DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

DEVELOPMENT OF A DECISION SUPPORT TOOL FOR ANALYTIC CUSTOMER RELATIONSHIP MANAGEMENT INTEGRATING DATA MINING AND MULTI CRITERIA DECISION MAKING METHODS

by
Sedef ÇALI

July, 2018
İZMİR

DEVELOPMENT OF A DECISION SUPPORT TOOL FOR ANALYTIC CUSTOMER RELATIONSHIP MANAGEMENT INTEGRATING DATA MINING AND MULTI CRITERIA DECISION MAKING METHODS

A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for the Degree of Master of Science in
Industrial Engineering, Industrial Engineering Program

by
Sedef ÇALI

July, 2018
İZMİR

M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"DEVELOPMENT OF A DECISION SUPPORT TOOL FOR ANALYTIC CUSTOMER RELATIONSHIP MANAGEMENT INTEGRATING DATA MINING AND MULTI CRITERIA DECISION MAKING METHODS"** completed by **SEDEF ÇALI** under supervision of **ASST. PROF. DR. ŞEBNEM YILMAZ BALAMAN** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

Asst. Prof. Dr. Şebnem YILMAZ BALAMAN

Supervisor

Prof. Dr. Hasan SELİM

(Jury Member)

Doç. Dr. Yiğit KAZANÇOĞLU

(Jury Member)

Prof. Dr. Latif SALUM

Director

Graduate School of Natural and Applied Sciences

ACKNOWLEDGEMENTS

First of all, I would like to thank to my supervisor Asst. Prof. Dr. Şebnem YILMAZ BALAMAN for her academic support, guidance, and patient. I am grateful to her because she has believed and encouraged me to cope with scientific projects successfully. She has dedicated her countless times to my questions. I have been so lucky to work with her.

This work was supported by Dokuz Eylül University Scientific Research Coordination Unit. Project Name: Development of a Decision Support Tool for Analytic Customer Relationship Management Integrating Data Mining and Multi Criteria Decision Making Methods. Project Number: 2017.KB.FEN.026

I would like to express my thanks to Natural Language Processing Group of Istanbul Technical University (ITU) for providing me the state of the art natural language processing tools.

Finally, my special thanks go to my parents, Nevser ÇALI and Kasım ÇALI, my brother Mehmet ÇALI and my grandmother Münevver EVGİN for their endless love and support.

Sedef ÇALI

DEVELOPMENT OF A DECISION SUPPORT TOOL FOR ANALYTIC CUSTOMER RELATIONSHIP MANAGEMENT INTEGRATING DATA MINING AND MULTI CRITERIA DECISION MAKING METHODS

ABSTRACT

In recent years, there is an enormous interest in sharing a wide range of experiences and opinions regarding various products and services in blogs, social media platforms and websites specialized on customer reviews. The customer reviews derived from those platforms involve valuable information for potential customers, who might read and evaluate the comments of experienced customers before making a purchase decision on a specific product or service. Furthermore, the companies may measure customer satisfaction regarding to their products or services through online customer reviews and use this information in customer relationship management applications. In this thesis, a decision support tool, which can be used by potential customers and companies, is developed to measure and evaluate the customer satisfaction level on a specific product or service and to enable potential customers ranking the products/services according to this evaluation. The decision support system mainly consists of two phases. In the first phase, sentiment analysis is employed to convert the online customer reviews into customer satisfaction scores. In the second phase, the alternatives are ranked by using a novel multi criteria decision making (MCDM) methodology according to the performance scores obtained in the first level. The MCDM methodology developed in the second phase integrates intuitionistic fuzzy (IF) ELECTRE and VIKOR methods in a novel way. The system utilizes intuitionistic fuzzy sets (IFSs) to effectively represent the customer reviews including hesitant expressions in decision matrix. The applicability of the developed decision support system is explored by a case study, in which customer reviews about hotel experiences are evaluated using lexicon based sentiment analysis and alternative hotels are ranked according to the findings from the sentiment analysis by the IF ELECTRE integrated with VIKOR methodology.

Keywords: Customer satisfaction, Sentiment analysis, Product ranking, MCDM

ANALİTİK MÜŞTERİ İLİŞKİLERİ YÖNETİMİ İÇİN VERİ MADENCİLİĞİ VE ÇOK KRİTERLİ KARAR VERME YÖNTEMLERİNİ BİRLEŞTİREN BİR KARAR DESTEK ARACI GELİŞTİRİLMESİ

ÖZ

Son yıllarda, çeşitli ürünler ve hizmetler ile ilgili bloglarda, sosyal medya platformlarında ve ürün değerlendirme sitelerinde deneyim ve fikir paylaşma konusuna büyük ilgi duyulmaktadır. Bu müşteri değerlendirmeleri, bir ürünü veya hizmeti satın alma kararı vermeden önce deneyimli müşterilerin görüşlerini okuyup değerlendirmekte olan potansiyel müşteriler için değerli bir bilgi kaynağıdır. Dahası, şirketler internet ortamındaki müşteri değerlendirmeleri vasıtasıyla ürünlerine/hizmetlerine ilişkin müşteri memnuniyet ölçümü yapabilmekte ve edinilen bilgiler ışığında müşteri ilişkileri yönetimi uygulamalarını güncelleyebilmektedirler. Bu tez çalışmasında, müşteri memnuniyetini ölçme, değerlendirme ve bu değerlendirmeye bağlı olarak ürün sıralaması yapma konusunda potansiyel müşterilerin ve firmaların kullanabileceği bir karar destek sistemi geliştirilmiştir. Bu karar destek sistemi iki aşamadan oluşmaktadır. İlk aşamada müşteri değerlendirmelerinin müşteri memnuniyet puanlamasına dönüştürülmesi için duygu analizi kullanılmıştır. İkinci aşamada ise ilk aşamadan elde edilen sonuçlar doğrultusunda ve yeni geliştirilen çok kriterli karar verme (ÇKKV) yöntemi aracılığıyla alternatif ürünler sıralanmıştır. İkinci aşama için geliştirilen ÇKKV yöntemi, sezgisel bulanık ELECTRE yönteminin VIKOR yöntemi ile entegre edilmesine dayanmaktadır. Ayrıca, tereddütlük içeren müşteri değerlendirmelerini karar matrisinde etkili bir şekilde ifade edebilmek için, sistem, sezgisel bulanık küme teorisinden yararlanmaktadır. Geliştirilen yaklaşımın uygulanabilirliği, otel deneyimleri ile ilgili müşteri değerlendirmelerinin sözlük temelli duygu analizi kullanılarak incelendiği ve farklı otel seçeneklerinin duygu analizi sonuçları üzerinden VIKOR entegreli sezgisel bulanık ELECTRE yöntemi ile sıralandığı bir uygulama çalışmasıyla ortaya konulmuştur.

Anahtar kelimeler: Müşteri memnuniyeti, Duygu analizi, Ürün sıralama, ÇKKV

CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

Page

CHAPTER ONE
INTRODUCTION

The comments and opinions of experienced users about a product or service alternative may have a significant impact on the purchasing decision of potential customers. In recent years, e-trade sector has been developing and the number of e-trade web sites and social media platforms has been increasing which enable consumers to easily share their comments about a product and potential customers to read and evaluate these comments before making decision on purchasing an item. In addition, companies can organize their production or marketing processes by reading these negative or positive comments on their products. Considering the fact that the comments on the products on the internet significantly impact the purchasing decisions, these comments should be taken into account by potential customers who attempt to specify the best alternatives of the product they focus on and by the companies which aim to analyze the satisfaction level of customers on the products they produce or trade. However, in parallel with the rise in the number of internet users, the number of people who buy items via e-trade web sites and the number of comments on products has been rapidly increasing and it is nearly impossible to examine and analyze the huge number of comments and opinions in detail. Analyzing these comments and opinions in a comprehensive, cost-effective and reliable way and utilization from them in decision making by the firms and potential customers are crucial. In addition, in the competitive environment of today's global economy, customers encounter so many alternatives of a product with less cost or higher quality. Hence, consumers should investigate and evaluate these alternatives in detail to select the most appropriate one among them. Ranking alternative products to select the most appropriate one requires considering different properties of the product as well as the weights reflecting the relative importance of these properties.

1.1 The Role of Online Reviews in Analytic Customer Relationship Management

Customer relationship management (CRM) has various definitions. Kincaid (2003) defines the CRM as “the strategic use of information, processes, technology, and people to manage the customer's relationship with a company (Marketing, Sales, Services and Support) across the whole customer life cycle" (p. 41). Analytic CRM focuses on acquisition, storage, processing and analyzing of data regarding customers. Kracklauer, Mills, & Seifert (2004) divides analytic CRM in four phases, namely customer identification, customer attraction, customer development and customer retention. The core driver of customer identification is to specify the target customers and gathering data associated with to the profitable groups of customers. Customer attraction focuses on organization of sales and marketing campaigns to attract the target customers. Customer development monitors behaviors of target customers and strives for creating more transactions by employing a variety of tools and methods such as up-and cross selling. Customer retention focuses on preventing the loss of the existing customers.

Customer satisfaction is an important factor for a company to retain the existing customers and high satisfaction levels provide competitive advantage for companies. Kracklauer et al. (2004) defines the customer satisfaction as "the result of a process of comparison between the customer's expectations (personal standard, image of the manufacturer, claims of the manufacturer, knowledge of alternatives) and his or her perceptions (actual experience, subjective impression of product performance, appropriateness of product for his needs)" (p. 5). Since, in most cases, retaining the existing customers requires less cost than acquiring new customers (Roberts, 2000), it is crucial to monitor, evaluate and improve the customer satisfaction for CRM managers.

Traditionally, the companies make use of market surveys to get information on the requirements of existing and potential customers and to measure the satisfaction of customers on a specific product or service. However, measuring customer satisfaction through analyzing online customer reviews is less time consuming in comparison with market surveys and requires less cost. The companies can acquire more reliable and larger amount of information through online reviews since the user generated contents are created by the users voluntarily. Nowadays, companies widely utilize sentiment analysis approach so as to measure and analyze the customer satisfaction on their products/services. Sentiment analysis is a specific type of text mining which focuses on extracting the emotions, opinions, feelings and attributes from the texts. Sentiment analysis is a powerful method to analyze the online customer reviews and transform them into valuable quantitative information for companies and potential customers.

1.2 Scope and Purpose of the Thesis

In this thesis, a decision support system is developed to measure and assess the customer satisfaction level on different alternatives of a product and to enable potential customers ranking these alternatives according to this assessment. In this scope, Sentiment Analysis, Text Mining and Intuitionistic Fuzzy Set (IFS) Theory based MCDM are integrated. First of all, a JAVA based computer program is developed to analyze the online product comments utilizing aspect level sentiment analysis and to detect the sentiment tendency (positive, negative or hesitant) reflected by these comments. Then, the alternative products are ranked using MCDM considering the relative importance of different properties of the products and the suggested alternative is selected. The decision support system can be utilized by the potential customers in analyzing the online product comments to select the most appropriate alternative practically and reliably. In addition, companies can make use of the developed system to evaluate the customer satisfaction level regarding to their product(s) and/or service(s) effectively and reorganize their production processes, operational activities or marketing policies according to the outputs from this analysis.

The main purpose of integrating IFS theory to the developed decision support system is to cope with the hesitancies and vagueness in the customer reviews. Atanassov (1999) gave an example to explain the use of IFSs in decision making problems; Let X be a set of countries with elected governments and each element $x \in X$ indicates the countries. The membership function $\mu(x)$ indicates percentage of the electorate having voted for the government in country x, the non-membership function $v(x)$ represents percentage of the electorate having not voted for the government in country x. Besides membership and non-membership, Atanassov (1999) defined the hesitancy degree $\pi(x)$ representing the percentage of the invalid votes in country x and explained that we never know that the vote rate of the elected government would increase or decrease if the invalid votes were accepted as valid due to the undefinable polarity of the invalid votes. In the light of this example, this study classifies the statements in the customer reviews as positive, negative and hesitant to obtain the performance scores corresponding to alternatives. To this aim, the percentage of the positive sentences corresponding to each criterion of each alternative is considered as votes reflecting customer satisfaction, the percentage of the negative sentences regarding each criterion of each alternative is considered as votes for customer dissatisfaction and the percentage of the hesitant sentences regarding each criterion of each alternative is considered as the hesitancy degree, to emphasize on the uncertainty about the hesitant sentences whether reflect satisfaction or dissatisfaction.

There are limited number of product ranking studies based on analyzing online customer reviews in the literature (e.g. Abirami & Askerunisa, 2017; Kang & Park, 2014; Liu, Bi, & Fan, 2017; Najmi, Hashmi, Malik, Rezgui, & Khan, 2015; Peng, Kou, & Li, 2014; Zhang, Cheng, Liao, & Choudhary, 2011; Zhang, Narayanan, & Choudhary, 2010). Approaches for objective weighting of criteria are applied in a part of these studies, however none of them employs entropy method for objective weighting. Our study aims to develop a novel decision support system to rank different alternatives of a product/service determined by the potential customer according to a set of product properties and recommend the most appropriate alternative by analyzing the online reviews of experienced customers on that alternatives. Considering this problem as a group decision making (GDM) problem, each customer review is analyzed to obtain performance scores associated with alternatives and related group decision matrix is constructed. The relative importance of each criterion is calculated objectively based on the group decision matrix using entropy equations. The applicability of the proposed methodology is explored on hotel selection case based on the reviews related to different hotel alternatives. A number of hotel customers, which are treated as decision makers (DMs) in this study, have provided online comments about alternative hotels based on varying criteria on prominent characteristics of hotels. In other words, the problem of selection among different hotel alternatives according to a set of criteria, which is indeed a MCDM problem, is captured depending on the online customer reviews. The main reason of choosing hotel case to demonstrate the applicability of the proposed methodology is that customer reviews on hotels constitutes a convenient data set to observe the hesitancy since the customer may provide varying information involving conflicts about hotel features in the reviews.

There are several studies covering the hotel selection problem based on MCDM methods in the related literature (Peng, Zhang, & Wang, 2018; Yu, Wang, & Wang, 2017, 2018; Zaman, Botti, & Thanh, 2016). In a wide range of these studies, the ranking and selection of alternative hotels is conducted based on the numerical ratings corresponding to hotel alternatives provided by the experienced customers. However, none of these studies examined and evaluated the text reviews comprehensively.

The main novelties and contributions of this thesis to sentiment analysis literature can be explained as follows:

1. To the best our knowledge, this thesis is the first attempt to evaluate the online customer reviews in Turkish on hotel alternatives using aspect level sentiment analysis and IFS theory. In addition, this study presents the first product ranking study integrating sentiment classification and MCDM to analyze online reviews in Turkish.
2. This thesis presents the first research integrating aspect level sentiment analysis and a novel MCDM methodology which employs entropy method for determining the relative importance of criteria for decision making problems.
3. A novel sentiment classification algorithm is developed in this study that benefits from semantic rules and word distance rules based on Natural Language Processing (NLP) to overcome challenges about the lack of punctuations and long sentences for extracting sentiments accurately from online reviews. The algorithm can detect hesitant expressions besides positive and negative expressions.

The main novelties and contributions of this thesis to the MCDM literature can be explained as follows:

1. To the best of our knowledge, none of the outranking methodologies in the literature integrates ELECTRE and VIKOR methods under IFS theory. The main advantages of this integration are as follows; (1) This integration enables to select the most appropriate one among multiple alternatives considering a set of criteria, (2) It provides a complete ranking of alternatives, (3) It proposes different solutions and rankings according to different decision making strategies of DMs. (4) It captures uncertain situations including hesitancy in the evaluation process.
2. The methodology integrates Entropy Method in the MCDM process to handle ambiguity and vagueness in determining the weights of the criteria and weights of the DMs objectively.
3. The methodology utilizes the weighted distance measure to reflect the preference of each decision maker (DM) objectively to specify the weights of concordance sets, which is subjectively performed in a majority of the studies in the related literature.

The remaining of the thesis is structured as follows: Chapter 2 explains sentiment analysis. Chapter 3 presents a literature review on MCDM methodology, explains the steps of IF-ELECTRE integrated with VIKOR method developed in this study and explains computational experiments performed to demonstrate the applicability of the developed MCDM methodology considering different problems. In Section 4, the decision support system developed for product ranking based on an integration of sentiment analysis and MCDM is defined step by step. Section 5 covers the case study that employs the proposed decision support system. Finally, Section 6 presents the conclusions.

CHAPTER TWO
SENTIMENT ANALYSIS

2.1 Background of Sentiment Analysis

2.1.1 Big Data

Tech America Foundation's Federal Big Data Commission (2012) defines the Big Data as "a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management and analysis of the information" (p. 10). As it can be understood from this definition, the major characteristics of Big Data can be represented by three "V". *Volume* indicates the size of data, *velocity* shows the creation rate of data and *variety* means the structural heterogeneity of data (Gandomi & Haider, 2015). Big data includes both structured data and unstructured data. The data existing in relational databases and spreadsheets are regarded as structured data, which can be analyzed easily using computers. Unstructured texts, video, audio, speech and images can be given as examples for unstructured data, which must be converted to structured form to be analyzed using computers.

2.1.2 Text Mining

Linof & Berry (2011) defines data mining as "the process of finding and exploiting useful patterns in data" (p. 776). They highlight the appropriateness of texts for data mining applications since texts are also a type of data. In other words, text mining can be regarded as an application of data mining to text data (Linof & Berry, 2011). Text mining comprises the techniques to extract the meaningful information from textual data such as news, online forums, social network feeds and transform the texts to structured form by applying statistical analysis, computational linguistics and machine learning techniques (Gandomi & Haider, 2015).

Textual documents include objective and subjective expressions about entities, e.g. products, news, events. There are a number of text mining methods with different purposes, some of which are listed in the following (Gandomi & Haider, 2015).

1. Information extraction techniques, which aim to derive structured information from unstructured documents. The process starts with Named Entity Recognition which extracts important names from texts and assess them into the predefined categories. These names may belong to entities such as a person, a community, a place, a vehicle, a location etc. Then, the task of Relation Extraction aiming to explore the relations between the entities is performed.
2. Text summarization techniques to propose the summary of the documents automatically.
3. Question answering techniques to give answers to questions. An example is Apple's Siri, which is a well-known question answering system.
4. Sentiment analysis techniques that focus on subjective expressions describing emotions, opinions and feelings of writers, whereas abovementioned text mining techniques deal with the objective expressions used for describing a fact in order to understand and summarize the documents.

2.2 Sentiment Analysis

Sentiment analysis (or opinion mining) can be defined as a computational study to analyze the opinionated texts, which contains people's opinions, appraisals, emotions and sentiments related to entities.

Liu (2010) defines an opinion as a quintuple which can be represented by mainly five components $(e_i, a_{ij}, oo_{ijk}, h_k, t_l)$. The first component e_i indicates the entity answering the question of "what this opinion is expressing". Here, the entity can be a person, a product, an event or a place etc. The second component a_{ij} points out an aspect of entity e_i. For instance, the price can be an aspect of the entity automobile.

The third component oo_{ijk} indicates sentiment orientation or polarity of aspect a_{ij} of entity e_i. The sentiment orientation can be stated using the words such as positive, negative and neutral. The forth component h_k points out the opinion holder, in other words, writer of the opinion. Finally, the fifth component t_l indicates the time when the opinion is posted. Considering this definition, Liu states that the main purpose of sentiment analysis is to explore all opinion quintuples $(e_i, a_{ij}, oo_{ijk}, h_k, t_l)$ in a given opinionated document.

An example to the hotel reviews is given in Figure 2.1 to explain how the quintuples can be formed.

Figure 2.1 An example to the hotel reviews (Otelpuan, 2018)

The translation of the review into English is “The location was good. The sea was good. The staff was helpful”. The opinion holder (6377111) has posted the review in May, 2018. Three quintuples are listed as follows, which are established to express the sentences in the review in the structured form.

- (SheratonCesme, location, positive, 6377111, May-2018)
- (SheratonCesme, sea, positive, 6377111, May-2018)
- (SheratonCesme, staff, positive, 6377111, May-2018)

Sentiment classification, which focuses on categorization of texts according to their sentiment orientations, is one of the main tasks of sentiment analysis. It can be conducted in various ways either considering the number of sentiment types, such as binary classification (positive, negative) and ternary classification (positive, negative, neutral) or according to the context of reviews such as favorable-unfavorable, thumbs up-thumbs down, likely to win-unlikely to win. Nasukawa & Yi (2003) can be given as an example to sentiment classification studies, which proposed a system capable of favorability analysis related to a specific item (e.g. a camera) by classifying the opinions as positive (favorable) and negative (unfavorable). As another example, Kim & Hovy (2007) developed an election prediction system by categorizing the opinions gathered from election forums according to the specified political parties and according to the tendency of opinions as “likely to win” and “unlikely to win”. Turney (2002) presented an algorithm for automated review rating aiming at categorization of the customer reviews as “thumbs up” and “thumbs down” by determining average sentiment orientations of all phrases formed with adjectives or adverbs in the reviews.

2.3 Preliminary Studies to Sentiment Analysis

Several preliminary studies have to be performed to conduct sentiment analysis accurately and in a reasonable time. Data acquisition and text processing are the main preliminary studies to be performed before the sentiment analysis.

2.3.1 Data Acquisition

This study aims to collect the data which is going to be exposed to sentiment analysis. Data acquisition can be conducted using either a website’s Application Programming Interface (API) or a Web crawler (Balazs & Velásquez, 2016). For instance, one of the most well-known micro-blogging sites, namely Twitter, has its own APIs, Twitter REST API and Streaming API. On the other hand, the web pages can be scraped to extract the data automatically using web crawlers such as ParseHub (www.parsehub.com).

2.3.2 Text Preprocessing

The data extracted from various platforms such as websites involving product/service reviews, forums, micro-blogging sites, e-commerce websites etc. in data acquisition step are regarded as raw data and they need preprocessing. Some of the most popular preprocessing techniques are explained in the following (Balazs & Velásquez, 2016).

- Tokenization: This method segments the sentences into meaningful tokens which are words, symbols and phrases.
- Stemming: The aim of stemming is to obtain the common base form of a word by taking away its prefixes and suffixes. For instance, the word "odamdaki" is reduced to "oda" after stemming process is conducted.
- Part of Speech (POS) Tagging: This method labels the words such as noun, adjective, adverb, verb, and preposition.

The abovementioned techniques are also utilized in NLP.

2.4 Levels of Sentiment Classification

The studies based on sentiment classification are conducted at three levels, namely document level, sentiment level and aspect level. Document level sentiment classification aims in extracting the main sentiment about an entity from the whole document. For instance, a review on a product or service can be regarded as an opinionated document, which includes evaluations of an opinion holder about the entity. This research area focuses on the product/service review as a whole and determines the polarity of the review to understand whether the opinion holder liked the product/service. Sentence level sentiment classification, which analyzes each sentence of the review, investigates the sentiment polarity of opinions expressed in each sentence of the text. As a result, the sentences are labeled as positive, negative and neutral.

Both of the abovementioned methods are typically used to categorize the opinions according to the sentiments; however they ignore the targets of the opinions, in other words the specific aspect(s) of the product/service that the opinion holder has focused on. Aspect level sentiment classification handles this problem and determines the sentiment polarity of opinions focusing on each aspect of a product/service in a sentence. For example, when considering the product review on a specific cell phone, the opinion holder (experienced customer) may express positive or negative opinions about different attributes of the cell phone. These attributes are named as *aspects* and are extracted from the reviews to classify the sentiment polarity on each aspect as positive, negative, neutral or other forms. Because of the abovementioned advantage of this sentiment classification method, this study uses aspect level sentiment classification, which is further explained in the following sub-section.

2.4.1 Aspect Level Sentiment Classification

Aspect level sentiment classification consists of two major subsequent steps, namely aspect extraction and sentiment orientation identification. Aspect level sentiment analysis starts with aspect extraction. The purpose of this step is to discover the aspects of product/service handled in the text. Hu & Liu (2004) proposed a commonly used aspect extraction method, frequency based aspect extraction, which is used in this thesis as well. The steps of this method are expressed as follows;

1. Firstly, the process of Part of Speech Tagging is implemented to the crawled reviews by utilizing an NLP Software.
2. The words which have “noun” tag are determined and these words are put into a list.
3. The frequency of the words in the list are identified and they are sorted in descending order according to their frequency.
4. A frequency threshold is determined experimentally.
5. The words with frequency values which are greater than or equal to the threshold are defined as aspects.

After extraction of aspects, sentiment orientation identification is implemented. In this step, the sentiment orientation, in other words, sentiment polarity of the sentences for each aspect is investigated. Sentiment orientation identification can be performed through either lexicon based approaches or machine learning based approaches. Machine learning based approaches employ trained data to classifier algorithms so as to learn the differentiating characteristics of the documents and to predict the polarities of the actual documents. The most well-known machine learning classification algorithms are; Support Vector Machines (SVM), Naïve Bayes, and Maximum Entropy. On the other hand, the lexicon based approaches focus on sentiment words and phrases in the sentences for identifying the sentiment orientation of the sentences. In this approach, it is essential to detect the negations and "but" clauses in sentences besides sentiment words and phrases. A lexicon based approach for sentiment orientation identification has been employed by Hu & Liu (2004) and Ding, Liu, & Yu (2008), which follows the following steps.

The first step identifies all of the sentiment words and phrases in a sentence. Three types of sentiment words are considered; the positive sentiment words describing desired situations are assigned the score of +1, the negative sentiment words describing undesired situations are assigned the score of -1 and the context dependent words are assigned the score of 0. The context dependent words are the words with a meaning that is changeable according to the situation in which they have been used. For instance, the word *low* expresses positive opinion in *low price,* whereas it expresses negative opinion in *low quality*. The second step detects whether the sentence includes negation words or not. Negation words (e.g., *not*) convert the sentiment orientation to its opposite. The third step detects "but" clauses. The word *but* also converts the sentiment orientation in the sentence to the opposite starting from the point in the sentence it is observed. The forth step aggregates the scores by considering the closeness of the sentiment words to the aspect expressions and determine the final sentiment orientation of sentence for each aspect.

Here, the abovementioned procedure is explained through an example considering the sentence "This hotel is low cost, however its location is not good". Firstly, the aspects and sentiment words in the sentence are determined and the scores are assigned to the sentiment words. The aspects in this sentence are *cost* and *location*. The sentiment words in this sentence are *low* and *good*. The sentence is transformed to "This hotel is low cost [0], however its location is not good [+1]." Since the word *low* is context dependent word, it is assigned the score of 0 and the score of +1 is assigned to the word *good*. Then, the negations are searched. The sentence is transformed to "This hotel is low cost [0], however its location is not good [-1]". The score of the word *good* is changed as -1 since negation is observed. Then, the *but* clauses are investigated. The sentence is transformed to "This hotel is low cost [+1], however its location is not good [-1]". The first part of the sentence, in other words the part of the sentence before the word *however* is considered as positive since the part before *however* is negative. Therefore, the score of the word *low* is determined as +1. Finally, the aggregation scores are determined by taking into account the distances between sentiment words and aspects. Distance refers to the number of words between a sentiment word and an aspect word. The sentiment word *low* is close to the aspect *cost*, and the sentiment word *good* is close to the aspect *location*. As a result, the sentiment polarity is defined as positive for aspect of price and negative for aspect of location.

The studies in the current literature on the related field are commonly employs the abovementioned method, however the steps of the procedure can be modified. In this thesis, we have considered the basic elements of this procedure such as negation, distances between words however we have also created some rules besides these elements to facilitate the lexicon based sentiment orientation identification. These rules are explained in Chapter 5.

2.5 Generation of Sentiment Lexicon

As stated previously, the lexicon based approaches are based on sentiment words and phrases. This section explains how the sentiment words and phrases are determined. Approaches that are commonly used for compiling sentiment word list are; dictionary based approach, corpus based approach and manual approach.

Hu & Liu (2004) can be given as an example to the studies that employ a dictionary based approach. The procedure starts with determination of seed words manually, a small set of sentiment words of which orientations are known (e.g. good, small, terrible, high). Then, this set is extended by adding their synonyms and antonyms by the help of an online dictionary such as WordNet (Miller, 1995) and finally, the lexicon is generated after making the last corrections manually.

Apart from a small set of sentiment words, the corpus based approaches considers the conjunctions and connectives so as to discover the other words in a large corpus. Hatzivassiloglou & McKeown (1997) presents one of the most powerful techniques for corpus based approach. The first step of this technique is to compile a small set of sentiment words of which sentiment polarities are known. Then, new adjectives are extracted from the corpus by utilizing linguistic rules. They created some rules regarding conjunctions and connectives (e.g., either-or, neither-nor, but) to discover the new words. According to one of the rules proposed in Hatzivassiloglou & McKeown (1997), the adjectives existing in the both sides of the conjunction “and” have the same polarity label. The sentence, “The foods are fresh and delicious”, can be given as an example. If it is known that *fresh* is a positive adjective, the system deduces that *delicious* is a positive adjective as well. Then, delicious is added to the sentiment word list labeled as positive.

We have utilized dictionary based approach in order to compile sentiment word lists in this thesis. We have explained the procedure of compiling sentiment lexicons in Section 4.2.1.1.3.

2.6 A Literature Review on Sentiment Analysis

2.6.1 Sentiment Analysis for Product/Service Evaluation

In the literature involving the studies to evaluate the products/services based on sentiment analysis, aspect level sentiment analysis have been generally conducted to improve the performance of classification process and propose new techniques to obtain better results in extraction of aspects and opinions (Cruz, Troyano, Enríquez, Ortega, & Vallejo, 2013; Peñalver-Martinez et al., 2014; Quan & Ren, 2014). However, the studies employing aspect level sentiment analysis in a number of different research fields such as business intelligence are also available in the literature. These studies provide aids for decision making to manufacturers whose aim is to derive useful information from big data to monitor and measure customer satisfaction and weaknesses of features belonging to their products/services or extracting customer requirements. Among them, Zhang, Xu, & Wan (2012) developed a methodology to determine the weaknesses of products based on aspect level sentiment analysis. They evaluated online Chinese reviews about body wash products of a cosmetic manufacturer and revealed the most unsatisfied feature of the product which needs to be improved. Jin, Liu, Ji, & Liu (2016) employed aspect level sentiment analysis to help designers who deal with the market-driven product design by extracting useful information on customer requirements from big data involving consumer opinions. They analyzed the reviews to identify the strengths and weaknesses of features of products, then utilized Kalman filter approach to extract the trends in customer requirements and Bayesian approach to compare the competitive products. Qi, Zhang, Jeon, & Zhou (2016) proposed a method to filter out useful online reviews to facilitate the product design and conducted sentiment analysis based conjoint analysis to measure the impact of product features on customer satisfaction. They applied KANO method with conjoint analysis into online reviews about cell phones in Chinese for developing product improvement strategies. Wu, Wang, Li, & Lang (2014) proposed a study which handles the usability problems of products that leads to customer dissatisfaction by analyzing online customer reviews with the help of sentiment analysis. They utilized rule-based classifier based on Apiori algorithm to detect the sentences including the customer opinions on usability of product features and specified the sentiment orientation of sentences as positive or negative. They conducted a case study on a universal remote control product to illustrate the proposed method.

Sentiment analysis has a broad application area. The main fields are; finance, in which the sentiment orientation of articles are analyzed to determine their effects on the market price (Li, Xie, Chen, Wang, & Deng, 2014; Tetlock, 2007; Tetlock & Saar-Tsechansky, 2008), box office predictions, in which the comments posted on micro-blogs are utilized to estimate the movie sales (Du, Xu, & Huang, 2014; Hur, Kang, & Cho, 2016; Yu, Liu, Huang, & An, 2012), prediction on political elections (Tumasjan, Sprenger, Sandner, & Welpe, 2010), recommender systems (García-Cumbreras, Montejo-Ráez, & Díaz-Galiano, 2013) and product design (Jin et al., 2016; Qi et al., 2016).

Another research field which is also handled in this thesis is product ranking based on sentiment analysis. This research field has recently drawn the attention of researchers, however, the number of papers which is directly related to this field is scarce. Zhang et al (2010) proposed a methodology which handles the product ranking considering product features through online reviews. Using dynamic programing, they identified both subjective sentences in which opinions regarding a product are directly expressed and comparative sentences in which opinions regarding to a product are expressed through comparing with other products. They categorized the type of sentences in reviews as positive or negative by employing lexicon based sentiment analysis to build a weighted and directed graph indicating the relative quality of products and they proposed an improved page rank algorithm to mine this graph to conduct product ranking. The proposed methodology is applied to online reviews on the product categories of camera and television collected from an e-commerce web site. Zhang et al. (2011) developed a model to analyze customer reviews regarding camera and television products and ranked the products taking into account some properties of customer reviews such as posting date and usefulness to assign different weightings to each review. They also utilized SVM algorithm to separate the sentences including irrelevant comments from the reviews for improvement of the extraction of customer opinions regarding product quality. Najmi at al. (2015) conducted a study employing lexicon-based sentiment analysis into online reviews regarding product categories of HD television and camera crawled from an e-commerce web site with the purpose of creating ranking lists considering not only the sentiment score of reviews but also brand score of each product and the usefulness of each review.

2.6.2 Studies in Turkish

The researches in the field of sentiment analysis have recently been growing for Turkish, but there are still fewer papers compared to the number of papers in English in the same field. Among the papers that employs sentiment analyses for texts written in Turkish, Iskender & Batı (2015) proposed a study which focuses on ranking the Turkish universities according to their entrepreneurship and innovativeness. The Scientific and Technological Research Council of Turkey (TUBITAK) has proposed Entrepreneurial and Innovativeness Index (EIUI) which appraises the universities based on several criteria regarding to entrepreneurship and innovativeness. This foundation ranks universities by calculating this index annually. Iskender & Batı (2015) modified the calculation process of this index by adding a new parameter, namely “measuring university student’s entrepreneurial and innovative behaviors” and proposed a new ranking list. For this purpose, they analyzed the data collected by investigating the comments on social media regarding to 50 universities using machine learning based sentiment classification technique. It is concluded that the ranking list obtained in the study is has a significant correlation with the TUBITAK’s ranking list. Kaya, Fidan, & Toroslu (2012) applied sentiment classification to political columns including positive and negative criticism on political party, person and event by utilizing four machine learning algorithms, namely SVM, the Naive Bayes Classification, Maximum Entropy Classification and the N gram based character Language Model and compared the classification performance of these methods. They conducted several experiments based on different features, namely unigrams, bigrams, adjectives, roots and effective words. As a result, they observed that Maximum Entropy and N gram based Language Model have better performance than the others. In their other study, Kaya, Fidan & Toroslu (2013) conducted a study to classify political columns as positive or negative by applying transfer learning technique. They utilized social media accounts of columnists and journalist to extract important features for training phase of machine learning based sentiment classification. They achieved 26 % increase in accuracy of the classification of Turkish columns with this technique. Kaya & Conley (2016) proposed a study to predict the winner of a popular voice contest in Turkey by applying lexicon-based sentiment classification to the dataset obtained from social media. They established a sentiment lexicon specific to this study and translated an English sentiment lexicon to Turkish and compares the performances of two lexicons in classification of the dataset according to polarities and in prediction of the winner of contest. They also used a frequency based statistical classification technique and K-means clustering approach for comparison of the classification results and noticed that the ad hoc sentiment lexicon they developed outperforms translated sentiment lexicon. Türkmen, Omurca, & Ekinci (2016) conducted a research by performing aspect level sentiment analysis on Turkish hotel reviews. They determined the aspects of hotels based on heuristic rules, Pointwise Mutual Information and pruning methods. They created a sentiment lexicon which labels the sentiment words as positive, negative and neutral. They also generated an algorithm to calculate the overall sentiment of each aspect using sentiment lexicon. Ekinci, Türkmen, & Omurca (2017) proposed a methodology which extracts multi word aspects from user-generated contents in Turkish by utilizing word N-grams, Pointwise Mutual Information and heuristic rules to construct ranking lists and propose the most popular hotels and cell phones in the online reviews in Turkish. Türkmenoğlu & Tantug (2014) presented a study which implements lexicon based and machine learning based sentiment analysis methods using data about movies collected from social media for binary (positive and negative) classification to compare the performance of the methods. To this aim, they translated English sentiment lexicon to Turkish to be used in lexicon based sentiment classification and utilized SVM, Naïve Bayes and Decision Tree for machine learning based sentiment classification. Machine learning based sentiment analysis provided better classification results than lexicon based method. Vural, Cambazoglu, Senkul, & Tokgoz (2013) developed a framework for sentiment analysis in texts written in Turkish by customizing SentiStrength (Thelwall, Buckley, Paltogluo, Cai, & Kappas, 2010) which is a lexicon based sentiment analysis library in English generated with the aim of splitting the given text into sentences and extracting the polarity of each sentence by assigning a polarity score ranging from -5 to +5 to each word in sentences as well as classification of whole text as positive or negative. They translated the sentiment lexicon of SentiStrenght into Turkish and implemented the developed framework to movie reviews for measuring the performance of classification. Dehkharghani, Yanikoglu, Saygin, & Oflazer (2017) proposed a comprehensive study that conducts sentiment analysis at different levels such as aspect level, sentence level and document level by considering linguistic issues like negations and intensifications for Turkish reviews. They used dependency parsing, a NLP tool, and polarity resources such as SentiTurkNet (Dehkharghani, Saygin, Yanikoglu, & Oflazer, 2016). They implemented the proposed system into movie reviews by performing ternary and binary classification.

2.6.3 Studies that Integrate Sentiment Analysis and MCDM Methods

A few studies exist in the literature that integrate sentiment analysis and MCDM methods to evaluate the customer reviews and rank the product/service alternatives. Among them, Kang & Park (2014) presented a study that employs sentiment analysis and VIKOR method. The customer reviews are analyzed based on aspect level sentiment analysis to measure customer satisfaction. VIKOR method was used for final evaluation of customer satisfaction and product ranking. The weights of product features were determined based on term presence approach considering the number of reviews in which the term exists. The frequency of the term in each review is not important in this approach. A case study to rank the mobile application services was conducted to illustrate the developed method. A sensitivity analysis was also performed to reveal how the rankings are affected according to different strategies and to propose the features that needs improvement. Peng et al. (2014) integrated fuzzy MCDM into opinion mining. However, text mining techniques were utilized only for extracting key features of products and their importance. The performance scores of products were determined considering the views of experts, who evaluated the alternatives with reference to each key feature using linguistic variables which then transformed to fuzzy numbers. Peng et al. (2014) focused on Chinese reviews about mobile phones and offered using fuzzy PROMETHEE for the ranking of alternatives. Abirami & Askerunisa (2017) focused on extracting the level of satisfaction of customers regarding to ten hospitals in India through comments in social media by applying aspect level sentiment analysis. After determination of satisfaction levels, SAW and TOPSIS methods were used for ranking the hospitals. The statistical correlation test was implemented to compare the ranking results obtained by the proposed method with the ranking in the website. They concluded that, TOPSIS method outperforms SAW method. Liu et al. (2017) proposed the first study to convert the sentiment polarities into intuitionistic fuzzy numbers. They evaluated online Chinese reviews about automobiles and categorized the sentences into positive, negative and neutral polarity classes. They classified a sentence as neutral if it includes either no sentiment words or both positive and negative sentiment words. They ranked products based on PROMETHEE II and determined the criteria weights subjectively.

CHAPTER THREE
THE PROPOSED MULTI CRITERIA DECISION MAKING METHODOLOGY

Multi Criteria Decision Making (MCDM) is a field of operation research and a branch of decision making. According to Hwang & Yoon (1981), MCDM problems can be divided into two main classes, namely multiple attribute decision making (MADM) and multiple objective decision making (MODM). MODM handles the problems in a continuous decision space and aims to obtain the optimal values of objectives subject to set of conflicting constraints. On the other hand, MADM focuses on the problems which aims to determine the best alternative among a set of predetermined alternatives considering a set of conflicting decision criteria. The decision space is discrete in this type of problems. The term MCDM is often used instead of MADM in the literature (Triantaphyllou, 2000). In this thesis, the term MCDM is used to point out MADM problems. MCDM methods can be classified in various ways. Among them, MCDM methods can be classified as individual decision making and GDM methods according to the number of DMs in the problem. A part of this thesis focuses on developing a GDM methodology. In multi criteria group decision making (MCGDM) problems, the alternatives are evaluated by multiple DMs and the problem is represented by group decision matrix which is formed via aggregating the individual evaluation of each DM.

In a MCDM problem, DMs assess a finite set of alternatives with reference to a finite set of decision criteria considering a weight for each criterion. The set of alternatives can be expressed by notation $A = \{A_1, A_2, \dots A_m\}$, and the set of criteria can be expressed by notation $C = \{C_1, C_2, \dots C_n\}$. The weights of criteria are denoted by $w = \{w_1, w_2, \dots, w_n\}$ and indicate the relative importance of criteria. This MCDM problem can be represented in matrix format. Decision matrix Y, illustrated in Equation (3.1), is a (mxn) dimension matrix in which an element of the matrix "y_{ij}" indicates the performance score of i-th alternative according to j-th criterion.

$$Y = \begin{array}{c} i/j \\ A_1 \\ A_2 \\ .. \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & .. & .. \; C_n \end{array} \\ \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \end{array} \tag{3.1}$$

There are a number of MCDM methods with different characteristics in the literature. Figure 3.1 illustrates the classification of MCDM methods (Hwang & Yoon, 1981). This thesis proposes a novel MCDM methodology based on the integration of two well-known MCDM methods, ELECTRE I and VIKOR, to solve the decision making problem handled in this study. Both of the methods are explained in detail in the following sub-sections along with the main advantages/disadvantages of the methods and the reasons of integrating these methods to create a more powerful MCDM methodology for outranking problems.

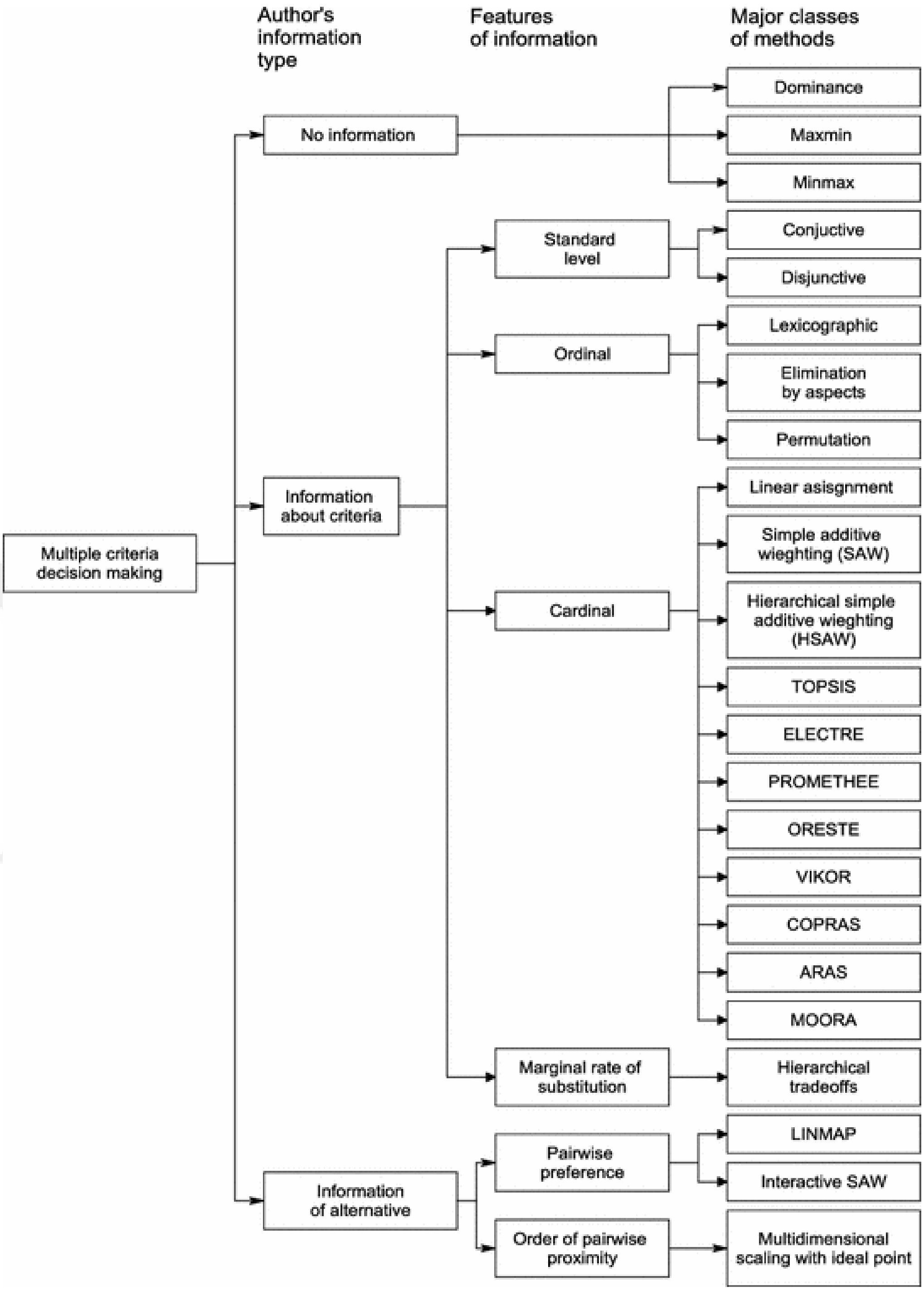

Figure 3.1 The classification scheme for MCDM methods (Zardari, Ahmed, Shirazi & Yusop, 2015)

3.1 ELECTRE Method

The family of ELECTRE methods are known as outranking methods and the first version of these methods, ELECTRE I, is proposed by Roy (1968). After the first article on ELECTRE I, different versions of ELECTRE methods were introduced such as ELECTRE II, ELECTRE III, ELECTRE IV, ELECTRE IS and ELECTRE TRI (renamed as ELECTRE TRI-B after the development of its new version, ELECTRE TRI-C and ELECTRE TRI-nC as an extension of ELECTRE TRI-C). Each version of ELECTRE methods were developed for proposing solutions to various types of problematic such as choice problematic, ranking problematic and sorting problematic (Figueira, Greco, Roy, & Slowi´nski, 2010). ELECTRE I and IS were designed for choice problematic which aims to identify the smallest set of alternatives for selecting the best among them. ELECTRE II, III, and IV were designed to be employed in the ranking problematic which aims to rank the alternatives from the best to the worst. ELECTRE TRI, TRI-C and TRI-nC were proposed for sorting problematic aiming in the assignment of the alternatives to pre-defined categories.

The calculation process of ELECTRE I method is based on pairwise comparison of the alternatives so as to build outranking relations. The concordance and discordance indices are utilized to analyze the outranking relations between the alternatives. The dominated alternatives are eliminated by considering threshold values defined via dominance relationships and the partial preference ordering of the alternatives is determined.

The steps of ELECTRE I are expressed as follows (Triantaphyllou, 2000).

Step 1: The decision matrix, in other words, evaluation matrix is formed in this step. The decision matrix is a *mxn* dimension matrix and it can be denoted with $Y = [y_{ij}]_{mxn}$ as shown in Eq. (3.2). It points out that the problem has *m* alternatives and these alternatives are evaluated according to *n* criteria. The notation of y_{ij} indicates the evaluation value of i-th alternative with reference to j-th criterion.

$$Y = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ r_{21} & r_{22} & \dots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \tag{3.2}$$

Step 2: The evaluation matrix is normalized by using Eq. (3.3) and normalized decision matrix $R = [r_{ij}]_{mxn}$, shown in Eq. (3.4), is established.

$$r_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{m} y_{ij}^2}} \quad i = 1, \ldots, m \quad j = 1, \ldots n \tag{3.3}$$

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \ldots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{3.4}$$

Step 3: The weighted normalized decision matrix $V = [v_{ij}]_{mxn}$ is established by multiplying each criterion weight with each normalized evaluation value in the column which belongs to the related criterion. The weights of criteria determined by DM should be normalized as well. In other words, $\sum_{i=1}^{n} w_j$ should be equal to 1. The calculation of the weighted normalized decision matrix can be described as Eq. (3.5).

$$V = \begin{bmatrix} w_1 & 0 & \cdots & 0 \\ 0 & w_2 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_n \end{bmatrix} * \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \ldots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \ldots & v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \tag{3.5}$$

Step 4: The concordance and discordance sets are determined by comparing the alternatives with each other. All criteria for which A_a is preferred to A_b are put into the concordance set C_{ab} as defined in Eq. (3.6).

$$C_{ab} = \{j |\ v_{aj} \geq v_{bj}\}, \text{ for } j = 1,2, \ldots n \tag{3.6}$$

The discordance set D_{ab}, defined by Eq. (3.7), is the complementary subset.

$$D_{ab} = \{j |\ v_{aj} < v_{bj}\}, \text{ for } j = 1,2, \ldots n \tag{3.7}$$

Step 5: The concordance matrix is formed by calculating its components, namely concordance indices. Each concordance index reflecting the superiority degree of alternative A_a to alternative A_b is calculated by summing up the weights of criteria, which are contained in the concordance set, based on the Eq. (3.8).

$$c_{ab} = \sum_{j \in C_{ab}} w_j \text{ , for } j = 1,2, \dots n \tag{3.8}$$

Considering the abovementioned equation, it can be said that the concordance matrix includes the information regarding to the differences among weights. The concordance matrix *C* is described in Eq. (3.9).

$$C = \begin{bmatrix} - & c_{12} & c_{13} & \cdots & c_{1m} \\ c_{21} & - & c_{23} & \dots & c_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ c_{m1} & c_{m2} & c_{m3} & \cdots & - \end{bmatrix} \tag{3.9}$$

Step 6: The discordance matrix is formed by calculating related components, namely discordance indices. Each discordance index, reflecting inferiority degree of alternative A_a to alternative A_b, is computed by the Eq. (3.10).

$$d_{ab} = \frac{\max\limits_{j \in D_{ab}} \left| v_{aj} - v_{bj} \right|}{\max\limits_{j \in J} \left| v_{aj} - v_{bj} \right|} \tag{3.10}$$

Considering the abovementioned equation, it can be said that the discordance matrix includes the information regarding to the differences among performance values. The discordance matrix *D* is expressed by Eq. (3.11).

$$D = \begin{bmatrix} - & d_{12} & d_{13} & \cdots & d_{1m} \\ d_{21} & - & d_{23} & \dots & d_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & d_{m3} & \cdots & - \end{bmatrix} \tag{3.11}$$

Step 7: Concordance and discordance dominance matrices are established using threshold values. Alternative A_a can dominate alternative A_b in the condition that the related concordance index c_{ab} is higher than or equal to the threshold value $\bar{c}$. The average of the concordance indices can be assigned as threshold value $\bar{c}$ as illustrated in the Eq. (3.12).

$$\bar{c} = \frac{1}{m(m-1)} \sum_{a=1}^{m} \sum_{b=1}^{m} c_{ab} \text{ where } a \neq b \tag{3.12}$$

The elements of dominance concordance matrix defined by Eq. (3.13) and Eq. (3.14) is formed based on the threshold value.

$$f_{ab} = 1, \quad if\ c_{ab} \geq \bar{c} \tag{3.13}$$

$$f_{ab} = 0, \quad if\ c_{ab} < \bar{c} \tag{3.14}$$

Similarly, the average of the discordance indices can be assigned as threshold value $\bar{d}$ as illustrated by Eq. (3.15).

$$\bar{d} = \frac{1}{m(m-1)} \sum_{a=1}^{m} \sum_{b=1}^{m} d_{ab} \text{ where } a \neq b \tag{3.15}$$

The elements of dominance discordance matrix is defined with Eq. (3.16) and Eq. (3.17) and constructed based on the threshold value as well.

$$g_{ab} = 1, \quad if\ d_{ab} \leq \bar{d} \tag{3.16}$$

$$g_{ab} = 0, \quad if\ d_{ab} > \bar{d} \tag{3.17}$$

Step 8: The aggregate dominance matrix E is established by multiplying the dominance concordance matrix by the dominance discordance matrix. The elements of aggregate dominance matrix can be calculated using Eq. (3.18).

$$e_{ab} = f_{ab} * g_{ab} \tag{3.18}$$

Step 9: The partial preference ordering of the alternatives are acquired from aggregate dominance matrix. The less favorable alternatives are eliminated in this step. For instance, $e_{ab} = 1$ means that alternative A_a is dominated by alternative A_b according to both the concordance concept and the discordance concept. We can determine the best alternative by searching for the column involving no elements that is equal to one in aggregate dominance matrix.

For instance, let's consider an aggregate dominance matrix as follows:

$$E = \begin{array}{cc} & \begin{array}{cccc} A1 & A2 & A3 & A4 \end{array} \\ \begin{array}{c} A1 \\ A2 \\ A3 \\ A4 \end{array} & \begin{bmatrix} - & 1 & 0 & 1 \\ 0 & - & 0 & 0 \\ 0 & 1 & - & 1 \\ 0 & 1 & 0 & - \end{bmatrix} \end{array}$$

According to this matrix, it can be deduced that alternative A_2 is dominated by A_1, A_3 and A_4. Alternative A_4 is dominated by A_1 and A_3. Therefore, A_2 and A_4 are eliminated by ELECTRE. However, we cannot compare alternative A_1 with alternative A_3 because they have no elements equal to 1. Hence, no deduction can be identified regarding to the preference relation between $A_1$and A_3. This implies an important shortcoming of ELECTRE I, namely partial ranking.

3.2 VIKOR Method

VIKOR, developed by Opricovic (1998), is a distance-based method proposing compromise solution that is the closest one to the ideal solution of the decision making problem with conflicting criteria. VIKOR method proposes compromise solution (one or a set) and compromise ranking list to be accepted by DMs by providing a maximum group utility for the "majority" and a minimum individual regret for the "opponent" (Opricovic & Tzeng, 2007). VIKOR method gives the opportunity to DMs to reflect their preferences represented by the relative importance of the criteria taken into account in the ranking process. Moreover, different ranking lists can be specified according to different strategies followed by DMs.

VIKOR method is designed to solve the MCDM problems of which characteristics are listed as follows (Opricovic & Tzeng, 2007).

- The problem includes conflicting and non-commensurable criteria.
- The DM desires to obtain the solution that is closest to the ideal solution.
- The weights are assigned to represent the preferences of DMs.
- All criteria are used to assess the alternatives.

The steps of VIKOR method are explained as follows;

Suppose that there exist *m* alternatives (i=1,2,…m) evaluated according to *n* criteria (j=1,2,…n). The notation of f_{ij} indicates the evaluation value of i-th alternative according to j-th criterion. The notation w_j represents the weights of criteria.

Step 1: Specify the best f_j^*, and the worst f_j^- values among all criterion functions.

$f_j^* = \max_i f_{ij}$ and $f_j^- = \min_i f_{ij}$, if the j-th function represents a benefit.

$f_j^* = \min_i f_{ij}$ and $f_j^- = \max_i f_{ij}$, if the j-th function represents a cost.

Step 2: Calculate the values S (group utility) by Eq. (3.19) and R (individual regret) by Eq. (3.20) for each alternative.

$$S_i = \sum_{j=1}^{n} w_j \, (f_j^* - f_{ij})/(f_j^* - f_j^-) \tag{3.19}$$

$$R_i = \max_j [\frac{w_j\left(f_j^* - f_{ij}\right)}{f_j^* - f_j^-}] \tag{3.20}$$

Step 3: Calculate the values Q by Eq. (3.21) for each alternative

$$Q_i = \gamma * \frac{S_i - S^*}{S^- - S^*} + (1-\gamma) * \left(\frac{R_i - R^*}{R^- - R^*}\right) \qquad i = 1,2, \dots m \tag{3.21}$$

where $S^- = max\, S_i$; $S^* = min\, S_i$; $R^- = maxR_i$; $R^* = minR_i$ and γ is defined as a weight for the strategy of maximum group utility, whereas $(1-\gamma)$ is defined as a weight of the individual regret.

Step 4: Rank the alternatives, sorting by the values S, R and Q in descending order. Suppose that A_1 is the first in the ranking according to the values of Q. We accept alternative A_1 as compromise solution if it satisfies the following two conditions:

Condition 1. Acceptable advantage:

$$Q(A_2) - Q(A_1) \geq DQ \tag{3.22}$$

A_2 is the second alternative in ranking according to values of Q and DQ = 1/ (m-1)

Condition 2. Acceptable stability in decision making:

Alternative A_1 must be in the first position of the ranking lists created considering S and/or R. This compromise solution is stable within a decision making process, which could be "voting by majority rule" ($\gamma > 0.5$ is needed), or "by consensus" ($\gamma \approx 0.5$ is needed), or "with veto" ($\gamma < 0.5$ is needed) (Opricovic & Tzeng, 2004). Here, γ is the weight of decision making strategy. When $\gamma > 0.5$, the values Q_i follow majority rule. If alternative A_1 satisfies only one condition, then a set of compromise solutions is proposed. If Condition 2 is not satisfied, then A_1 and A_2 are the compromise solutions. If Condition 1 is not satisfied, then A_1, A_1,… A_m are the compromise solutions where

$$Q(A_m) - Q(A_1) < DQ \text{ and } DQ = 1 \,/\, (m-1) \tag{3.23}$$

3.3 The Reason of Integration of VIKOR with ELECTRE

ELECTRE I is a simple and useful methodology. It has an advantage in proposing the best solution with pairwise comparison approach, but it has several shortcomings, mainly in the ranking procedure. The major disadvantage is that it provides partial ranking. This method identifies the alternatives that dominate other alternatives according to concordance and discordance criteria. It is possible to come across the situations in which the preference relation between some alternatives cannot be determined. Therefore, ELECTRE I method is convenient for the problems aiming in determining only the best alternatives instead of a complete ranking list and for the problems in which there exist a few criteria with a large number of alternatives. On the other hand, VIKOR has advantages in terms of providing complete ranking. Therefore, the integration of VIKOR to ELECTRE I leads to overcome the weaknesses of ELECTRE I. Zandi & Roghanian (2013) proposed a methodology integrating ELECTRE I and VIKOR to take the advantages of both methods under fuzzy set theory. We extended this methodology under intuitionistic fuzzy environment and developed a novel MCDM methodology, namely “IF-ELECTRE integrated with VIKOR”. Moreover, the MCDM methodology used in this study differs from the methodology developed by Zandi & Roghanian (2013) in terms of determination of the criteria weights through entropy equations to capture the vagueness and disagreements among the DMs and establish a more reliable matrix for criteria weights by using an objective weighting approach. Three different concordance and discordance sets (strong, midrange and weak) are specified and the relative importance of each concordance sets is determined via weighted distance approach that benefits from Euclidean distance measure.

3.4 Studies Extending ELECTRE with Intuitionistic Fuzzy Set Theory

A number of studies that integrate ELECTRE methods with IFS theory and apply this integration to various outranking problems exist in the literature. Among them, Wu & Chen (2011) proposed a MCDM approach which is the first attempt to use ELECTRE based on IFS theory. They introduced different kinds of concordance and discordance sets utilizing the characteristics of IFS theory and ranking process based on the concepts of positive and negative ideal solutions. Shen, Xu, & Xu (2016) developed an outranking method for MCGDM dealing with sorting problematic. They proposed outranking relations utilizing from characteristics of IFSs. The developed method is applied to a case study regarding bridge risk assessment. Devi & Yadav

(2013) proposed an extension of ELECTRE method for selection of plant location problem in which decision matrix is generated based on triangular IFSs. Vahdani, Mousavi, Moghaddam, & Hashemi (2013) presented an extending ELECTRE method under IFS environment and they applied it to select best flexible manufacturing system. In this paper, the new discordance index is proposed utilizing fuzzy distance measure. Yunna, Jinying, Jianping, Shuai, & Haobo (2016) proposed a methodology handling offshore wind power site selection using ELECTRE-III method based on IFS theory. Hashemi, Hajiagha, Zavadskas, & Mahdiraji (2016) extended ELECTRE-III method providing from interval-valued IFS concept in which elements are defined by membership and non-membership interval. The developed method is applied to an investment project selection and an air conditioning system selection problem. Xu & Shen (2014) proposed an extended ELECTRE I method based on interval-valued IFSs for GDM problems. A new entropy model is proposed in order to obtain weights of the criteria in this study. The developed method is illustrated by implementing to a supplier selection problem. Zhang, Peng, Wang, & Wang (2017) developed an outranking approach based on ELECTRE-I method in which the DMs express their judgments on the alternatives with linguistic terms instead of numerical values. Therefore, new outranking relationships are introduced for linguistic intuitionistic fuzzy numbers to use in MCDM problems, and a coal mine safety evaluation problem is applied to demonstrate the developed method.

3.5 Intuitionistic Fuzzy Set Theory

Fuzzy set theory presented by Zadeh (1965a) differentiates from the classical set theory since the elements of a set is defined with their membership degree to the set. Let X be a universal set and a fuzzy set A in X is represented by Eq. (3.24).

$$A = \{< x, \mu_A(x) > | x \epsilon X\} \tag{3.24}$$

where $\mu_A(x): X \to [0, 1]$ indicates the membership degree of the element $x \in X$ to A subset of X.

IFS theory introduced by Atanassov (1986) considers non-membership degree of an element to the set as well as membership degree.

Let X be a universal set and an IFS A in X is represented as shown in Eq. (3.25).

$$A = \{< x, \mu_A(x), v_A(x) > | x \epsilon X\} \tag{3.25}$$

where the functions $\mu_A(x): X \rightarrow [0, 1]$ and $v_A(x): X \rightarrow [0, 1]$ represent the membership degree and non-membership degree of the element $x \in X$ to A subset of X and for every $x \in X$ in the following condition defined by Eq. (3.26).

$$0 \leq \mu_A(x) + v_A(x) \leq 1 \tag{3.26}$$

Atanassov (1986) defines function $\pi_A(x): X \rightarrow [0,1]$ as in the following:

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x) \tag{3.27}$$

In Eq. (3.27), $\pi_A(x)$ indicates the hesitancy (i.e. indeterminacy or uncertainty) degree of the element $x \in X$ to subset A.

3.5.1 Intuitionistic Fuzzy Numbers and Some Operational Laws

IFSs are composed of intuitionistic fuzzy numbers (IFNs), in other words intuitionistic fuzzy values (IFVs), which are characterized by the degree of membership (μ) and the degree of non-membership (v) of an element (Xu, 2007). The operational laws of IFNs (Eq. (3.28) and Eq. (3.29)) are used to develop intuitionistic fuzzy aggregation operators required for aggregating intuitionistic fuzzy information. For this purpose, intuitionistic fuzzy weighted averaging (IFWA) operator (Xu, 2007) is used in this study. Two basic operational laws for IFNs are defined as follows (Xu, 2007; Xu and Yager, 2006). Let $\alpha = (\mu_\alpha, v_\alpha)$ and $\beta = (\mu_\beta, v_\beta)$ be two IFNs, then;

$$\alpha \oplus \beta = \left(\mu_\alpha + \mu_\beta - \mu_\alpha * \mu_\beta, 1 - v_\alpha * v_\beta\right) \tag{3.28}$$

$$\delta\alpha = (1 - (1 - \mu_\alpha)^\delta,\ 1 - {v_\alpha}^\delta), \text{ where } \delta > 0 \qquad (3.29)$$

3.5.2 Distances for Intuitionistic Fuzzy Sets

In this study, distance measure between IFSs, which is firstly introduced by Atanassov (1986), is applied for describing the differences between IFSs. The distance measure specifies the difference or similarity between IFSs. In other words, if the distance between two IFSs is high, the difference between these IFSs is high as well and the similarity between these IFSs is low. Distance measures between IFSs have been used commonly in application areas such as machine learning, decision making, pattern recognition and market prediction (Wang & Xin, 2005). Atanassov (1986) and Szmidt & Kacprzyk (2000) generalized Hamming distance, Euclidean distance and their normalized counterparts. Szmidt & Kacprzyk (2000) presented concepts of distances between IFSs based on geometrical representations. Let A and B be two IFSs in $X = \{x_1, x_2, \dots x_n\}$. Szmidt & Kacprzyk (2000) proposed four widely used distance measures between IFSs A and B. These measures are defined in the following;

- The Hamming distance is defined by Eq. (3.30).

$$d_H(A,B) = \frac{1}{2}\sum_{j=1}^{n}(|\mu_A(x_j) - \mu_B(x_j)| + |v_A(x_j) - v_B(x_j)| + |\pi_A(x_j) - \pi_B(x_j)|) \qquad (3.30)$$

- The normalized Hamming distance is defined by Eq. (3.31).

$$d_{nH}(A,B) = \frac{1}{2n}\sum_{j=1}^{n}(|\mu_A(x_j) - \mu_B(x_j)| + |v_A(x_j) - v_B(x_j)| + |\pi_A(x_j) - \pi_B(x_j)|) \qquad (3.31)$$

- The Euclidean distance is defined by Eq. (3.32).

$$d_E(A,B) = \sqrt{\frac{1}{2}\sum_{j=1}^{n}\left(\mu_A(x_j) - \mu_B(x_j)\right)^2 + \left(v_A(x_j) - v_B(x_j)\right)^2 + \left(\pi_A(x_j) - \pi_B(x_j)\right)^2} \qquad (3.32)$$

- The normalized Euclidean distance is defined by Eq. (3.33)

$$d_{nE}(A,B) = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}\left(\mu_A(x_j)-\mu_B(x_j)\right)^2+\left(v_A(x_j)-v_B(x_j)\right)^2+\left(\pi_A(x_j)-\pi_B(x_j)\right)^2} \quad (3.33)$$

In this paper, the Euclidean distance is used to measure the difference between evaluation values of alternatives which are defined as IFSs.

3.5.3 Linguistic Variables

Linguistic variables are variables of which values are not numbers but words or, more generally, linguistic labels of fuzzy sets (Zadeh, 1983). They can be applied when crisp data are inefficient to describe the real life situations in MCDM (Wang & Lee, 2009). Linguistic variables can be quantified and used as mathematical operators utilizing IFS theory (Büyüközkan & Göçer, 2017). For instance, the evaluation score of alternatives can be defined as linguistic variables such as “very good”, “good” and “medium good”. These linguistic variables can be expressed by IFNs. The importance of criteria and DMs are also defined by DMs using linguistic variables expressed with IFNs such as “very important”, “important” and “medium”. Hence, the weights of criteria and DMs are obtained based on these variables (Boran, Genc, Kurt, & Akay, 2009). In our study, DMs evaluate the alternatives according to each criterion using linguistic variables expressed by IFNs which is shown in Table 3.1.

Table 3.1 Linguistic variables for the evaluation of alternatives (Boran et al.,2009)

Linguistic variables	**Intuitionistic fuzzy numbers**
Extremely good (EG) / extremely high (EH)	(1.00, 0.00, 0.00)
Very very good (VVG) / very very high (VVH)	(0.90, 0.10, 0.00)
Very good (VG) / very high (VH)	(0.80, 0.10, 0.10)
Good (G) / high (H)	(0.70, 0.20, 0.10)
Medium good (MG) / medium high (MH)	(0.60, 0.30, 0.10)
Fair (F) / medium (M)	(0.50, 0.40, 0.10)
Medium bad (MB) / medium low (ML)	(0.40, 0.50, 0.10)
Bad (B) / low (L)	(0.25, 0.60, 0.15)
Very bad (VB) / very low (VL)	(0.10, 0.75, 0.15)
Very very bad (VVB) / very very low (VVL)	(0.10, 0.90, 0.00)

3.5.4 The Entropy Concept

The concept of entropy in information theory was firstly proposed by Shannon (1948) which presented an equation to measure the uncertainty in information based on probability theory. The formulation of Shannon's Entropy is depicted in Eq. (3.34).

$$H(p_1, p_2, \dots p_n) = -\sum_{i=1}^{n} p_i \ln p_i \tag{3.34}$$

where p_i $(i = 1,2, \dots n)$ are probabilities of random variable.

Several studies are conducted regarding entropy concept. Among them, Zadeh (1965b) introduced the fuzziness degree of fuzzy sets which is referred as entropy of a fuzzy set. De Luca & Termini (1972) proposed non-probabilistic entropy measure for fuzzy sets. De Luca-Termini entropy for fuzzy sets is depicted in Eq. (3.35) (Vlochos & Sergiadis, 2007).

$$E_{LT}^{FS}(\tilde{A}) = -\frac{1}{n \ln 2} \sum_{i=1}^{n} [\mu_{\tilde{A}}(x_i) \ln \mu_{\tilde{A}}(x_i) + (1 - \mu_{\tilde{A}}(x_i)) \ln(1 - \mu_{\tilde{A}}(x_i))] \tag{3.35}$$

De Luca-Termini entropy measure, denoted by $E_{LT}^{FS}(\tilde{A})$, describes the degree of fuzziness of an IFS $\tilde{A}$. Szmidt & Kacprzyk (2001) extended the axioms proposed by De Luca & Termini (1972) and presented a non-probabilistic type entropy measure for IFSs on the basis of geometric interpretation of IFSs. Further, Vlochos & Sergiadis (2007) extended the De Luca-Termini non-probabilistic entropy for IFSs and they asserted that intuitionistic fuzzy entropy (IF-entropy) measure describes not only fuzziness but also intuitionism of an IFS. The equation for IF-entropy measure proposed by Vlachos & Sergiadis (2007) is defined by Eq. (3.36).

$$\begin{aligned} E_{LT}^{IFS}(A) = -\frac{1}{n \ln 2} \sum_{i=1}^{n} [&\mu_A(x_i) \ln \mu_A(x_i) + v_A(x_i) \ln v_A(x_i) - (1 \\ &- \pi_A(x_i)) \ln(1 - \pi_A x_i)) - \pi_A(x_i) \ln 2) \end{aligned} \tag{3.36}$$

IF-entropy measure, denoted by $E_{LT}^{IFS}(A)$, comprises the degree of fuzziness and the degree of intuitionism of an IFS A.

In this study, the entropy method is used for assigning weights to the criteria and DMs in the MCDM methodology developed in this thesis. Zeleny (1976) introduced the concept of using entropy to measure and assign the criterion weight. According to Zeleny (1976), more distinct individual criterion scores means larger corresponding entropy weight of criterion. Moreover, the larger the entropy measure of a criterion, the less information is transmitted by the related criterion, hence the criterion weight is smaller. This methodology employs Entropy measure to determine criteria weights based on the idea in Zeleny (1976). However, we use entropy equation proposed by Vlochos & Sergiadis (2007) whereas Zeleny (1976) employs Shannon's entropy. Moreover, the methodology developed in this paper utilizes Entropy measure as an objective weighting approach for weighting DMs based on Zeleny (1976)'s methodology. To this aim, we extract uncertainty degree of each individual decision matrix using entropy measure and determine the weights corresponding to each DM according to obtained entropy measures.

3.6 MCDM based on IFS Theory

Let $X = \{x_1, x_2, \dots, x_n\}$ the set of criteria and $A = \{A_1, A_2, \dots, A_m\}$ the set of alternatives. Alternative A_i is represented as an IFS of the following form (Eq. 3.37).

$$A_i = \left\{< x_j, X_{ij} > \middle| x_j \in X \right\} \tag{3.37}$$

where $X_{ij} = (\mu_{ij}, v_{ij})$.

X_{ij} defines the degree of satisfaction and dissatisfaction of the ith alternative according to the jth criterion, respectively denoted by μ_{ij} and v_{ij} in Eq. (3.38) and Eq. (3.39).

$$0 \leq \mu_{ij}(x) + v_{ij}(x) \leq 1, \qquad i = 1,2, \dots m, \qquad j = 1,2, \dots n \tag{3.38}$$

$$\pi_{ij}(x) = 1 - \mu_{ij}(x) - v_{ij}(x) \tag{3.39}$$

$\pi_{ij}(x)$ is the hesitancy degree of the *i*th alternative according to the *j*th criterion. Hence, the intuitionistic fuzzy decision matrix (IF-decision matrix) M is defined with Eq. (3.40).

$$M = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{bmatrix} = \begin{bmatrix} (\mu_{11}, v_{11}, \pi_{11}) & \cdots & (\mu_{1n}, v_{1n}, \pi_{1n}) \\ \vdots & \ddots & \vdots \\ (\mu_{m1}, v_{m1}, \pi_{m1}) & \cdots & (\mu_{mn}, v_{mn}, \pi_{mn}) \end{bmatrix} \tag{3.40}$$

Let $E = \{E_1, E_2, \dots, E_k\}$ the set of DMs. In MCGDM problems based on IFS theory, each DM expresses his/her evaluation on alternatives with reference to each criterion using IFNs. Then, all individual evaluations are aggregated to propose group evaluation. Each individual evaluation on alternatives proposed by each DM are shown by individual IF-decision matrix $Z^{(k)} = (z_{ij}^{(k)})_{mxn}$ in Eq. (3.41).

$$Z^{(k)} = \begin{bmatrix} z_{11}^{(k)} & \cdots & z_{1n}^{(k)} \\ \vdots & \ddots & \vdots \\ z_{m1}^{(k)} & \cdots & z_{mn}^{(k)} \end{bmatrix} = \begin{bmatrix} (\mu_{11}^{(k)}, v_{11}^{(k)}, \pi_{11}^{(k)}) & \cdots & (\mu_{1n}^{(k)}, v_{1n}^{(k)}, \pi_{1n}^{(k)}) \\ \vdots & \ddots & \vdots \\ (\mu_{m1}^{(k)}, v_{m1}^{(k)}, \pi_{m1}^{(k)}) & \cdots & (\mu_{mn}^{(k)}, v_{mn}^{(k)}, \pi_{mn}^{(k)}) \end{bmatrix} \tag{3.41}$$

where $z_{ij}^{(k)}$ indicates the evaluation of E_k on alternative A_i with reference to criterion x_j.

3.7 Proposed IF-ELECTRE Integrated with VIKOR Methodology

This section explains the procedure of MCGDM methodology based on integration of ELECTRE and VIKOR methods under IF environment. This methodology can be implemented to the decision making problems in which a decision committee with a specified number of experts evaluates the alternatives as well as to the problems in which a vast number of people evaluate the alternatives. According to the type of the problem the steps of the methodology may differentiate. Due to the type of the problem handled in this thesis, construction of group decision matrix is based on calculating the percentages of the votes given by a vast amount of people. The sentences in online reviews can be seen as a vote from a customer. On the other hand, steps of the methodology for the problems needing expert opinions for decision making are also proposed. For this type of problems, certain number of experts assess the alternatives through linguistic variables and the group decision matrix is established by aggregating opinions of all experts using IFWA operator. After the construction of group decision matrix, the same steps are conducted for both of the problems. In this chapter, we explain the steps of the developed MCDM methodology considering the problem with certain number of DMs. In the last section of Chapter four, the differences in the first step of the methodology for the problems involving a vast number of DMs can be observed. The methodology mainly consists of 12 steps which are explained in detail in this section. The flow chart of developed methodology is illustrated in Figure 3.2.

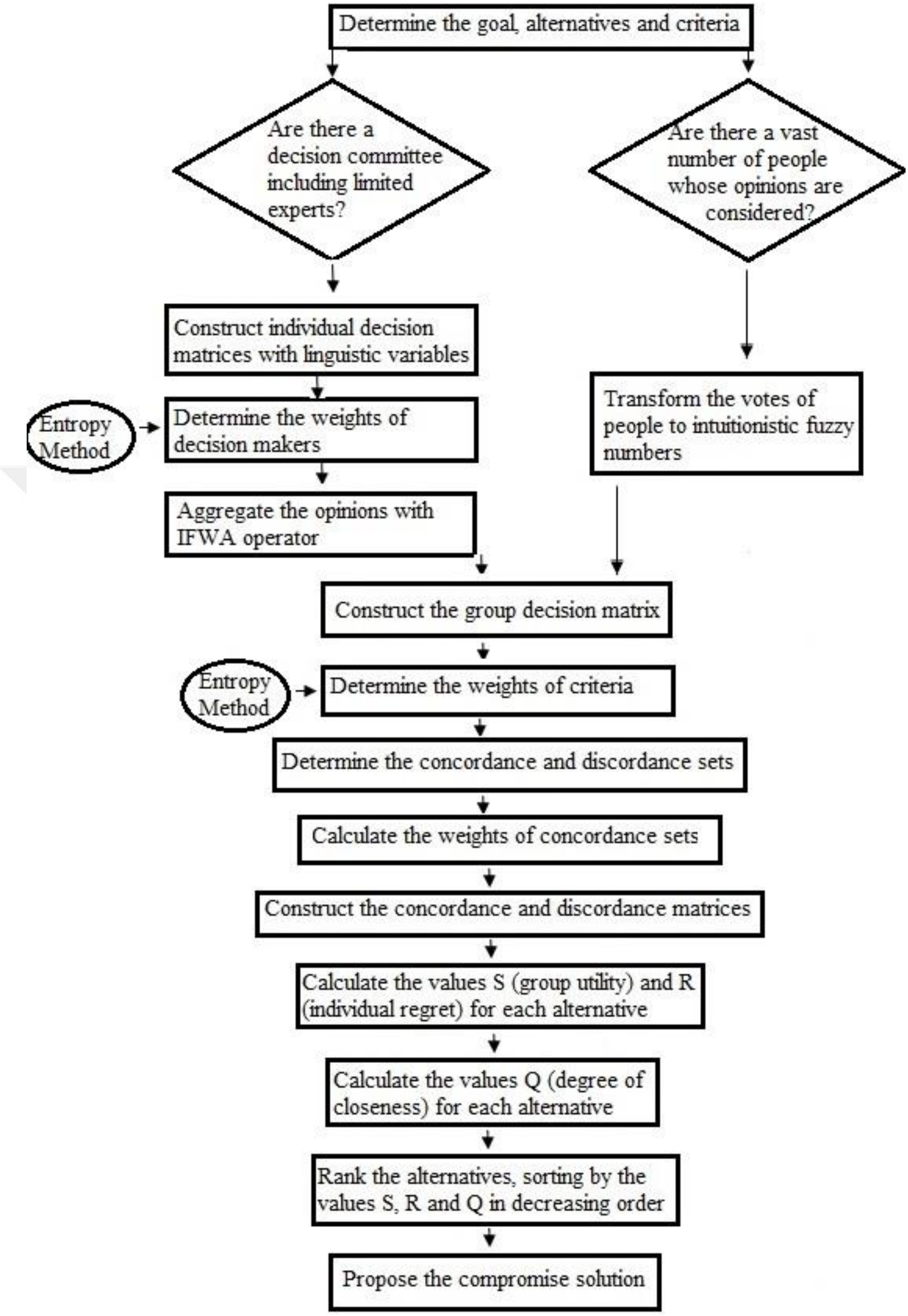

Figure 3.2 The flow chart of the developed methodology: IF-ELECTRE integrated with VIKOR

The notations for the proposed MCDM methodology are as follows:

$A = \{A_1, A_2, \dots, A_m\}$ is the set of alternatives,
$C = \{C_1, C_2, \dots, C_n\}$ is the set of criteria,
$\mathrm{E} = \{E_1, E_2, \dots, E_k\}$ is the set of DMs.
W = $\{w_1, w_2, \dots, w_n\}$ is the set of weights assigned to criteria
$\delta = \{\delta_1, \delta_2, \dots\ \delta_k\}$ is the set of weights assigned to DMs.

3.7.1 Determination of the Goal, Alternatives and Criteria

Decision committee identifies the goal and scope of the decision making problem, as well as the alternatives and the criteria that will be used to evaluate alternatives.

3.7.2 Construction of the Individual Decision Matrices

DMs evaluate the alternatives with reference to each criterion using linguistic variables represented by IFNs, therefore each individual decision matrix is formed according to evaluation of each DM.

3.7.3 Determination of the Weights of Decision Makers

Suppose that there exists k DMs. Each DM E_k may have different level of experience and knowledge on the alternatives, so the relative importance for each DM should be determined. There are two methods to obtain the weights of DMs. The subjective methods, which deal with preferences and judgments of DMs to obtain weights, evaluate DMs according to their characteristics such as social positions, experiences on related problem etc. The studies applied subjective methods generally use linguistic variables to express relative importance of DMs or assume that the weights related to DMs are pre-determined. The methodology developed in this thesis obtains the weights of DMs objectively by objective weighting methods since these methods are independent of psychological effects and they are based on a mathematical background. Proposed method directly uses individual decision matrix which expresses opinion of DM related to alternatives to determine the weights and measures the uncertainties of individual decision matrices. If the uncertainty of an individual decision matrix is low, it means that more information is transmitted by the DM who constructs the so-called individual decision matrix. Therefore, a relatively higher value is assigned as the weight of DM. The uncertain information contained by an IFS can be measured by means of entropy. Wei & Tang (2011) obtained the weights of DMs from intuitionistic preference relation matrices which express the preference information of DMs for each pair of alternatives. Each individual intuitionistic preference relation matrix is regarded as an IFS and the uncertainty of them are calculated based on entropy method. In a similar way, our methodology utilizes objective weighting method based on entropy measure for obtaining the weights of DMs. To this aim, each individual decision matrix $Z^k = (z_{ij}^k)_{mxn}$ is considered as an IFS and then the uncertain information of each Z^k is measured using entropy equation. As stated previously, we apply IF-entropy measure proposed by Vlachos & Sergiadis (2007) to calculate uncertain information of each $Z^{(k)}$.

The weighting method used in this study is explained as follows. Firstly, the following Eq. (3.42) is used to calculate entropy measure denoted by $E_{LT}^{IFS}\left(Z^{(k)}\right)$ for each $Z^{(k)}$.

$$E_{LT}^{IFS}\left(Z^{(k)}\right) = -\frac{1}{mn\ln 2}\sum_{j=1}^{n}\sum_{i=1}^{m}[\mu_{ij}\ln\mu_{ij} + v_{ij}\ln v_{ij} - (1 - \pi_{ij})\ln(1 - \pi_{ij})) - \pi_{ij}\ln 2] \tag{3.42}$$

where

$Z^{(k)}$ indicates individual IF-decision matrix of E_k $j = 1, 2, \dots, n$ $i = 1,2, \dots m$

The degree of divergence for each $Z^{(k)}$ which increases with the decrease of entropy measure is calculated as following Eq. (3.43);

$$d_{Z^{(k)}} = 1 - E_{LT}^{IFS}\left(Z^{(k)}\right) \tag{3.43}$$

Finally, the weights of DMs indicated by a set $\delta = \{\delta_1, \delta_2, \dots \delta_k\}$ are calculated by Eq. (3.44).

$$\delta_k = \frac{d_{Z^{(k)}}}{\sum_{k=1}^{K} d_{Z^{(k)}}} \tag{3.44}$$

where $\delta_k \geq 0,\ k = 1,2, \dots K$ and $\sum_{k=1}^{K} \delta_k = 1$.

It is concluded that the weight of E_k has a higher value given that the entropy measure of $Z^{(k)}$ has a lower value. In other words, a higher value is assigned to the weight of E_k if a low degree of uncertainty is obtained for $Z^{(k)}$.

3.7.4 Construction of Group Decision Matrix

The individual evaluation of each DM is represented by an IF-decision matrix $Z^k = (z_{ij}^k)_{mxn}$ and aggregated in order to construct a group decision matrix $Z = (z_{ij})_{mxn}$ using IFWA operator (Xu, 2007). The elements of group decision matrix z_{ij} are calculated by Eq. (3.45). The weights of DMs are important factors that impact the accuracy of the aggregation process, which can be formulated by Eq. (3.45).

$$\begin{aligned} z_{ij} &= IFWA_{\delta}(z_{ij}^{(1)}, z_{ij}^{(2)}, \dots, z_{ij}^{(K)}) \\ &= \delta_1 z_{ij}^{(1)} \oplus \delta_2 z_{ij}^{(2)} \oplus \delta_3 z_{ij}^{(3)} \oplus \dots \oplus \delta_K z_{ij}^{(K)} \\ &= (1 - \textstyle\prod_{k=1}^{K}\left(1 - \mu_{ij}^{(k)}\right)^{\delta_k},\ \prod_{k=1}^{K}\left(v_{ij}^{(k)}\right)^{\delta_k}, \prod_{k=1}^{K}\left(1 - \mu_{ij}^{(k)}\right)^{\delta_k} - \\ &\quad \textstyle\prod_{k=1}^{K}(v_{ij}^{(k)})^{\delta_k}) \end{aligned} \tag{3.45}$$

The group decision matrix $Z = (z_{ij})_{mxn}$ is represented with Eq. (3.46).

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{m1} & \cdots & z_{mn} \end{bmatrix} = \begin{bmatrix} (\mu_{11}, v_{11}, \pi_{11}) & \cdots & (\mu_{1n}, v_{1n}, \pi_{1n}) \\ \vdots & \ddots & \vdots \\ (\mu_{m1}, v_{m1}, \pi_{m1}) & \cdots & (\mu_{mn}, v_{mn}, \pi_{mn}) \end{bmatrix} \tag{3.46}$$

3.7.5 Calculating the Weights of Criteria Using Entropy Method

Since the weights of criteria have a significant impact on the ranking results (Mareschal, 1988), the determination of criteria weights reliably is critical in MCDM. The approaches aiming at specifying weights can be categorized into subjective approaches and objective approaches (Ma, Fan, & Huang, 1999). In the studies that apply subjective approaches (Tavana, Zareinejad, Di Caprio, & Kaviani, 2016; Roostaee, Izadikhah, Lotfi, & Rostamy-Malkhalifeh, 2012), each DM expresses his/her evaluation on importance of criteria and the subjective weights are derived from these evaluations by subjective approaches such as AHP (Saaty, 1980) and Delphi methods (Hwang & Lin, 1987). On the other hand, in studies that apply objective approaches, objective weights are derived considering the information provided by decision matrix. The weights of criteria can be determined objectively by calculating entropy measures of criteria (Zeleny, 1976). Low values of entropy reveals that the evaluation scores of the alternatives according to a criterion are less similar (Hung & Chen, 2009) and more information is transmitted by the criterion, and thus the weight of criterion is higher (Zeleny, 1976). In this step, the weights of criteria are obtained using the IF-entropy measure proposed by Vlachos & Sergiadis (2007).

Several studies (i.e. Hung & Chen, 2009; Zhang & Liu, 2011) used entropy method with the aim of determining the weights of criteria based on IF-decision matrix. The entropy weights of criteria are calculated using Eq. (3.47), Eq. (3.48) and Eq. (3.49), respectively.

Considering each criterion as IFS, the following equation is used in order to measure the entropy value of each criterion;

$$E_{LT}^{IFS}(C_j) = -\frac{1}{m\ln 2}\sum_{i=1}^{m}[\mu_{ij}\ln\mu_{ij} + v_{ij}\ln v_{ij} - (1 - \pi_{ij})\ln(1-\pi_{ij})) - \pi_{ij}\ln 2] \quad (3.47)$$

$j = 1, 2, \ldots, n \;\; i = 1,2, \ldots m$

where C_j indicates the jth criterion. Here, if μ_{ij}=0, v_{ij}=0, π_{ij}=1, then, $\mu_{ij} \ln \mu_{ij}$=0, $v_{ij} \ln v_{ij}$=0, $(1-\pi_{ij}) \ln(1-v_{ij})$=0, respectively. $E_{LT}^{IFS}(C_j)$ comprises the hesitancy degree and the fuzziness degree of the IFS C_j. Then, the degree of divergence (d_j) of the average intrinsic information provided by the corresponding performance scores associated with criterion C_j can be calculated using the following equation:

$$d_j = 1 - E_{LT}^{IFS}(C_j) \tag{3.48}$$

here, d_j indicates the degree of divergence which increases if the entropy value decreases. Therefore, the entropy weights of criteria is determined as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{3.49}$$

where w_j indicates the entropy weight of jth criterion. It is concluded that the weight of a criterion has higher value in the condition that the entropy of the criterion has lower value.

3.7.6 Identification of the Concordance and Discordance Sets

Three different concordance and discordance sets are generated using the concepts of score function, accuracy function and hesitancy degree based on Wu & Chen (2011). In this step, score function (Chen & Tan, 1994) and accuracy function (Hong & Choi, 2000) are used to compare the IFVs based on Eq. (3.50) and Eq. (3.51), respectively:

$$S(x_{ij}) = \mu_{ij} - v_{ij} \tag{3.50}$$

$$S(x_{ij}) = \mu_{ij} + v_{ij} \tag{3.51}$$

where x_{ij} is IFV. For example, let $x_1 = (0.80, 0.10)$, $x_2 = (0.55, 0.25)$ and $x_3 = (0.60, 0.30)$ be three IFVs. The score of these values are calculated as 0.70, 0.30 and 0.30 by score function, respectively. Higher score degree means larger IFVs. Therefore the largest value is the first one. In the condition that the score degrees of IFVs are equal (as in the case that second and third scores), the accuracy scores of IFVs are evaluated. The accuracy scores of the second and third are calculated as 0.80 and 0.90 by accuracy function, respectively. Higher accuracy degree means larger IFVs. Hence, the third is larger than the second. In the condition that the accuracy degrees are also equal, IFVs are considered as equal as well.

As a result, it is concluded that larger IFVs have larger membership degree, smaller non-membership degree and smaller hesitation degree. On the basis of the above explanation, the strong, midrange and weak concordance and discordance sets are generated. Given the pairwise comparison of alternatives A_a and A_b, concordance sets consist of all criteria where A_a is either preferred or judged as equal to A_b, whereas discordance sets consist of all criteria for which A_a is worse than A_b.

The strong concordance set C'_{ab} can be formulated by Eq. (3.52).

$$C'_{ab} = \{j \mid \mu_{aj} \geq \mu_{bj},\ v_{aj} < v_{bj}\ and\ \pi_{aj} < \pi_{bj}\} \quad (3.52)$$

The midrange concordance set C''_{ab} can be formulated by Eq. (3.53).

$$C''_{ab} = \{j \mid \mu_{aj} \geq \mu_{bj},\ v_{aj} < v_{bj}\ and\ \pi_{aj} \geq \pi_{bj}\} \quad (3.53)$$

The weak concordance set C'''_{ab} can be formulated by Eq. (3.54).

$$C'''_{ab} = \{j \mid \mu_{aj} \geq \mu_{bj},\ v_{aj} \geq v_{bj}\} \quad (3.54)$$

The strong discordance set D'_{ab} can be defined by Eq. (3.55).

$$D'_{ab} = \{j \,|\mu_{aj} < \mu_{bj},\ v_{aj} \geq v_{bj}\ and\ \pi_{aj} \geq \pi_{bj}\} \tag{3.55}$$

The midrange discordance set D''_{ab} can be defined by Eq. (3.56).

$$D''_{ab} = \{j \,|\mu_{aj} < \mu_{bj},\ v_{aj} \geq\ v_{bj}\ and\ \pi_{aj} < \pi_{bj}\} \tag{3.56}$$

The weak discordance set D'''_{ab} can be defined by Eq. (3.57).

$$D'''_{ab} = \{j \,|\mu_{aj} < \mu_{bj},\ v_{aj} <\ v_{bj}\} \tag{3.57}$$

3.7.7 Calculating the Weights of Concordance Sets

Here, the relative importance of the three different concordance sets established in the previous step are determined based on the weighted distance measure, which is employed for describing the differences between IFSs. The higher distance measure means the higher difference between two IFSs. Since the distance measure evaluates the dominance degree between IFNs, we utilized weighted distance measure $w_j * d(z_{aj}, z_{bj})$ to calculate total dominance degree of concordance sets. Total dominance degrees of strong, midrange and weak concordance sets can be defined as Eq. (3.58), Eq. (3.59) and Eq. (3.60), respectively.

$$dd' = \sum_{\substack{a,b=1 \\ a\neq b}}^{m} \sum_{j\in C'_{ab}} w_j * d(z_{aj}, z_{bj}), \tag{3.58}$$

$$dd'' = \sum_{\substack{a,b=1 \\ a\neq b}}^{m} \sum_{j\in C''_{ab}} w_j * d(z_{aj}, z_{bj}), \tag{3.59}$$

$$dd''' = \sum_{\substack{a,b=1 \\ a\neq b}}^{m} \sum_{j\in C'''_{ab}} w_j * d(z_{aj}, z_{bj}). \tag{3.60}$$

Therefore, the weights of strong, midrange and weak concordance sets can be calculated with Eq. (3.61), Eq. (3.62) and Eq. (3.63), respectively. (Zhang et al., 2017).

$$w_{C'} = \frac{dd'}{dd' + dd'' + dd'''} \tag{3.61}$$

$$w_{C''} = \frac{dd''}{dd' + dd'' + dd'''} \tag{3.62}$$

$$w_{C'''} = \frac{dd'''}{dd' + dd'' + dd'''} \tag{3.63}$$

where $w_j * d(z_{aj}, z_{bj})$ indicates the dominance degree of alternative A_a over alternative A_b according to criterion C_j which is a member of concordance set and $d(z_{aj}, z_{bj})$ indicates distance measure for alternatives A_a and A_b according to C_j which is computed using Euclidean distance measure calculated by Eq. (3.32).

3.7.8 Construction of the Concordance Matrix

Concordance matrix is composed of concordance indices which reflect the degree of superiority of one alternative over another alternative. Each concordance index is calculated by utilizing the comprehensive concordance index (Figueira et al., 2010). The calculation of concordance index g_{ab} which reflects the superiority of alternative A_a over alternative A_b can be formulated with Eq. (3.64).

$$g_{ab} = w_{C'} * \sum_{j \in C'_{ab}} w_j + w_{C''} * \sum_{j \in C''_{ab}} w_j + w_{C'''} * \sum_{j \in C'''_{ab}} w_j \tag{3.64}$$

where the criteria weights are denoted by w_j and the weights of the strong, midrange and weak concordance sets are indicated by $w_{C'}$, $w_{C''}$ and $w_{C'''}$, respectively. Consequently, the concordance matrix G is constructed as shown in Eq. (3.65).

$$G = \begin{bmatrix} - & g_{12} & \cdots & \cdots & g_{1m} \\ g_{21} & - & g_{23} & \cdots & g_{2m} \\ \cdots & \cdots & - & \cdots & \cdots \\ g_{(m-1)1} & \cdots & \cdots & - & g_{(m-1)m} \\ g_{m1} & g_{m2} & \cdots & g_{m(m-1)} & - \end{bmatrix} \tag{3.65}$$

3.7.9 Construction of the Discordance Matrix

Discordance matrix is composed of discordance indices which reflect the degree of inferiority of one alternative to another alternative. The calculation of discordance index f_{ab} which reflects the inferiority of alternative A_a over alternative A_b based on the criteria in discordance sets can be formulated by Eq. (3.66) (Zhang et al., 2017)

$$f_{ab} = \frac{\max_{j \in D'_{ab} \cup D''_{ab} \cup D'''_{ab}} w_j * d(z_{aj}, z_{bj})}{\max_{j \in J} d(z_{aj}, z_{bj})} \tag{3.66}$$

$d(z_{aj}, z_{bj})$ indicates the distance between the performance score of alternative A_a and the performance score of alternative A_b according to criterion C_j calculated using Eq. (3.67). Thereby, the discordance matrix F is formed as shown in Eq. (3.67).

$$F = \begin{bmatrix} - & f_{12} & \cdots & \cdots & f_{1m} \\ f_{21} & - & f_{23} & \cdots & f_{2m} \\ \cdots & \cdots & - & \cdots & \cdots \\ f_{(m-1)1} & \cdots & \cdots & - & f_{(m-1)m} \\ f_{m1} & f_{m2} & \cdots & f_{m(m-1)} & - \end{bmatrix} \tag{3.67}$$

3.7.10 Calculate the Group Utility Values S and Individual Regret Values R for Each Alternative

In this step, VIKOR method is incorporated into the methodology to eliminate the disadvantage of ELECTRE I in terms of providing partial ranking by generating a complete ranking list. VIKOR presents two different ranking lists according to maximum group utility of majority, defined by $min\ S_i$ and minimum individual regret of the opponent, defined by $minR_i$.

Then, it aggregates group utility values (S_i) and individual regret values (R_i) by considering the weight of γ determined according to the strategy of DM and calculates the coefficients (Q_i) indicating the degree of closeness to ideal solutions for each alternative. Therefore, the compromise ranking list and the compromise solution is determined according to descending order of Q_i. Opricovic & Tzeng (2007) demonstrated the similarity between the discordance condition concept in ELECTRE and individual regret characteristic (R_i) in VIKOR and similarity between concordance condition concept in ELECTRE and group utility characteristic (S_i) in VIKOR. Thus, they introduced aggregating discordance index and aggregating concordance index so as to realize the complete ranking. After conducting a numerical experiment, they acquired the same ranking results according to ordering of R_i values in VIKOR with the results obtained using the aggregating discordance index. They also obtained similar ranking results via aggregating concordance index and with the ranking results obtained based on ordering of S_i values in VIKOR.

These concordance and discordance indices are specified through concordance and discordance matrices established in the previous steps and they are employed to determine R_i and S_i values in VIKOR method. The aggregating discordance index of alternative A_a can be calculated using Eq. (3.68).

$$f_a = R_a / C \tag{3.68}$$

where $C = \max_j w_j$ and $f_a = \max_i f_{ai} \;\; i \neq a \;\; i = \{1,2, \dots m\}$

The aggregating concordance index of alternative A_a can be calculated with Eq. (3.69).

$$g_a = 1 - S_a \tag{3.69}$$

where $g_a = \sum_{i \neq a}^{m} g_{ai} \; / \; (m-1)$ and $g_{ai} = w_{C'} * \sum_{j \epsilon C'_{ai}} w_j + w_{C''} * \sum_{j \in C''_{ai}} w_j + w_{C'''} * \sum_{j \in C'''_{ai}} w_j$ and alternatives $i = \{1,2, \dots m\}$ and criteria $j = \{1,2, \dots n\}$.

Therefore, the values R of each alternative i is calculated with Eq. (3.70).

$$R_i = f_i * C \tag{3.70}$$

The values S of each alternative i is calculated by Eq. (3.71).

$$S_i = 1 - g_i \tag{3.71}$$

3.7.11 Computing the Degree of Closeness Coefficients (Q) for Each Alternative

Q represents aggregation of the values of S and R using weight γ. For each alternative, the values of Q_i is determined based on values of S_i and values of R_i as in the following Eq. (3.72).

$$Q_i = \gamma * \frac{S_i - S^*}{S^- - S^*} + (1 - \gamma) * \left(\frac{R_i - R^*}{R^- - R^*}\right) \qquad i = 1,2, \ldots m \tag{3.72}$$

where $S^- = max\, S_i$; $S^* = min\, S_i$; $R^- = maxR_i$; $R^* = minR_i$;

The notation of γ indicates a weight for the strategy of maximum group utility, whereas $(1 - \gamma)$ indicates a weight of the individual regret. The DMs can express their preferences for the strategy of maximum group utility by means of γ value. If DMs prefer to emphasize on the "majority of criteria", a value greater than 0.5 is assigned to γ. Then, the ranking list follows the strategy of maximum group utility. If DMs want to increase the effect of unsatisfied criteria on the ranking of alternatives, a value less than 0.5 is assigned to γ. Then the ranking list follows the strategy of minimum individual regret. If the consensus is preferred, 0.5 is assigned to γ.

3.7.12 Rank the Alternatives, Sorting by the Values S, R and Q in Decreasing Order

In this step, three ranking lists are obtained in decreasing order of the values S, R and Q. The solution according to $min\, S_i$ represent the situation of maximum group utility, whereas the solution according to $minR_i$ represent the situation of minimum individual regret. The alternative at the first position in the ranking list based on Q_i values is accepted as compromise solution provided that following two conditions are satisfied;

Condition 1. Acceptable advantage:

Consider alternative A_1 is in the first position of the ranking list. The condition of acceptable advantage expressed by Eq. (3.73) must be satisfied.

$$Q(A_2) - Q(A_1) \geq DQ \tag{3.73}$$

where A_2 is the second alternative in ranking according to values Q, and $DQ = 1$ / $(m - 1)$.

Condition 2. Acceptable stability in decision making:

The alternative A_1 must also be the best in the ranking list obtained based on *S* and/or *R*. This compromise solution is stable within a decision making process, which could be "voting by majority rule" ($\gamma > 0.5$ is needed), or "by consensus" ($\gamma \approx 0.5$ is needed), or "with veto" ($\gamma < 0.5$ is needed). Here, γ is the weight of decision making strategy of maximum group utility (Opricovic & Tzeng, 2004). If one of the above mentioned conditions is not satisfied by alternative A_1, then a set of compromise solutions is presented.

- If Condition 2 is not satisfied, then A_1 and A_2 are the compromise solutions.
- If Condition 1 is not satisfied, then A_1, A_2,… A_m are the compromise solutions where $Q(A_m) - Q(A_1) < DQ$ and $DQ = 1$ / $(m - 1)$.

3.8 Computational Experiments

In this section, the applicability of the developed MCDM methodology is explored through four different examples with the aim of testing whether the methodology presents coherent solutions and rankings. To this aim, (1) the individual decision matrices from studies in the current literature, in which a GDM problem is under consideration, (2) a decision matrix from studies in the current literature, in which a GDM problem is not under consideration, are taken as input to explore the applicability of our methodology both on GDM problems and individual decision making problems. The weights of criteria and the weights of DMs in the examples are calculated according to the objective weighting procedure of our methodology. We present three different rankings for each example according to different weights of decision making strategy of maximum group utility or ("majority of criteria"), denoted by γ. We set γ 0.25 (for "individual regret"), 0.50 (for "consensus") and 0.75 (for "majority rule") to present different ranking lists for DMs who consider different strategies.

3.8.1 Experiment 1 - Manufacturing System Selection

The method developed in this study is applied to the case study presented in Vahdani et al. (2013). This study deals with the selection of flexible manufacturing systems (FMSs). A committee of three DMs evaluates five alternatives of FMSs with reference to five criteria by the linguistic variables. The alternatives are A1, A2, A3, A4 and A5. The criteria set consists of five criteria; C1: Quality of results, C2: Ease of use, C3: Competitive, C4: Adaptability and C5: Expandability. An IF-ELECTRE method is developed in Vahdani et al. (2013) in which the preference order based on relative superiority of the alternatives are changeable according to the threshold values of concordance and discordance indices. They applied pairwise comparisons and illustrated the binary relations such as preference, indifference and incomparable between alternatives using decision graph. Considering these relationships between alternatives, Vahdani et al. (2013) proposed the ranking result as A3>A1>A2>A4>A5. They also conducted sensitivity analysis by changing threshold values and conclude that A3 is the dominant alternative and A5 is the worst alternative for each situation in sensitivity analysis. They compared their results by applying IF-TOPSIS method which is developed by Boran et al. (2009). IF-TOPSIS ranking was obtained as A3>A4>A1>A2>A5. We have utilized the individual decision matrices presented in Vahdani et al. (2013) as input in our methodology and calculated the weights of DMs and the weights of criteria based on entropy equations. The weights of three DMs are obtained as 0.401, 0.285 and 0.314 and the weights of five criteria are 0.268, 0.210, 0.271, 0.128 and 0.123, respectively. We set the value of $\gamma = 0.75$, $\gamma = 0.50$ and $\gamma = 0.25$, in each of condition the same ranking is obtained; A3>A4>A2>A1>A5. Similar to the results of Vahdani et al (2013), applying our methodology we obtained that the best alternative is A3 and the worst alternative is A5 as well. The method proposed in

Vahdani et al (2013) has some similarities to our method. For instance, Vahdani et al (2013) extended ELECTRE method based on IFS theory and made use of concordance and discordance relations. However, their method is choice problematic and proposes partial ranking whereas our methodology provides complete ranking by the integration of IF-ELECTRE method with VIKOR. In addition, the weights of criteria and the weights of DMs are expressed by linguistic variables and obtained based on subjective approaches in Vahdani et al (2013), whereas the weights of criteria and the weights of DMs are calculated objectively in our methodology.

3.8.2 Experiment 2 - Project Manager Selection

The second application of the methodology developed in this study is performed using the case study data presented by Wu & Chen (2011) in which an IF-ELECTRE method is proposed. Selection of project manager problem is considered in this paper. Six alternatives are considered, namely A1, A2, A3, A4, A5 and A6. The evaluation criteria are; C1: Self-confidence, C2: Personality, C3: Past experience and C4: Proficiency in project management. Decision makers' evaluations are expressed by interval value fuzzy numbers and they are transformed into IFNs in the study. The weights of criteria are pre-determined and they are expressed by crisp values. Wu & Chen (2011) proposed three different concordance and discordance sets. However, the weights of concordance and discordance sets are determined based on preference of DM. In other words, all of the weights in the study are determined subjectively. They proposed complete ranking by integrating the "closeness to ideal points" concept of TOPSIS method to ELECTRE method. As a result, Wu & Chen (2011) proposed the ranking as A6>A4>A5>A3>A2>A1.

We have taken the IF-decision matrix in Wu & Chen (2011) as input because no individual decision matrices are identified in the study since the study do not deal with GDM. The weights are re-calculated objectively using the related steps of our methodology using entropy equation and weighted distance measure. The weights of four criteria are obtained as 0.140, 0.252, 0.212 and 0.396 and the weights of strong concordance sets, midrange concordance sets and weak concordance sets are obtained as 0.24, 0.26 and 0.50, respectively. Moreover, three different values are assigned to γ. The ranking is obtained as A6>A5>A2>A3>A4>A1 for $\gamma = 0.75$, A6>A5>A3>A2>A4>A1 for $\gamma = 0.50$ and A6>A3>A5>A2>A4>A1 for $\gamma = 0.25$. Considering these three cases, it can be concluded that A6 is superior than the other alternatives considering the given criteria set. The value of γ has a significant effect on the position of A3 in the ranking list that the position of A3 is effected positively when the strategy of minimum individual regret was considered to be important by DM.

3.8.3 Experiment 3 – Financial Evaluation of Companies

Thirdly, the method developed in this thesis is applied to the real case study in Joshi & Kumar (2014) in which an IF-TOPSIS method is proposed. In this article, the alternative organizations are evaluated according to some financial criteria. The alternative organizations are A1: Bajaj Steel, A2: H.D.F.C. Bank, A3: Tata Steel, A4: Infotech Enterprises. The criteria are C1: Earnings per share (EPS), C2: Face Value, C3: P/C (Put-Call) Ratio, C4: Dividend and C5: P/E (Price-to-earnings) Ratio.

In Joshi & Kumar (2014) actual numerical values are crawled regarding criteria of each alternative from related website. The crawled crisp numerical values are utilized to construct fuzzy decision matrix. Then, the fuzzy decision matrix is converted into IF-decision matrix using conversion theorem. They utilized IF-entropy measure developed by Chen & Li (2010) to calculate the weights of criteria objectively and applied the proposed IF-TOPSIS method to the case study, obtain the final ranking as A3>A1>A4>A2. In addition, they obtained different rankings by applying TOPSIS method (Hwang & Yoon, 1981) and fuzzy TOPSIS method (Jahanshahloo, Hosseinzadeh, & Izadikhah, 2006) to the case study. The final rankings in these cases are obtained as A3>A4>A1>A2 and A3>A1>A4>A2, respectively. Moreover, they proposed a portfolio selection problem in order to compare the performance of their IF-TOPSIS method with TOPSIS and fuzzy TOPSIS methods. To this aim, they constructed different portfolios according to different rankings and then analyzed the returns of portfolios and involved risk of each portfolio. They concluded that higher portfolio returns with slightly high portfolio risk are obtained when they construct the portfolios based on the ranking proposed by IF-TOPSIS method.

We have applied our methodology to IF-decision matrix presented in Kumar et al. (2014) since this case study do not handle a GDM problem. Different criteria weights are obtained by our methodology since the entropy equation in this study is different from the entropy equation in Joshi & Kumar (2014). The weights of five criteria are calculated as 0.167, 0.152, 0.145, 0.383 and 0.153, respectively. We assigned three different values to γ as in the other experiments. The ranking is obtained as A3>A1>A2>A4 for $\gamma = 0.75$, A3>A1>A4>A2 for $\gamma = 0.50$ and A3>A1>A4>A2 for $\gamma = 0.25$. A3 is proposed as the best alternative for each of the three γ values. It can also be observed that, the position of A4 is affected positively when the importance of maximum group utility is decreased.

3.8.4 Experiment 4 – University Leader Selection

The last computational experiment is performed using the illustrative example in Yue (2014). Yue (2014) proposed an extended TOPSIS method for solving GDM problems in which decision information are expressed by IFNs. The weights of DMs are obtained objectively based on the concept of closeness to ideal solution of TOPSIS method. In addition, they proposed an extended relative closeness equation to compute the weights of DMs, which considers relative closeness of each individual decision to ideal decisions. They utilized Euclidean distance measure in calculating the separations of individual decisions from the ideal decisions. However, the weights of criteria are specified by DMs subjectively. The weights of criteria are expressed by crisp values in the study.

In this example, four leaders (A1, A2, A3 and A4) at a university are evaluated by three different decision making group which are D1, D2 and D3 with reference to three criteria, namely C1: Work experience, C2: Academic performance, C3: Personality based on questionnaires survey. The first decision group consists of teachers, the second decision group consists of researchers and the third decision group consist of undergraduate students. The DMs vote the leaders according to each criterion. In the study, the percentages of members of each group DMs who vote in favor are considered as membership degrees, the percentages of members of each group DMs who vote against are considered as non-membership degrees and the percentages of members of each group of DMs who abstain from voting are considered as hesitation degrees. Therefore, the individual decision matrices are constructed based on IFSs obtained from crisp values. These individual decision matrices are taken as the input data for the application of our methodology.

In this computational experiment, the weights of DMs and the weights of criteria are calculated using entropy equations. Therefore, the weights of DMs are calculated as 0.28, 0.35 and 0.37, whereas the weights of criteria are calculated as 0.307, 0.343 and 0.350, respectively. We have set γ values as 0.75, 0.50 and 0.25 as in the other experiments. The final ranking is obtained as A2>A3>A4>A1 for each of this cases. The best alternative is obtained as A2, Yue (2014) proposed the same solution.

The comparison of the results of above mentioned four studies and the results obtained by our methodology according to each case study is summarized in Table 3.2 for $\gamma = 0.50$.

Table 3.2 The comparison of results of computational experiments with the results of related articles

Computational Experiment	**Related Article**	**Ranking obtained in related article**	**Ranking obtained by IF-ELECTRE based on VIKOR (for $\gamma = 0.5$)**
Manufacturing System Selection	Vahdani et al. (2013)	A3 > A1 > A2 > A4 > A5	A3 > A4 > A2 > A1 > A5
Project Manager Selection	Wu & Chen (2011)	A6 > A4 > A5 > A3 > A2 > A1	A6 > A5 > A3 > A2 > A4 > A1
Financial Evaluation of Companies	Joshi & Kumar (2014)	A3 > A1 > A4 > A2	A3 > A1 > A4 > A2
University Leader Selection	Yue (2014)	A2 > A3 > A4 > A1	A2 > A3 > A4 > A1

CHAPTER FOUR
THE PROPOSED DECISION SUPPORT SYSTEM

4.1 Problem Statement

The main purpose of this study is to develop a decision support system for the potential customers who tend to read the reviews of experienced customers on products before purchasing process and for the companies to evaluate the customer satisfaction level associated with their product(s) and/or service(s) and reorganize their operational activities or marketing policies according to the outputs. Considering the fact that, analyzing all of the reviews in detail takes up so much time, which is nearly impossible for DMs, the proposed system is designed so as to extract the useful information from the web site including huge amount of data within seconds.

The entity that a customer tends to purchase can be a tangible product (e.g. a cell phone) or a service (e.g. booking in a hotel). The customer determines the alternatives of a product/service to be ranked according to their performance scores. With the purpose of obtaining the performance scores, the decision support system collects the reviews on each alternative products using Web crawler. These reviews need preprocessing and so they are parsed by NLP tool. The reviews are analyzed based on aspect level sentiment analysis for identifying the sentiment orientation of each sentence in each review. The reviews include different opinions on a product. The customers use positive sentences to express the satisfaction, negative sentences to express the dissatisfaction and hesitant expression to express hesitancy in their evaluations. The system transforms the texts to numerical values to be utilized in decision making process.

We applied the developed decision support system to the hotel selection case and explained the decision making procedure of the developed system considering hotel selection domain in this paper, however the system can be modified for different types of products or services. The notations indicating the sets and variables to identify our problem can be defined as follows:

- The notation “J” represents the set of criteria for the handled product or service,
  J = (1, 2 , … , n).
- The notation “I” represents the set of alternatives for the handled product or service,
  I = (1, 2 , … , m).
- The notation “K” represents the set of reviews for the product/service alternative
  K = (1, 2 , … ,k).
- The notation “T” represents the set of sentences that comprise the review for the product/service alternative,
  T = (1, 2 , … ,t).
- The notation “P” represents the set of aspect expressions that indicate criteria
  P = (1, 2 , … ,p).
- $H = \{H_1,\ H_2, \cdots, H_m\}$ is the set of hotel alternatives and $C = \{C_1,\ C_2, \cdots, C_n\}$ is the set of aspect groups (criteria) of hotel.
- $C_j = \left\{AE_1,\ AE_2, \cdots, AE_p\right\}$ "C_j"describes the aspect group (criterion) which can be identified by several aspect expressions denoted by "AE_j".
- AE_j indicates the aspect expression (noun or noun phrase) that describes the criterion C_j
- $SL = \{SL^+, SL^-, SL_{hes}\}$ describes the set of sentiment lexicons which includes positive sentiment lexicons denoted by SL^+, negative sentiment lexicons denoted by SL^- and hesitant sentiment lexicon denoted by SL_{hes}.
- $SL^+ = SL_j^+ \cup SL_{gen}^+$ and $SL^- = SL_j^- \cup SL_{gen}^-$describes the positive/negative sentiment lexicons "SL^+/SL^-" that are composed of general positive/negative sentiment lexicons “SL_{gen}^+/SL_{gen}^-“ and specific positive/negative sentiment lexicons created for each criterion “SL_j^+/SL_j^-“.
- Let $K_i = \{K_{i1},\ K_{i2}, \cdots, K_{ik}\}$ be a set of reviews regarding to *i*th hotel.
- Let $T_{ik} = \{T_{ik1},\ T_{ik2}, \cdots, T_{ikt}\}$ be a set of all sentences in the review K_{ik}.

4.2 The Steps of Decision Support System

The decision support system developed in this study consists of mainly two phases. The first phase aims in measuring the customer satisfaction corresponding to alternative products. The aspect level sentiment analysis is employed in this phase. Using the output of this phase the decision matrix of the problem can be constructed. The performance scores, which can be described as customer satisfaction measures related to alternative products according to each criterion, can be obtained from the decision matrix. When constructing decision matrix, IFS theory is utilized. Then, the second phase is conducted for product ranking using the MCDM methodology, which is described in the previous chapter. The proposed methodology is illustrated in Figure 4.1.

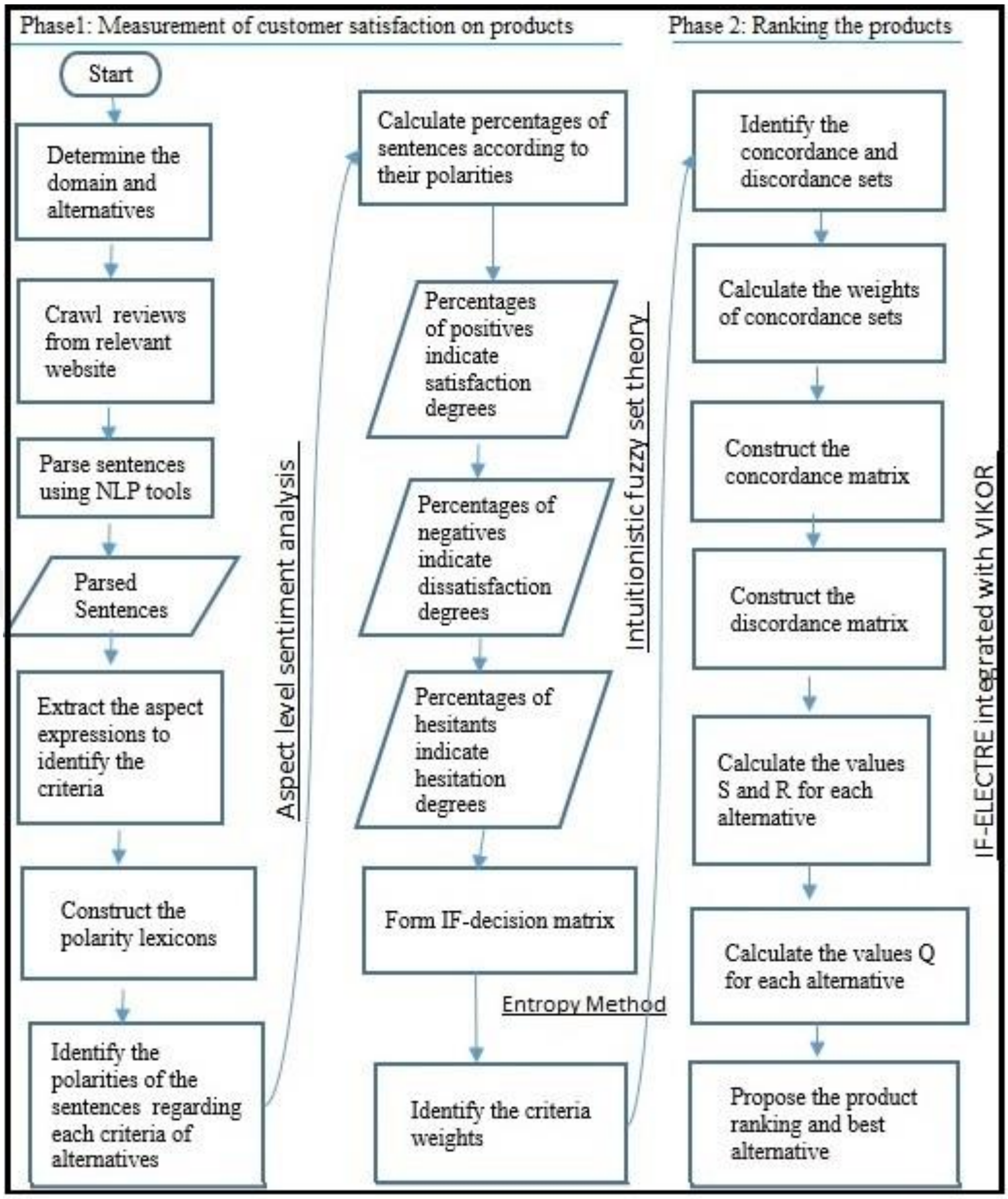

Figure 4.1 The Decision Support System

4.2.1 Measuring the Customer Satisfaction on Products by Aspect Level Sentiment Analysis

Online customer reviews are raw data which are collected from the relevant web site. These data can be described as unstructured data because they are not categorized to obtain the necessary information. This phase transforms the unstructured data into structured data utilizing text mining techniques. This phase occurs in three steps which are discussed in the following sub-sections.

4.2.1.1 Data Preparation

This step involves three subtasks, namely crawling and pre-processing, aspect extraction and compiling sentiment lexicons. This step starts with gathering the customer reviews and processing the reviews using NLP tools. It continues with determination of criteria, in other words, aspect groups. This step ends up with the construction of sentiment lexicons. These subtasks are explained below in detail.

4.2.1.1.1 Crawling and Pre-processing. The online reviews are crawled from the relevant web site using web crawler. All reviews are parsed by ITU Turkish NLP Web Service (Eryiğit, 2014; Eryiğit, Nivre, & Oflazer, 2008). ITU Turkish NLP Web Service presents many NLP tools such as tokenization, normalization, spelling correction, morphological analysis and dependency parsing. The text can be divided into its smallest units by tokenization tool. These smallest units, namely tokens, can be words, punctuation marks and numbers. We divide the customer reviews into tokens and analyze them grammatically with the help of ITU Turkish NLP Web Service. An example of sentence can be seen in Table 4.1. The sentence is separated into tokens and the root of words are extracted. Then, the part of speech (POS) categories (e.g., Noun, Verb, Adjective, and Conjunction) are assigned to tokens. In Table 4.1, the minor POS represents the category of the root, whereas the major POS represents the category of word. The column of morphological features expresses affixes of each token and indicates how the word has transformed from root to its last state. The column of dependency label expresses the mission of the token in the sentence. For example, Table 4.1 includes a parsed Turkish sentence “Yemekler güzeldi ama hizmetten memnun kalmadım.” (i.e. “The foods are good, but I am not satisfied with service.”). The first token is the word *yemekler (‘foods’)* and the root of the word *yemekler* is *yemek* (‘food’). The major and minor POS tag are noun.

Table 4.1 An example result of parsing a sentence via ITU NLP Web Service

Position	Token	Root	Major POS	Minor POS	Morphological Features		Dependency Label
1	Yemekler	yemek	Noun	Noun	A3pl|Pnon|Nom	3	Subject
2	_	güzel	Adverb	Adverb	_	3	Deriv
3	güzeldi	_	Verb	Zero	Past|A3sg	7	Coordination
4	ama	ama	Conj	Conj	_	3	Conjuction
5	hizmetten	hizmet	Noun	Noun	A3sg|Pnon|Abl	7	Modifier
6	memnun	memnun	Adj	Adj	_	7	MWE
7	kalmadım	kal	Verb	Verb	Neg|Past|A1sg	0	Predicate
8	.	.	Punc	Punc	_	7	Punctuation

4.2.1.1.2. Aspect Extraction. This step aims to identify the criteria of alternatives. The frequency based aspect extraction method based on Hu & Liu (2004) is employed in this step. The frequency of words is considered to determine the aspects of alternatives that are frequently mentioned by the reviewers. The words which describe an aspect of the alternatives are generally noun and noun phrases. The tokens in all reviews are filtered according to their major POS labels. The number of occurrences of the filtered words are determined and the frequent aspects are categorized as aspect groups. The main purpose of grouping the relational aspects is to determine the criteria for the second phase. Since the hotel selection case is handled in this thesis, these steps are implemented so as to identify aspect groups of hotels. As a result, the aspect groups are identified as *swimming*, *staff & service*, *location*, *room*, *food* and *expenditure*. The aspect group *staff & service* includes aspect *staff* and aspect *service*. The aspect expressions are noun and noun phrases that indicate the aspect in the text. For instance, the aspect expression *waiter* indicates the aspect *staff*. The aspect expression *speed of service* expresses the aspect *service*. The aspect groups (criteria) and the aspect expressions indicating the aspects are illustrated in Table 4.2. The aspects are categorized as implicit aspects and explicit aspects. The explicit aspects appear in the sentence as noun or noun phrase, whereas the implicit aspects do not appear in sentence, they are implied by the words such as adjectives (Hu & Liu, 2004). For instance, the sentence "otel çok pahalıydı" (the hotel was expensive) includes implicit aspect. The adjective "expensive" implies the aspect *price*, thereby indicating the aspect group *expenditure*.

Table 4.2 The criteria and aspect expressions used for expressing them

Aspect Groups (Criteria)	**Notations**	**Aspect Expressions**	**Explanation**
Swimming	C1	havuz (pool) deniz (sea, seaside) sahil (beach)…	-This criterion comprises all facilities in the hotel regarding swimming.
Staff & Service	C2	hizmet (service) çalışan (personal garson (waiter)…	-This criterion indicates both satisfaction with service level and the behaviors of staffs to customers.
Room	C3	banyo (bath) mobilya (furniture) yalıtım (isolation)…	-This criterion expresses all features of a hotel room from its design to conformity.
Location	C4	merkez (center) çevre (neighborhood) ulaşım (access)…	-This criterion reflects satisfaction of customers with the location of the hotel.
Food	C5	yemek (food) restoran (restaurant) kahvaltı (breakfast)…	-This criterion reflects satisfaction of customers with foods in terms of quality, variety and presentation.
Expenditures	C6	harcama (expenditure) ücret (price) ekstra (extra)…	-This criterion evaluates the hotel in terms of money spent within the period of stay.

4.2.1.1.3 Compiling Sentiment Lexicons. In this step, dictionary based approach is utilized to compile sentiment lexicons. As people typically describe their feeling on entities or aspects of entities using the adjectives or adjective phrases, we deal with adjectives and adjective phrases to derive sentiment words. Sentiment words are labeled to describe positive, negative and hesitant sentiment orientation. We compile sentiment lexicons for hotel domain to extract the sentiment orientations of sentences in the customer reviews. The positive and negative sentiment lexicons are constructed for each aspect group (criterion). We also compile three lexicons including the sentiment words, namely general positive sentiment lexicon, general negative sentiment lexicon and hesitant words lexicon, which can describe all the aspects. Although we generally focus on adjectives and adjective phrases in extracting sentiments, we also handle some common sentiment verbs such as “beğenmek” (to like), “beğenmemek” (to dislike),“memnun kalmak” (to be satisfied with) and “tavsiye etmek” (to recommend) which have higher frequency in the reviews.

To compile the sentiment lexicons, first of all, the tokens with the adjective labels are filtered from the dataset. This filtered words are called as seed words. In this step SentiTurkNet (Dehkharghani et al., 2016) is utilized, which is the first Turkish sentiment dictionary, to extend our lexicons. SentiTurkNet enables adding the synonyms of seed words to our lexicons and checking the polarities of these words. The seed words are finally categorized according to the aspect group (criterion) they can be used as a modifier.

However, the words may have disparate connotations in different application fields or some sentiment words may peculiar to only one aspect. For example, the adjective “comfortable” is used to describe a room and “delicious” is used to describe a food. Since a lexicon for a specific field is not available, we assigned the sentiment words to related aspect group (criterion) manually. Table 4.3 shows some examples for sentiment words and phrases with their labels.

Table 4.3 The examples for sentiment words and phrases with their labels

Sentiment words or phrases	Label 1	Label 2
yardımsever (helpful), güleryüzlü (genial)	servicePos	
yavaş (slow)	serviceNeg	
yakın (close to)	locationPos	
expensive (pahalı)	expenditureNeg	
ücretsiz (free), ucuz (cheap)	expenditurePos	
eski moda (old fashioned)	roomNeg	
büyük (spacious)	roomPos	swimmingPos
dalgalı (rough)	swimmingNeg	
lezzetli (delicious)	foodPos	
düzenli (organized)	roomPos	servicePos
lezzetsiz (untasteful)	foodNeg	
harika (great), iyi (nice), muhteşem (amazing)	generalPos	
kötü (bad), berbat (awful), zayıf (poor)	generalNeg	
fena değil (so-so), idare eder (spotty)	hesitantWords	

4.2.1.2 Identifying the Sentiment Orientation of Sentences for Each Criterion

The system considers the sentences as measurement units of the reviews. If the general opinion associated with an aspect group (criterion) of specific alternative product is desired to be known, the number of positive, negative and hesitant sentences must be calculated by analyzing the reviews about the relevant alternative. It has been noticed that the customers express their opinions using two types of sentences. In the first type of sentences, the aspects are appeared before the sentiment words, whereas in the second type of sentences the sentiment words are appeared before the relevant aspects. The following examples depict the first and second type of sentences, respectively.

Example 1. "Yemekler orta düzeydi ancak çalışanlar oldukça nazikti. Otelin konumu merkezi yerdeydi" (The foods are on average, but the staff is very friendly. The location is also very central).

Example 2. “Muhteşem yemekler, kibar ve deneyimli çalışanlar. Otelde iyi ve profesyonel bir hizmet veriliyor” (Amazing food, very kind and experienced staff. The hotel provides well and professional service).

The system takes into account the positions of sentiment words and aspect expression while investigating sentiment orientation of a sentence. It is also realized that the qualifier (sentiment word or phrase) is generally close to related word (aspect expression).

Another important issue is that most of the reviews are lack of punctuations. The developed decision support system is able to notice the end of the sentence by following the punctuations. Since some reviewers do not use punctuations properly, the system keeps searching for the sentiment orientation of an aspect expression within an irrelevant sentence. Considering this situation, some distance rules and semantic rules are introduced to the system. During the development of the decision support system, customer reviews on hotels have been examined carefully to create the rules. Distance rules, which are defined as follows, are created by trial and error.

Rule D1: Only if the sentiment words are detected, the relevant aspect expressions must be searched within the following five tokens.

Rule D2: If an aspect expression and a sentiment word indicating the so-called aspect expression are detected then keep searching for another sentiment words within the following five tokens.

Rule D3: After the last word is detected, keep searching for negations within the following three tokens.

Rule D4: After the last word is detected, keep searching for the aspect expressions and sentiment words within the following fourteen tokens.

Semantic rules facilitate the process of sentiment classification, especially dealing with negation and some POS particles, and have a positive effect on the classification result (Appel, Chiclana, Carter, & Fujita, 2016). The studies on sentence-level sentiment classification are available in literature which handle POS particles for generation of semantic rules to determine sentiment orientation of sentences (Xie et al., 2014; Appel et al., 2016). We benefit from semantic rules, which are defined as follows, to separate the sentence into clauses for simplifying the process of extraction of sentiment word and related aspect expression. We utilized morphological tagger of ITU NLP Web Service to detect the suffixes of tokens. Morphological features of tokens can be seen in sixth column of Table 4.1.

Rule S1: If the token of which morphological feature including “Past”, “Pres”, “Neces”, “Able” is appeared in a sentence then the sentence should be divided into two parts from this token.

Abbreviations mentioned in *Rule S1* indicate the suffix of verb and verbal in tense forms (-di/-dı etc.) in modal forms (-meli/-malı etc.).

Rule S2: If any token such as “rağmen” (although), “karşın” (despite), “hariç” (except), “dışında” (without) is detected in a sentence then the sentence should be divided into two parts from this token.

The sentence connectors mentioned in *Rule S2* enable to detect the clauses in which different topics are discussed.

Example 3. “Çok güzel bir konumda olmasına *rağmen* hizmet kalitesi çok kötü” (Service quality is awful *although* it has a good location).

Rule S3: If the token of which POS tag is “PastPart” and morphological feature includes abbreviation of “Loc” is detected in a sentence then the sentence should be divided into two parts from this token.

Example 4. “Otelin muhteşem lokasyonunu *düşündüğümüzde* ücreti uygun bulduk” (We found the price acceptable *considering* the wonderful location of the hotel).

Example 5. “Öğle yemeği *yediğimizde* ekstra ücret veriyorduk” (We paid extra price *when* eating the launch there).

Negation Handling: Negation expressions reverse the sentiment orientations. The expression of “değil” (am/is/are not) is a commonly used negation in Turkish. In addition, this paper takes into account the words such as “olmalı” (must be), “olmamalı” (must not be), “olurdu” (should/would have been), “diyemem” (I cannot say), “olmadığından” (was/were not), “olmayan” (not to be) as negation expressions.

The procedure to determine the sentiment orientation of a sentence for each criterion using our methodology is depicted by the algorithm shown in Figure 4.2.

```
Initialize S (C_j) ← 0
For each token in sentence T_ikt do {
    For each Criterion C_j in the set C do {
        If token tkn_a ∈ the set Criterion C_j then {
            Create a <AE, SW> couple for Criterion C_j
            Set the first element of <AE, SW> couple ← tkn_a
        }
        Search the next tokens based on Distance Rules
        If token tkn_b ∈ the set SL_j or the set SL_gen then {
            Set the second element of <AE, SW> couple ← tkn_b
            If token tkn_b ∈ the set SL_j^+ or the set SL_gen^+ then {
                Set Polarity (<AE, SW> couple) ← 1
            }
            If token tkn_b ∈ the set SL_j^- or the set SL_gen^- then {
                Set Polarity (<AE, SW> couple) ← -1
            }
        }
        Search the next tokens based on Distance Rules
        If token tkn_c ∈ the set Negations then {
            Set Polarity (<AE, SW> couple) ← Polarity (<AE, SW> couple)*(-1)
        }
        If token tkn_d ∈ the set SL_hes then {
            Set Sentiment orientation of sentence T_ikt for criterion C_j ← hesitant
        }
        S (C_j) ← S(C_j) + Polarity (<AE, SW> couple)
    }
    For each criterion C_j in the set C do {
        If S (C_j) > 0 then {
            Sentiment orientation of sentence T_ikt for criterion C_j ← positive
        }
        If S (C_j) < 0 then {
            Sentiment orientation of sentence T_ikt for criterion C_j ← negative
        }
        If S (C_j) == 0 then {
            Sentiment orientation of sentence T_ikt for criterion C_j ← hesitant
        }
    }
}
```

Figure 4.2 The algorithm that specifies the sentiment orientation of sentence T_{ikt} for each criterion

The developed system split reviews into sentences using punctuations such as full stop, exclamation point, question mark and triple dot. Then, sentiment orientation of each sentence is examined for each criterion. For this purpose, the system searches the aspect expressions and related sentiment words in sentences and saved them in a list named as <AspectExpression, SentimentWords> couple. <AE, SW> couples can be detected in a sentence in two ways; 1) the aspect is detected before sentiment, 2) the sentiment is detected before aspect. The system uses a similar approach for both of the orders. For a sentence in which the aspect is detected first, all captured aspect expressions are assigned as the first elements of <AE, SW> couple lists considering the aspect set they belong. Secondly, the system looks for sentiment words which describe the relevant aspects by the help of sentiment lexicons. If the captured sentiment word or phrases are relevant, they are assigned as the second elements of <AE, SW> couple lists. The polarities of sentiment words are introduced as a sentiment label to <AE, SW> couple lists. Thirdly, the system looks for negation words affecting each <AE, SW> couple lists. If a negation word or phrase is extracted, the sentiment label of the <AE, SW> couple list is reversed. When identifying <AE, SW> couple lists, the system obeys some Distance Rules and Linguistic Rules. For the sentences in which sentiment word is detected first, the order of the process is reversed. This process is explained by the following example:

Example 6. “Otel çok pahalı. Hizmet idare eder. Odalar düzenli ve büyük ama mobilyalar eski. Marinada güzel bir konumu var ancak merkeze uzak. Yemekleri lezzetli değil. Otelin harika kumsalından ve temiz denizinden bahsetmezsem olmaz. Havuzlarını beğendim.” (The hotel is very expensive. The service is, honestly, spotty. The rooms are tidy and spacious, but the furniture are old. The hotel has a good location on the marina, but far from the city center. Foods are not delicious. I have to tell you that the hotel has a wonderful beach with clean sea. I like the pools.)

The review is parsed by ITU NLP Web Service. The system perceives each sentence in review considering full stop. It searches for <AE, SW> couples available in each sentences. The algorithm starts with the first sentence. It catches the sentiment word of “pahalı” (expensive) which has labeled as expenditureNeg in sentiment lexicon and perceives that this sentiment word represents the implicit aspect expression “fiyat” (price). Thereby, it identifies the sentiment orientation of the sentence for criteria *Expenditure* as negative. In the second sentence, the system catches the aspect expression “hizmet” (service) and the sentiment phrase “fena değil” (spotty) which has labeled as HesitantWords. The sentiment orientation of the sentence is identified as hesitant. In the third sentence, the aspect expression “oda” (room) is detected. The sentiment words “düzenli” (tidy) and “geniş” (spacious) which have the label of roomPos are detected. Then, the aspect expression “mobilya” (furniture) which is also a member of criteria *Room* is noticed. The sentiment word “eski” (old) correlated with aspect expression “mobilya” (furniture) is detected. It is concluded that sentiment orientation of third sentence mentioned on criteria *Room* is positive since the number of positive labed <AE, SW> couples is more than the number of negative labeled <AE, SW> couples. In the fourth sentence, the sentiment word “iyi” (good) labeled as generalPos is correlated with aspect expression “konum” (location) and the sentiment word “uzak” (far) labeled as locationNeg is correlated with aspect expression “merkez” (central). It is concluded that sentiment orientation of the fourth sentence mentioned on criteria *Location* is hesitant since the number of positive labed <AE, SW> couples is equal to the number of negative labeled <AE, SW> couples. In the fifth sentence, the aspect expression “yemek” (food), the sentiment word “lezzetli” (delicious) which has the label of foodPos and the negation word “değil” (not) are detected, thus it is determined that the sentence reflects customer dissatisfaction (negative sentiment orientation) about criteria *Food*. In the sixth sentence <beach, wonderful> and <sea, clean> are detected and it is determined that the sentence reflects customer satisfaction (positive sentiment orientation) about criteria *Swimming*. In the seventh sentence, <pool, to like> is detected and it is determined that this is the second sentence that reflects customer satisfaction (positive sentiment orientation) about criteria *Swimming*. Table 4.4 depicts the structured form of this review K_{ik}. It includes <AE, SW> couples which are detected in each sentence.

Table 4.4 The structured data regarding to the review K_{ik}

K_{ik}	T_{ikt}	**Aspect expression**	**Related criteria**	**Sentiment word or phrase**	**Related label**	**Negation**
k=1	t=1	fiyat (price)	Expenditure	pahalı (expensive)	expensiveNeg	-
	2	hizmet (service)	Service &Staff	idare eder (spotty)	hesitantWords	-
	3	oda (room)	Room	düzenli (tidy)	roomPos	-
	3	oda (room)	Room	büyük (spacious)	roomPos	-
	3	mobilya (furniture)	Room	eski (old)	roomNeg	-
	4	konum (location)	Location	iyi (good)	generalPos	-
	4	merkez (center)	Location	uzak (far)	locationNeg	-
	5	yemek (food)	Food	lezzetli (delicious)	foodPos	değil(not)
	6	kumsal (beach)	Swimming	harika (wonderful)	generalPos	-
	6	deniz (sea)	Swimming	temiz (clean)	generalPos	-
	7	havuz (pool)	Swimming	beğenmek (to like)	generalPos	-

The sentiment orientation of each sentence regarding each criterion is determined based on the following rules:

Rule S1: **If** the number of positive labeled <AE, SW> couples regarding criterion C_j is higher than the number of negative labeled <AE, SW> regarding criterion C_j in a sentence **then** this sentence has positive sentiment orientation regarding criterion C_j.

Rule S2: **If** the number of negative labeled <AE, SW> couples regarding criterion C_j is higher than the number of positive labeled <AE, SW> couples regarding criterion C_j in a sentence **then** this sentence has negative sentiment orientation regarding criterion C_j.

Rule S3: **If** the number of positive labeled <AE, SW> couples regarding criterion C_j is equal to the number of negative labeled <AE, SW> couples regarding criterion C_j in a sentence, **or** the sentence includes hesitant sentiment expressions **then** this sentence has hesitant sentiment orientation regarding criterion C_j.

The calculation of total sentences classified according to each polarity and each criterion is illustrated through the review example K_{ik} and depicted in Table 4.5. These structured forms are constructed for each review that belongs to each alternative available in our dataset.

Table 4.5 The structured data pertain to K_{ik} indicating number of classified sentences for each criterion

Aspect Group (Criterion)	**Number of sentences about the criterion**	**Number of sentences with positive orientation**	**Number of sentences with negative orientation**	**Number of sentences with hesitant orientation**
Swimming	2	2	0	0
Staff & Service	1	0	0	1
Room	1	1	0	0
Location	1	0	0	1
Food	1	0	1	0
Expenditure	1	0	1	0

4.2.1.3 Transforming the Result of Aspect Level Sentiment Analysis to Intuitionistic Fuzzy Numbers

The IFS theory developed by Atanassov (1986) provides a suitable tool to deal with vagueness and hesitancy that commonly encountered in real life decision making problems. IFNs are defined by degree of membership (μ) and the degree of non-membership (v) of an element, which are the basic components of an IFS (Xu, 2007). The performance score of each alternative according to each criterion can be denoted by IFNs considering;

- the percentage of the positive sentences related to each criterion of each alternative as a representation of customer satisfaction
- the percentage of the negative sentences related to each criterion of each alternative as a representation of customer dissatisfaction
- the percentage of the neutral sentences related to each criterion of each alternative as a representation of hesitancy degree

Consider $X_{ij} = (\mu_{ij}, v_{ij})$ as an IFN indicating the performance score of the *i*th alternative according to the *j*th criterion. μ_{ij} indicates satisfaction degree of *i*th alternative according to the *j*th criterion, v_{ij} indicates dissatisfaction degree of *i*th alternative according to the *j*th criterion and $\pi_{ij} = 1 - \mu_{ij} - v_{ij}$ indicates hesitation degree of *i*th alternative according to the *j*th criterion. The formulations to calculate these indicators are given as follows:

$$\mu_{ij} = \frac{T_{ij}^{pos}}{T_{ij}^{pos} + T_{ij}^{neg} + T_{ij}^{hes}} \tag{4.1}$$

$$v_{ij} = \frac{T_{ij}^{neg}}{T_{ij}^{pos} + T_{ij}^{neg} + T_{ij}^{hes}} \tag{4.2}$$

$$\pi_{ij} = \frac{T_{ij}^{hes}}{T_{ij}^{pos} + T_{ij}^{neg} + T_{ij}^{hes}} \tag{4.3}$$

where $\mu_{ij} + v_{ij} + \pi_{ij} = 1$, $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$,

T_{ij}^{pos}= the number of positive sentences regarding the *j*th criterion in the reviews of the *i*th alternative,

T_{ij}^{neg}= the number of negative sentences regarding the *j*th criterion in the reviews of the *i*th alternative,

T_{ij}^{hes} = the number of hesitant sentences regarding the *j*th criterion in the reviews of the *i*th alternative.

4.2.2 Ranking the Products Using the MCDM Methodology

The second stage of the decision support system involves evaluating the performance of alternatives with respect to each criterion to rank the alternatives from the best to the worst and selecting the best one among them. We employed IF-ELECTRE integrated with VIKOR methodology, which is explained in detail in Chapter four. IF-group decision matrix is established by using Equations (4.1), (4.2) and (4.3), then the process continues with the next step in Section (3.7.5).

4.3 The Process of JAVA Development for Decision Support Tool

The decision support tool is developed using Java computer programming language in NetBeans which is a Java development kit. Four projects are developed in order to complete the decision support tool. A screenshot of the projects for decision support tool are illustrated in Figure 4.3.

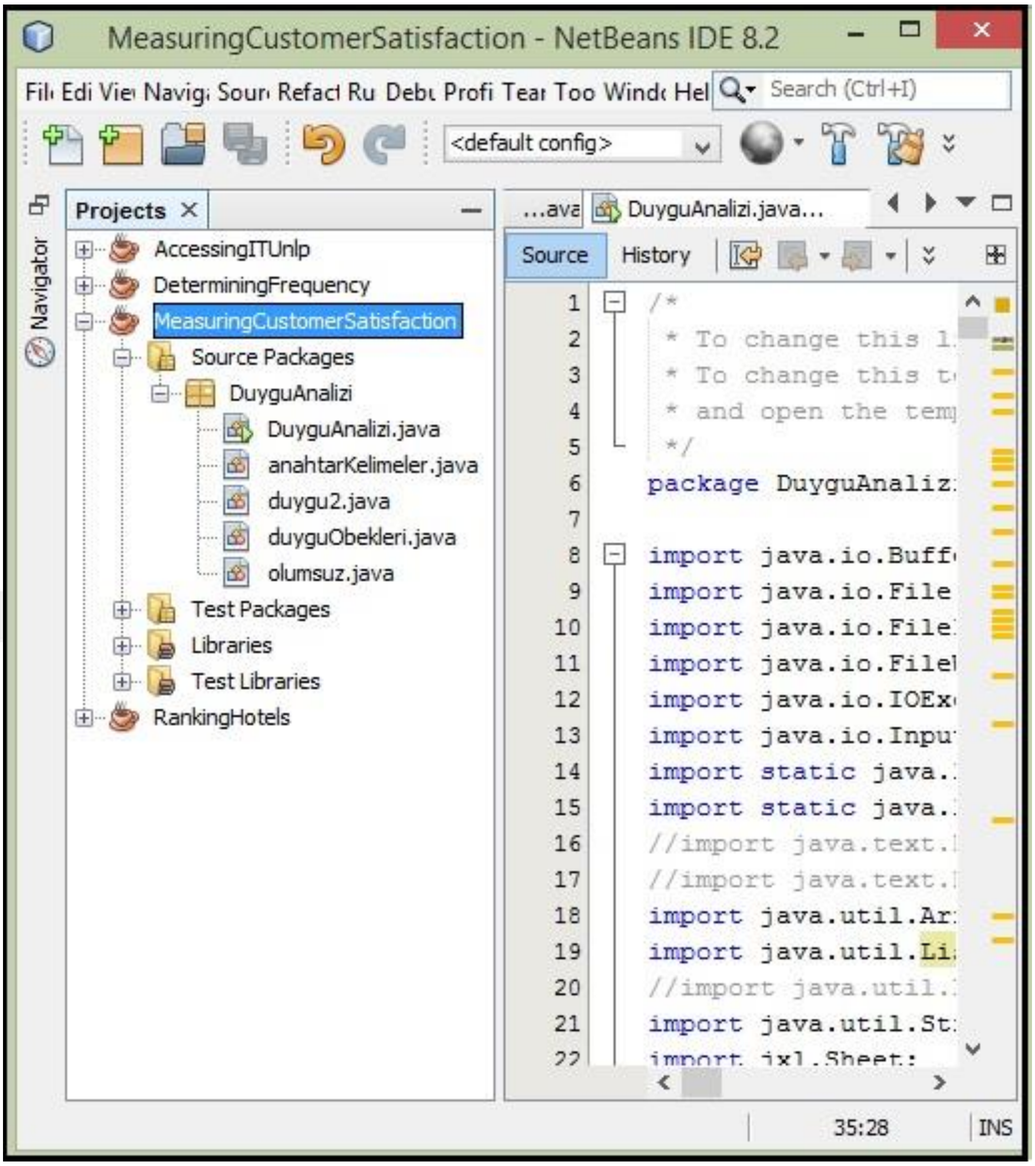

Figure 4.3 Screenshot of developed JAVA projects for decision support tool

The project of AccesingITUnlp aims to access ITU NLP Web Service to parse the crawled reviews. The project of DeterminingFrequency aims to determine frequency of the words in the given texts. Determination of sentiment words and aspect expressions are realized using this project. The project of MeasuringCustomerSatisfaction aims to discover the sentiment orientation of each sentence in the customer reviews. Finally, the project of RankingHotels aims to rank the alternatives using IF-ELECTRE integrated with VIKOR. Since all of the projects consist of 3418 lines of code, we have not included the whole projects and their codes in thesis.

CHAPTER FIVE
CASE STUDY AND RESULTS

5.1 Implementation of the Proposed Decision Support System

The decision support system developed in this study is applied to a case study which focuses on hotel reviews for determining the best hotel among a set of alternative hotels based on aspect level sentiment classification and IF-ELECTRE integrated with VIKOR method. To this aim, we have analyzed the reviews on five five-star hotels located in Çeşme, one of the most popular touristic counties in Turkey. The alternative hotels and the notations that represent these hotels are; H1 - Boyalık Beach Hotel & Spa, H2 - Sheraton Cesme Hotel Resort & Spa, H3 - Ilıca Hotel Spa & Wellness Resort, H4 - Altın Yunus Resort & Thermal Hotel, H5 - Grand Hotel Ontur.

Firstly, we have crawled the customer reviews on these hotels from “otelpuan.com” (https://www.otelpuan.com/tr) in July 2017, which is a website for evaluation and review of hotels located in Turkey, involving both the comments directly posted by the experienced customers and tele-surveys about the hotels conducted by tour companies.

The number of reviews collected for each hotel alternative are; 338, 317, 320, 294 and 390, respectively. These reviews include 6159 sentences computed considering the full stops in each review. These hotels are evaluated based on six criteria, which are determined at the aspect extraction step (please see “Section 4.2.1.1.2. Aspect extraction”); C1: Swimming, C2: Staff & Service, C3: Room, C4: Location, C5: Food, C6: Expenditures. After completing the first stage of the decision support system (please see “Section 4.2.1 Measuring the customer satisfaction on products by aspect level sentiment analysis”), the results of sentiment classification are obtained, which are depicted in Figure 5.1 and in Figure 5.2.

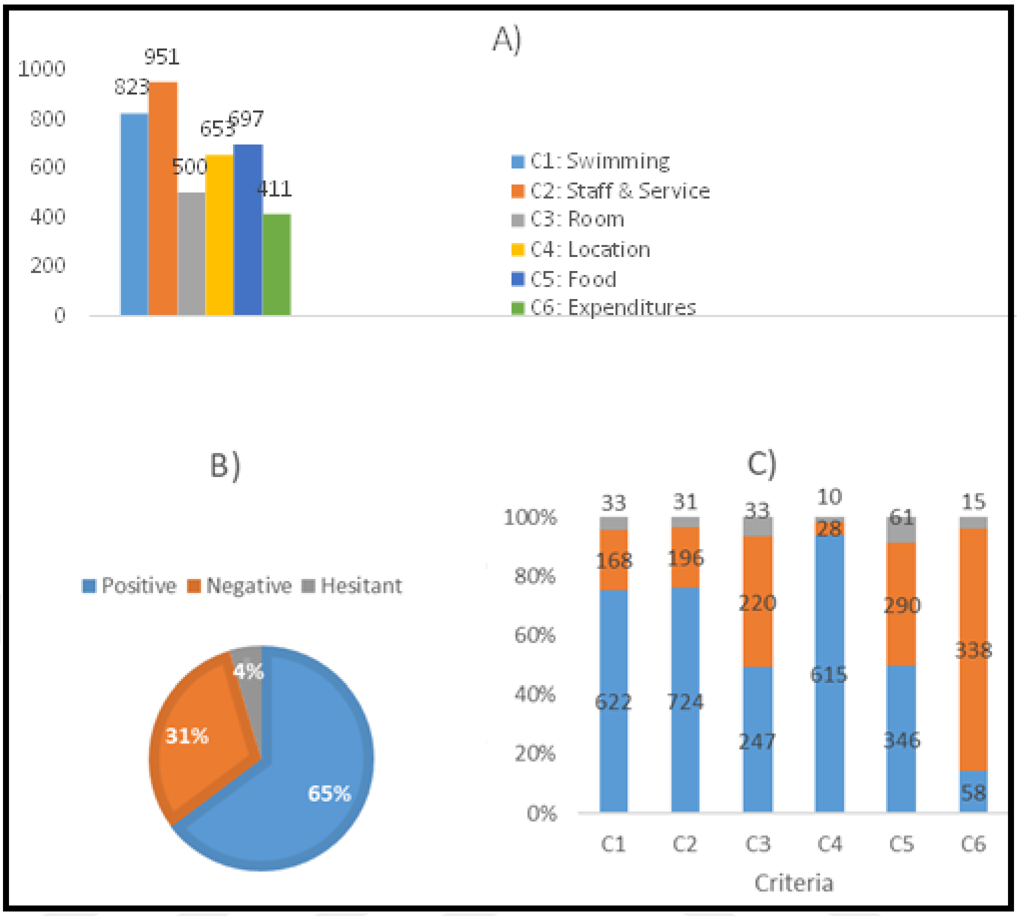

Figure 5.1 Distribution of extracted sentences according to each criterion and each polarity label

The sentences which include an opinion can be called as opinionated sentence. The distributions of opinioned sentences extracted from all reviews are depicted in Figure 5.1. It can be observed from the part A of the figure, the number of opinioned sentences related to criterion *Staff & Service* is 951, meaning that the customers have frequently mentioned about the criterion *Staff & Service*. The positive sentences constitute 65% of total opinionated sentences as seen at the part B of the figure. The percentages of positive, negative and hesitant sentences for each criterion are illustrated at part C of the figure. The figure also shows that, the experienced customers have generally mentioned about the criterion *Location* using positive expressions, whereas they have mostly complained about the criterion *Expenditures*. The customers have mostly satisfied with the criterion *Staff & Service* and they have felt hesitation on the criterion *Food* in general.

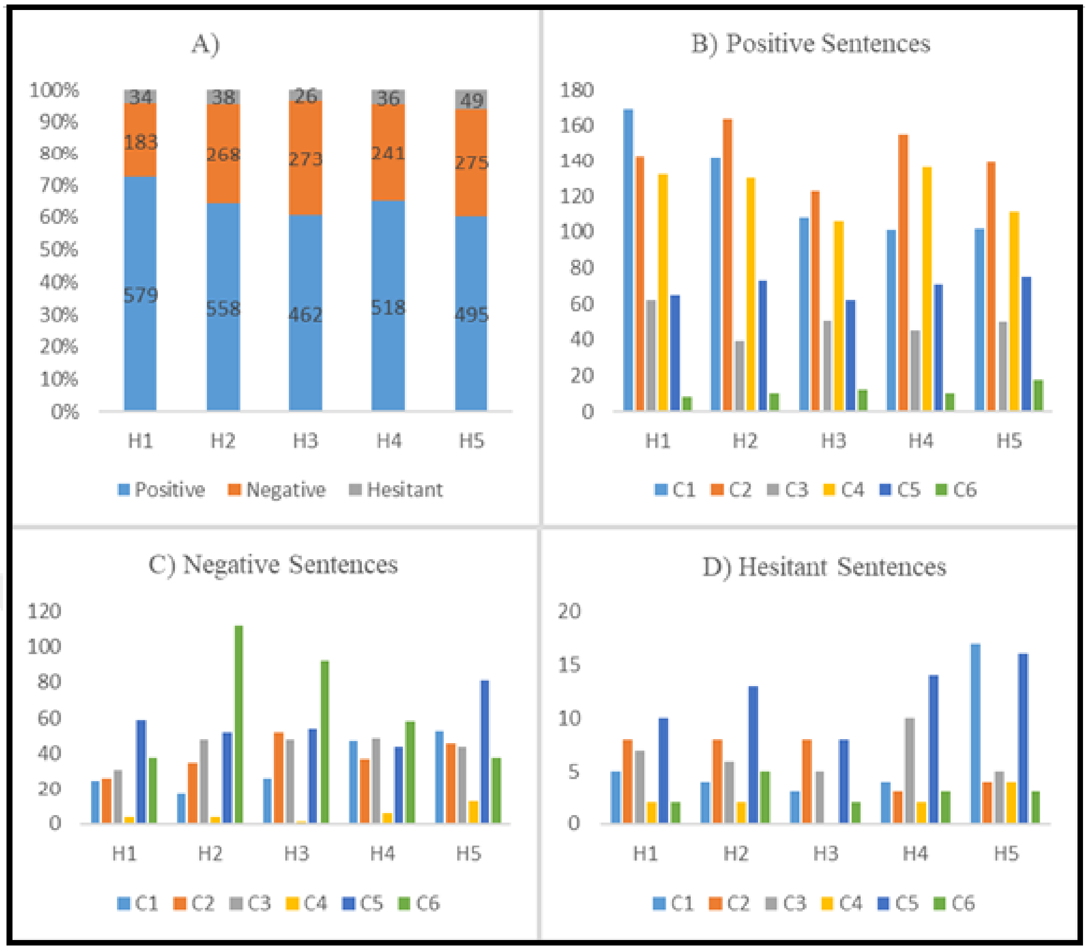

Figure 5.2 Distribution of opinionated sentences according to each hotel alternative and each criteria

The opinionated sentences are analyzed according to each hotel alternative as it can be seen in Figure 5.2. The part A of the figure shows the rates of positive, negative and hesitant sentences in the reviews for each hotel alternative. The reviews on alternative H1 contains positive sentences with 72%. H2 and H4 have the same rate for positive sentences, which is approximately 65%. H3 and H5 have the same rate for positive sentences, which is approximately 61%. It can be observed from the part B of the figure that the customers of H1 have mostly satisfied with the criterion *Swimming*. According to the customers of the other hotels, the most satisfied criterion is *Staff & Service*. The part C of the figure shows that the customers of H2, H3 and H4 have mostly complained about *Expenditures*. In addition, the customers of H1 and H4 have dissatisfied with the criterion *Food* mostly. The prices should be checked and if possible reduced by the top management of H2 to preclude the customer complaints about extra prices in the hotel. The hotel H5 should improve the criterion *Food* to enhance the level of customer satisfaction. According to part D of the figure, the customers of H5 have expressed opinions including hesitation on the criterion *Swimming* whereas the customer of the other hotels have expressed opinions including hesitation on the criterion *Food*. The hotel H5 should enhance the facilities regarding criterion *Swimming* to attract the attention of hesitant customers.

The number of opinionated sentences obtained based on aspect level sentiment analysis are transformed into IFNs (as described in "Section 4.2.1.3. Transforming the result of aspect level sentiment analysis to intuitionistic fuzzy numbers") indicating performance scores corresponding to each alternative with reference to each criterion using Eq. (4.1), Eq. (4.2) and Eq. (4.3), therefore, the IF-decision matrix is constructed as depicted in Table 5.1.

Table 5.1 Intuitionistic fuzzy decision matrix

	Criteria					
	C1	C2	C3	C4	C5	C6
H1	(0.849, 0.125)	(0.807, 0.146)	(0.620, 0.310)	(0.956, 0.028)	(0.485, 0.440)	(0.166, 0.791)
H2	(0.871, 0.104)	(0.792, 0.169)	(0.419, 0.516)	(0.955, 0.029)	(0.528, 0.376)	(0.078, 0.881)
H3	(0.788, 0.189)	(0.672, 0.284)	(0.490, 0.461)	(0.990, 0.009)	(0.500, 0.435)	(0.113, 0.867)
H4	(0.664, 0.309)	(0.794, 0.189)	(0.432, 0.471)	(0.944, 0.041)	(0.550, 0.341)	(0.140, 0.816)
H5	(0.593, 0.308)	(0.735, 0.243)	(0.505, 0.444)	(0.867, 0.101)	(0.436, 0.470)	(0.305, 0.644)

We have employed entropy concept to obtain weights of criteria. The process of determination of weights is performed using Eq. (3.47), Eq. (3.48) and Eq. (3.49). The entropy values, divergences and entropy weights are presented in Table 5.2. According to Table 5.2, it can be deducted that the most important criterion is *Location* for this dataset.

Table 5.2 The weights of criteria calculated based on entropy method

Criteria						
	C1	C2	C3	C4	C5	C6
Entropy values	0.7245	0.7456	0.9824	0.2496	0.9879	0.6335
Divergences	0.2755	0.2544	0.0176	0.7504	0.0121	0.3665
Weights	0.1643	0.1518	0.0105	0.4476	0.0072	0.2186

Then, the remaining steps of IF-ELECTRE integrated with VIKOR method are applied to obtain the complete ranking list; The strong, midrange and weak concordance sets are specified based on Eq. (3.52), Eq. (3.53) and Eq. (3.54), respectively. The strong, midrange and weak discordance sets are specified based on Eq. (3.55), Eq. (3.56) and Eq. (3.57), respectively. The weights of concordance sets are calculated using Eq. (3.61), Eq. (3.62) and Eq. (3.63). The weight of strong concordance set $w_{C'}$is 0.58, the weight of midrange concordance set $w_{C''}$ is 0.40 and the weight of weak concordance set $w_{C'''}$ is 0.02. After each concordance index is calculated via Eq. (3.64), the concordance matrix is constructed as follows:

$$G = \begin{bmatrix} - & 0.4124 & 0.2184 & 0.4684 & 0.4244 \\ 0.0982 & - & 0.1568 & 0.2747 & 0.4189 \\ 0.2640 & 0.3928 & - & 0.3613 & 0.3594 \\ 0.0029 & 0.0975 & 0.1785 & - & 0.3539 \\ 0.0876 & 0.0936 & 0.1798 & 0.0936 & - \end{bmatrix}$$

After each discordance index is computed using Eq. (3.66), the discordance matrix is constructed as follows:

$$F = \begin{bmatrix} - & 0.0175 & 0.0936 & 0.0034 & 0.1370 \\ 0.0957 & - & 0.1150 & 0.0675 & 0.2036 \\ 0.1460 & 0.1517 & - & 0.1388 & 0.2186 \\ 0.1643 & 0.1643 & 0.1643 & - & 0.2186 \\ 0.1643 & 0.1643 & 0.2373 & 0.1863 & - \end{bmatrix}$$

This concordance and discordance matrices are used to obtain the parameters of VIKOR. The values of R_i indicating individual regret of opponent are determined based on Eq. (3.68) and Eq. (3.70). The values of S_i indicating group utility of majority are determined based on Eq. (3.69) and Eq. (3.71). The values of Q_i indicating degree of closeness to ideal solution are determined based on Eq. (3.72). The results are depicted in Table 5.3.

Table 5.3 The results of ranking for alternative hotels according to values Q, S and R

	Hotels					**Results of ranking**
	H1	**H2**	**H3**	**H4**	**H5**	
Q ($\gamma = 0.5$)	0.0	0.5755	0.3396	0.8273	1.0	H1>H3>H2>H4>H5
S	0.6191	0.7628	0.6556	0.8417	0.8863	H1>H3>H2>H4>H5
R	0.0613	0.0911	0.0978	0.0978	0.1062	H1>H2>H3=H4>H5

If DM assigns γ = 1 in other words, focuses on strategy of maximum group utility (min S_i), the ranking is obtained as H1>H3>H2>H4>H5, where “>” operator points out the relation “preferred to”. H1 is determined as best hotel and H3 is the second preferred hotel according to the “majority rule”. If DM points out the importance of minimum individual regret (minR_i) by assigning γ = 0, the ranking is obtained as H1>H2>H3=H4>H5. The best hotel is not changed and determined as H1. However, H2 replaces with H3. H2 is preferred to H3 according to the strategy of minimum individual regret. In addition, the performance of H3 is regarded as equal to the performance of H4 and H5 is found in the worst position of the ranking list. If DM assigns γ = 0.5 by considering consensus, in other words, determines equal contribution level to maximum group utility or (“majority of criteria”) and minimum individual regret for ranking procedure, the ranking is obtained as H1>H3>H2>H4>H5. Consequently, H1 is recommended to DM as the best hotel alternative by the decision support system.

We have also conducted a sensitivity analysis so as to determine how the strategies of DMs impact the positions of hotels in the final ranking list. Therefore, we have observed the changes in ranking results according to 8 different strategies of DMs, which can be seen in Table 5.4. It can be inferred from Table 5.4 that H1 is the best hotel for all situations, but the position of H2 and H3 changes according to γ value. It is observed that H3 is more preferable than H2 when a value higher than 0.20 is assigned to γ, in other words, when DMs follow the strategy of maximum group utility. In this case, the values of S have higher impact on the calculation of Q values. On the other hand, H2 is superior over H3 when the value of γ is assigned as lower than 0.20. The position of H3 is getting worse in the case that DMs support the strategy of minimum individual regret. In this case, the values of R have a higher impact on the calculation of Q values, in other words, the unsatisfied criteria significantly affect the determination of compromise ranking. Moreover, when considering the impact of only R value in determination of compromise ranking ($\gamma = 0$), the position of H3 and H4 becomes the same. The degree of closeness to ideal (Q) for H4 is slightly improved, however this improvement is not sufficient to replace H4 with H3.

Table 5.4 Sensitivity Analysis

	Hotels					
	H1	H2	H3	H4	H5	Ranking
Q ($\gamma = 1.00$)	0.0	0.5379	0.1366	0.8333	1.0	H1 > H3 > H2 > H4 >H5
Q ($\gamma = 0.80$)	0.0	0.5630	0.2719	0.8293	1.0	H1 > H3 > H2 > H4 >H5
Q ($\gamma = 0.60$)	0.0	0.5881	0.4072	0.8252	1.0	H1 > H3 > H2 > H4 >H5
Q ($\gamma = 0.50$)	0.0	0.6006	0.4749	0.8232	1.0	H1 > H3 > H2 > H4 >H5
Q ($\gamma = 0.40$)	0.0	0.6132	0.5425	0.8212	1.0	H1 > H3 > H2 > H4 >H5
Q ($\gamma = 0.20$)	0.0	0.6383	0.6778	0.8172	1.0	H1 > H2 > H3 > H4 >H5
Q ($\gamma = 0.10$)	0.0	0.6508	0.7755	0.8152	1.0	H1 > H2 > H3 > H4 >H5
Q ($\gamma = 0.00$)	0.0	0.6634	0.8132	0.8132	1.0	H1 > H2 > H3 = H4 >H5

To check the accuracy of the results, we have also crawled the scores, which range between interval 0 and 10, given by customers for each hotel alternative available from the website: otelpuan.com. The average customer ratings for H1, H2, H3, H4 and H5 is 8.1, 7.8, 7.6, 7.6 and 7.4, respectively. Therefore, the ranking result according to the customer ratings is H1>H2>H3=H4>H5. This ranking result is the same with the ranking result proposed by our methodology according to the strategy of minimum individual regret. H1 is the best hotel both according to our methodology and according to customer ratings on the website.

CHAPTER SIX
CONCLUSION

Customer reviews can be regarded as valuable sources for companies to understand about which aspects of their products/services the customers mostly complaint and which strategies they should follow to increase the customer satisfaction. Companies have employed traditional approach - conducting customer surveys -, which is costly and time consuming, to monitor customer satisfaction for a long time, however, with the growing increase in the number of online reviews, analyzing them to measure the customer satisfaction related to the performances of alternative products or services has begun to take its place in recent years. Considering these realities, this thesis presents a decision support tool which can be used both by the potential customers to evaluate the opinions of the experienced users of the product or service they tend to buy and to select the best one among a set of alternatives, and by the companies to monitor the customer satisfaction related to the product/service they produce or trade for taking the necessary precautions to increase the satisfaction. We have integrated sentiment analysis and MCDM methods in development of the decision support tool.

The proposed methodology in this thesis is composed of two stages. The first stage covers the measurement of customer satisfaction to obtain performance scores related to alternatives to be utilized in decision making process. This stage is carried out by using lexicon based aspect level sentiment analysis. The methodology makes use of frequency based approaches in determination of important criteria and construction of sentiment lexicons. Firstly, frequency based aspect extraction method is utilized, then related aspect expressions are manually grouped together to identify the important criteria of the decision making problem. Similarly, sentiment words and phrases are extracted based on frequency based method. Then, they are grouped together according to the criteria they are used to express and sentiment orientation they describe. The sentences of the reviews are examined to decide whether they include an opinion related to any criterion or not. For this purpose, a classification algorithm is developed by employing a rule-based NLP. The rules are introduced to describe how positive, negative and hesitant sentences will be classified. Semantic rules and word distance rules are also created for overcoming challenges in classification process which the lack of punctuations and long sentences lead to. The positive, negative and hesitant sentences that are extracted for each criterion and alternative are transformed into performance scores. The system utilizes IFS theory to represent the performance scores of alternatives due to the convenience of IFSs to cope with vagueness and uncertainty. After obtaining the performance scores, the product ranking stage is carried out by applying IF-ELECTRE integrated with VIKOR method which is a novel MCGDM approach proposed in this thesis.

An important contribution of this thesis to the related literature is development of a hybrid MCGDM approach, namely IF-ELECTRE integrated with VIKOR. This method is based on the integration of ELECTRE and VIKOR methods under IF environment extending Zandi & Roghanian (2013). In order to overcome the shortcoming of IF ELECTRE in terms of ranking process, i.e. partial ranking, it is integrated with VIKOR method, which provides complete ranking. The MCDM methodology is applied to four cases (Manufacturing System Selection, Project Manager Selection, Financial Evaluation of Companies, and University Leader Selection) derived from the literature and the ranking results are compared to explore the applicability of the proposed methodology in different fields.

The proposed decision support tool is applied to a case study which deals with online reviews on hotels in Turkish to illustrate its implementation. It is used to rank the alternative hotels handled in the case study and recommend the best one among them according to the selected criteria. Since the methodology investigates the weaknesses of each alternative hotel according to a set of criteria in the case study, recommendations for hotel managements are provided to enhance customer satisfaction levels according to different aspects of the hotels which the customers feel hesitancy and dissatisfaction.

This thesis has other important contributions to the literature. To the best our knowledge, it is the first study applying an integration of aspect level sentiment analysis and MCDM methods to online Turkish reviews to propose a complete product ranking. The decision support system developed in this study deals with expressions involving hesitation that indicate the hesitancy of customer on the performance of a product in the reviews to provide a more reliable classification. Also, considering the difficulty of determining the criteria weights accurately from the online reviews, entropy method is introduced, which is a convenient approach to cope with the vagueness and hesitation in the determination of unknown weights objectively. This study extracts the weights of criteria on the basis of IF-entropy concept through the decision matrix constructed by online reviews. In addition, the weights are assigned to DMs objectively using entropy method. NLP-based rules are created to be used in aspect level sentiment classification of Turkish sentences in this study. Although these rules are specifically created for Turkish, the logic behind the rules can be adapted for different languages.

The limitation of this paper is that it employs semi-automatic approaches for grouping aspect expressions and constructing sentiment lexicons. Also, the implicit aspect expressions are taken into account only in criterion related to price. For the future research, a complete automatic sentiment analysis can be carried out. Also, topic modeling approaches such as Latent Dirichlet Allocation for extracting and grouping of aspects can be employed.

REFERENCES

Abirami, A. M., & Askarunisa, A. (2017). Sentiment analysis model to emphasize the impact of online reviews in healthcare industry. *Online Information Review*, *41*(4), 471-486. Retrieved September 8, 2017, from Emerald Insight database.

Appel, O., Chiclana, F., Carter, J., & Fujita, H. (2016). A hybrid approach to the sentiment analysis problem at the sentence level. *Knowledge-Based Systems*, *108*, 110-124. Retrieved April 5, 2017, from Elsevier Science Direct database.

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *20*(1), 87-96. Retrieved September 4, 2017, from Elsevier Science Direct Database.

Atanassov, K. T. (1999). *Intuitionistic fuzzy sets*. Berlin: Springer.

Boran, F. E., Genc, S., Kurt, M. & Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Systems with Applications*, *36*(8), 11363–11368. July 7, 2017, from Elsevier Science Direct database.

Büyüközkan. G. & Göçer, F. (2017). Application of a new combined intuitionistic fuzzy MCDM approach based on axiomatic design methodology for the supplier selection problem. *Applied Soft Computing*, *52*, 1222-1238. Retrieved October 9, 2017, from Elsevier Science Direct database.

Chen, S. M., & Tan, I. M. (1994). Handling multicriteria fuzzy decision-making problems based on vague set theory. *Fuzzy Sets and Systems*, *67*(2), 163-172.

Chen, T. Y. & Li, C. H. (2010). Determining objective weights with intuitionistic fuzzy entropy measures: A comparative analysis. *Information Sciences*, *180*(21), 4207–4222. Retrieved October 20, 2017, from Elsevier Science Direct database.

Cruz, F. L., Troyano, J. A., Enríquez, F., Ortega, F. J., & Vallejo, C. G. (2013). 'Long autonomy or long delay?' The importance of domain in opinion mining. *Expert Systems with Applications*, *40*(8), 3174-3184. Retrieved February 09, 2018, from Elsevier Science Direct database.

Dehkharghani, R., Saygin, Y., Yanikoglu, B., & Oflazer, K. (2016). SentiTurkNet: A Turkish polarity lexicon for sentiment analysis. *Language Resources and Evaluation*, *50*(3), 667-685. January 11, 2017, from Springer Link database.

Dehkharghani, R., Yanikoglu, B., Saygin, Y., & Oflazer, K. (2017). Sentiment analysis in Turkish at different granularity levels. *Natural Language Engineering*, *23*(4), 535-559. January 27, 2017, from Cambridge University Press database.

De Luca, A. & Termini, S. (1972). A definition of a nonprobabilistic entropy in the setting of fuzzy sets theory. *Information and Control*, *20*(4), 301-302. Retrieved November 23, 2017, from Elsevier Science Direct database.

Devi, K., & Yadav, S. P. (2013). A multicriteria intuitionistic fuzzy group decision making for plant location selection with ELECTRE method. *The International Journal of Advanced Manufacturing Technology*, *66*(9-12), 1219-1229. Retrieved August 19, 2017, from Springer Link database.

Ding, X., Liu, B., & Yu, P. S. (2008, February). A holistic lexicon-based approach to opinion mining. In *Proceedings of the 2008 international conference on web search and data mining* (231-240). ACM.

Du, J., Xu, H., & Huang, X. (2014). Box office prediction based on microblog. *Expert Systems with Applications*, *41*(4), 1680-1689. Retrieved February 19, 2018, from Elsevier Science Direct database.

Ekinci, E., Türkmen, H., & Omurca, S. I. (2017). Multi-word aspect term extraction using Turkish user reviews. *International Journal of Computer Engineering and*

Information Technology (IJCEIT), *9*(1), 15-23. Retrieved February 11, 2018, from www.ijceit.org/published/volume9/issue1/3Vol9No1.pdf.

Eryiğit, G. (2014). ITU Turkish NLP web service, In *Proceedings of the Demonstrations at the 14th Conference of the European Chapter of the Association for Computational Linguistics (EACL 2014)*, (1-4). Sweden.

Eryiğit, G., Nivre, J., & Oflazer, K. (2008). Dependency parsing of Turkish. *Computational Linguistics*, *34*(3), 357-389. Retrieved January 26, 2017, from MIT Press Journals.

Figueira, J., Greco, S., Roy, B., & Slowi´nski, R. (2010). ELECTRE methods: Main features and recent developments. In C. Zopounidis, & P.M. Pardalos (Eds.), *Handbook of multicriteri analysis. Applied optimization* (51–89). Berlin: Springer.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137-144. Retrieved September 24, 2017, from Elsevier Science Direct database.

García-Cumbreras, M. Á., Montejo-Ráez, A., & Díaz-Galiano, M. C. (2013). Pessimists and optimists: Improving collaborative filtering through sentiment analysis. *Expert Systems with Applications*, *40*(17), 6758-6765. Retrieved February 8, 2018, from Elsevier Science Direct database.

Hashemi, S. S., Hajiagha, S. H. R., Zavadskas, E. K. & Mahdiraji, H. A. (2016). Multi criteria group decision making with ELECTRE III method based on interval-valued intuitionistic fuzzy information. *Applied Mathematical Modelling*, *40*(2), 1554–1564. Retrieved April 13, 2017, from Elsevier Science Direct database.

Hatzivassiloglou, V., & McKeown, K. R. (1997, July). Predicting the semantic orientation of adjectives. In *Proceedings of the 35th Annual Meeting of the Association for Computational Linguistics and Eighth Conference of the European*

Chapter of the Association for Computational Linguistics (pp. 174-181). Association for Computational Linguistics.

Hong, D. H., & Choi, C. H. (2000). Multicriteria fuzzy decision-making problems based on vague set theory. *Fuzzy Sets and Systems*, *114*(1), 103-113. Retrieved October 15, 2017, from Elsevier Science Direct database.

Hu, M., & Liu, B. (2004, August). Mining and summarizing customer reviews. In *Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (68-177).Washington, USA: ACM.

Hung, C. C. & Chen, L. H. (2009). A multiple criteria group decision making model with entropy weight in an intuitionistic fuzzy environment. In X. Huang, SI. Ao & O. Castillo (Eds.), *Intelligent automation and computer engineering. Lecture notes in electrical engineering* (17-26). Netherlands: Springer.

Hur, M., Kang, P., & Cho, S. (2016). Box-office forecasting based on sentiments of movie reviews and independent subspace method. *Information Sciences*, *372*, 608-624. Retrieved June 20, 2018 from Elsevier Science Direct database.

Hwang, C. -L. & Lin, M. -J. (1987). *Group decision making under multiple criteria: Methods and applications*. Berlin: Springer.

Hwang C.-L., & Yoon K. (1981). *Multiple attribute decision making. Methods and applications a state of the art survey*. In Lecture Notes in Economics and Mathematical Systems 186. Berlin: Springer-Verlag.

Iskender, E., & Batı, G. B. (2015). Comparing Turkish universities entrepreneurship and innovativeness index's rankings with sentiment analysis results on social media. *Procedia- Social and Behavioral Sciences, 195*, 1543-1552. Retrieved January 11, 2017, from Elsevier Science Direct database.

Jahanshahloo, G. R., Hosseinzadeh, L. F. & Izadikhah M. (2006). Extension of the TOPSIS method for decision-making problems with fuzzy data. *Applied Mathematics and Computation*, *181*(2), 1544–1551. Retrieved June 20, 2018, from Elsevier Science Direct database.

Jin, J., Liu, Y., Ji, P., & Liu, H. (2016). Understanding big consumer opinion data for market- driven product design, *International Journal of Production Research*, *54*(10), 3019-3041. Retrieved April 5, 2017, from Taylor & Francis database.

Joshi, D. & Kumar, S. (2014). Intuitionistic fuzzy entropy and distance measure based TOPSIS method for multi-criteria decision making. *Egyptian Informatics Journal*, 15(2), *97*–104. Retrieved October 20, 2017, from Elsevier Science Direct database.

Kang, D., & Park, Y. (2014). Review-based measurement of customer satisfaction in mobile service: Sentiment analysis and VIKOR approach. *Expert Systems with Applications*, *41*(4), 1041-1050. Retrieved December 1, 2016, from Elsevier Science Direct database.

Kaya, M., & Conley, S. (2016). Comparison of sentiment lexicon development techniques for event prediction. *Social Network Analysis and Mining*, *6*(1), 7. Retrieved January 11, 2017, from Springer Link database.

Kaya, M., Fidan, G., & Toroslu, I. H. (2012, December). Sentiment analysis of Turkish political news. In *Proceedings of the 2012 IEEE/WIC/ACM International Joint Conferences on* Web *Intelligence and Intelligent Agent Technology* (174-180). USA: IEEE Computer Society.

Kaya, M., Fidan, G., & Toroslu, I. H. (2013). Transfer learning using Twitter data for improving sentiment classification of Turkish political news. In E. Gelenbe, & R. Lent (Eds.). *Information Sciences and Systems 2013* (139-148). Switzerland: Springer.

Kim, S. M., & Hovy, E. (2007, June). Crystal: Analyzing predictive opinions on the web. In *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)* (1056-1064). Prague: Association for Computational Linguistic.

Kincaid, J. W. (2003). *Customer relationship management: Getting it right!* New Jersey: Prentice Hall PTR.

Kracklauer, A. H., Mills, D. Q., & Seifert, D. (2004). Customer management as the origin of collaborative customer relationship management. In A. H. Kracklauer, D. Q., Mills & D. Seifert (Eds.). *Collaborative customer relationship management* (3-6). Berlin, Heidelberg: Springer.

Liu, B. (2010). Sentiment analysis and subjectivity. In N. Indurkhya, & F. J. Damerau (Eds.). Handbook of natural language processing (2nd ed.) (627-666). United States of America: CRC Press.

Li, X., Xie, H., Chen, L., Wang, J., & Deng, X. (2014). News impact on stock price return via sentiment analysis. *Knowledge-Based Systems*, *69*, 14-23. Retrieved February 8, 2018, from Elsevier Science Direct database.

Liu, Y., Bi, J. W., & Fan, Z. P. (2017). Ranking products through online reviews: A method based on sentiment analysis technique and intuitionistic fuzzy set theory. *Information Fusion*, *36*, 149-161. Retrieved December 01, 2016, from Elsevier Science Direct database.

Ma, J., Fan, Z. P. & Huang, L. H. (1999). A subjective and objective integrated approach to determine attribute weights. *European Journal of Operational Research*, *112*(2), 397-404.

Mareschal, B. (1988). Weight stability intervals in multicriteria decision aid. *European Journal of Operational Research*, *33*(1), 54-64.

Miller, G. A. (1995). WordNet: a lexical database for English. *Communications of the ACM*, *38*(11), 39-41. Retrieved June 18, 2018, from ACM database.

Najmi, E., Hashmi, K., Malik, Z., Rezgui, A., & Khan, H. U. (2015). CAPRA: A comprehensive approach to product ranking using customer reviews. *Computing*, *97*(8), 843-867. Retrieved January 11, 2017, from Springer Link database.

Nasukawa, T., & Yi, J. (2003, October). Sentiment analysis: capturing favorability using natural language processing. In *Proceedings of the 2nd International Conference on Knowledge Capture* (70-77). New York: ACM.

Opricovic, S. (1998). *Multicriteria optimization of civil engineering systems*. Phd Thesis, Faculty of Civil Engineering, Belgrade.

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research*, *156*(2), 445-455. Retrieved September 4, 2017, from Elsevier Science Direct database.

Opricovic, S., & Tzeng, G. H. (2007). Extended VIKOR method in comparison with outranking methods. *European Journal of Operational Research*, *178*(2), 514-529. Retrieved August 21, 2017, from Elsevier Science Direct database.

Otelpuan (2018). *Konumu güzeldi denizi iyiydi*. Retrieved June 11, 2018, from https://www.otelpuan.com/tr/Sheraton-Hotel-Cesme.

Peng, Y., Kou, G., & Li, J. (2014). A fuzzy promethee approach for mining customer reviews in Chinese. *Arabian Journal for Science and Engineering*, *39*(6), 5245-5252. Retrieved December 1, 2016, from Springer Link database.

Peñalver-Martinez, I., Garcia-Sanchez, F., Valencia-Garcia, R., Rodriguez-Garcia, M. A., Moreno, V., Fraga, A., & Sanchez-Cervantes, J. L. (2014). Feature-based opinion mining through ontologies. *Expert Systems with Applications*, *41*(13), 5995-6008. Retrieved February 9, 2018, from Elsevier Science Direct database.

Qi, J., Zhang, Z., Jeon, S., & Zhou, Y. (2016). Mining customer requirements from online reviews: A product improvement perspective. *Information & Management*, *53*(8), 951-963. Retrieved January 11, 2017, from SAGE journals database.

Roberts, J. H. (2000). Developing new rules for new markets. *Journal of the Academy of Marketing Science*, *28*(1), 31-44. Retrieved June 20, 2018 from Springer Link.

Roostaee, R., Izadikhah, M., Lotfi, F. H., & Rostamy-Malkhalifeh, M., A (2012). Multi Criteria Intuitionistic Fuzzy Group Decision Making Method for Supplier Selection with VIKOR Method. *International Journal of Fuzzy System Applications*, *2*(1), 1-17. Retrieved August 20, 2017, from IGI Global.

Roy, B. (1968). Classement et choix en presence de points de vue multiples (La methode ELECTRE). *Revue Francaise D Informatique de Recherche Operationnelle*, *2*(8), 57–75. Retrieved June 18, 2018, from http://www.numdam.org/item?id=RO_1968_2_1_57_0.

Saaty, T. L. (1980). *The analytic hierarchy process*. New York: McGraw-Hill.

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*(3), 379–423. Retrieved November 23, 2017, from http://math.harvard.edu/~ctm/home/text/others/shannon/entropy/entropy.

Shen, F., Xu, J. & Xu, Z. (2016). An outranking sorting method for multi-criteria group decision making using intuitionistic fuzzy sets. *Information Sciences*, *334-335*, 338-353. Retrieved July 7, 2017, from Elsevier Science Direct database.

Szmidt, E., & Kacprzyk, J. (2000). Distances between intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *114*, 505-518. Retrieved September 4, 2017, from Elsevier Science Direct database.

Tavana, M., Zareinejad, M., Di Caprio, D. & Kaviani, M. A. (2016). An integrated intuitionistic fuzzy AHP and SWOT method for outsourcing reverse logistics. *Applied Soft Computing*, *40*, 544–557. Retrieved October 9, 2017, from Elsevier Science Direct database.

TechAmerica Foundation's Federal Big Data Commission. (2012). *Demystifying big data: A practical guide to transforming the business of Government*. Retrieved June 6, 2018, from https://bigdatawg.nist.gov/_uploadfiles/M0068_v1_3903747095.pdf

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, *62*(3), 1139-1168. Retrieved February 8, 2018, from Wiley database.

Tetlock, P. C., & Saar-Tsechansky, M. (2008). More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, *63*(3), 1437-1467. Retrieved February 8, 2018, from Wiley database.

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment strength detection in short informal text. *Journal of the Association for Information Science and Technology*, *61*(12), 2544-2558. Retrieved February 8, 2018, from Wiley database.

Triantaphyllou E. (2000). Multi-criteria decision making methods: A comparative study. Boston: Springer.

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2010, May). Predicting elections with Twitter: What 140 characters reveal about political sentiment. In *Proceedings of the Fourth International AAAI Conference on Weblogs and Social*

Media (178-185). California: Association for the Advancement of Artificial Intelligence.

Turney, P. D. (2002, July). Thumbs up or thumbs down? : Semantic orientation applied to unsupervised classification of reviews. In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics* (417-424). Philadelphia: Association for Computational Linguistic.

Türkmen, H., Omurca, I. S., & Ekinci, E. (2016). An aspect based sentiment analysis on Turkish hotel reviews. *Girne American University Journal of Social and Applied Sciences*, *6*, 9-15. Retrieved April 7, 2017, from https://www.researchgate.net/publication/284487943.

Türkmenoğlu, C., & Tantug, (2014, June). Sentiment analysis in Turkish media. In *Proceedings of Workshop on Issues of Sentiment Discovery and Opinion Mining, International Conference of Machine Learning (ICML)*, Beijing, China.

Vahdani, B., Mousavi, S.M., Moghaddam, R. T. & Hashemi, H. (2013). A new design of the elimination and choice translating reality method for multi-criteria group decision-making in an intuitionistic fuzzy environment. *Applied Mathematical Modelling*, 37(4), 1781-1799. Retrieved August 19, 2017, from Elsevier Science Direct database.

Vlachos, I. K., & Sergiadis, G. D. (2007). Intuitionistic fuzzy information – Applications to pattern recognition. *Pattern Recognition Letters*, *28*(2), 197–206. Retrieved October 22, 2017, from Elsevier Science Direct database.

Vural, A. G., Cambazoglu, B. B., Senkul, P., & Tokgoz, Z. O. (2013). A framework for sentiment analysis in Turkish: Application to polarity detection of movie reviews in Turkish. In E. Gelenbe, & R. Lent (Eds.), *Computer and Information Sciences III* (437-445). London: Springer.

Wang, T. C. & Lee, H. D. (2009). Developing a fuzzy TOPSIS approach based on subjective weights and objective weights. *Expert Systems with Applications*, *36*(5), 8980-8985. Retrieved November 23, 2017, from Elsevier Science Direct database.

Wang, W. & Xin, X. (2005). Distance measure between intuitionistic fuzzy sets. *Pattern Recognition Letters*, *26*(13), 2063–2069. Retrieved October 15, 2017, from Elsevier Science Direct database.

Wei, C. & Tang, X. (2011). An intuitionistic fuzzy group decision-making approach based on entropy and similarity measures. *International Journal of Information Technology & Decision Making*, *10*(6), 1111–1130. Retrieved November 13, 2017, from World Scientific database.

Wu, M. C., & Chen, T. Y. (2011). The ELECTRE multicriteria analysis approach based on Atanassov's intuitionistic fuzzy sets. *Expert Systems with Applications*, *38*(10), 12318-12327. Retrieved August 18, 2017, from Elsevier Science Direct database.

Wu, M., Wang, L., Li, M., & Long, H. (2014). An approach of product usability evaluation based on web mining in feature fatigue analysis. *Computers & Industrial Engineering*, *75*, 230-238. Retrieved December 1, 2017, from Elsevier Science Direct database.

Xie, Y., Chen, Z., Zhang, K., Cheng, Y., Honbo, D. K., Agrawal A., & Choudhary, A.N. (2014). MuSES: Multilingual sentiment elicitation system for social media data. *IEEE Intelligent Systems*, *29*(4), 34–42. Retrieved February 14, 2018, from IEEE Xplore database.

Xu, J. & Shen, F. (2014). A new outranking choice method for group decision making under Atanassov's interval-valued intuitionistic fuzzy environment. *Knowledge-Based Systems*, *70*, 177–188. Retrieved October 16, 2017, from Elsevier Science Direct database.

Xu, Z. S. (2007). Intuitionistic fuzzy aggregation operators. *IEEE Transactions on Fuzzy Systems*, *15*(6), 1179–1187. Retrieved September 9, 2017, from IEEE Xplore database.

Xu Z, Yager R. R (2006). Some geometric aggregation operators based on intuitionistic fuzzy sets. *International Journal of General Systems*, *35*(4), 417–433. Retrieved September 4, 2017, from Taylor & Francis database.

Yue, Z., (2014). TOPSIS-based group decision-making methodology in intuitionistic fuzzy setting. *Information Sciences*, *277*, 141–153. Retrieved November 4, 2017, from Elsevier Science Direct database.

Yunna, W., Jinying, Z., Jianping, Y., Shuai, G. & Haobo, Z. (2016). Study of decision framework of offshore wind power station site selection based on ELECTRE-III under intuitionistic fuzzy environment: A case of China. *Energy Conversion and Management*, *113*, 66–81. Retrieved July 7, 2017, from Elsevier Science Direct database.

Yu, S., Wang, J., & Wang, J. Q. (2017). An interval type-2 fuzzy likelihood-based MABAC approach and its application in selecting hotels on a tourism website. *International Journal of Fuzzy Systems*, *19*(1), 47-61. Retrieved February 23, 2018, from Springer Link database.

Yu, S., Wang, J., & Wang, J. Q. (2018). An extended TODIM approach with intuitionistic linguistic numbers. *International Transactions in Operational Research*, *25*(3), 781-805. Retrieved February 23, 2018, from Wiley database.

Yu, X., Liu, Y., Huang, X., & An, A. (2012). Mining online reviews for predicting sales performance: A case study in the movie domain. *IEEE Transactions on Knowledge and Data Engineering*, *24*(4), 720-734. Retrieved February 8, 2018, from IEEE Xplore database.

Zadeh, L. A. (1965a) Fuzzy sets. *Information and Control*, *8*(3), 338-353. Retrieved September 5, 2017, from Elsevier Science Direct.

Zadeh, L. A. (1965b). Fuzzy sets and systems. In *Proceedings of the Symposium on Systems Theory* (29-37). New York: Polytechnic Press of the Polytechnic Institute of Brooklyn.

Zadeh, L. A. (1983). Linguistic variables, approximate reasoning and dispositions. *Medical Informatics*, *8*(3), 173-186. Taylor & Francis database.

Zaman, M., Botti, L., & Thanh, T. V. (2016). Weight of criteria in hotel selection: An empirical illustration based on TripAdvisor criteria. *European Journal of Tourism Research*, *13*, 132-138. Retrieved February 23, 2018, from ProQuest database.

Zandi, A. & Roghanian, E. (2013). Extension of Fuzzy ELECTRE based on VIKOR method. *Computers & Industrial Engineering*, *66*(2), 258–263. Retrieved January 06, 2017, from Elsevier Science Direct database.

Zardari, N. H., Ahmed, K., Shirazi, S. M., & Yusop Z. B. (2015) Literature Review. In: *Weighting methods and their effects on multi-criteria decision making model outcomes in water resources management* (7-67). Cham: Springer.

Zeleny, M. (1976). The attribute-dynamic attitude model. *Management Science*, *23*(1), 12-26. Retrieved November 23, 2017, from JSTOR database.

Zhang, H. Y., Peng, H. G., Wang, J., & Wang, J. Q. (2017). An extended outranking approach for multi-criteria decision-making problems with linguistic intuitionistic fuzzy numbers. *Applied Soft Computing*, *59*, 462–474. Retrieved October 9, 2017, from Elsevier Science Direct database.

Zhang, K., Cheng, Y., Liao, W. K., & Choudhary, A. (2011, August). Mining millions of reviews: A technique to rank products based on importance of reviews.

In *Proceedings of the 13th International Conference on Electronic Commerce, 12*. New York: ACM.

Zhang, K., Narayanan, R., & Choudhary, A. N. (2010). Voice of customers: Mining online customer reviews for product feature-based ranking. *WOSN'10*, 11-11, USA: USENIX Association Berkeley.

Zhang, S. F. & Liu, S. Y. (2011). A GRA-based intuitionistic fuzzy multi-criteria group decision making method for personnel selection. *Expert Systems with Applications*, *38*(9), 11401-11405. Retrieved October 9, 2017, from Elsevier Science Direct database.

Zhang, W., Xu, H., & Wan, W. (2012). Weakness finder: Find product weaknesses from Chinese reviews by using aspects based sentiment analysis. *Expert Systems with Applications*, *39*(11), 10283-10291. Retrieved April 6, 2017, from Elsevier Science Direct database.