28 | 51,02 |
| 385,0 | 0,0 | 136,0 | 158,0 | 20,0 | 903,0 | 768,0 | 28 | 55,55 |
| 500,1 | 0,0 | 0,0 | 200,0 | 3,0 | 1124,4 | 613,2 | 28 | 44,13 |
| 450,1 | 50,0 | 0,0 | 200,0 | 3,0 | 1124,4 | 613,2 | 28 | 39,38 |
| 397,0 | 17,2 | 158,0 | 167,0 | 20,8 | 967,0 | 633,0 | 28 | 55,65 |
| 333,0 | 17,5 | 163,0 | 167,0 | 17,9 | 996,0 | 652,0 | 28 | 47,28 |
| 334,0 | 17,6 | 158,0 | 189,0 | 15,3 | 967,0 | 633,0 | 28 | 44,33 |
| 405,0 | 0,0 | 0,0 | 175,0 | 0,0 | 1120,0 | 695,0 | 28 | 52,30 |
| 200,0 | 200,0 | 0,0 | 190,0 | 0,0 | 1145,0 | 660,0 | 28 | 49,25 |
| 516,0 | 0,0 | 0,0 | 162,0 | 8,3 | 801,0 | 802,0 | 28 | 41,37 |
| 145,0 | 116,0 | 119,0 | 184,0 | 5,7 | 833,0 | 880,0 | 28 | 29,16 |
| 160,0 | 128,0 | 122,0 | 182,0 | 6,4 | 824,0 | 879,0 | 28 | 39,40 |
| 234,0 | 156,0 | 0,0 | 189,0 | 5,9 | 981,0 | 760,0 | 28 | 39,30 |
| 250,0 | 180,0 | 95,0 | 159,0 | 9,5 | 860,0 | 800,0 | 28 | 67,87 |
| 475,0 | 0,0 | 0,0 | 162,0 | 9,5 | 1044,0 | 662,0 | 28 | 58,52 |
| 285,0 | 190,0 | 0,0 | 163,0 | 7,6 | 1031,0 | 685,0 | 28 | 53,58 |
| 356,0 | 119,0 | 0,0 | 160,0 | 9,0 | 1061,0 | 657,0 | 28 | 59,00 |
| 275,0 | 180,0 | 120,0 | 162,0 | 10,4 | 830,0 | 765,0 | 28 | 76,24 |
| 500,0 | 0,0 | 0,0 | 151,0 | 9,0 | 1033,0 | 655,0 | 28 | 69,84 |
| 165,0 | 0,0 | 143,6 | 163,8 | 0,0 | 1005,6 | 900,9 | 3 | 14,40 |
| 165,0 | 128,5 | 132,1 | 175,1 | 8,1 | 1005,8 | 746,6 | 3 | 19,42 |
| 178,0 | 129,8 | 118,6 | 179,9 | 3,6 | 1007,3 | 746,8 | 3 | 20,73 |
| 167,4 | 129,9 | 128,6 | 175,5 | 7,8 | 1006,3 | 746,6 | 3 | 14,94 |
| 172,4 | 13,6 | 172,4 | 156,8 | 4,1 | 1006,3 | 856,4 | 3 | 21,29 |
| 173,5 | 50,1 | 173,5 | 164,8 | 6,5 | 1006,2 | 793,5 | 3 | 23,08 |
| 167,0 | 75,4 | 167,0 | 164,0 | 7,9 | 1007,3 | 770,1 | 3 | 15,52 |
| 173,8 | 93,4 | 159,9 | 172,3 | 9,7 | 1007,2 | 746,6 | 3 | 15,82 |
| 190,3 | 0,0 | 125,2 | 166,6 | 9,9 | 1079,0 | 798,9 | 3 | 12,55 |
| 250,0 | 0,0 | 95,7 | 191,8 | 5,3 | 948,9 | 857,2 | 3 | 8,49 |
| 213,5 | 0,0 | 174,2 | 159,2 | 11,7 | 1043,6 | 771,9 | 3 | 15,61 |
| 194,7 | 0,0 | 100,5 | 170,2 | 7,5 | 998,0 | 901,8 | 3 | 12,18 |
| 251,4 | 0,0 | 118,3 | 192,9 | 5,8 | 1043,6 | 754,3 | 3 | 11,98 |
| 165,0 | 0,0 | 143,6 | 163,8 | 0,0 | 1005,6 | 900,9 | 14 | 16,88 |
| 165,0 | 128,5 | 132,1 | 175,1 | 8,1 | 1005,8 | 746,6 | 14 | 33,09 |
| 178,0 | 129,8 | 118,6 | 179,9 | 3,6 | 1007,3 | 746,8 | 14 | 34,24 |
| 167,4 | 129,9 | 128,6 | 175,5 | 7,8 | 1006,3 | 746,6 | 14 | 31,81 |
| 172,4 | 13,6 | 172,4 | 156,8 | 4,1 | 1006,3 | 856,4 | 14 | 29,75 |
| 173,5 | 50,1 | 173,5 | 164,8 | 6,5 | 1006,2 | 793,5 | 14 | 33,01 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 167,0 | 75,4 | 167,0 | 164,0 | 7,9 | 1007,3 | 770,1 | 14 | 32,90 |
| 173,8 | 93,4 | 159,9 | 172,3 | 9,7 | 1007,2 | 746,6 | 14 | 29,55 |
| 190,3 | 0,0 | 125,2 | 166,6 | 9,9 | 1079,0 | 798,9 | 14 | 19,42 |
| 250,0 | 0,0 | 95,7 | 191,8 | 5,3 | 948,9 | 857,2 | 14 | 24,66 |
| 213,5 | 0,0 | 174,2 | 159,2 | 11,7 | 1043,6 | 771,9 | 14 | 29,59 |
| 194,7 | 0,0 | 100,5 | 170,2 | 7,5 | 998,0 | 901,8 | 14 | 24,28 |
| 251,4 | 0,0 | 118,3 | 192,9 | 5,8 | 1043,6 | 754,3 | 14 | 20,73 |
| 165,0 | 0,0 | 143,6 | 163,8 | 0,0 | 1005,6 | 900,9 | 28 | 26,20 |
| 165,0 | 128,5 | 132,1 | 175,1 | 8,1 | 1005,8 | 746,6 | 28 | 46,39 |
| 178,0 | 129,8 | 118,6 | 179,9 | 3,6 | 1007,3 | 746,8 | 28 | 39,16 |
| 167,4 | 129,9 | 128,6 | 175,5 | 7,8 | 1006,3 | 746,6 | 28 | 41,20 |
| 172,4 | 13,6 | 172,4 | 156,8 | 4,1 | 1006,3 | 856,4 | 28 | 33,69 |
| 173,5 | 50,1 | 173,5 | 164,8 | 6,5 | 1006,2 | 793,5 | 28 | 38,20 |
| 167,0 | 75,4 | 167,0 | 164,0 | 7,9 | 1007,3 | 770,1 | 28 | 41,41 |
| 173,8 | 93,4 | 159,9 | 172,3 | 9,7 | 1007,2 | 746,6 | 28 | 37,81 |
| 190,3 | 0,0 | 125,2 | 166,6 | 9,9 | 1079,0 | 798,9 | 28 | 24,85 |
| 250,0 | 0,0 | 95,7 | 191,8 | 5,3 | 948,9 | 857,2 | 28 | 27,22 |
| 213,5 | 0,0 | 174,2 | 159,2 | 11,7 | 1043,6 | 771,9 | 28 | 44,64 |
| 194,7 | 0,0 | 100,5 | 170,2 | 7,5 | 998,0 | 901,8 | 28 | 37,27 |
| 251,4 | 0,0 | 118,3 | 192,9 | 5,8 | 1043,6 | 754,3 | 28 | 33,27 |
| 165,0 | 0,0 | 143,6 | 163,8 | 0,0 | 1005,6 | 900,9 | 56 | 36,56 |
| 165,0 | 128,5 | 132,1 | 175,1 | 8,1 | 1005,8 | 746,6 | 56 | 53,72 |
| 178,0 | 129,8 | 118,6 | 179,9 | 3,6 | 1007,3 | 746,8 | 56 | 48,59 |
| 167,4 | 129,9 | 128,6 | 175,5 | 7,8 | 1006,3 | 746,6 | 56 | 51,72 |
| 172,4 | 13,6 | 172,4 | 156,8 | 4,1 | 1006,3 | 856,4 | 56 | 35,85 |
| 173,5 | 50,1 | 173,5 | 164,8 | 6,5 | 1006,2 | 793,5 | 56 | 53,77 |
| 167,0 | 75,4 | 167,0 | 164,0 | 7,9 | 1007,3 | 770,1 | 56 | 53,46 |
| 173,8 | 93,4 | 159,9 | 172,3 | 9,7 | 1007,2 | 746,6 | 56 | 48,99 |
| 190,3 | 0,0 | 125,2 | 166,6 | 9,9 | 1079,0 | 798,9 | 56 | 31,72 |
| 250,0 | 0,0 | 95,7 | 191,8 | 5,3 | 948,9 | 857,2 | 56 | 39,64 |
| 213,5 | 0,0 | 174,2 | 159,2 | 11,7 | 1043,6 | 771,9 | 56 | 51,26 |
| 194,7 | 0,0 | 100,5 | 170,2 | 7,5 | 998,0 | 901,8 | 56 | 43,39 |
| 251,4 | 0,0 | 118,3 | 192,9 | 5,8 | 1043,6 | 754,3 | 56 | 39,27 |
| 165,0 | 0,0 | 143,6 | 163,8 | 0,0 | 1005,6 | 900,9 | 100 | 37,96 |
| 165,0 | 128,5 | 132,1 | 175,1 | 8,1 | 1005,8 | 746,6 | 100 | 55,02 |
| 178,0 | 129,8 | 118,6 | 179,9 | 3,6 | 1007,3 | 746,8 | 100 | 49,99 |
| 167,4 | 129,9 | 128,6 | 175,5 | 7,8 | 1006,3 | 746,6 | 100 | 53,66 |
| 172,4 | 13,6 | 172,4 | 156,8 | 4,1 | 1006,3 | 856,4 | 100 | 37,68 |
| 173,5 | 50,1 | 173,5 | 164,8 | 6,5 | 1006,2 | 793,5 | 100 | 56,06 |
| 167,0 | 75,4 | 167,0 | 164,0 | 7,9 | 1007,3 | 770,1 | 100 | 56,81 |
| 173,8 | 93,4 | 159,9 | 172,3 | 9,7 | 1007,2 | 746,6 | 100 | 50,94 |
| 190,3 | 0,0 | 125,2 | 166,6 | 9,9 | 1079,0 | 798,9 | 100 | 33,56 |
| 250,0 | 0,0 | 95,7 | 191,8 | 5,3 | 948,9 | 857,2 | 100 | 41,16 |
| 213,5 | 0,0 | 174,2 | 159,2 | 11,7 | 1043,6 | 771,9 | 100 | 52,96 |
| 194,7 | 0,0 | 100,5 | 170,2 | 7,5 | 998,0 | 901,8 | 100 | 44,28 |
| 251,4 | 0,0 | 118,3 | 192,9 | 5,8 | 1043,6 | 754,3 | 100 | 40,15 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 28 | 57,03 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 28 | 44,42 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 28 | 51,02 |
| 446,0 | 24,0 | 79,0 | 162,0 | 10,3 | 967,0 | 712,0 | 28 | 53,39 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 3 | 35,36 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 3 | 25,02 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 3 | 23,35 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 7 | 52,01 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 7 | 38,02 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 7 | 39,30 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 56 | 61,07 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 56 | 56,14 |
| 446,0 | 24,0 | 79,0 | 162,0 | 11,6 | 967,0 | 712,0 | 56 | 55,25 |
| 446,0 | 24,0 | 79,0 | 162,0 | 10,3 | 967,0 | 712,0 | 56 | 54,77 |
| 387,0 | 20,0 | 94,0 | 157,0 | 14,3 | 938,0 | 845,0 | 28 | 50,24 |
| 387,0 | 20,0 | 94,0 | 157,0 | 13,9 | 938,0 | 845,0 | 28 | 46,68 |
| 387,0 | 20,0 | 94,0 | 157,0 | 11,6 | 938,0 | 845,0 | 28 | 46,68 |
| 387,0 | 20,0 | 94,0 | 157,0 | 14,3 | 938,0 | 845,0 | 3 | 22,75 |
| 387,0 | 20,0 | 94,0 | 157,0 | 13,9 | 938,0 | 845,0 | 3 | 25,51 |
| 387,0 | 20,0 | 94,0 | 157,0 | 11,6 | 938,0 | 845,0 | 3 | 34,77 |
| 387,0 | 20,0 | 94,0 | 157,0 | 14,3 | 938,0 | 845,0 | 7 | 36,84 |
| 387,0 | 20,0 | 94,0 | 157,0 | 13,9 | 938,0 | 845,0 | 7 | 45,90 |
| 387,0 | 20,0 | 94,0 | 157,0 | 11,6 | 938,0 | 845,0 | 7 | 41,67 |
| 387,0 | 20,0 | 94,0 | 157,0 | 14,3 | 938,0 | 845,0 | 56 | 56,34 |
| 387,0 | 20,0 | 94,0 | 157,0 | 13,9 | 938,0 | 845,0 | 56 | 47,97 |
| 387,0 | 20,0 | 94,0 | 157,0 | 11,6 | 938,0 | 845,0 | 56 | 61,46 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 355,0 | 19,0 | 97,0 | 145,0 | 13,1 | 967,0 | 871,0 | 28 | 44,03 |
| 355,0 | 19,0 | 97,0 | 145,0 | 12,3 | 967,0 | 871,0 | 28 | 55,45 |
| 491,0 | 26,0 | 123,0 | 210,0 | 3,9 | 882,0 | 699,0 | 28 | 55,55 |
| 491,0 | 26,0 | 123,0 | 201,0 | 3,9 | 822,0 | 699,0 | 28 | 57,92 |
| 491,0 | 26,0 | 123,0 | 210,0 | 3,9 | 882,0 | 699,0 | 3 | 25,61 |
| 491,0 | 26,0 | 123,0 | 210,0 | 3,9 | 882,0 | 699,0 | 7 | 33,49 |
| 491,0 | 26,0 | 123,0 | 210,0 | 3,9 | 882,0 | 699,0 | 56 | 59,59 |
| 491,0 | 26,0 | 123,0 | 201,0 | 3,9 | 822,0 | 699,0 | 3 | 29,55 |
| 491,0 | 26,0 | 123,0 | 201,0 | 3,9 | 822,0 | 699,0 | 7 | 37,92 |
| 491,0 | 26,0 | 123,0 | 201,0 | 3,9 | 822,0 | 699,0 | 56 | 61,86 |
| 424,0 | 22,0 | 132,0 | 178,0 | 8,5 | 822,0 | 750,0 | 28 | 62,05 |
| 424,0 | 22,0 | 132,0 | 178,0 | 8,5 | 882,0 | 750,0 | 3 | 32,01 |
| 424,0 | 22,0 | 132,0 | 168,0 | 8,9 | 822,0 | 750,0 | 28 | 72,10 |
| 424,0 | 22,0 | 132,0 | 178,0 | 8,5 | 822,0 | 750,0 | 7 | 39,00 |
| 424,0 | 22,0 | 132,0 | 178,0 | 8,5 | 822,0 | 750,0 | 56 | 65,70 |
| 424,0 | 22,0 | 132,0 | 168,0 | 8,9 | 822,0 | 750,0 | 3 | 32,11 |
| 424,0 | 22,0 | 132,0 | 168,0 | 8,9 | 822,0 | 750,0 | 7 | 40,29 |
| 424,0 | 22,0 | 132,0 | 168,0 | 8,9 | 822,0 | 750,0 | 56 | 74,36 |
| 202,0 | 11,0 | 141,0 | 206,0 | 1,7 | 942,0 | 801,0 | 28 | 21,97 |
| 202,0 | 11,0 | 141,0 | 206,0 | 1,7 | 942,0 | 801,0 | 3 | 9,85 |
| 202,0 | 11,0 | 141,0 | 206,0 | 1,7 | 942,0 | 801,0 | 7 | 15,07 |
| 202,0 | 11,0 | 141,0 | 206,0 | 1,7 | 942,0 | 801,0 | 56 | 23,25 |
| 284,0 | 15,0 | 141,0 | 179,0 | 5,5 | 842,0 | 801,0 | 28 | 43,73 |
| 284,0 | 15,0 | 141,0 | 179,0 | 5,5 | 842,0 | 801,0 | 3 | 13,40 |
| 284,0 | 15,0 | 141,0 | 179,0 | 5,5 | 842,0 | 801,0 | 7 | 24,13 |
| 284,0 | 15,0 | 141,0 | 179,0 | 5,5 | 842,0 | 801,0 | 56 | 44,52 |
| 359,0 | 19,0 | 141,0 | 154,0 | 10,9 | 942,0 | 801,0 | 28 | 62,94 |
| 359,0 | 19,0 | 141,0 | 154,0 | 10,9 | 942,0 | 801,0 | 28 | 59,49 |
| 359,0 | 19,0 | 141,0 | 154,0 | 10,9 | 942,0 | 801,0 | 3 | 25,12 |
| 359,0 | 19,0 | 141,0 | 154,0 | 10,9 | 942,0 | 801,0 | 3 | 23,64 |
| 359,0 | 19,0 | 141,0 | 154,0 | 10,9 | 942,0 | 801,0 | 7 | 35,75 |
| 359,0 | 19,0 | 141,0 | 154,0 | 10,9 | 942,0 | 801,0 | 7 | 38,61 |
| 359,0 | 19,0 | 141,0 | 154,0 | 10,9 | 942,0 | 801,0 | 56 | 68,75 |
| 359,0 | 19,0 | 141,0 | 154,0 | 10,9 | 942,0 | 801,0 | 56 | 66,78 |
| 436,0 | 0,0 | 0,0 | 218,0 | 0,0 | 838,4 | 719,7 | 28 | 23,85 |
| 289,0 | 0,0 | 0,0 | 192,0 | 0,0 | 913,2 | 895,3 | 90 | 32,07 |
| 289,0 | 0,0 | 0,0 | 192,0 | 0,0 | 913,2 | 895,3 | 3 | 11,65 |
| 393,0 | 0,0 | 0,0 | 192,0 | 0,0 | 940,6 | 785,6 | 3 | 19,20 |
| 393,0 | 0,0 | 0,0 | 192,0 | 0,0 | 940,6 | 785,6 | 90 | 48,85 |
| 393,0 | 0,0 | 0,0 | 192,0 | 0,0 | 940,6 | 785,6 | 28 | 39,60 |
| 480,0 | 0,0 | 0,0 | 192,0 | 0,0 | 936,2 | 712,2 | 28 | 43,94 |
| 480,0 | 0,0 | 0,0 | 192,0 | 0,0 | 936,2 | 712,2 | 7 | 34,57 |
| 480,0 | 0,0 | 0,0 | 192,0 | 0,0 | 936,2 | 712,2 | 90 | 54,32 |
| 480,0 | 0,0 | 0,0 | 192,0 | 0,0 | 936,2 | 712,2 | 3 | 24,40 |
| 333,0 | 0,0 | 0,0 | 192,0 | 0,0 | 931,2 | 842,6 | 3 | 15,62 |
| 255,0 | 0,0 | 0,0 | 192,0 | 0,0 | 889,8 | 945,0 | 90 | 21,86 |
| 255,0 | 0,0 | 0,0 | 192,0 | 0,0 | 889,8 | 945,0 | 7 | 10,22 |
| 289,0 | 0,0 | 0,0 | 192,0 | 0,0 | 913,2 | 895,3 | 7 | 14,60 |
| 255,0 | 0,0 | 0,0 | 192,0 | 0,0 | 889,8 | 945,0 | 28 | 18,75 |
| 333,0 | 0,0 | 0,0 | 192,0 | 0,0 | 931,2 | 842,6 | 28 | 31,97 |
| 333,0 | 0,0 | 0,0 | 192,0 | 0,0 | 931,2 | 842,6 | 7 | 23,40 |
| 289,0 | 0,0 | 0,0 | 192,0 | 0,0 | 913,2 | 895,3 | 28 | 25,57 |
| 333,0 | 0,0 | 0,0 | 192,0 | 0,0 | 931,2 | 842,6 | 90 | 41,68 |
| 393,0 | 0,0 | 0,0 | 192,0 | 0,0 | 940,6 | 785,6 | 7 | 27,74 |
| 255,0 | 0,0 | 0,0 | 192,0 | 0,0 | 889,8 | 945,0 | 3 | 8,20 |
| 158,8 | 238,2 | 0,0 | 185,7 | 0,0 | 1040,6 | 734,3 | 7 | 9,62 |
| 239,6 | 359,4 | 0,0 | 185,7 | 0,0 | 941,6 | 664,3 | 7 | 25,42 |
| 238,2 | 158,8 | 0,0 | 185,7 | 0,0 | 1040,6 | 734,3 | 7 | 15,69 |
| 181,9 | 272,8 | 0,0 | 185,7 | 0,0 | 1012,4 | 714,3 | 28 | 27,94 |
| 193,5 | 290,2 | 0,0 | 185,7 | 0,0 | 998,2 | 704,3 | 28 | 32,63 |
| 255,5 | 170,3 | 0,0 | 185,7 | 0,0 | 1026,6 | 724,3 | 7 | 17,24 |
| 272,8 | 181,9 | 0,0 | 185,7 | 0,0 | 1012,4 | 714,3 | 7 | 19,77 |
| 239,6 | 359,4 | 0,0 | 185,7 | 0,0 | 941,6 | 664,3 | 28 | 39,44 |
| 220,8 | 147,2 | 0,0 | 185,7 | 0,0 | 1055,0 | 744,3 | 28 | 25,75 |
| 397,0 | 0,0 | 0,0 | 185,7 | 0,0 | 1040,6 | 734,3 | 28 | 33,08 |
| 382,5 | 0,0 | 0,0 | 185,7 | 0,0 | 1047,8 | 739,3 | 7 | 24,07 |
| 210,7 | 316,1 | 0,0 | 185,7 | 0,0 | 977,0 | 689,3 | 7 | 21,82 |
| 158,8 | 238,2 | 0,0 | 185,7 | 0,0 | 1040,6 | 734,3 | 28 | 21,07 |
| 295,8 | 0,0 | 0,0 | 185,7 | 0,0 | 1091,4 | 769,3 | 7 | 14,84 |
| 255,5 | 170,3 | 0,0 | 185,7 | 0,0 | 1026,6 | 724,3 | 28 | 32,05 |
| 203,5 | 135,7 | 0,0 | 185,7 | 0,0 | 1076,2 | 759,3 | 7 | 11,96 |
| 397,0 | 0,0 | 0,0 | 185,7 | 0,0 | 1040,6 | 734,3 | 7 | 25,45 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 381,4 | 0,0 | 0,0 | 185,7 | 0,0 | 1104,6 | 784,3 | 28 | 22,49 |
| 295,8 | 0,0 | 0,0 | 185,7 | 0,0 | 1091,4 | 769,3 | 28 | 25,22 |
| 228,0 | 342,1 | 0,0 | 185,7 | 0,0 | 955,8 | 674,3 | 28 | 39,70 |
| 220,8 | 147,2 | 0,0 | 185,7 | 0,0 | 1055,0 | 744,3 | 7 | 13,09 |
| 316,1 | 210,7 | 0,0 | 185,7 | 0,0 | 977,0 | 689,3 | 28 | 38,70 |
| 135,7 | 203,5 | 0,0 | 185,7 | 0,0 | 1076,2 | 759,3 | 7 | 7,51 |
| 238,1 | 0,0 | 0,0 | 185,7 | 0,0 | 1118,8 | 789,3 | 28 | 17,58 |
| 339,2 | 0,0 | 0,0 | 185,7 | 0,0 | 1069,2 | 754,3 | 7 | 21,18 |
| 135,7 | 203,5 | 0,0 | 185,7 | 0,0 | 1076,2 | 759,3 | 28 | 18,20 |
| 193,5 | 290,2 | 0,0 | 185,7 | 0,0 | 998,2 | 704,3 | 7 | 17,20 |
| 203,5 | 135,7 | 0,0 | 185,7 | 0,0 | 1076,2 | 759,3 | 28 | 22,63 |
| 290,2 | 193,5 | 0,0 | 185,7 | 0,0 | 998,2 | 704,3 | 7 | 21,86 |
| 181,9 | 272,8 | 0,0 | 185,7 | 0,0 | 1012,4 | 714,3 | 7 | 12,37 |
| 170,3 | 155,5 | 0,0 | 185,7 | 0,0 | 1026,6 | 724,3 | 28 | 25,73 |
| 210,7 | 316,1 | 0,0 | 185,7 | 0,0 | 977,0 | 689,3 | 28 | 37,81 |
| 228,0 | 342,1 | 0,0 | 185,7 | 0,0 | 955,8 | 674,3 | 7 | 21,92 |
| 290,2 | 193,5 | 0,0 | 185,7 | 0,0 | 998,2 | 704,3 | 28 | 33,04 |
| 381,4 | 0,0 | 0,0 | 185,7 | 0,0 | 1104,6 | 784,3 | 7 | 14,54 |
| 238,2 | 158,8 | 0,0 | 185,7 | 0,0 | 1040,6 | 734,3 | 28 | 26,91 |
| 186,2 | 124,1 | 0,0 | 185,7 | 0,0 | 1083,4 | 764,3 | 7 | 8,00 |
| 339,2 | 0,0 | 0,0 | 185,7 | 0,0 | 1069,2 | 754,3 | 28 | 31,90 |
| 238,1 | 0,0 | 0,0 | 185,7 | 0,0 | 1118,8 | 789,3 | 7 | 10,34 |
| 252,5 | 0,0 | 0,0 | 185,7 | 0,0 | 1111,6 | 784,3 | 28 | 19,77 |
| 382,5 | 0,0 | 0,0 | 185,7 | 0,0 | 1047,8 | 739,3 | 28 | 37,44 |
| 252,5 | 0,0 | 0,0 | 185,7 | 0,0 | 1111,6 | 784,3 | 7 | 11,48 |
| 316,1 | 210,7 | 0,0 | 185,7 | 0,0 | 977,0 | 689,3 | 7 | 24,44 |
| 186,2 | 124,1 | 0,0 | 185,7 | 0,0 | 1083,4 | 764,3 | 28 | 17,60 |
| 170,3 | 155,5 | 0,0 | 185,7 | 0,0 | 1026,6 | 724,3 | 7 | 10,73 |
| 272,8 | 181,9 | 0,0 | 185,7 | 0,0 | 1012,4 | 714,3 | 28 | 31,38 |
| 339,0 | 0,0 | 0,0 | 197,0 | 0,0 | 968,0 | 781,0 | 3 | 13,22 |
| 339,0 | 0,0 | 0,0 | 197,0 | 0,0 | 968,0 | 781,0 | 7 | 20,97 |
| 339,0 | 0,0 | 0,0 | 197,0 | 0,0 | 968,0 | 781,0 | 14 | 27,04 |
| 339,0 | 0,0 | 0,0 | 197,0 | 0,0 | 968,0 | 781,0 | 28 | 32,04 |
| 339,0 | 0,0 | 0,0 | 197,0 | 0,0 | 968,0 | 781,0 | 90 | 35,17 |
| 339,0 | 0,0 | 0,0 | 197,0 | 0,0 | 968,0 | 781,0 | 180 | 36,45 |
| 339,0 | 0,0 | 0,0 | 197,0 | 0,0 | 968,0 | 781,0 | 365 | 38,89 |
| 236,0 | 0,0 | 0,0 | 194,0 | 0,0 | 968,0 | 885,0 | 3 | 6,47 |
| 236,0 | 0,0 | 0,0 | 194,0 | 0,0 | 968,0 | 885,0 | 14 | 12,84 |
| 236,0 | 0,0 | 0,0 | 194,0 | 0,0 | 968,0 | 885,0 | 28 | 18,42 |
| 236,0 | 0,0 | 0,0 | 194,0 | 0,0 | 968,0 | 885,0 | 90 | 21,95 |
| 236,0 | 0,0 | 0,0 | 193,0 | 0,0 | 968,0 | 885,0 | 180 | 24,10 |
| 236,0 | 0,0 | 0,0 | 193,0 | 0,0 | 968,0 | 885,0 | 365 | 25,08 |
| 277,0 | 0,0 | 0,0 | 191,0 | 0,0 | 968,0 | 856,0 | 14 | 21,26 |
| 277,0 | 0,0 | 0,0 | 191,0 | 0,0 | 968,0 | 856,0 | 28 | 25,97 |
| 277,0 | 0,0 | 0,0 | 191,0 | 0,0 | 968,0 | 856,0 | 3 | 11,36 |
| 277,0 | 0,0 | 0,0 | 191,0 | 0,0 | 968,0 | 856,0 | 90 | 31,25 |
| 277,0 | 0,0 | 0,0 | 191,0 | 0,0 | 968,0 | 856,0 | 180 | 32,33 |
| 277,0 | 0,0 | 0,0 | 191,0 | 0,0 | 968,0 | 856,0 | 360 | 33,70 |
| 254,0 | 0,0 | 0,0 | 198,0 | 0,0 | 968,0 | 863,0 | 3 | 9,31 |
| 254,0 | 0,0 | 0,0 | 198,0 | 0,0 | 968,0 | 863,0 | 90 | 26,94 |
| 254,0 | 0,0 | 0,0 | 198,0 | 0,0 | 968,0 | 863,0 | 180 | 27,63 |
| 254,0 | 0,0 | 0,0 | 198,0 | 0,0 | 968,0 | 863,0 | 365 | 29,79 |
| 307,0 | 0,0 | 0,0 | 193,0 | 0,0 | 968,0 | 812,0 | 180 | 34,49 |
| 307,0 | 0,0 | 0,0 | 193,0 | 0,0 | 968,0 | 812,0 | 365 | 36,15 |
| 307,0 | 0,0 | 0,0 | 193,0 | 0,0 | 968,0 | 812,0 | 3 | 12,54 |
| 307,0 | 0,0 | 0,0 | 193,0 | 0,0 | 968,0 | 812,0 | 28 | 27,53 |
| 307,0 | 0,0 | 0,0 | 193,0 | 0,0 | 968,0 | 812,0 | 90 | 32,92 |
| 236,0 | 0,0 | 0,0 | 193,0 | 0,0 | 968,0 | 885,0 | 7 | 9,99 |
| 200,0 | 0,0 | 0,0 | 180,0 | 0,0 | 1125,0 | 845,0 | 7 | 7,84 |
| 200,0 | 0,0 | 0,0 | 180,0 | 0,0 | 1125,0 | 845,0 | 28 | 12,25 |
| 225,0 | 0,0 | 0,0 | 181,0 | 0,0 | 1113,0 | 833,0 | 7 | 11,17 |
| 225,0 | 0,0 | 0,0 | 181,0 | 0,0 | 1113,0 | 833,0 | 28 | 17,34 |
| 325,0 | 0,0 | 0,0 | 184,0 | 0,0 | 1063,0 | 783,0 | 7 | 17,54 |
| 325,0 | 0,0 | 0,0 | 184,0 | 0,0 | 1063,0 | 783,0 | 28 | 30,57 |
| 275,0 | 0,0 | 0,0 | 183,0 | 0,0 | 1088,0 | 808,0 | 7 | 14,20 |
| 275,0 | 0,0 | 0,0 | 183,0 | 0,0 | 1088,0 | 808,0 | 28 | 24,50 |
| 300,0 | 0,0 | 0,0 | 184,0 | 0,0 | 1075,0 | 795,0 | 7 | 15,58 |
| 300,0 | 0,0 | 0,0 | 184,0 | 0,0 | 1075,0 | 795,0 | 28 | 26,85 |
| 375,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1038,0 | 758,0 | 7 | 26,06 |
| 375,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1038,0 | 758,0 | 28 | 38,21 |
| 400,0 | 0,0 | 0,0 | 187,0 | 0,0 | 1025,0 | 745,0 | 28 | 43,70 |
| 400,0 | 0,0 | 0,0 | 187,0 | 0,0 | 1025,0 | 745,0 | 7 | 30,14 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 250,0 | 0,0 | 0,0 | 182,0 | 0,0 | 1100,0 | 820,0 | 7 | 12,73 |
| 250,0 | 0,0 | 0,0 | 182,0 | 0,0 | 1100,0 | 820,0 | 28 | 20,87 |
| 350,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1050,0 | 770,0 | 7 | 20,28 |
| 350,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1050,0 | 770,0 | 28 | 34,29 |
| 203,5 | 305,3 | 0,0 | 203,5 | 0,0 | 963,4 | 630,0 | 7 | 19,54 |
| 250,2 | 166,8 | 0,0 | 203,5 | 0,0 | 977,6 | 694,1 | 90 | 47,71 |
| 157,0 | 236,0 | 0,0 | 192,0 | 0,0 | 935,4 | 781,2 | 90 | 43,38 |
| 141,3 | 212,0 | 0,0 | 203,5 | 0,0 | 971,8 | 748,5 | 28 | 29,89 |
| 166,8 | 250,2 | 0,0 | 203,5 | 0,0 | 975,6 | 692,6 | 3 | 6,90 |
| 122,6 | 183,9 | 0,0 | 203,5 | 0,0 | 958,2 | 800,1 | 90 | 33,19 |
| 183,9 | 122,6 | 0,0 | 203,5 | 0,0 | 959,2 | 800,0 | 3 | 4,90 |
| 102,0 | 153,0 | 0,0 | 192,0 | 0,0 | 887,0 | 942,0 | 3 | 4,57 |
| 102,0 | 153,0 | 0,0 | 192,0 | 0,0 | 887,0 | 942,0 | 90 | 25,46 |
| 122,6 | 183,9 | 0,0 | 203,5 | 0,0 | 958,2 | 800,1 | 28 | 24,29 |
| 166,8 | 250,2 | 0,0 | 203,5 | 0,0 | 975,6 | 692,6 | 28 | 33,95 |
| 200,0 | 133,0 | 0,0 | 192,0 | 0,0 | 965,4 | 806,2 | 3 | 11,41 |
| 108,3 | 162,4 | 0,0 | 203,5 | 0,0 | 938,2 | 849,0 | 28 | 20,59 |
| 305,3 | 203,5 | 0,0 | 203,5 | 0,0 | 965,4 | 631,0 | 7 | 25,89 |
| 108,3 | 162,4 | 0,0 | 203,5 | 0,0 | 938,2 | 849,0 | 90 | 29,23 |
| 116,0 | 173,0 | 0,0 | 192,0 | 0,0 | 909,8 | 891,9 | 90 | 31,02 |
| 141,3 | 212,0 | 0,0 | 203,5 | 0,0 | 971,8 | 748,5 | 7 | 10,39 |
| 157,0 | 236,0 | 0,0 | 192,0 | 0,0 | 935,4 | 781,2 | 28 | 33,66 |
| 133,0 | 200,0 | 0,0 | 192,0 | 0,0 | 927,4 | 839,2 | 28 | 27,87 |
| 250,2 | 166,8 | 0,0 | 203,5 | 0,0 | 977,6 | 694,1 | 7 | 19,35 |
| 173,0 | 116,0 | 0,0 | 192,0 | 0,0 | 946,8 | 856,8 | 7 | 11,39 |
| 192,0 | 288,0 | 0,0 | 192,0 | 0,0 | 929,8 | 716,1 | 3 | 12,79 |
| 192,0 | 288,0 | 0,0 | 192,0 | 0,0 | 929,8 | 716,1 | 28 | 39,32 |
| 153,0 | 102,0 | 0,0 | 192,0 | 0,0 | 888,0 | 943,1 | 3 | 4,78 |
| 288,0 | 192,0 | 0,0 | 192,0 | 0,0 | 932,0 | 717,8 | 3 | 16,11 |
| 305,3 | 203,5 | 0,0 | 203,5 | 0,0 | 965,4 | 631,0 | 28 | 43,38 |
| 236,0 | 157,0 | 0,0 | 192,0 | 0,0 | 972,6 | 749,1 | 7 | 20,42 |
| 173,0 | 116,0 | 0,0 | 192,0 | 0,0 | 946,8 | 856,8 | 3 | 6,94 |
| 212,0 | 141,3 | 0,0 | 203,5 | 0,0 | 973,4 | 750,0 | 7 | 15,03 |
| 236,0 | 157,0 | 0,0 | 192,0 | 0,0 | 972,6 | 749,1 | 3 | 13,57 |
| 183,9 | 122,6 | 0,0 | 203,5 | 0,0 | 959,2 | 800,0 | 90 | 32,53 |
| 166,8 | 250,2 | 0,0 | 203,5 | 0,0 | 975,6 | 692,6 | 7 | 15,75 |
| 102,0 | 153,0 | 0,0 | 192,0 | 0,0 | 887,0 | 942,0 | 7 | 7,68 |
| 288,0 | 192,0 | 0,0 | 192,0 | 0,0 | 932,0 | 717,8 | 28 | 38,80 |
| 212,0 | 141,3 | 0,0 | 203,5 | 0,0 | 973,4 | 750,0 | 28 | 33,00 |
| 102,0 | 153,0 | 0,0 | 192,0 | 0,0 | 887,0 | 942,0 | 28 | 17,28 |
| 173,0 | 116,0 | 0,0 | 192,0 | 0,0 | 946,8 | 856,8 | 28 | 24,28 |
| 183,9 | 122,6 | 0,0 | 203,5 | 0,0 | 959,2 | 800,0 | 28 | 24,05 |
| 133,0 | 200,0 | 0,0 | 192,0 | 0,0 | 927,4 | 839,2 | 90 | 36,59 |
| 192,0 | 288,0 | 0,0 | 192,0 | 0,0 | 929,8 | 716,1 | 90 | 50,73 |
| 133,0 | 200,0 | 0,0 | 192,0 | 0,0 | 927,4 | 839,2 | 7 | 13,66 |
| 305,3 | 203,5 | 0,0 | 203,5 | 0,0 | 965,4 | 631,0 | 3 | 14,14 |
| 236,0 | 157,0 | 0,0 | 192,0 | 0,0 | 972,6 | 749,1 | 90 | 47,78 |
| 108,3 | 162,4 | 0,0 | 203,5 | 0,0 | 938,2 | 849,0 | 3 | 2,33 |
| 157,0 | 236,0 | 0,0 | 192,0 | 0,0 | 935,4 | 781,2 | 7 | 16,89 |
| 288,0 | 192,0 | 0,0 | 192,0 | 0,0 | 932,0 | 717,8 | 7 | 23,52 |
| 212,0 | 141,3 | 0,0 | 203,5 | 0,0 | 973,4 | 750,0 | 3 | 6,81 |
| 212,0 | 141,3 | 0,0 | 203,5 | 0,0 | 973,4 | 750,0 | 90 | 39,70 |
| 153,0 | 102,0 | 0,0 | 192,0 | 0,0 | 888,0 | 943,1 | 28 | 17,96 |
| 236,0 | 157,0 | 0,0 | 192,0 | 0,0 | 972,6 | 749,1 | 28 | 32,88 |
| 116,0 | 173,0 | 0,0 | 192,0 | 0,0 | 909,8 | 891,9 | 28 | 22,35 |
| 183,9 | 122,6 | 0,0 | 203,5 | 0,0 | 959,2 | 800,0 | 7 | 10,79 |
| 108,3 | 162,4 | 0,0 | 203,5 | 0,0 | 938,2 | 849,0 | 7 | 7,72 |
| 203,5 | 305,3 | 0,0 | 203,5 | 0,0 | 963,4 | 630,0 | 28 | 41,68 |
| 203,5 | 305,3 | 0,0 | 203,5 | 0,0 | 963,4 | 630,0 | 3 | 9,56 |
| 133,0 | 200,0 | 0,0 | 192,0 | 0,0 | 927,4 | 839,2 | 3 | 6,88 |
| 288,0 | 192,0 | 0,0 | 192,0 | 0,0 | 932,0 | 717,8 | 90 | 50,53 |
| 200,0 | 133,0 | 0,0 | 192,0 | 0,0 | 965,4 | 806,2 | 7 | 17,17 |
| 200,0 | 133,0 | 0,0 | 192,0 | 0,0 | 965,4 | 806,2 | 28 | 30,44 |
| 250,2 | 166,8 | 0,0 | 203,5 | 0,0 | 977,6 | 694,1 | 3 | 9,73 |
| 122,6 | 183,9 | 0,0 | 203,5 | 0,0 | 958,2 | 800,1 | 3 | 3,32 |
| 153,0 | 102,0 | 0,0 | 192,0 | 0,0 | 888,0 | 943,1 | 90 | 26,32 |
| 200,0 | 133,0 | 0,0 | 192,0 | 0,0 | 965,4 | 806,2 | 90 | 43,25 |
| 116,0 | 173,0 | 0,0 | 192,0 | 0,0 | 909,8 | 891,9 | 3 | 6,28 |
| 173,0 | 116,0 | 0,0 | 192,0 | 0,0 | 946,8 | 856,8 | 90 | 32,10 |
| 250,2 | 166,8 | 0,0 | 203,5 | 0,0 | 977,6 | 694,1 | 28 | 36,96 |
| 305,3 | 203,5 | 0,0 | 203,5 | 0,0 | 965,4 | 631,0 | 90 | 54,60 |
| 192,0 | 288,0 | 0,0 | 192,0 | 0,0 | 929,8 | 716,1 | 7 | 21,48 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 157,0 | 236,0 | 0,0 | 192,0 | 0,0 | 935,4 | 781,2 | 3 | 9,69 |
| 153,0 | 102,0 | 0,0 | 192,0 | 0,0 | 888,0 | 943,1 | 7 | 8,37 |
| 141,3 | 212,0 | 0,0 | 203,5 | 0,0 | 971,8 | 748,5 | 90 | 39,66 |
| 116,0 | 173,0 | 0,0 | 192,0 | 0,0 | 909,8 | 891,9 | 7 | 10,09 |
| 141,3 | 212,0 | 0,0 | 203,5 | 0,0 | 971,8 | 748,5 | 3 | 4,83 |
| 122,6 | 183,9 | 0,0 | 203,5 | 0,0 | 958,2 | 800,1 | 7 | 10,35 |
| 166,8 | 250,2 | 0,0 | 203,5 | 0,0 | 975,6 | 692,6 | 90 | 43,57 |
| 203,5 | 305,3 | 0,0 | 203,5 | 0,0 | 963,4 | 630,0 | 90 | 51,86 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1012,0 | 830,0 | 3 | 11,85 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1012,0 | 830,0 | 7 | 17,24 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1012,0 | 830,0 | 28 | 27,83 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1012,0 | 830,0 | 90 | 35,76 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1012,0 | 830,0 | 120 | 38,70 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1025,0 | 821,0 | 3 | 14,31 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1025,0 | 821,0 | 7 | 17,44 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1025,0 | 821,0 | 28 | 31,74 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1025,0 | 821,0 | 90 | 37,91 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1025,0 | 821,0 | 120 | 39,38 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1056,0 | 809,0 | 3 | 15,87 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1056,0 | 809,0 | 7 | 9,01 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1056,0 | 809,0 | 28 | 33,61 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1056,0 | 809,0 | 90 | 40,66 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1056,0 | 809,0 | 120 | 40,86 |
| 238,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1119,0 | 789,0 | 7 | 12,05 |
| 238,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1119,0 | 789,0 | 28 | 17,54 |
| 296,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1090,0 | 769,0 | 7 | 18,91 |
| 296,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1090,0 | 769,0 | 28 | 25,18 |
| 297,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1040,0 | 734,0 | 7 | 30,96 |
| 480,0 | 0,0 | 0,0 | 192,0 | 0,0 | 936,0 | 721,0 | 28 | 43,89 |
| 480,0 | 0,0 | 0,0 | 192,0 | 0,0 | 936,0 | 721,0 | 90 | 54,28 |
| 397,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1040,0 | 734,0 | 28 | 36,94 |
| 281,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1104,0 | 774,0 | 7 | 14,50 |
| 281,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1104,0 | 774,0 | 28 | 22,44 |
| 500,0 | 0,0 | 0,0 | 200,0 | 0,0 | 1125,0 | 613,0 | 1 | 12,64 |
| 500,0 | 0,0 | 0,0 | 200,0 | 0,0 | 1125,0 | 613,0 | 3 | 26,06 |
| 500,0 | 0,0 | 0,0 | 200,0 | 0,0 | 1125,0 | 613,0 | 7 | 33,21 |
| 500,0 | 0,0 | 0,0 | 200,0 | 0,0 | 1125,0 | 613,0 | 14 | 36,94 |
| 500,0 | 0,0 | 0,0 | 200,0 | 0,0 | 1125,0 | 613,0 | 28 | 44,09 |
| 540,0 | 0,0 | 0,0 | 173,0 | 0,0 | 1125,0 | 613,0 | 7 | 52,61 |
| 540,0 | 0,0 | 0,0 | 173,0 | 0,0 | 1125,0 | 613,0 | 14 | 59,76 |
| 540,0 | 0,0 | 0,0 | 173,0 | 0,0 | 1125,0 | 613,0 | 28 | 67,31 |
| 540,0 | 0,0 | 0,0 | 173,0 | 0,0 | 1125,0 | 613,0 | 90 | 69,66 |
| 540,0 | 0,0 | 0,0 | 173,0 | 0,0 | 1125,0 | 613,0 | 180 | 71,62 |
| 540,0 | 0,0 | 0,0 | 173,0 | 0,0 | 1125,0 | 613,0 | 270 | 74,17 |
| 350,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 775,0 | 7 | 18,13 |
| 350,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 775,0 | 14 | 22,53 |
| 350,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 775,0 | 28 | 27,34 |
| 350,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 775,0 | 56 | 29,98 |
| 350,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 775,0 | 90 | 31,35 |
| 350,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 775,0 | 180 | 32,72 |
| 385,0 | 0,0 | 0,0 | 186,0 | 0,0 | 966,0 | 763,0 | 1 | 6,27 |
| 385,0 | 0,0 | 0,0 | 186,0 | 0,0 | 966,0 | 763,0 | 3 | 14,70 |
| 385,0 | 0,0 | 0,0 | 186,0 | 0,0 | 966,0 | 763,0 | 7 | 23,22 |
| 385,0 | 0,0 | 0,0 | 186,0 | 0,0 | 966,0 | 763,0 | 14 | 27,92 |
| 385,0 | 0,0 | 0,0 | 186,0 | 0,0 | 966,0 | 763,0 | 28 | 31,35 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 978,0 | 825,0 | 180 | 39,00 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 978,0 | 825,0 | 360 | 41,24 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,0 | 3 | 14,99 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 978,0 | 825,0 | 3 | 13,52 |
| 382,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1047,0 | 739,0 | 7 | 24,00 |
| 382,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1047,0 | 739,0 | 28 | 37,42 |
| 382,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1111,0 | 784,0 | 7 | 11,47 |
| 281,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1104,0 | 774,0 | 28 | 22,44 |
| 339,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1069,0 | 754,0 | 7 | 21,16 |
| 339,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1069,0 | 754,0 | 28 | 31,84 |
| 295,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1069,0 | 769,0 | 7 | 14,80 |
| 295,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1069,0 | 769,0 | 28 | 25,18 |
| 238,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1118,0 | 789,0 | 28 | 17,54 |
| 296,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1085,0 | 765,0 | 7 | 14,20 |
| 296,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1085,0 | 765,0 | 28 | 21,65 |
| 296,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1085,0 | 765,0 | 90 | 29,39 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 879,0 | 825,0 | 3 | 13,52 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 978,0 | 825,0 | 7 | 16,26 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 978,0 | 825,0 | 28 | 31,45 |
| 331,0 | 0,0 | 0,0 | 192,0 | 0,0 | 978,0 | 825,0 | 90 | 37,23 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,0 | 7 | 18,13 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,0 | 28 | 32,72 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,0 | 90 | 39,49 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,0 | 180 | 41,05 |
| 349,0 | 0,0 | 0,0 | 192,0 | 0,0 | 1047,0 | 806,0 | 360 | 42,13 |
| 302,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 817,0 | 14 | 18,13 |
| 302,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 817,0 | 180 | 26,74 |
| 525,0 | 0,0 | 0,0 | 189,0 | 0,0 | 1125,0 | 613,0 | 180 | 61,92 |
| 500,0 | 0,0 | 0,0 | 200,0 | 0,0 | 1125,0 | 613,0 | 90 | 47,22 |
| 500,0 | 0,0 | 0,0 | 200,0 | 0,0 | 1125,0 | 613,0 | 180 | 51,04 |
| 500,0 | 0,0 | 0,0 | 200,0 | 0,0 | 1125,0 | 613,0 | 270 | 55,16 |
| 540,0 | 0,0 | 0,0 | 173,0 | 0,0 | 1125,0 | 613,0 | 3 | 41,64 |
| 252,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1111,0 | 784,0 | 7 | 13,71 |
| 252,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1111,0 | 784,0 | 28 | 19,69 |
| 339,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1060,0 | 754,0 | 28 | 31,65 |
| 393,0 | 0,0 | 0,0 | 192,0 | 0,0 | 940,0 | 758,0 | 3 | 19,11 |
| 393,0 | 0,0 | 0,0 | 192,0 | 0,0 | 940,0 | 758,0 | 28 | 39,58 |
| 393,0 | 0,0 | 0,0 | 192,0 | 0,0 | 940,0 | 758,0 | 90 | 48,79 |
| 382,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1047,0 | 739,0 | 7 | 24,00 |
| 382,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1047,0 | 739,0 | 28 | 37,42 |
| 252,0 | 0,0 | 0,0 | 186,0 | 0,0 | 1111,0 | 784,0 | 7 | 11,47 |
| 252,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1111,0 | 784,0 | 28 | 19,69 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 970,0 | 850,0 | 7 | 14,99 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 970,0 | 850,0 | 28 | 27,92 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 970,0 | 850,0 | 90 | 34,68 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 970,0 | 850,0 | 180 | 37,33 |
| 310,0 | 0,0 | 0,0 | 192,0 | 0,0 | 970,0 | 850,0 | 360 | 38,11 |
| 525,0 | 0,0 | 0,0 | 189,0 | 0,0 | 1125,0 | 613,0 | 3 | 33,80 |
| 525,0 | 0,0 | 0,0 | 189,0 | 0,0 | 1125,0 | 613,0 | 7 | 42,42 |
| 525,0 | 0,0 | 0,0 | 189,0 | 0,0 | 1125,0 | 613,0 | 14 | 48,40 |
| 525,0 | 0,0 | 0,0 | 189,0 | 0,0 | 1125,0 | 613,0 | 28 | 55,94 |
| 525,0 | 0,0 | 0,0 | 189,0 | 0,0 | 1125,0 | 613,0 | 90 | 58,78 |
| 525,0 | 0,0 | 0,0 | 189,0 | 0,0 | 1125,0 | 613,0 | 270 | 67,11 |
| 322,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 800,0 | 14 | 20,77 |
| 322,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 800,0 | 28 | 25,18 |
| 322,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 800,0 | 180 | 29,59 |
| 302,0 | 0,0 | 0,0 | 203,0 | 0,0 | 974,0 | 817,0 | 28 | 21,75 |
| 397,0 | 0,0 | 0,0 | 185,0 | 0,0 | 1040,0 | 734,0 | 28 | 39,09 |
| 480,0 | 0,0 | 0,0 | 192,0 | 0,0 | 936,0 | 721,0 | 3 | 24,39 |
| 522,0 | 0,0 | 0,0 | 146,0 | 0,0 | 896,0 | 896,0 | 7 | 50,51 |
| 522,0 | 0,0 | 0,0 | 146,0 | 0,0 | 896,0 | 896,0 | 28 | 74,99 |
| 273,0 | 105,0 | 82,0 | 210,0 | 9,0 | 904,0 | 680,0 | 28 | 37,17 |
| 162,0 | 190,0 | 148,0 | 179,0 | 19,0 | 838,0 | 741,0 | 28 | 33,76 |
| 154,0 | 144,0 | 112,0 | 220,0 | 10,0 | 923,0 | 658,0 | 28 | 16,50 |
| 147,0 | 115,0 | 89,0 | 202,0 | 9,0 | 860,0 | 829,0 | 28 | 19,99 |
| 152,0 | 178,0 | 139,0 | 168,0 | 18,0 | 944,0 | 695,0 | 28 | 36,35 |
| 310,0 | 143,0 | 111,0 | 168,0 | 22,0 | 914,0 | 651,0 | 28 | 33,69 |
| 144,0 | 0,0 | 175,0 | 158,0 | 18,0 | 943,0 | 844,0 | 28 | 15,42 |
| 304,0 | 140,0 | 0,0 | 214,0 | 6,0 | 895,0 | 722,0 | 28 | 33,42 |
| 374,0 | 0,0 | 0,0 | 190,0 | 7,0 | 1013,0 | 730,0 | 28 | 39,05 |
| 159,0 | 149,0 | 116,0 | 175,0 | 15,0 | 953,0 | 720,0 | 28 | 27,68 |
| 153,0 | 239,0 | 0,0 | 200,0 | 6,0 | 1002,0 | 684,0 | 28 | 26,86 |
| 310,0 | 143,0 | 0,0 | 168,0 | 10,0 | 914,0 | 804,0 | 28 | 45,30 |
| 305,0 | 0,0 | 100,0 | 196,0 | 10,0 | 959,0 | 705,0 | 28 | 30,12 |
| 151,0 | 0,0 | 184,0 | 167,0 | 12,0 | 991,0 | 772,0 | 28 | 15,57 |
| 142,0 | 167,0 | 130,0 | 174,0 | 11,0 | 883,0 | 785,0 | 28 | 44,61 |
| 298,0 | 137,0 | 107,0 | 201,0 | 6,0 | 878,0 | 655,0 | 28 | 53,52 |
| 321,0 | 164,0 | 0,0 | 190,0 | 5,0 | 870,0 | 774,0 | 28 | 57,21 |
| 366,0 | 187,0 | 0,0 | 191,0 | 7,0 | 824,0 | 757,0 | 28 | 65,91 |
| 280,0 | 129,0 | 100,0 | 172,0 | 9,0 | 825,0 | 805,0 | 28 | 52,82 |
| 252,0 | 97,0 | 76,0 | 194,0 | 8,0 | 835,0 | 821,0 | 28 | 33,40 |
| 165,0 | 0,0 | 150,0 | 182,0 | 12,0 | 1023,0 | 729,0 | 28 | 18,03 |
| 156,0 | 243,0 | 0,0 | 180,0 | 11,0 | 1022,0 | 698,0 | 28 | 37,36 |
| 160,0 | 188,0 | 146,0 | 203,0 | 11,0 | 829,0 | 710,0 | 28 | 32,84 |
| 298,0 | 0,0 | 107,0 | 186,0 | 6,0 | 879,0 | 815,0 | 28 | 42,64 |
| 318,0 | 0,0 | 126,0 | 210,0 | 6,0 | 861,0 | 737,0 | 28 | 40,06 |
| 287,0 | 121,0 | 94,0 | 188,0 | 9,0 | 904,0 | 696,0 | 28 | 41,94 |
| 326,0 | 166,0 | 0,0 | 174,0 | 9,0 | 882,0 | 790,0 | 28 | 61,23 |
| 356,0 | 0,0 | 142,0 | 193,0 | 11,0 | 801,0 | 778,0 | 28 | 40,87 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 132,0 | 207,0 | 161,0 | 179,0 | 5,0 | 867,0 | 736,0 | 28 | 33,30 |
| 322,0 | 149,0 | 0,0 | 186,0 | 8,0 | 951,0 | 709,0 | 28 | 52,42 |
| 164,0 | 0,0 | 200,0 | 181,0 | 13,0 | 849,0 | 846,0 | 28 | 15,09 |
| 314,0 | 0,0 | 113,0 | 170,0 | 10,0 | 925,0 | 783,0 | 28 | 38,46 |
| 321,0 | 0,0 | 128,0 | 182,0 | 11,0 | 870,0 | 780,0 | 28 | 37,26 |
| 140,0 | 164,0 | 128,0 | 237,0 | 6,0 | 869,0 | 656,0 | 28 | 35,23 |
| 288,0 | 121,0 | 0,0 | 177,0 | 7,0 | 908,0 | 829,0 | 28 | 42,13 |
| 298,0 | 0,0 | 107,0 | 210,0 | 11,0 | 880,0 | 744,0 | 28 | 31,87 |
| 265,0 | 111,0 | 86,0 | 195,0 | 6,0 | 833,0 | 790,0 | 28 | 41,54 |
| 160,0 | 250,0 | 0,0 | 168,0 | 12,0 | 1049,0 | 688,0 | 28 | 39,45 |
| 166,0 | 260,0 | 0,0 | 183,0 | 13,0 | 859,0 | 827,0 | 28 | 37,91 |
| 276,0 | 116,0 | 90,0 | 180,0 | 9,0 | 870,0 | 768,0 | 28 | 44,28 |
| 322,0 | 0,0 | 116,0 | 196,0 | 10,0 | 818,0 | 813,0 | 28 | 31,18 |
| 149,0 | 139,0 | 109,0 | 193,0 | 6,0 | 892,0 | 780,0 | 28 | 23,69 |
| 159,0 | 187,0 | 0,0 | 176,0 | 11,0 | 990,0 | 789,0 | 28 | 32,76 |
| 261,0 | 100,0 | 78,0 | 201,0 | 9,0 | 864,0 | 761,0 | 28 | 32,40 |
| 237,0 | 92,0 | 71,0 | 247,0 | 6,0 | 853,0 | 695,0 | 28 | 28,63 |
| 313,0 | 0,0 | 113,0 | 178,0 | 8,0 | 1002,0 | 689,0 | 28 | 36,80 |
| 155,0 | 183,0 | 0,0 | 193,0 | 9,0 | 1047,0 | 697,0 | 28 | 18,28 |
| 146,0 | 230,0 | 0,0 | 202,0 | 3,0 | 827,0 | 872,0 | 28 | 33,06 |
| 296,0 | 0,0 | 107,0 | 221,0 | 11,0 | 819,0 | 778,0 | 28 | 31,42 |
| 133,0 | 210,0 | 0,0 | 196,0 | 3,0 | 949,0 | 795,0 | 28 | 31,03 |
| 313,0 | 145,0 | 0,0 | 178,0 | 8,0 | 867,0 | 824,0 | 28 | 44,39 |
| 152,0 | 0,0 | 112,0 | 184,0 | 8,0 | 992,0 | 816,0 | 28 | 12,18 |
| 153,0 | 145,0 | 113,0 | 178,0 | 8,0 | 1002,0 | 689,0 | 28 | 25,56 |
| 140,0 | 133,0 | 103,0 | 200,0 | 7,0 | 916,0 | 753,0 | 28 | 36,44 |
| 149,0 | 236,0 | 0,0 | 176,0 | 13,0 | 847,0 | 893,0 | 28 | 32,96 |
| 300,0 | 0,0 | 120,0 | 212,0 | 10,0 | 878,0 | 728,0 | 28 | 23,84 |
| 153,0 | 145,0 | 113,0 | 178,0 | 8,0 | 867,0 | 824,0 | 28 | 26,23 |
| 148,0 | 0,0 | 137,0 | 158,0 | 16,0 | 1002,0 | 830,0 | 28 | 17,95 |
| 326,0 | 0,0 | 138,0 | 199,0 | 11,0 | 801,0 | 792,0 | 28 | 40,68 |
| 153,0 | 145,0 | 0,0 | 178,0 | 8,0 | 1000,0 | 822,0 | 28 | 19,01 |
| 262,0 | 111,0 | 86,0 | 195,0 | 5,0 | 895,0 | 733,0 | 28 | 33,72 |
| 158,0 | 0,0 | 195,0 | 220,0 | 11,0 | 898,0 | 713,0 | 28 | 8,54 |
| 151,0 | 0,0 | 185,0 | 167,0 | 16,0 | 1074,0 | 678,0 | 28 | 13,46 |
| 273,0 | 0,0 | 90,0 | 199,0 | 11,0 | 931,0 | 762,0 | 28 | 32,24 |
| 149,0 | 118,0 | 92,0 | 183,0 | 7,0 | 953,0 | 780,0 | 28 | 23,52 |
| 143,0 | 169,0 | 143,0 | 191,0 | 8,0 | 967,0 | 643,0 | 28 | 29,72 |
| 260,0 | 101,0 | 78,0 | 171,0 | 10,0 | 936,0 | 763,0 | 28 | 49,77 |
| 313,0 | 161,0 | 0,0 | 178,0 | 10,0 | 917,0 | 759,0 | 28 | 52,44 |
| 284,0 | 120,0 | 0,0 | 168,0 | 7,0 | 970,0 | 794,0 | 28 | 40,93 |
| 336,0 | 0,0 | 0,0 | 182,0 | 3,0 | 986,0 | 817,0 | 28 | 44,86 |
| 145,0 | 0,0 | 134,0 | 181,0 | 11,0 | 979,0 | 812,0 | 28 | 13,20 |
| 150,0 | 237,0 | 0,0 | 174,0 | 12,0 | 1069,0 | 675,0 | 28 | 37,43 |
| 144,0 | 170,0 | 133,0 | 192,0 | 8,0 | 814,0 | 805,0 | 28 | 29,87 |
| 331,0 | 170,0 | 0,0 | 195,0 | 8,0 | 811,0 | 802,0 | 28 | 56,61 |
| 155,0 | 0,0 | 143,0 | 193,0 | 9,0 | 1047,0 | 697,0 | 28 | 12,46 |
| 155,0 | 183,0 | 0,0 | 193,0 | 9,0 | 877,0 | 868,0 | 28 | 23,79 |
| 135,0 | 0,0 | 166,0 | 180,0 | 10,0 | 961,0 | 805,0 | 28 | 13,29 |
| 266,0 | 112,0 | 87,0 | 178,0 | 10,0 | 910,0 | 745,0 | 28 | 39,42 |
| 314,0 | 145,0 | 113,0 | 179,0 | 8,0 | 869,0 | 690,0 | 28 | 46,23 |
| 313,0 | 145,0 | 0,0 | 127,0 | 8,0 | 1000,0 | 822,0 | 28 | 44,52 |
| 146,0 | 173,0 | 0,0 | 182,0 | 3,0 | 986,0 | 817,0 | 28 | 23,74 |
| 144,0 | 136,0 | 106,0 | 178,0 | 7,0 | 941,0 | 774,0 | 28 | 26,14 |
| 148,0 | 0,0 | 182,0 | 181,0 | 15,0 | 839,0 | 884,0 | 28 | 15,52 |
| 277,0 | 117,0 | 91,0 | 191,0 | 7,0 | 946,0 | 666,0 | 28 | 43,57 |
| 298,0 | 0,0 | 107,0 | 164,0 | 13,0 | 953,0 | 784,0 | 28 | 35,86 |
| 313,0 | 145,0 | 0,0 | 178,0 | 8,0 | 1002,0 | 689,0 | 28 | 41,05 |
| 155,0 | 184,0 | 143,0 | 194,0 | 9,0 | 880,0 | 699,0 | 28 | 28,99 |
| 289,0 | 134,0 | 0,0 | 195,0 | 6,0 | 924,0 | 760,0 | 28 | 46,24 |
| 148,0 | 175,0 | 0,0 | 171,0 | 2,0 | 1000,0 | 828,0 | 28 | 26,92 |
| 145,0 | 0,0 | 179,0 | 202,0 | 8,0 | 824,0 | 869,0 | 28 | 10,54 |
| 313,0 | 0,0 | 0,0 | 178,0 | 8,0 | 1000,0 | 822,0 | 28 | 25,10 |
| 136,0 | 162,0 | 126,0 | 172,0 | 10,0 | 923,0 | 764,0 | 28 | 29,07 |
| 155,0 | 0,0 | 143,0 | 193,0 | 9,0 | 877,0 | 868,0 | 28 | 9,74 |
| 255,0 | 99,0 | 77,0 | 189,0 | 6,0 | 919,0 | 749,0 | 28 | 33,80 |
| 162,0 | 207,0 | 172,0 | 216,0 | 10,0 | 822,0 | 638,0 | 28 | 39,84 |
| 136,0 | 196,0 | 98,0 | 199,0 | 6,0 | 847,0 | 783,0 | 28 | 26,97 |
| 164,0 | 163,0 | 128,0 | 197,0 | 8,0 | 961,0 | 641,0 | 28 | 27,23 |
| 162,0 | 214,0 | 164,0 | 202,0 | 10,0 | 820,0 | 680,0 | 28 | 30,65 |
| 157,0 | 214,0 | 152,0 | 200,0 | 9,0 | 819,0 | 704,0 | 28 | 33,05 |
| 149,0 | 153,0 | 194,0 | 192,0 | 8,0 | 935,0 | 623,0 | 28 | 24,58 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 135,0 | 105,0 | 193,0 | 196,0 | 6,0 | 965,0 | 643,0 | 28 | 21,91 |
| 159,0 | 209,0 | 161,0 | 201,0 | 7,0 | 848,0 | 669,0 | 28 | 30,88 |
| 144,0 | 15,0 | 195,0 | 176,0 | 6,0 | 1021,0 | 709,0 | 28 | 15,34 |
| 154,0 | 174,0 | 185,0 | 228,0 | 7,0 | 845,0 | 612,0 | 28 | 24,34 |
| 167,0 | 187,0 | 195,0 | 185,0 | 7,0 | 898,0 | 636,0 | 28 | 23,89 |
| 184,0 | 86,0 | 190,0 | 213,0 | 6,0 | 923,0 | 623,0 | 28 | 22,93 |
| 156,0 | 178,0 | 187,0 | 221,0 | 7,0 | 854,0 | 614,0 | 28 | 29,41 |
| 236,9 | 91,7 | 71,5 | 246,9 | 6,0 | 852,9 | 695,4 | 28 | 28,63 |
| 313,3 | 0,0 | 113,0 | 178,5 | 8,0 | 1001,9 | 688,7 | 28 | 36,80 |
| 154,8 | 183,4 | 0,0 | 193,3 | 9,1 | 1047,4 | 696,7 | 28 | 18,29 |
| 145,9 | 230,5 | 0,0 | 202,5 | 3,4 | 827,0 | 871,8 | 28 | 32,72 |
| 296,0 | 0,0 | 106,7 | 221,4 | 10,5 | 819,2 | 778,4 | 28 | 31,42 |
| 133,1 | 210,2 | 0,0 | 195,7 | 3,1 | 949,4 | 795,3 | 28 | 28,94 |
| 313,3 | 145,0 | 0,0 | 178,5 | 8,0 | 867,2 | 824,0 | 28 | 40,93 |
| 151,6 | 0,0 | 111,9 | 184,4 | 7,9 | 992,0 | 815,9 | 28 | 12,18 |
| 153,1 | 145,0 | 113,0 | 178,5 | 8,0 | 1001,9 | 688,7 | 28 | 25,56 |
| 139,9 | 132,6 | 103,3 | 200,3 | 7,4 | 916,0 | 753,4 | 28 | 36,44 |
| 149,5 | 236,0 | 0,0 | 175,8 | 12,6 | 846,8 | 892,7 | 28 | 32,96 |
| 299,8 | 0,0 | 119,8 | 211,5 | 9,9 | 878,2 | 727,6 | 28 | 23,84 |
| 153,1 | 145,0 | 113,0 | 178,5 | 8,0 | 867,2 | 824,0 | 28 | 26,23 |
| 148,1 | 0,0 | 136,6 | 158,1 | 16,1 | 1001,8 | 830,1 | 28 | 17,96 |
| 326,5 | 0,0 | 137,9 | 199,0 | 10,8 | 801,1 | 792,5 | 28 | 38,63 |
| 152,7 | 144,7 | 0,0 | 178,1 | 8,0 | 999,7 | 822,2 | 28 | 19,01 |
| 261,9 | 110,5 | 86,1 | 195,4 | 5,0 | 895,2 | 732,6 | 28 | 33,72 |
| 158,4 | 0,0 | 194,9 | 219,7 | 11,0 | 897,7 | 712,9 | 28 | 8,54 |
| 150,7 | 0,0 | 185,3 | 166,7 | 15,6 | 1074,5 | 678,0 | 28 | 13,46 |
| 272,6 | 0,0 | 89,6 | 198,7 | 10,6 | 931,3 | 762,2 | 28 | 32,25 |
| 149,0 | 117,6 | 91,7 | 182,9 | 7,1 | 953,4 | 780,3 | 28 | 23,52 |
| 143,0 | 169,4 | 142,7 | 190,7 | 8,4 | 967,4 | 643,5 | 28 | 29,73 |
| 259,9 | 100,6 | 78,4 | 170,6 | 10,4 | 935,7 | 762,9 | 28 | 49,77 |
| 312,9 | 160,5 | 0,0 | 177,6 | 9,6 | 916,6 | 759,5 | 28 | 52,45 |
| 284,0 | 119,7 | 0,0 | 168,3 | 7,2 | 970,4 | 794,2 | 28 | 40,93 |
| 336,5 | 0,0 | 0,0 | 181,9 | 3,4 | 985,8 | 816,8 | 28 | 44,87 |
| 144,8 | 0,0 | 133,6 | 180,8 | 11,1 | 979,5 | 811,5 | 28 | 13,20 |
| 150,0 | 236,8 | 0,0 | 173,8 | 11,9 | 1069,3 | 674,8 | 28 | 37,43 |
| 143,7 | 170,2 | 132,6 | 191,6 | 8,5 | 814,1 | 805,3 | 28 | 29,87 |
| 330,5 | 169,6 | 0,0 | 194,9 | 8,1 | 811,0 | 802,3 | 28 | 56,62 |
| 154,8 | 0,0 | 142,8 | 193,3 | 9,1 | 1047,4 | 696,7 | 28 | 12,46 |
| 154,8 | 183,4 | 0,0 | 193,3 | 9,1 | 877,2 | 867,7 | 28 | 23,79 |
| 134,7 | 0,0 | 165,7 | 180,2 | 10,0 | 961,0 | 804,9 | 28 | 13,29 |
| 266,2 | 112,3 | 87,5 | 177,9 | 10,4 | 909,7 | 744,5 | 28 | 39,42 |
| 314,0 | 145,3 | 113,2 | 178,9 | 8,0 | 869,1 | 690,2 | 28 | 46,23 |
| 312,7 | 144,7 | 0,0 | 127,3 | 8,0 | 999,7 | 822,2 | 28 | 44,52 |
| 145,7 | 172,6 | 0,0 | 181,9 | 3,4 | 985,8 | 816,8 | 28 | 23,74 |
| 143,8 | 136,3 | 106,2 | 178,1 | 7,5 | 941,5 | 774,3 | 28 | 26,15 |
| 148,1 | 0,0 | 182,1 | 181,4 | 15,0 | 838,9 | 884,3 | 28 | 15,53 |
| 277,0 | 116,8 | 91,0 | 190,6 | 7,0 | 946,5 | 665,6 | 28 | 43,58 |
| 298,1 | 0,0 | 107,5 | 163,6 | 12,8 | 953,2 | 784,0 | 28 | 35,87 |
| 313,3 | 145,0 | 0,0 | 178,5 | 8,0 | 1001,9 | 688,7 | 28 | 41,05 |
| 155,2 | 183,9 | 143,2 | 193,8 | 9,2 | 879,6 | 698,5 | 28 | 28,99 |
| 289,0 | 133,7 | 0,0 | 194,9 | 5,5 | 924,1 | 760,1 | 28 | 46,25 |
| 147,8 | 175,1 | 0,0 | 171,2 | 2,2 | 1000,0 | 828,5 | 28 | 26,92 |
| 145,4 | 0,0 | 178,9 | 201,7 | 7,8 | 824,0 | 868,7 | 28 | 10,54 |
| 312,7 | 0,0 | 0,0 | 178,1 | 8,0 | 999,7 | 822,2 | 28 | 25,10 |
| 136,4 | 161,6 | 125,8 | 171,6 | 10,4 | 922,6 | 764,4 | 28 | 29,07 |
| 154,8 | 0,0 | 142,8 | 193,3 | 9,1 | 877,2 | 867,7 | 28 | 9,74 |
| 255,3 | 98,8 | 77,0 | 188,6 | 6,5 | 919,0 | 749,3 | 28 | 33,80 |
| 272,8 | 105,1 | 81,8 | 209,7 | 9,0 | 904,0 | 679,7 | 28 | 37,17 |
| 162,0 | 190,1 | 148,1 | 178,8 | 18,8 | 838,1 | 741,4 | 28 | 33,76 |
| 153,6 | 144,2 | 112,3 | 220,1 | 10,1 | 923,2 | 657,9 | 28 | 16,50 |
| 146,5 | 114,6 | 89,3 | 201,9 | 8,8 | 860,0 | 829,5 | 28 | 19,99 |
| 151,8 | 178,1 | 138,7 | 167,5 | 18,3 | 944,0 | 694,6 | 28 | 36,35 |
| 309,9 | 142,8 | 111,2 | 167,8 | 22,1 | 913,9 | 651,2 | 28 | 38,22 |
| 143,6 | 0,0 | 174,9 | 158,4 | 17,9 | 942,7 | 844,5 | 28 | 15,42 |
| 303,6 | 139,9 | 0,0 | 213,5 | 6,2 | 895,5 | 722,5 | 28 | 33,42 |
| 374,3 | 0,0 | 0,0 | 190,2 | 6,7 | 1013,2 | 730,4 | 28 | 39,06 |
| 158,6 | 148,9 | 116,0 | 175,1 | 15,0 | 953,3 | 719,7 | 28 | 27,68 |
| 152,6 | 238,7 | 0,0 | 200,0 | 6,3 | 1001,8 | 683,9 | 28 | 26,86 |
| 310,0 | 142,8 | 0,0 | 167,9 | 10,0 | 914,3 | 804,0 | 28 | 45,30 |
| 304,8 | 0,0 | 99,6 | 196,0 | 9,8 | 959,4 | 705,2 | 28 | 30,12 |
| 150,9 | 0,0 | 183,9 | 166,6 | 11,6 | 991,2 | 772,2 | 28 | 15,57 |
| 141,9 | 166,6 | 129,7 | 173,5 | 10,9 | 882,6 | 785,3 | 28 | 44,61 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 297,8 | 137,2 | 106,9 | 201,3 | 6,0 | 878,4 | 655,3 | 28 | 53,52 |
| 321,3 | 164,2 | 0,0 | 190,5 | 4,6 | 870,0 | 774,0 | 28 | 57,22 |
| 366,0 | 187,0 | 0,0 | 191,3 | 6,6 | 824,3 | 756,9 | 28 | 65,91 |
| 279,8 | 128,9 | 100,4 | 172,4 | 9,5 | 825,1 | 804,9 | 28 | 52,83 |
| 252,1 | 97,1 | 75,6 | 193,8 | 8,3 | 835,5 | 821,4 | 28 | 33,40 |
| 164,6 | 0,0 | 150,4 | 181,6 | 11,7 | 1023,3 | 728,9 | 28 | 18,03 |
| 155,6 | 243,5 | 0,0 | 180,3 | 10,7 | 1022,0 | 697,7 | 28 | 37,36 |
| 160,2 | 188,0 | 146,4 | 203,2 | 11,3 | 828,7 | 709,7 | 28 | 35,31 |
| 298,1 | 0,0 | 107,0 | 186,4 | 6,1 | 879,0 | 815,2 | 28 | 42,64 |
| 317,9 | 0,0 | 126,5 | 209,7 | 5,7 | 860,5 | 736,6 | 28 | 40,06 |
| 287,3 | 120,5 | 93,9 | 187,6 | 9,2 | 904,4 | 695,9 | 28 | 43,80 |
| 325,6 | 166,4 | 0,0 | 174,0 | 8,9 | 881,6 | 790,0 | 28 | 61,24 |
| 355,9 | 0,0 | 141,6 | 193,3 | 11,0 | 801,4 | 778,4 | 28 | 40,87 |
| 132,0 | 206,5 | 160,9 | 178,9 | 5,5 | 866,9 | 735,6 | 28 | 33,31 |
| 322,5 | 148,6 | 0,0 | 185,8 | 8,5 | 951,0 | 709,5 | 28 | 52,43 |
| 164,2 | 0,0 | 200,1 | 181,2 | 12,6 | 849,3 | 846,0 | 28 | 15,09 |
| 313,8 | 0,0 | 112,6 | 169,9 | 10,1 | 925,3 | 782,9 | 28 | 38,46 |
| 321,4 | 0,0 | 127,9 | 182,5 | 11,5 | 870,1 | 779,7 | 28 | 37,27 |
| 139,7 | 163,9 | 127,7 | 236,7 | 5,8 | 868,6 | 655,6 | 28 | 35,23 |
| 288,4 | 121,0 | 0,0 | 177,4 | 7,0 | 907,9 | 829,5 | 28 | 42,14 |
| 298,2 | 0,0 | 107,0 | 209,7 | 11,1 | 879,6 | 744,2 | 28 | 31,88 |
| 264,5 | 111,0 | 86,5 | 195,5 | 5,9 | 832,6 | 790,4 | 28 | 41,54 |
| 159,8 | 250,0 | 0,0 | 168,4 | 12,2 | 1049,3 | 688,2 | 28 | 39,46 |
| 166,0 | 259,7 | 0,0 | 183,2 | 12,7 | 858,8 | 826,8 | 28 | 37,92 |
| 276,4 | 116,0 | 90,3 | 179,6 | 8,9 | 870,1 | 768,3 | 28 | 44,28 |
| 322,2 | 0,0 | 115,6 | 196,0 | 10,4 | 817,9 | 813,4 | 28 | 31,18 |
| 148,5 | 139,4 | 108,6 | 192,7 | 6,1 | 892,4 | 780,0 | 28 | 23,70 |
| 159,1 | 186,7 | 0,0 | 175,6 | 11,3 | 989,6 | 788,9 | 28 | 32,77 |
| 260,9 | 100,5 | 78,3 | 200,6 | 8,6 | 864,5 | 761,5 | 28 | 32,40 |

87