Broker-based trade allocation in market-based multi-agent environments

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BROKER-BASED TRADE ALLOCATION IN MARKET-BASED MULTI-AGENT ENVIRONMENTS

A Thesis Submitted in Fulfilment of the Requirements for the Award of the Degree of

Doctor of Philosophy

from

UNIVERSITY OF WOLLONGONG

by

Dien Tuan Le

School of Computing and Information Technology
Faculty of Engineering and Information Science

2017
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CERTIFICATION

I, Dien Tuan Le, declare that this thesis, submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Computing and Information Technology, Faculty of Engineering and Information Science, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

(Signature Required)

Dien Tuan Le
08 January 2017
Dedicated to

My wife Đặng Mỹ Phượng Phan
, My children
, My Parents and my Family
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Publications

The following is a list of research papers, which have been already published or accepted during my PhD study.

Published Papers

- **Dien Tuan Le**, Minjie Zhang and Fenghui Ren, A Multi-Criteria Group Based Matching Approach of Buyers and Sellers Through a Broker in Open E-Marketplaces. *In Post-Proceedings of the Ninth International Workshop on Agent-based Complex Automated Negotiations (ACAN2016)*, accepted and in press. (This publication forms the part of Chapter 3)

- **Dien Tuan Le**, Fenghui Ren and Minjie Zhang, Membership Function Based Matching Approach of Buyers and Sellers through a Broker in Open E-Marketplace. *In Post-Proceedings of International Joint Agents Workshop and Symposium (IJAWS 2015)*, accepted and in press. (This publication forms the part of Chapter 3)


Papers under Working

• Dien Tuan Le, Minjie Zhang and Fenghui Ren, A Broker-Based Buyer and Seller Modelling Approach for Trade Allocation in Market Environments, will be submitted to *Decision Support Systems*. (This work is from a part of Chapter 4)

• Dien Tuan Le, Minjie Zhang and Fenghui Ren. Broker-Based Multi-Objective Optimization Approach for Trade Allocation in Market Environments, will be submitted to *the International Journal of Intelligent Systems*. (This work is from a part of Chapter 5)
ABSTRACT

e-marketplaces have been growing rapidly in the recent years due to the development of Internet technologies. Many bright outlooks of e-marketplaces will lead to appear the new highlight of electronic transaction markets and the trend of intelligent business environments in the future. Although e-marketplaces offer buyers access to a huge number of products provided by sellers and allow sellers access to more potential buyers, there is a great need of efficient and scalable methods for buyers and sellers to interact with each other to achieve business transactions successfully. Thus, broker-based trade allocation, where a broker works as an intermediary between multiple buyers and multiple sellers, is an attractive research direction in recent years, especially when broker-based trading processes are carried out under the complex electronic transaction environments. Multi-agent technologies are the major technologies for developing broker-based approaches in market environments. This thesis investigates the challenging issues of broker-based trade allocation in market-based multi-agent environments so that the allocation pairs between buyers and sellers are determined to satisfy buyers’ requirements under the consideration of multi-attribute trading and different objectives. Through this PhD study, five broker-based approaches are proposed and developed to allocate efficiently buyers’ requirements to sellers’ offers in market environments, including

1. A broker-based behavior prediction of buyers and sellers approach, which is developed to satisfy buyers’ requirements and maximize a broker’s expected profit under the consideration of degrees of satisfaction of buyers and sellers, and prediction results of their behaviors.

2. A broker-based modelling uncertain information of attributes in buyers’ requirements approach, which is developed to satisfy buyers’ requirements and maximize the satisfaction degree of all buyers based on the modelling uncertain information of attributes in buyers’ requirements.
3. A broker-based modelling sellers’ pricing offers as per trade volumes approach, which is proposed to satisfy buyers’ requirements and maximize the satisfaction degree of all buyers under the consideration of sellers’ pricing offers as per trade volumes, buyers’ satisfaction degrees as per trade volumes, and buyers’ satisfaction degree as per other attributes.

4. A broker-based multi-objective optimization approach, which is proposed to maximize a broker’s benefit, a broker’s turnover and the satisfaction degree of all buyers through allocating buyers’ requirements to sellers’ offers under a multi-attribute trading.

5. A broker-based buyer’s constraint relaxation approach, which is proposed to select a potential seller to satisfy a buyer’s requirements through a broker under the consideration of a buyer’s constraint relaxation and sellers’ bonus and reward programs.
I would firstly like to express my deepest gratitude to Prof Minjie Zhang for being my principle supervisor during my PhD study and research. It has been a great honour for me to do my thesis under Prof Minjie’s supervision, who always gives me very detailed and thoroughly constructions on my research without uncountable-hour work. Without her encouragement, guidance, research training, care and support, it would have been impossible for me to accomplish my PhD study. I will never forget my first paper in my PhD study, she spent a lot of time on training me to write it although she had a high blood pressure on this time. I am also deeply grateful to my co-supervisor Dr. Fenghui Ren to share his strong research vision with me and help me to come up with many good ideas. Specially, he spent a lot of time on helping me to improve my papers related to my proposed approaches and experiments. Additionally, I wish to thank my research group, Prof Xudong Luo, Dr. Quan Bai, Dr. Chao Yu, Dr. Dayong Ye, Dr. Yan Kong, Dr. Ahmed Moustafa, Dr. Xing Su, Xishun Wang, Jihang Zhang and Lei Niu, who often give me discussions in the laboratory and such discussions have improved my research. My thanks also go to my friends at Wollongong, i.e., Dr. Ngoc Trung Ngo, Dr. Van Tuc Nguyen and Dr. The Vu Tran. They make my life in Wollongong so memorable.

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Chapter 1

Introduction

In recent years, due to the rapid development of information technologies, e-marketplaces have been popularly used and remarkably developed to help users to carry out electronic business transactions efficiently. Intelligent systems in e-marketplaces are able to gather commodities and shoppers’ useful information and provide efficient ways to support users to make the right decisions. Due to the increasing number of buyers and sellers, and the vast amount of transaction information in e-marketplaces, it is not easy for both buyers and sellers to find a potential partner to satisfy requirements from both sides. This limitation offers a broker an opportunity to work in e-marketplaces.

A broker in e-marketplaces acts as a third party to facilitate interactions between buyers and sellers to satisfy buyers’ requirements. Furthermore, a broker can help both buyers and sellers to reduce time consumption to locate and process the transaction information to make their decisions. Thus, a broker plays a significant role in maintaining electronic transaction operations, bringing benefits to individual participants, and increasing electronic transaction efficiency in e-marketplaces. As a result, a broker technique has become more widely used in some e-marketplaces such as financial, agricultural, and power markets [32]. Such e-marketplaces are usually large, distributed
1.1 Research Background

and unpredictable, and are also able to operate in complex electronic transaction environments. In recent years, the artificial intelligent-based approaches have focused on studying the broker technique as the third party in the trading process between buyers and sellers. In particular, some approaches have focused on the broker-based buyer and seller modelling, and the broker-based trading allocation under the consideration of multi-attribute trading and different objectives [137, 62, 75]. Thus, broker-based trade allocation in market-based multi-agent environments under the consideration of buyer and seller modelling is an important research issue and also a challenging problem.

The purpose of this thesis is to study and develop broker-based trade allocation approaches based on the consideration of buyer modelling and management, seller modelling and management, and a broker’s trade allocation strategies to help a broker to satisfy buyers’ requirements and achieve a broker’s the goals, i.e., the maximization of the satisfaction degree of all buyers, a broker’s profit and a broker’s turnover in market-based multi-agent environments. Section 1.1 of this chapter gives an overview of research background of this thesis. Section 1.2 lays out the four research issues and the four objectives of this thesis. The contributions of this thesis are presented in Section 1.3 and the structure of this thesis is given in Section 1.4.

1.1 Research Background

In this section, some research background knowledge about this thesis is introduced. Subsection 1.1.1 presents concepts and applications of multi-agent systems. Market-based multi-agent environments are introduced in Subsection 1.1.2. Subsection 1.1.3 gives an overview of broker modelling approaches in market-based environments. Finally, Subsection 1.1.4 lays out some main challenges of broker-based trade allocation strategies in market-based multi-agent environments.
1.1.1 Multi-agent systems (MASs)

In general, an agent in an intelligent system has been widely studied and used in different areas for many years. There is still an ongoing debate about the definition of an agent. The following definition of an agent has been widely accepted by researchers and industrial practitioners.

“An agent is an encapsulated computational system that is situated in some environment and that is capable of flexible, autonomous action in that environment in order to meet its design objectives” [131]

From this definition, agent operations in an environment are presented in Figure 1.1 as follows.

![Figure 1.1: Agent and its environments](109)

The definition above means that an agent is expected to have the most common properties of its computation, i.e., autonomy, reactivity, pro-activeness and social ability [127, 130, 59]. Each agent may have more than these four properties but these four properties are common properties for an agent. These properties make agents more useful for the information-rich and process-rich environments of electronic commerce [91]. Agents can be wisely applied to comparatively small systems and complex systems such as intelligent business systems, medical care systems, the air-traffic control systems and so on. Actually, agents are always applied in these systems individually.
but there are still limitations of using MASs for these systems.

An MAS is an intelligent system consisting of a set of agents in the system where they can interact with each other in a given environment to achieve a common goal or their individual goals. These agents can cooperate or compete with each other and share or not share knowledge with each other [128], [14]. In an MAS, an agent can perform tasks individually or collaboratively with other agents when coping with complex problems. Research directions in MASs have focused on the construction of complex systems relating to agents where they can have different or even conflicting goals, and the coordination/cooperation of agents’ behaviors in such systems. Furthermore, MASs are applied to many real-world systems to model, simulate and solve real-world problems because they have some benefits such as the ability to provide efficiency, robustness and scalability, and the ability to solve distributed problems [129]. In recent years, MASs have attracted much attention from researchers and industrial practitioners in a wide range of applications such as air traffic control, engineering, science, computer-based applications as well as other disciplines because they have abilities of autonomous learning [126], [18], [35], [1], independent decision making [17], [135], [47], collaborative problem solving [57], [58], [3], [7], as well as automatic self-adaption. These abilities have been widely employed in open and dynamic environments through homogenous or heterogeneous autonomous agents [73], [43], [107]. Currently, agent and multi-agent technologies have been also widely applied to develop various industrial and commercial applications such as e-markets [30], [54], [107], e-governments [49], [81], [134], Internet-based grid systems [37], [27], [121], [139], pervasive computing [110], [92], [116] and so on.
1.1.2 Market-based multi-agent environments

e-marketplaces are becoming more and more dominant in modern transaction environments in recent years because of their preeminence in automatic electronic transactions and low cost. On the other hand, agent technologies are one of the most useful and powerful technologies to make e-marketplaces more distinct. Thus, agent technologies and e-marketplaces are among the most important and exciting areas of research and application development in e-marketplaces. Combining these two fields offers important opportunities for organizations to carry out automatic electronic transactions based on web environments and for developers to develop tools to facilitate business transactions in e-marketplaces [123]. Furthermore, agent technologies in e-marketplaces are a promising tool to solve commercial activities such as information gathering, auctions, negotiation, shopping, trading and so on [34, 38, 41, 96, 105].

Agents can carry out major actions in electronic transaction systems. Firstly, they are able to act on behalf of their owners to find useful information and fulfil electronic transactions in e-marketplaces. Secondly, they can locate potential partners to satisfy buyers’ requirements with less cost. Thirdly, they can make rational decisions on behalf of humans and negotiate the price of a commodity with other agents to make a deal. In fact, agents have been used in many electronic transaction systems to facilitate various commercial actions. Specially, autonomous and intelligent agents are applied to solve some common functions of complex business processes as follows [11].

- Allocating buyers to sellers

- Facilitating the information exchange, goods, services, and payments in market-based multi-agent environments

- Providing an institutional infrastructure, such as a legal and regulatory framework, which enables the efficient functioning of the market
1.1. Research Background

Agents in market-based environments can carry out functions such as buying and selling products and other services. Other key applications of agents in e-marketplaces include negotiation, matching, locating potential partners, managing supply chains, auctions, coalition formation and so on [94]. Furthermore, it is expected that partially or fully automating some of the transaction processes in market-based multi-agent environments will achieve significant cost savings. Agents act on behalf of buyers, sellers, brokers, vendors, manufacturers, etc. in order to achieve business goals. To make market-based multi-agent environments successful, agents should be able to carry out tasks in intelligent ways such as analysis, decision-making and negotiation through reasoning and learning [102]. Furthermore, agents can save time, money and effort by automating simple tasks such as matching, searching, sorting and monitoring. In addition, market-based environments are usually complex environments; thus, intelligent agents are able to do their autonomous decision making based on the uncertain and incomplete information, and learn and adapt themselves to the changing environments. For instance, intelligent agents in market-based environments are able to perform autonomous cooperation through agent communication languages to exchange information and knowledge to coordinate their activities [97].

1.1.3 Broker modelling in market-based environments

With the tremendous development of electronic commerce applications in modern business, the number of buyers, sellers, and automated transactions has rapidly increased in recent years [83, 53]. The human matching processes are not efficient methods to solve buyers' demands because they have to contact buyers by telephone calls, emails or fax as the main communication means. Thus, broker modelling techniques tend to become overwhelmed by available information to allocate buyers' requirements to sellers' offers efficiently. The large size and complex e-marketplace environments such
as financial, agricultural and power e-marketplaces necessitate the existence of brokers. For example, in a power e-marketplace [69], brokers’ mission is to maximize their profits by buying energy in a wholesale market and selling energy through contracts in retail markets such as households, small and medium enterprises and owners of electric vehicles. Furthermore, brokers compete with each other to try to attract buyers by offering energy services to buyers through tariff contracts and by negotiating with larger buyers to achieve individual contracts.

A broker is considered as a third party in the trading processes between buyers and sellers, and acts on someone’s behalf like a negotiator to obtain a reasonable contract or the best deal between buyers and sellers. Thus, broker modelling in e-marketplaces becomes a very active direction in recent years [32], [70], [108]. More recently industrial practitioners and researchers work has been based on exploiting transaction information, which can be collected from e-marketplaces to propose sophisticated approaches of trade allocation using broker-based techniques [98]. Furthermore, e-marketplaces have become wider and more complex than in the past because electronic business transactions happen actively worldwide and the electronic transaction amount is continuously increasing day by day. So, broker modeling becomes active in complex electronic transaction environments. In recent years, more attention has been paid to research on brokers or intermediaries as the third party of a trading process in e-marketplaces [103, 104, 140, 46, 125] and applications [16, 33, 69].

1.1.4 Challenges of broker-based trade allocation

Due to the information revolution, e-marketplaces have experienced rapid development in modern business. Business organizations and buyers are more and more relying on electronic transaction processes in market environments [122]. The rapid development of e-marketplaces have attracted a great attention of researchers and industrial
practitioners to improve their quality [71]. Due to the wide range of e-marketplaces, there is the huge amount of trading information from buyers and sellers and it is usually difficult for both buyers or sellers to find and select useful information as well as to distinguish relevant and irrelevant trading information to determine their suitable transaction partners. This limitation requests brokers to facilitate interactions between buyers and sellers [21, 45, 86, 25, 113]. In particular, a broker is illustrated in e-marketplaces and is presented in Figure 1.2 as follows.

Figure 1.2: A broker’s main functions in e-marketplaces [19]

- **Seller:** A seller, such as an individual person, a company or an organization, owns a certain product or service that can be offered to a potential buyer through a broker under certain constraints. The constraints can be crisp values, interval values or can be expressed by special offers to buyers through a broker. For example, a seller can offer discount prices to a buyer as per trade volumes.

- **Buyer:** A buyer, such as an individual person, a company or an organization, is interested in buying a certain product or service from a potential seller through a broker under certain constraints. Similarly, the constraints can be crisp values, internal values or can be expressed by special requirements to sellers through a
1.1. Research Background

broker. For example, a buyer can express a buyer’s satisfaction degrees as per trade volumes.

- **Broker:** A broker acts as a middleman between buyers and sellers to carry out trade allocation processes to meet buyers’ and sellers’ needs. A broker’s mission is to understand buyers’ requirements and sellers’ offers to carry out trade allocation to achieve its objectives. Depending on specific situations in market-based environments, a broker’s trade allocation strategy is to maximize the satisfaction degree of all buyers, a broker’s turnover, a broker’s profit or multi-objectives related to buyers, sellers and a broker.

Implementing e-marketplaces based on MAS technologies can bring even more benefit to the users and society [74]. Researchers in the field of artificial intelligence have developed many e-marketplaces based on MAS approaches for different applications where agents act on behalf of organizations or their human users to carry out the tasks of business trading [44]. In agent-based e-marketplaces, the agents can be classified into three types: broker agents, buyer agents and seller agents. A buyer agent acts on behalf of a buyer interacting with a broker agent by sending a buyer’s requirements to a broker agent. Similarly, a seller agent represents a seller to interact with a broker agent. After a broker agent receives buyers’ requirements and sellers’ offers, the trade allocation processes with the assistance of a broker agent can be carried out as the trade allocation processes without the assistance of a broker agent, which are required by human users or organizations. However, broker-based trade allocation in market-based multi-agent environments is challenged to satisfy human users or organizations under the vast amount of information from buyers’ requirements and sellers’ offers. Thus, research challenges of broker-based trade allocation in market-based multi-agent environments are discussed in this thesis as follows.
1.2 Research Issues and Objectives of This Thesis

The purpose of this thesis is to study broker-based trade allocation approaches in market-based multi-agent environments and develop solutions to solve the challenging
research issues related to the broker-based trade allocation problems so that a broker’s
decisions can satisfy buyers’ requirements and support market efficiency, and partic-
ipant efficiency related to buyers, sellers and a broker. This thesis focuses on four
research issues as follows.

**Issue 1: Uncertain information of attributes in buyers’ requirements**

Due to limited knowledge about some attributes of products in e-marketplaces, it
may be difficult for buyers to express their preferences of products with exact numerical
values. One of the major issues of broker-based trade allocation is how to model
uncertain information of attributes in buyers’ requirements because modelling this
uncertain information can help a broker agent to carry out trade allocation to satisfy
buyers’ requirements. This issue is related to **Challenge 1**.

**Issue 2: Behavior prediction for trade agents**

In e-marketplaces, if a broker agent wants to make good decisions for allocating
buyers’ requirements to sellers’ offers, a broker agent needs to predict the behaviors of
trade agents based on historical transaction data. Therefore, how to predict buyers’
and sellers’ behaviors is also an important issue because the prediction results can
help a broker agent to calculate its expected profits in trade allocation processes. This
issue is related to **Challenge 1**.

**Issue 3: Trade allocation under the consideration of sellers’ price offers as
per trade volumes and buyers’ satisfaction degrees as per trade volumes**

In e-marketplaces, a seller has different price offers corresponding to different trade
volumes. In general, a seller’s price offers can be linear pricing, prices of discouraging
consumption, and prices of encouraging consumption as per trade volumes. Thus, a
broker agent needs to communicate with a seller to model a seller’s price function to
carry out trade allocation. Furthermore, a buyer has also different satisfaction de-
greses corresponding to different trade volumes so modelling a buyer’s requirements
related to trade volumes is necessary for a broker agent to satisfy these requirements. Therefore, how to develop broker-based trade allocation approaches under the consideration of sellers’ price offers as per trade volumes, buyers’ satisfaction degrees as per trade volumes, or buyers and sellers’ other requests, is a necessary issue in market environments. This issue is related to Challenge 2.

Issue 4: Multi-objective optimization through trade allocation under a multi-attribute trading

Trade allocation is to allocate buyers’ requirements to sellers’ offers to satisfy needs from both sides in market environments. Although many researchers and industrial practitioners have paid much attention to allocate buyers’ requirements to sellers’ offers under different objectives, there is a great need of efficient approaches for trade allocation under the consideration of multi-objective models. Thus, how to develop a multi-objective optimization function for a broker agent under the consideration of the satisfaction degrees of buyers, a broker’s turnovers and a broker’s benefits is an important issue in market-based multi-agent environments. This issue is related to Challenge 3.

Focussing on the above four research issues, this thesis has the following four objectives.

- **Objective 1:** Broker-based trade allocation to maximize the satisfaction degree of all buyers under modelling uncertain information of attributes in buyers’ requirements.

  Developing a method to help a broker agent model uncertain information of attributes in buyers’ requirements before carrying out trade allocation to maximize the satisfaction degree of all buyers.
• **Objective 2:** Broker-based trade allocation to maximize a broker’s expected profit under the consideration of buyers’ and sellers’ satisfaction degrees, and prediction results of buyers’ and sellers’ behaviors.

Developing a broker-based trade allocation approach to maximize a broker’s expected profit under the consideration of buyers’ and sellers’ satisfaction degrees, and prediction results of buyers’ and sellers’ behaviors.

• **Objective 3:** Broker-based trade allocation under the consideration of sellers’ price offers as per trade volumes and buyers’ satisfaction degrees as per trade volumes; or buyer’s constraint relaxation.

Developing two broker-based trade allocation approaches under the consideration of sellers’ price offers as per trade volumes, buyers’ satisfaction degrees as per trade volumes, or buyers’ other requirements. In particular, the first approach is related to model sellers’ pricing offers as per trade volumes and buyers’ satisfaction degrees as per trade volumes; and the second approach is related to use a buyer’s constraint relaxation when a broker agent cannot find any seller to satisfy a buyer’s requirements.

• **Objective 4:** A broker-based multi-objective optimization for allocating buyers’ requirements to sellers’ offers under a multi-attribute trading.

Developing a broker-based multi-objective optimization approach for trade allocation under the consideration of multi-attribute trading and sellers’ discount price offers as per trade volumes. The approach should maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit.
1.3 Contributions of This Thesis

This thesis focused on the four research issues and objectives, which are related to Challenges 1, 2 and 3. Thus, this thesis makes the following contributions.

1. A broker-based trade allocation approach is proposed to satisfy buyers’ requirements and maximize a broker’s expected profit by using Bayes’ rules to predict buyers’ and sellers’ behaviors.

To achieve Objective 2, a broker-based trade allocation approach is proposed in this thesis to allocate buyers’ requirements to sellers’ offers through a broker agent based on Bayes’ rules to predict buyers’ and sellers’ behaviors. The major contributions of this proposed approach include (i) an abstract model of a broker agent, that is applicable to a broad range of market types; (ii) predicting buyers’ and sellers’ behaviors by using Bayes’ rules so that a broker agent can identify appropriate allocation pairs between buyers and sellers; and (iii) an objective function and a set of constraints to help a broker agent to maximize its expected profit under the consideration of buyers’ and sellers’ satisfaction degrees.

2. A broker-based trade allocation approach is proposed and developed to seek optimal allocation pairs based on modelling uncertain information of attributes in buyers’ requirements.

To achieve Objective 1, a broker-based trade allocation approach is proposed under the consideration of buyers’ satisfaction degrees for uncertain information of attributes and other attributes in buyers’ requirements as per sellers’ offers in market-based multi-agent environments. The contributions of this proposed approach are that (i) a broker agent models uncertain information of attributes in buyers’ requirements through interactions between a broker agent and a buyer; (ii) a broker agent’s trade allocation processes are carried to sat-
1.3. Contributions of This Thesis

isfy buyers’ requirements and maximize the satisfaction degree of all buyers in a multi-attribute trading based on a generated objective function; and (iii) a broker agent’s strategy is proposed to allocate buyers’s requirements to sellers’ offers based on buyers’ feedback from determined allocation results.

3. A broker-based buyer’s constraint relaxation approach for trade allocation in e-marketplaces is proposed to help a broker to find a potential seller to satisfy a buyer’s requirements.

The broker-based trade allocation approach is proposed to find a potential seller to satisfy a buyer’s requirements. This proposed approach includes three components: a seller selection, a constraint relaxation, and a decision making. The major contributions of the proposed approach are that (i) the trading process between buyers and sellers through a broker agent is modeled by using constraints through the consideration of multiple attributes of a buyer’s requirements and sellers’ offers; and (ii) a buyer can utilize a relaxation method with constraints to change its requirements in difficult situations when a broker agent cannot find any seller to satisfy the buyer’s requirements.

4. A broker-based approach is proposed to carry out trade allocation under the consideration of modelling sellers’ price offers, buyers’ satisfaction degrees as per trade volumes, and buyers’ other requirements in market-based multi-agent environments.

A broker-based trade allocation approach is proposed to allocate buyers’ requirements to sellers’ offers. The major contributions of this proposed approach are that (i) a broker agent can model sellers’ price offers as per corresponding to the different trade volumes through interactions between a broker agent and a seller; (ii) due to a buyer’s different trade volume demands, a broker agent models the
buyer’s satisfaction degrees as per corresponding to the different trade volumes based on interactions between a broker agent and a buyer; and (iii) to carry out a broker agent’s trade allocation processes, an objective function and a set of constraints are generated to help a broker agent to maximize the satisfaction degree of all buyers.

Both contributions 3 and 4 can achieve Objective 3 of this thesis from different perspectives and with different goals.

5. A broker-based multi-objective optimization approach for trade allocation is proposed to maximize a broker’s benefit, the satisfaction degree of all buyers and a broker’s turnover through trade allocation in market-based multi-agent environments.

To achieve Objective 4, a broker-based multi-objective optimization approach for trade allocation in market-based multi-agent environments is proposed in this thesis. The major contributions of this proposed approach are that (i) a proposed framework is applicable to help a broker agent to achieve its goals; (ii) a formula system is generated to calculate buyers’ satisfaction degrees for a multi-attribute trading; and (iii) a multi-objective model is built to help a broker agent to maximize a broker’s benefit, the satisfaction degree of all buyers and a broker’s turnover.

1.4 The Structure of This Thesis

The rest of this thesis is organized as follows.

Chapter 2 reviews the current literature, in particular, in regard to an overview of broker-based techniques in market-based environments including broker-based learning for decision making, broker-based negotiation and broker-based provider selections for
1.4. The Structure of This Thesis

buyers, and broker-based trade allocation under the consideration of broker-based buyer modelling and management, broker-based seller modelling and management, and broker-based matching strategies.

Chapter 3 proposes two broker-based trade allocation approaches based on buyer modelling in e-marketplaces. The first approach is to carry out trade allocation through a broker by predicting buyers' and sellers' behaviors to maximize a broker's expected profit and the second approach is to carry out trade allocation through a broker in modelling uncertain information of attributes in buyers' requirements to maximize the satisfaction degree of all buyers.

Chapter 4 proposes a broker-based trade allocation approach based on seller modelling in e-marketplaces. In particular, this approach helps a broker to allocate buyers' requirements to sellers' offers based on modelling sellers' price offers as per trade volumes to maximize the satisfaction degree of all buyers.

Chapter 5 proposes a broker-based multi-objective optimization approach for trade allocation in e-marketplaces. In particular, a broker's trade allocation process is carried out based on a multi-objective function to maximize the satisfaction degree of all buyers, a broker's turnover, and a broker's benefit.

Chapter 6 proposes a broker-based buyer's constraint relaxation approach for trade allocation in e-marketplaces. This approach helps a broker to find a potential seller to satisfy a buyer's requirements under the consideration of a buyer's constraint relaxation and sellers' the bonus and reward programs.

Chapter 7 concludes the thesis with a summary of contributions and points out the future work.
Chapter 2

Literature Review

This chapter reviews existing methods and approaches, which are relevant to the topic of the thesis. In particular, Section 2.1 gives an overview of broker-based techniques in market-based environments including broker-based learning for decision making, broker-based negotiation and broker-based potential provider selections for buyers. Section 2.2 presents broker-based trade allocation under the consideration of broker-based buyer modelling and management, broker-based seller modelling and management, and broker-based matching strategies between buyers and sellers.

2.1 Broker-Based Techniques in Market Environments

Recently, due to the fast development of internet technologies, e-marketplaces have been successfully applied to intelligent business environments and they provide efficient electronic transaction environments between buyers and sellers. Thus, more and more organizations have changed their business transactions based on e-marketplaces. However, the number of buyers, sellers and electronic transactions in e-marketplaces have rapidly increased in recent years [53, 67] so both buyers and sellers face abundant information in large scale and complex market environments and it is difficult
for them to make decisions. Therefore, broker-based techniques have been emerged to facilitate transactions between buyers and sellers [19]. These techniques can save the searching time to satisfy buyers’ requirements, improve the efficiency of transactions between buyers and sellers, find the optimal allocation pairs, and support their decision making.

The outline of this section is presented as follows. Subsection 2.1.1 provides a detailed review of broker-based learning for decision making. Subsection 2.1.2 presents a detailed review of broker-based negotiation and Subsection 2.1.3 provides a detailed review of broker-based potential provider selections for buyers.

2.1.1 Broker-based learning for decision making in market environments

Due to the requirement of scalability, the spatial and temporal constraints of market-based environments, and the lack of the accurate information of environment status, a broker only has local views of market environments. In order to satisfy buyers’ requirements as per sellers’ offers and achieve brokers’ utilities, researchers have developed many different learning approaches to support brokers’ decision making in market environments. In [103], Reddy et al. studied the specification of the market strategies to support their autonomous broker agents to earn profits in the smart grid market. In their approach, broker agents interact with producers and consumers through a tariff market so that broker agents can keep supply and demand balances in market environments to earn high profits. They have shown that broker agents can achieve the high profits if broker agents can learn their strategies using Markov Decision Processes (MDPs) and Q-learning. However, their approach is only based on the situations of the tariff market in the Smart Grid domain and it is difficult to be applied to a wholesale market. Furthermore, broker agents’ strategies are limited by the number of
2.1. Broker-Based Techniques in Market Environments

economic signals such as fixed rates of electricity consumption and production for all market participants. If participants are able to change their requirements in market environments, their broker agents face difficulties in open market environments.

Wang et al. [125] proposed an intelligent broker model with smart trading strategies to solve the dynamics and complexity in the smart grid market. Their broker’s responsibilities are firstly to predict short-term demands of various consumers and then to carry out the action to buy energy from the wholesale market through auctions, and finally to sell energy to consumers in the retail market. Based on predicted results of customers’ demands, their broker can utilize a Markov Decision Process for the one-day-ahead auction in the wholesale market. Furthermore, their broker employs reinforcement learning processes to optimize prices for different types of consumers in competition market environments with other brokers. Finally, their broker not only competes with other brokers to achieve high profits but also maintains balances of supply and demand in the smart grid market.

Peter et al. [99] used reinforcement learning with function approximation in the retail market to help broker agents make decisions on retail price. In particular, they proposed a novel class of autonomous broker agents to trade with customers in retail electricity markets. In addition, their brokers can make transactions in the large scope of a smart electricity markets and be able to achieve long-term, profit-maximizing policies. Furthermore, their brokers can adapt arbitrary economic signals from their market environments, and efficiently learn over the large state spaces resulting from these signals.

Nogueira et al. [95] proposed a distributed multi-agent system based on a broker in electronic insurance markets, where customers are grouped together using machine learning techniques. The proposed system can better match customers and insurance product offers using a metric to determine the representative insurance product con-
configuration of each group, generating the automatic construction of customers' profiles and measuring customers' preferences on all the attributes of an insurance product.

In summary, in market-based environments, where buyers and sellers do not often reveal their truthful trading information, broker-based learning is useful for a broker to predict behaviors of buyers and/or sellers or adjust trading strategies to carry out allocating buyers' requirements to sellers' offers so that buyers' requirements are satisfied and a broker's the goals are successfully achieved.

2.1.2 Broker-based negotiation in market environments

Due to internet development, e-marketplaces are rapidly exploding. In recent years, many organizations use them as the main means to carry out their business transaction processes to achieve business efficiency, cost savings and high productivity. To cope with the new business environments, intelligent systems in e-marketplaces are fast generated based on the foundation of agent technologies with a strong emphasis on carrying out the automatic negotiations during the trading processes [77, 79, 93, 106].

Due to a wide range of buyers and sellers in e-marketplaces, it is not easy for buyers and sellers to carry out negotiations directly so third party approaches are widely employed such as brokers or mediators to handle negotiation strategies. During the last decade, there had been a growth of research activities related to automatic negotiation in e-marketplaces through a third party.

In [13], Balachandran et al. proposed a negotiation model under a multi-issue trading for e-marketplaces, in which agents autonomously negotiate each other on the multi-attribute terms of transactions. In their approach, fuzzy logic is used to help buyer agents express their preferences on the products in fuzzy terms. A broker agent's mission is to handle the negotiation strategies between buyer agents and seller agents. After a broker agent receives buyers' requests and registration information,
the negotiation processes are carried out. In particular, a broker agent asks the sellers to provide their offers as per the restrictions in buyers' requests. Then, a broker agent negotiates with sellers through several rounds of negotiations. The negotiation processes are done until a satisfactory solution is found or the maximum number of rounds is reached. After that, a broker agent finds the best offer and sends the best offer to the buyer agent. The buyer agent then sends the negotiation results to the end users, who are ultimately responsible for making the decision on which goods to buy. However, a broker agent in their approach did not consider a buyer's concession polices when a broker agent cannot find any seller to satisfy a buyer's requests through the negotiation processes.

In [23], Bui et al. proposed a negotiation support system under a multi-attribute trading to support electronic transactions in market environments, related to buyers, sellers and brokers. The system is able to determine the potential parties to prospective transactions in less time consumption. On the other hand, the system also tends to increase buyers' and sellers' satisfaction with the overall transaction experience since the incremental concessions are made from them during negotiation processes. Furthermore, the final transaction prices approximate to the average market prices. It means that this system could be helpful in improving electronic transaction efficiency in market environments. Although the trust issue plays an important role in developing sustained business transactions in e-marketplaces, authors have not solved the trust in their algorithm and not proposed any mechanism to increase the trust in their system.

In [12], Balachandran et al. proposed the multi-service negotiation model through a mediator agent to satisfy customers' requirements. This model is illustrated in Figure 2.1. Negotiations in this model are carried out through a mediator agent who acts as a intermediary between the service provider agents and the customer agents. The main purpose of a mediator agent is firstly to seek a bundle of services from the
service providers to satisfy the customer’s requirements through a series of negotiations and secondly to adapt the bundle in case of service failure. Their negotiation model is related to a process, which includes a number of offer/reply cycles, as part of an iterative improvement cycle between participating agents and a mediator agent. This model is an extension of the Contract-Net Protocol [112] that adds a round of counter proposals from the mediator agent and the other service providers.

Wu et al. [132] proposed the broker-based framework for automated Service Level Agreement (SLA) negotiation with multiple service providers. SLA bargaining aims to satisfy a customer’s requirements and relies on the proposed strategies for generating counter proposals to the service provider’s offers. Based on a customer’s requirements, the broker selects a suitable service provider based on a utility-driven selection algorithm. Then, a broker negotiates the SLA terms with that provider based on a customer’s requirements.

In summary, due to the rapid development of internet technologies, more and more business organizations have transferred their traditional transactions to automatic electronic transactions in e-marketplaces. It is time-consuming for buyers and sellers
to collect the necessary information to make their decision because they are faced with abundant information in e-marketplaces so it is difficult for them to negotiate with each other directly. Thus, broker-based negotiation is one of the major approaches to help a broker to allocate buyers' requirements to sellers' offers successfully in e-marketplaces.

2.1.3 Broker-based potential provider selections for buyers in market environments

In a wide range of e-marketplaces such as financial, agricultural, power and cloud markets, it is too difficult for individual buyers to interact directly with providers to find a potential provider and it sometimes ends in failure. Thus, intermediaries such as brokers, market makers, or middlemen are highly needed to link with buyers and providers to facilitate the finding of a potential provider as per a buyer's requirements and generally reducing searching costs [32]. Selecting a suitable provider as per a buyer's specific requirements in e-marketplaces through a broker is also an active research direction in recent years. In particular, some broker-based approaches have been developed to select a potential provider for a buyer in e-marketplaces as follows.

Achar et al. [2] proposed broker-based architecture to select a potential provider from multiple providers in cloud markets. The diagram of broker-based architecture in cloud markets is shown in Figure 2.2. Figure 2.2 depicts that the broker acts as a middleman between a buyer and multiple providers and the broker's main mission is to select the most potential provider to satisfy the buyer's requirements. To solve this problem, their broker measures the quality of each provider and ranks providers as per the buyer's requirements by using TOPSIS method [124].

In e-marketplaces, building decision support systems for a customer to select the best provider to satisfy a customer's requirements in cloud markets is also active researches in recent years. Amato et al. [5, 4] proposed a model for measuring compliance
of SLAs from multiple providers as per a customer’s specific requirements through a broker so that the best proposal in the cloud market can be selected to satisfy the customer’s requirements.

There have been some discussions on selecting cloud service providers (CSP) and broker-based frameworks in the cloud environments [120, 55, 90, 42]. For instance, Buyya et al. [24] introduced the key role of cloud broker service to select cloud service providers in market-oriented cloud environments. Sundareswaran et al. [120] proposed a novel brokerage-based approach to select a service provider in cloud environments, where responsibilities of cloud brokers are to select the best cloud service provider. Geetha et al. [39] carried out a survey on the needs and issues of brokers in cloud environments and compared their features. However, clients do not have the ability to verify the results of the cloud service provider selections for a customer in cloud environments. Thus, Sianipar et al. [117] proposed a mechanism to verify the results of the cloud service provider selections for a customer through a cloud broker. The cloud brokerage architecture in their approach is presented in Figure 2.3. There are four entities in Figure 2.3, which are connected between each other. The customers use a verifier to verify the selected cloud service provider cluster through a

Figure 2.2: A broker-based architecture in cloud environments [2]
cloud broker. The cloud broker can also verify properties of the cloud service providers by sending their properties to the verifier.

All the above approaches focused on selecting the potential provider to satisfy a customer’s requirements through a broker in market environments. A broker’s main mission in these approaches is based on a customer’s requirements and providers’ offers under a multiple-attribute trading to find a potential provider. However, customers’ concession in these approaches is not considered when a broker cannot find any provider to satisfy a customer’s requirements. Thus, Chapter 6 of this thesis develops a broker-based buyer’s constraint relaxation approach for trade allocation in market environments. The proposed approach in this thesis can help a broker agent select a suitable seller under the consideration of a buyer’s relaxation with constraints to change a buyer’s requirements when a broker agent cannot find any seller to satisfy a buyer’s requirements.
2.2 Broker-Based Trade Allocation in Market Environments

Trade allocation, which is usually called trade determination problem [66], is a process of allocating buyers' requirements to sellers' offers in market environments. In general, trade allocation happens under a multi-attribute trading due to the large number of buyers and sellers and it is difficult for buyers and sellers to distinguish between useful and not useful materials to support their decisions. To solve this limitation, a broker acts as a middleman between buyers and sellers to carry out the allocation process in market environments [15, 31, 85, 10, 136]. Due to wide range and complex market environments, broker-based trade allocation in market environments faces several challenges (refer to Subsection 1.1.4). Thus, allocating buyers’ requirements to sellers’ offers based on a broker is an active research direction in recent years [64, 118]. This section reviews broker-based trade allocation in market environments under the consideration of broker-based buyer modelling and management, broker-based seller modelling and management, and broker-based trade allocation strategies between buyers’ requirements and sellers’ offers.

2.2.1 Broker-based buyer modelling and management

Due to buyers’ vague knowledge about some attributes of products, it may be difficult for them to express their preferences of products with specific values. Thus, buyers’ requirements are related to uncertain information in terms of the choices of product attribute level. It means that buyers can use natural languages to express their preferences. For example, in the considering the purchase of the washing machine, buyers can express their preferences of washing machine as per some attributes, i.e., price, cost of maintenance, simplicity, warranty time, delivery time in the following terms.
2.2. Broker-Based Trade Allocation in Market Environments

Price: the price of washing machine should be around $800.

Maintenance: in general, cost of maintenance should not be very high.

Simplicity: overall performance of the washing machine should be simple.

Warranty time: warranty time should be around one year.

Delivery time: delivery time should be around 5 days.

The italicized words in the above example are fuzzy or linguistic terms. The attributes including price, warranty time and delivery time can be expressed by fuzzy numbers while other attributes including cost of maintenance and simplicity are expressed by the fuzzy or linguistic terms [51].

When buyers lack of the information of their product attribute level for their choices, they would like to use their natural languages to express their preferences of product attributes. Therefore, the most important problem is how to find a good method to handle buyers' requirements related to the natural language representations of their preferences of product attributes in market environments. Thus, fuzzy logic is a potential methodology to represent and manipulate buyers' linguistic and vague concepts in numerical forms [88]. Furthermore, fuzzy sets and linguistic variables are popularly employed to approximate buyers' linguistically defined terms to estimate product attribute values of buyers' requirements in numerical numbers [50, 82].

Herrera et al. [51] developed the procedure of interpreting buyers' requirements related to use their natural languages to express their preferences of product attributes. In general, buyers' natural languages are usually related to using words or sentences to express their preferences. The words or sentences are flexible to express their preferences of product attributes. In [68], e-business strategies to support buyers were developed by using fuzzy logic and the game theory in competitive business environments. Their proposed method is very convenient for buyers to use because their proposed method permits buyers to use their natural language to input their
requirements in the electronic transaction processing to find potential products from sellers to satisfy buyers’ requirements.

Mohanty et al. [89] proposed a decision support tool by the consideration of buyers’ requirements related to express their product feature preferences by using their natural language as an input. Depending on buyers’ preferences in fuzzy terms, their method is employed to find the potential products from sellers to satisfy buyers’ requirements. Furthermore, some agent-based electronic transaction market systems, which are related to product attributes with fuzzy terms in buyers’ requirements already existed in the literature [48, 115, 133].

In the literature, modelling buyers’ requirements with uncertain information plays an important role in market environments because in the procedure of product purchases, buyers normally express their requirements and preferences in fuzzy or linguistic terms [28, 52, 88, 89]. It is clear that modelling buyers’ requirements with uncertain information objectively exists in market environments. Thus, a broker’s mission also includes modelling buyers’ requirements with uncertain information and managing other attributes to carry out the allocation of buyers’ requirements to sellers’ offers.

Much research on brokers, as a third party, in trading processes in market environments has been done recently based on assuming that values of attributes in buyers’ requirements and sellers’ offers are crisp. Jung et al. [65] used constraint satisfaction problem (CPS) to seek optimal allocation pairs through the brokerage to satisfy buyers’ and sellers’ various needs as per crisp values in buyers’ requirements and sellers’ offers and designed a multi-agent prototype of brokerage system to simulate the real estate on the internet. Their two layer ed multi-agent framework was proposed to support interactions between buyers and sellers through brokerage. In the competition layer, the brokerage processes is to allocate buyer agents to seller agents by using a functional relationship of a multi-agent framework, while in the constraint satisfaction
layer, a CPS model expresses the relationships between buyer agents and seller agents. Finally, a CPS solver is employed to seek the optimal allocation pairs.

Sarma et al. [114] analyzed market behaviors in large networks where buyer agents do not know seller agents and vice-versa. All trading processes between seller agents and buyer agents are constructed by broker agents under specific values of attributes in buyers' and sellers' requirements. Authors also proposed a polynomial time algorithm to compute equilibria in the network. In certain restricted settings, their algorithm is useful to reach the equilibrium. The limitation of their approach is that one buyer can buy one unit of a commodity at the most and one seller has one commodity to sell.

Sim et al. [118] focussed on allocating buyers' requests to sellers' advertisements through a broker under fixed values of attributes. The process of trade allocation and interactions between buyers and sellers consists of four stages: selecting requests and advertisements, evaluating connections, filtering connections and allocating requests to advertisements. In the stage of evaluating connections, they proposed a formula system to determine the utility of each connection between a buyer and a seller under considering multiple attributes.

In [67], Kang et al. indicated that due to the rapid development of electronic transactions based on internet, buyers and sellers are not still familiar with the electronic transaction systems and it is difficult for them to buy and sell products in e-marketplaces. To solve this limitation, the agent-based virtual marketplace system, where agents act on buyers' and sellers' behalf to carry out electronic transactions, was proposed to solve this limitation. In particular, in the broker-based transaction system [67] shown in Figure 2.4, the user agents do not make any efforts to search a transaction partner and a broker agent is responsible for finding the best deals by their proposed algorithm to seek the best transaction partner with the best offered price. Based on the test results of their proposed approach, although the broker-based
synchronous transaction took more time to make a deal than the other approach, it achieved better performance in terms of rate of best deals and a number of gained transactions.

Jiang et al. [62] further proposed a multi-objective optimization model in a multi-attribute trading as per crisp values in buyers’ requirements and sellers’ offers with quantity discounts. This model is established with the maximization of the trade volume, and buyers’ and sellers’ matching degree through matching between buyers’ requirements and sellers’ offers. In their approach, they introduced a new concept and a formula system to calculate buyers’ and sellers’ matching degree. Furthermore, they proposed a novel hybrid algorithm to solve their proposed model to find the optimal allocation pairs.

All the above approaches focused on allocating buyers’ requirements to sellers’ offers through a broker under a multi-attribute trading. A broker’s mission in these approaches considers buyers’ requirements and sellers’ offers as per crisp values so there is a great need for efficient approaches to model attributes with uncertain information.
in buyers’ requirements as well as to solve the trade allocation problem with the combination of crisp values and uncertain information in buyers’ requirements. Thus, Chapter 3 of this thesis develops the trade allocation approach to help a broker agent allocate buyers’ requirements to sellers’ offers under the combination of uncertain information and crisp values of attributes in buyers’ requirements.

2.2.2 Broker-based seller modelling and management

Modelling and managing attributes in seller’s offers through a broker is one of the most important challenges to carry out allocating buyers’ requirements to sellers’ offers or to select the best seller as per buyers’ requirements [119, 137]. Sundareswaran et al. [120] proposed a novel brokerage-based architecture in the cloud environment to select the service provider as per a customer’s requirements. They designed a unique indexing technique to manage the information of a large number of service providers and developed the algorithm to select the most efficient service provider to satisfy a customer’s requirements. In addition, modelling sellers’ price offers through a broker plays an important role to measure the satisfaction degree of buyers and sellers so numerous kinds of research has focussed on modelling and managing sellers’ price offers.

Pourerebrahimi et al. [100, 101] proposed an economic-based approach to allocate customers’ service requests to producers’ service offers in market-based grid environments. The interaction process between customers and producers in market-based grid environments through an auctioneer is shown in Figure 2.5. In their proposed approach, a customer agent’s service requests such as task details, task deadline and price constraints and a producer agent’s service offers such as resource details, resource deadline and price constraints are submitted to an auctioneer (a matchmaking coordinator). Furthermore, when customer and producer agents enter the market,
they define the initial price and then the price is dynamically updated during trading time using an intelligent price strategy. After that, an auctioneer uses a discriminatory pricing policy to determine the transaction price for each allocation pair between customers and producers. The pricing strategy satisfies the user requirements and constraints which are set by customers and producers.

In recent years, some researchers have focussed on sellers’ price offers to carry out trade allocation through a broker. For instance, Jiang et al. [60, 63] proposed an optimal allocation approach for a multi-attribute trading through a broker under simultaneously considering fuzzy information and indivisible demand. They firstly use fuzzy set theory to represent attributes in buyers’ requirements and sellers’ offers. Specifically, buyers and sellers’ price offers can be presented under fuzzy information. Secondly, they propose a method to calculate the matching degree based on the improved fuzzy information axiom. Then, based on calculation results of the matching degree, they generate a multi-objective model under a multi-attribute trading with indivisible demand and develop a new algorithm to solve their model.
In [75, 61], a broker considers a price attribute in sellers' offers and buyers' requirements as an attribute with soft constraints to calculate the matching degrees of buyers and sellers so that a broker carries out the matching processes between buyers' requirements and sellers' offers under a multi-attribute trading based on the matching degrees of buyers and sellers.

All the above approaches focused on allocating buyers' requirements to sellers' offers under the consideration of the price attribute with soft constraints. In real world, sellers usually offer prices of commodities as per trade volume so that sellers encourage buyers to buy many volume of commodities from sellers so there is a great need for efficient approaches to model sellers' price offers as per trade volume. Thus, Chapter 4 of this thesis develops a broker-based approach to allocate buyers' requirements to sellers' offers in market environments based on modelling sellers' price offers as per trade volume. This makes the work in Chapter 4 different from all the existing studies reviewed here.

2.2.3 Broker-based matching strategies between buyers' requirements and sellers' offers

Depending on specific situations in market environments, a broker will focus on its specific matching strategies so that buyers' requirements are satisfied and a broker's the goals are achieved. To achieve a broker's goals, broker-based matching strategies are expressed through a broker’s objective function to carry out matching between buyers’ requirements and sellers’ offers. In [76], Li et al. proposed an agent-based framework to match buyers with sellers through a broker by using a multi-objective optimization model. Figure 2.6 shows their framework. Their framework has three layers: the interface layer, the matching layer and the database layer. There are three types of potential users, i.e., buyer agents, seller agents and a broker agent in
2.2. Broker-Based Trade Allocation in Market Environments

Figure 2.6: The framework of the system to match buyers with sellers [76]

the interface layer. The matching layer is mainly to match buyers and sellers based on a multi-objective model under the consideration of the maximization of buyers and sellers’ evaluation. Furthermore, they generated a prototype system to allocate buyers’ requirements to sellers’ offers by using the proposed framework. However, the weights of individual attributes in buyer agents’ and seller agents’ requirements were not considered in their multi-objective optimization model.

Jiang et al. [61] proposed a mathematical model to carry out the trade allocation in a multi-attribute trading as per crisp values in buyers’ requirements and sellers’ offers. In particular, their model could maximize the matching degree and trading volume based on buyers’ requirements and sellers’ offers. Furthermore, their model considered the incomplete weight information to carry out a broker’s matching process.

Li et al. [75] proposed a new method to match buyers and sellers through a third party, namely a matchmaker, in market environments by using a multi-objective optimization model. In particular, their multi-objective optimization model could help a matchmaker to maximize total satisfaction of buyers and sellers. They also proposed a new genetic algorithm to solve the multi-objective optimization model to
find optimal matching pairs. However, a broker’s profit function was not considered in their proposed approach.

Yu-Lin et al. [137] proposed the single objective model to allocate buyers’ requirements to sellers’ offers under the same type of multi-attribute commodities through a broker. They proposed a formula system to calculate the degree of similarity of buyers’ requirements and sellers’ offers. Their model could maximize a broker’s income as the objective and was evaluated based on the dataset of residential second-hand house markets. However, their objective model is to achieve the maximization of the income of the broker without considering the satisfaction of all buyers.

All the above approaches focused on allocating buyers’ requirements to sellers’ offers based on a broker’s strategies using the objective functions. However, broker’s objective functions in these approaches focused on buyers’ and sellers’ utilities without the consideration of a broker’s turnover. Furthermore, their broker’s strategies do not consider sellers’ discount price offers as per buyers’ trade volume in a multi-objective model. Thus, Chapter 5 of this thesis develops a broker-based multi-objective optimization approach for trade allocation. In particular, broker-based trade allocation strategies in this proposed approach are to maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit under the consideration of sellers’ discount price offers as per trade volume.

2.3 Summary

In this chapter, the current literature regarding the research concerns of this thesis was reviewed and analyzed comprehensively. In particular, firstly, approaches related to broker-based techniques in market environments were reviewed in Section 2.1, where broker-based learning in decision making, broker-based negotiation, and broker-based provider selections for buyers in market environments were reviewed in detail. Sec-
ondly, broker-based trade allocation approaches in market environments were reviewed in Section 2.2, where broker-based trade allocation approaches are reviewed in detail under the consideration of broker-based buyer modelling and management, broker-based seller modelling and management, and broker-based trade allocation strategies in market environments.

Even though many researchers have proposed different strategies, mechanisms, and approaches to solve trade allocation through a broker in market environments, limitations still exist which require further research and improvement. This thesis proposes five broker-based approaches to achieve efficient trade allocation in market environments. The five approaches will be represented in the following three chapters.
Chapter 3

Broker-Based Buyer Modelling for Trade Allocation in Market Environments

This chapter focusses on broker-based buyer modelling for trade allocation in market environments, in which a broker is based on historical data to predict buyers’ and sellers’ behaviors or a broker interacts with a buyer to model uncertain information of attributes in a buyer’s requirements before a broker allocates buyers’ requirements to sellers’ offers.

Two broker-based buyer modelling approaches for trade allocation in market environments are proposed in this chapter. Section 3.1 proposed an approach for broker-based trade allocation through prediction of buyers’ and sellers’ behaviors and Section 3.2 presents an approach for broker-based trade allocation through modelling uncertain information of attributes in buyers’ requirements. This chapter is summarized by Section 3.3.
3.1 Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

3.1.1 Problem description and definitions

There are three main types of members in the trading process with multi-attribute trading, i.e., buyers, sellers and a broker. A general trading process can be presented by Figure 3.1.

A broker acts as a third party in market environments to facilitate interactions between buyers and sellers by satisfying both buyers’ and sellers’ needs [29, 40]. In this chapter, the mission of the broker is to allocate \( n (n \geq 1) \) buyers to \( m (m \geq 1) \) sellers under a multi-attribute trading in order to meet their requirements. Let’s assume that buyer \( B_i (i = 1, 2, \ldots n) \) and seller \( S_j (j = 1, 2, \ldots m) \) will have one unit of a multi-attribute commodity to buy or sell. Multiple attributes in buyers’ requirements and sellers’ offers are divided into two categories: attributes with hard constraints and attributes with soft constraints. Attributes with hard constraints mean that their
constraints must be satisfied in the final agreement. For example, a buyer would like to buy the exact size jacket as the most important factor in the buyer’s decision making. It means that the buyer wants to buy the jacket with a fixed size so the size of the jacket is the attribute with the hard constraint. On the other hand, attributes with soft constraints are attributes on which buyers or sellers are willing to negotiate [65]. Attributes with soft constraints are usually classified into three categories as follows:

(i) **Benefit soft constraints**: This means that the bigger the constraint’s values offered by sellers, the happier the buyers’ behaviors. For example, the quality of goods is called the attribute with benefit soft constraints.

(ii) **Cost soft constraints**: This means that the smaller the constraint’s values offered by sellers, the happier the buyers’ behaviors. For example, the price of goods is called the attribute with cost soft constraints.

(iii) **Interval soft constraints**: The constraint’s values are considered as interval soft constraints when the constraint’s values are given the interval values.

Based on the above concepts and notations, definitions related to a buyer agent, a seller agent and a broker agent are described as follows:

A buyer agent is considered as a buyer who would like to buy a particular commodity from a market environment to satisfy a buyer’s requirements.

**Definition 3.1.1.** A buyer agent $B_i$ ($i = 1, \ldots, n$) is defined as a 2-tuple $B_i = < ID_i, REQ_i >$, where $ID_i$ is $B_i$’s identification and $REQ_i$ indicates $B_i$’s requirements (see Definition 3.1.2).

**Definition 3.1.2.** $B_i$’s requirements are normally related to multiple attributes. Attributes with hard constraints and attributes with soft constraints in $B_i$’s requirements are presented by $REQH_i$ and $REQS_i$, respectively. In particular, $REQH_i$ is defined by the following format.
3.1. Broker-Based Trade Allocation through Prediction of Buyers' and Sellers' Behaviors

\[
REQH_i = \begin{pmatrix}
A_1 & A_2 & \ldots & A_h \\
C_{i1} & C_{i2} & \ldots & C_{ih}
\end{pmatrix},
\]

(3.1)

where \( h \) is a number of attributes with hard constraints; \( A_h \) indicates the \( h^{th} \) attribute name; \( C_{ih} \) is the constraint value of \( A_h \). Attributes with hard constraints are necessary conditions in the trading processes and must be satisfied. Thus, the weight of attributes with hard constraints does not need to be considered.

Similarly, \( REQS_i \) is defined by the following format.

\[
REQS_i = \begin{pmatrix}
A_1 & A_2 & \ldots & A_k \\
C_{i1} & C_{i2} & \ldots & C_{ik} \\
W_{i1} & W_{i2} & \ldots & W_{ik}
\end{pmatrix},
\]

(3.2)

where \( A_k \) indicates the \( k^{th} \) attribute name and \( C_{ik} \) is a constraint value of \( A_k \). If the constraint value \( C_{ik} \) is the interval value, the constraint value is called \([C_{ikL}, C_{ikU}]\), \( C_{ikL} \) is the lowest constraint value; \( C_{ikU} \) is the largest constraint value; \( W_{ik} \) is a weight value of \( A_k \) and \( k \) is a number of attributes with soft constraints in \( REQS_i \). Thus, \( \sum_{g=1}^k W_{ig} = 1, W_{ig} \geq 0 \).

A seller agent is considered as a company or an organization, which has the resources to provide to market environments.

**Definition 3.1.3.** A seller agent \( S_j \) \((j = 1, \ldots, m)\) is defined as a 2-tuple \( S_j = < ID_j, OFF_j > \), where \( ID_j \) is \( S_j \)'s identification and \( OFF_j \) indicates \( S_j \)'s offers (see Definition 3.1.4).

**Definition 3.1.4.** \( S_j \)'s offers are related to multiple attributes. Attributes with hard constraints and attributes with soft constraints are presented by \( OFFH_j \) and \( OFFS_j \).
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

in $S_j$’s offers, respectively. In particular, $OFFH_j$ is defined by the following format.

$$OFFH_j = \begin{pmatrix} A_1 & A_2 & \ldots & A_h \\ Q_{j1} & Q_{j2} & \ldots & Q_{jh} \end{pmatrix}, \quad (3.3)$$

where $h$ is a number of attributes with hard constraints; $A_h$ indicates the $h^{th}$ attribute name; $Q_{jh}$ is a constraint value of $A_h$. Similarly, the weight of attributes with hard constraints does not need to be considered.

Similarly, $OFFS_j$ is defined by the following format.

$$OFFS_j = \begin{pmatrix} A_1 & A_2 & \ldots & A_k \\ Q_{j1} & Q_{j2} & \ldots & Q_{jk} \\ W_{j1} & W_{j2} & \ldots & W_{jk} \end{pmatrix}, \quad (3.4)$$

where $A_k$ indicates the $k^{th}$ attribute name; $Q_{jk}$ is a constraint value of $A_k$; $W_{jk}$ is a weight value of $A_k$ and $k$ is a number of attributes with soft constraints in $OFFS_j$. Thus, $\sum_{g=1}^{k} W_{jg} = 1$, $W_{jg} \geq 0$.

A broker agent acts as a third party between buyer agents and seller agents to achieve a broker’s maximal expected profit through trade allocation.

Definition 3.1.5. A broker agent $BR$ is defined as a 4-tuple $BR = < B, S, H^B, H^S >$, where $B$ is a set of buyer agents, $S$ is a set of seller agents, $H^B$ is a set of buyer agents’ historical trading data, and $H^S$ is a set of seller agents’ historical trading data.

$H^{Bi}$ is the historical trading data of $B_i$ and $H^{Bi} \in H^B$. In particular, $H^{Bi}$ is represented by the following format.

$$H^{Bi} = \begin{pmatrix} x_{11}^{Bi} & x_{21}^{Bi} & \ldots & x_{q1}^{Bi} & y_{1}^{Bi} \\ \vdots & \vdots & \ldots & \vdots & \vdots \\ x_{1f}^{Bi} & x_{2f}^{Bi} & \ldots & x_{qf}^{Bi} & y_{f}^{Bi} \end{pmatrix}, \quad (3.5)$$
where each column indicates historical trading records for each attribute of $B_i$; $x_{qi}^{Bi}(q \in h+k)$ indicates a value of attribute $A_q$ in the transaction $f$ and the value of $x_{qi}^{Bi}$ can be quantitative or qualitative; $y_{fi}^{Bi}$ indicates $B_i$’s decision on the transaction $f$. If $y_{fi}^{Bi}=1$, this means that $B_i$ accepts a specific offer stored in the transaction $f$ and if $y_{fi}^{Bi}=0$ this means that $B_i$ does not accept a specific offer stored in the transaction $f$.

Similarly, $H^S_{Sj}$ is the historical trading data of $S_j$ and $H^S_{Sj} \in H^S$. In particular, $H^S_{Sj}$ is represented by the following format.

$$H^S_{Sj} = \begin{pmatrix} x_{11}^{Sj} & x_{21}^{Sj} & \cdots & x_{q1}^{Sj} & y_{1}^{Sj} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{1v}^{Sj} & x_{2v}^{Sj} & \cdots & x_{qv}^{Sj} & y_{v}^{Sj} \end{pmatrix}, \quad (3.6)$$

where each column indicates historical trading records of each attribute of $S_j$; $x_{qi}^{Sj}(q \in h+k)$ indicates a value of attribute $A_q$ in the transaction $v$ and the value of $x_{qi}^{Sj}$ can be quantitative or qualitative; $y_{vi}^{Sj}$ indicates $S_j$’s decision on the transaction $v$. If $y_{vi}^{Sj}=1$ this means that $S_j$ accepts a specific offer stored in the transaction $v$ and if $y_{vi}^{Sj}=0$ this means that $S_j$ does not accept a specific offer stored in the transaction $v$.

After a broker agent receives trading information in buyer agents’ requirements and seller agents’ offers, the key issue is that a broker agent is to allocate buyer agents’ requirements to seller agents’ offers to maximize a broker agent’s expected profit under a multi-attribute trading. The principle of the proposed approach is presented in the Subsection 3.1.2.

### 3.1.2 The principle of the proposed broker-based trade allocation approach

#### 3.1.2.1 Framework of the proposed broker-based trade allocation approach

The framework of the proposed approach to help a broker to carry out trade allocation using Bayes’ rules to predict buyers’ and sellers’ behaviors is presented in Figure 3.2.
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

Figure 3.2: The framework of the proposed broker-based trade allocation approach

In the framework, buyers’ requirements and sellers’ offers related to multi-attribute commodities are submitted to a broker. Based on these, a broker calculates buyers’ satisfaction degrees to determine a constraint satisfaction layer. The constraint satisfaction layer includes the group of buyers and the group of sellers who are considered to work in a broker’s trade allocation processes. After that, the objective optimization model and a set of constraints are generated to maximize a broker’s expected profit. Then, the proposed method related to Bayes’ rules is to predict buyers’ and sellers’ behaviors. Finally, the objective optimization model is solved by using the linear simplex programming method to find the optimal allocation pairs.
3.1. Broker-Based Trade Allocation through Prediction of Buyers' and Sellers' Behaviors

3.1.2.2 Building an objective function

As market environments become more and more complex, a broker needs to have knowledge of the markets to make more rational and appropriate decisions. To achieve knowledge of the markets, a broker needs to understand a local view of the markets based on buyers’ requirements, sellers’ offers and the history data of the trading processes. When the broker achieves this knowledge, decisions can be made to buy items from selected sellers and sell them to those buyers where buyers’ requirements are satisfied and a broker’s expected profit is maximally achieved.

To achieve the above mentioned purpose, the design of an objective function is necessary and comes from three considerations. (i) A broker predicts buyers’ and sellers’ behaviors based on buyers’ requirements and sellers’ offers, and the historical trading data of buyers and sellers; (ii) A broker should consider buying items from those sellers who satisfy the buyers’ requirements so that a broker achieves its expected profit maximally; and (iii) A broker needs to determine a broker’s expected profits from each transaction between buyers and sellers. In particular, the objective function is proposed as follows.

$$\max f_{BR} = \sum_{i=1}^{n} \sum_{j=1}^{m} (P_{B_i} \times P_{S_j} \times U_{B_iS_j}) \times x_{ij},$$

(3.7)

where $P_{B_i}$ is a probability value to reflect whether $B_i$’s requirements sent to $BR$ are satisfied by $B_i$; $P_{S_j}$ is a probability value to indicate whether $S_j$’s offers sent to $BR$ are satisfied by $S_j$; $U_{B_iS_j}$ is $BR$’s profits from a trading process between $B_i$ and $S_j$ through $BR$; $x_{ij}$ is a decision variable. Results of decision variables indicate that a broker makes decisions to buy a commodity from selected sellers and sell the commodity to those buyers where a broker can achieve its expected profit maximally; $n$ is the number of buyers engaging in market environments; and $m$ is the number of sellers engaging in market environments.
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

BR's profits in the trading processes are computed from the selling and buying prices. In general, there are two cases to calculate BR's profits as follows.

- Calculating BR’s profits without the consideration of buyer and seller’s satisfaction degree is presented as follows.

\[ U_{B,S}^i = (C_{ip} - Q_{jp}) \]  \hspace{1cm} (3.8)

- Calculating BR’s profits with the consideration of buyer and seller’s satisfaction degree is presented as follows.

\[ U_{B,S}^{B_i,S_j} = (C_{ip} - Q_{jp})(\alpha_1 \sum_{g=1}^{k} W_{ig} \beta_{ijg} + \alpha_2 \sum_{g=1}^{k} W_{jg} \delta_{ijg}), \]  \hspace{1cm} (3.9)

where \( C_{ip} \) is the price of one commodity, which \( B_i \) pays to \( BR \) and \( Q_{jp} \) is the price of one commodity, which \( BR \) pays to \( S_j \), \( \alpha_1 \) is the weight of all buyers’ satisfaction degree, \( \alpha_2 \) is the weight of all sellers’ satisfaction degree and \( \sum_{i=1}^{2} \alpha_i = 1 \). \( \beta_{ijg} \) is \( B_i \)'s satisfaction degree as per \( S_j \)'s offers for attribute \( A_g \). The calculation of \( \beta_{ijg} \) is presented at Sub sub section 3.1.2.3. \( \delta_{ijg} \) is \( S_j \)'s satisfaction degree as per \( B_i \)'s requirements for attribute \( A_g \). The calculation of \( \delta_{ijg} \) is presented at Sub sub section 3.1.2.4.

Thus, the objective function can be rewritten as follows.

\[
\max f_{BR} = \sum_{i=1}^{n} \sum_{j=1}^{m} (P_{BR}^i \times P_{S_j}^S \times (C_{ip} - Q_{jp}))(\alpha_1 \sum_{g=1}^{k} W_{ig} \beta_{ijg} + \alpha_2 \sum_{g=1}^{k} W_{jg} \delta_{ijg})) \times x_{ij},
\]  \hspace{1cm} (3.10)

The current objectives for a broker are (i) to how to determine \( x_{ij} \) so that buyers’ requirements are satisfied and (ii) to achieve a broker’s expected profit maximally. To meet the above two objectives, a broker’s objective function in Equation (3.10) must
satisfy a set of constraints as follows.

\[ \sum_{i=1}^{n} x_{ij} \leq 1, \forall j \in m \]  
\[ (3.11) \]

\[ \sum_{j=1}^{m} x_{ij} \leq 1, \forall i \in n \]  
\[ (3.12) \]

\[ x_{ij} = 1, 0, \forall i \in n, \forall j \in m \]  
\[ (3.13) \]

\[ \sum_{g=1}^{k} W_{ig} = 1, \forall i \in n \]  
\[ (3.14) \]

\[ \sum_{g=1}^{k} W_{jg} = 1, \forall j \in m \]  
\[ (3.15) \]

\[ x_{ij} = 0 \text{ if } \beta_{ijg} = -1, \text{ or } \beta_{ijg'} = -1 \text{ or } C_{ip} < Q_{jp}, \forall g \in k, \forall g' \in h, \]  
\[ (3.16) \]

where \( k \) is the number of attributes with soft constraints in buyers’ requirements and sellers’ offers; the objective function in Equation (3.10) is to maximize a broker’s expected profit under the consideration of the satisfaction degree of all buyers and all sellers; constraints in Equation (3.11) are that each seller only sells one unit of a commodity to a buyer maximally; constraints in Equation (3.12) are that each buyer only buys one unit of a commodity from a seller maximally; constraints in Equation (3.13) are constraints of decision variable, if \( B_i \) matches with \( S_j \), then \( x_{ij} = 1 \) and otherwise, \( x_{ij} = 0 \); constraints in Equation (3.14) indicate that the weight sum of attributes with soft constraints in a buyer’s requirements equals to 1. Similarly, constraints in Equation (3.15) denote that the weight sum of attributes with soft constraints in a seller’s requirements equals to 1; and constraints in Equation (3.16) indicate a constraint sat-
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

isfaction layer to work in a broker’s trade allocation process. The objective function in Equation (3.10) can be solved efficiently by well-known linear programming methods, such as simplex methods or an interior point method [36].

Based on Equation (3.10), it is clear that $C_i, Q_{jp}, \sum_{g=1}^{k} W_{ik} \beta_{ijk}$ and $\sum_{g=1}^{k} W_{ik} \delta_{ijk}$ are determined from buyers’ requirements and sellers’ offers while $P_{rB_i}$ and $P_{rS_j}$ are predicted from the historical trading data of buyers and sellers, respectively. Thus, probability of buyers’ behaviors can be rewritten in general as follows:

$$P_{rB} = \{P_{rB_1}, P_{rB_2}, \ldots, P_{rB_n}\}, \quad (3.17)$$

where $P_{rB}$ indicates a set of buyers’ predicted probability values.

Similarly, the probability of sellers’ behaviors can be rewritten in general as follows:

$$P_{rS} = \{P_{rS_1}, P_{rS_2}, \ldots, P_{rS_m}\}, \quad (3.18)$$

where $P_{rS}$ indicates a set of sellers’ predicted probability values.

After the objective function and a set of constraints are generated, the key issue is to predict the probability of buyers’ behaviors $P_{rB}$ and sellers’ behaviors $P_{rS}$. Thus, the proposed method related to Bayes’ rules is proposed to solve this issue in Subsubsection 3.1.2.5.

3.1.2.3 Building the calculation of buyers’ satisfaction degrees

Buyers’ satisfaction degrees play an important role in multi-attributes trading between buyers and sellers through a broker. It helps a broker to determine a constraint satisfaction layer and to satisfy buyers’ requirements through trade allocation. Let $S_i = \{S_1, S_2, \ldots, S_j\}$ match $B_i$ and $S_{iq}$ denote a set of constraint values from sellers $\{Q_{1q}, Q_{2q}, \ldots, Q_{jq}\}$ for the attribute $A_q$ ($q \in (h+k)$). $\beta_{ijk}$ is $B_i$’s satisfaction degree as per $S_j$’s offers for attribute $A_h$ with hard constraints. $\beta_{ijk}$’s values are only from one set with two members $\{-1,1\}$. $\beta_{ijk}$ is $B_i$’s satisfaction degree as per $S_j$’s offers for attribute
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

A_k with soft constraints. \( \beta_{ijk} \)'s values are changed to \{-1,0,1\}. In particular, \( \beta_{ijk} \) includes two intervals, one is one point and another is \( (0,1] \). A buyer of satisfaction degree is computed to attributes with hard constraints, namely \( \beta_{ijg'}(g' \in h) \), and attributes with soft constraints, namely \( \beta_{ijg}(g \in k) \), as follows:

(i) For **attribute type with hard constraints**

\[
\beta_{ijg} = \begin{cases} 
-1 & \text{if } C_{ig} \neq Q_{jg} \\
1 & \text{if } C_{ig} = Q_{jg} 
\end{cases}
\]  

\( \beta_{ijg} = -1 \) means that \( S_j \) does not match with \( B_i \) for the attribute \( A_{g'} \) while \( \beta_{ijg} = 1 \) means that \( S_j \) matches with \( B_i \) for the attribute \( A_{g'} \).

(ii) For **attribute type with benefit soft constraints**

Attributes with benefit soft constraints mean that the bigger \( S_j \)'s attribute value, the larger \( B_i \)'s happiness is. In particular, If \( C_{ig} > Q_{jg} \) then \( \beta_{ijg} = -1 \). It means that \( S_j \) does not satisfy \( B_i \). If \( C_{ig} \leq Q_{jg} \), then \( \beta_{ijg} \) is computed as follows:

\[
\beta_{ijg} = \left( \frac{Q_{jg} - Q_{\text{min}-g} + \phi}{Q_{\text{max}-g} - Q_{\text{min}-g} + \phi} \right)^t, 
\]  

where \( t = \frac{C_{ig}}{Q_{\text{min}-g}} \), \( Q_{\text{min}-g} \) and \( Q_{\text{max}-g} \) are the minimal and maximal values of \( Q_{jg} \) in \( S_{ig} \), respectively, where \( S_{ig} \) is a set of values for the attribute \( A_g \) in \( S_i \). A value \( t \in (0,1] \) helps a broker to carry out comparing a buyer’s satisfaction degree when \( t \) is used to compute \( \beta_{ijg} \). \( \phi = \frac{Q_{\text{min}-g}}{2} \) and \( \phi \) helps a broker to solve some special cases such as only one seller in the e-markets or \( Q_{\text{max}-g} = Q_{\text{min}-g} \). \( \beta_{ijg} \) increases when \( Q_{jg} \) increases or \( C_{ig} \) decreases.

\( \beta_{ijg} \) means that \( S_j \) matches with \( B_i \) for the attribute \( A_g \) with a buyer’s satisfaction degree \( \left( \frac{Q_{ig} - Q_{\text{min}-g} + \phi}{Q_{\text{max}-g} - Q_{\text{min}-g} + \phi} \right)^t \). \( \beta_{ijg} \) is in-between 0 and 1. If \( \beta_{ijg} \) is near 1, it means that \( B_i \) is highly satisfied by \( S_j \) for the attribute \( A_g \).
(iii) For attribute type with cost soft constraints

Attributes with cost soft constraints mean that the smaller $S_j$'s attribute value, the larger $B_i$'s happiness is. In particular, If $C_{ig} < Q_{jg}$ then $\beta_{ijg} = -1$. It means that $S_j$ does not satisfied $B_i$. If $C_{ig} \geq Q_{jg}$ then $\beta_{ijg}$ is computed as follows:

$$\beta_{ijg} = \left( \frac{Q_{\max-g} - Q_{jg} + \phi}{Q_{\max-g} - Q_{\min-g} + \phi} \right)^{\frac{1}{t}}, \quad (3.21)$$

where $\beta_{ijg}$ means that $S_j$ matches with $B_i$ for the attribute $A_g$ with a buyer's satisfaction degree $(\frac{Q_{\max-g} - Q_{jg} + \phi}{Q_{\max-g} - Q_{\min-g} + \phi})^{\frac{1}{t}}$; $\beta_{ijg}$ is in-between 0 and 1. If $\beta_{ijg}$ is near 1, it means that $B_i$ is highly satisfied by $S_j$ for attribute $A_g$. $\beta_{ijg}$ in this case increases when $Q_{jg}$ decreases or $C_{ig}$ increases.

(iv) For attribute type with benefit interval constraints

$$\beta_{ijg} = \begin{cases} 
-1 & \text{if } Q_{jg} < C_{igL} \\
\frac{Q_{jg} - C_{igL}}{C_{igU} - C_{igL}} & \text{if } C_{igL} \leq Q_{ig} < C_{igU} \\
1 & \text{if } Q_{jg} \geq C_{igU}
\end{cases}, \quad (3.22)$$

(v) For attribute type with cost interval constraints

$$\beta_{ijg} = \begin{cases} 
-1 & \text{if } Q_{jg} > C_{igU} \\
\frac{C_{igL} - Q_{jg}}{C_{igU} - C_{igL}} & \text{if } C_{igL} < Q_{ig} \leq C_{igU} \\
1 & \text{if } Q_{jg} \leq C_{igL}
\end{cases}, \quad (3.23)$$

3.1.2.4 Building the calculation of sellers’ satisfaction degrees

Let $B_j = \{B_1, B_2, \ldots, B_i\}$ match $S_j$ and $B_{jq}$ denote a set of constraint values from buyers $\{C_{1q}, C_{2q}, \ldots, C_{iq}\}$ for the attribute $A_q$ ($q \in (h + k)$). $\delta_{ijh}$ is $S_j$'s satisfaction degree as per $B_i$'s requirements for attribute $A_h$ with hard constraints. $\delta_{ijh}$’s values
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

are only from one set with two members \{-1,1\}. \(\delta_{ijk}\) is \(S_j\)'s satisfaction degree as per \(B_i\)'s requirements for attribute \(A_k\) with soft constraints. \(\delta_{ijk}\)'s values are changed to \{-1,(0,1]\}. In particular, \(\delta_{ijk}\) includes two intervals, one is one point and another is (0,1]. A seller’s satisfaction degree is computed to attributes with hard constraints, namely \(\delta_{ijg}'\), and attributes with soft constraints, namely \(\delta_{ijg}\), as follows:

(i) For attribute type with hard constraints

\[
\delta_{ijg}' = \begin{cases} 
-1 & \text{if } C_{ig}' \neq Q_{jg}' \\
1 & \text{if } C_{ig}' = Q_{jg}' 
\end{cases} \tag{3.24}
\]

\(\delta_{ijg}' = -1\) means that \(B_i\) does not match with \(S_j\) for the attribute \(A_{g}'\) while \(\delta_{ijg}' = 1\) means that \(B_i\) matches with \(S_j\) for the attribute \(A_{g}'\).

(ii) For attribute type with benefit soft constraints: if \(Q_{jg} > C_{ig}\) then \(\beta_{ijg} = -1\). It means that \(B_i\) does not satisfy \(S_j\). If \(Q_{jg} \leq C_{ig}\) then \(\delta_{ijg}\) is computed as follows:

\[
\delta_{ijg} = \left(\frac{C_{ig} - C_{\min-g} + \varphi}{C_{\max-g} - C_{\min-g} + \varphi}\right)^z, \tag{3.25}
\]

where \(z = \frac{Q_{jg}}{C_{\min-g}}\), \(C_{\min-g}\) and \(C_{\max-g}\) are the minimal and maximal values of \(C_{ig}\) in \(B_{jg}\), respectively, where \(B_{jg}\) is a set of values for the attribute \(A_{g}\) in \(B_j\). A value \(z \in (0,1]\) helps a broker to carry out comparing a seller’s satisfaction degree when \(z\) is used to compute \(\delta_{ijg}\). \(\varphi = \frac{C_{\min-g}}{2}\) and \(\varphi\) helps a broker to solve some special cases such as only one buyer in the e-markets or \(C_{\max-g} = C_{\min-g}\). In this case, \(\delta_{ijg}\) increases when \(C_{ig}\) increases or \(Q_{jg}\) decreases.

\(\delta_{ijg}\) means that \(S_j\) matches with \(B_i\) for the attribute \(A_{g}\) with a seller’s satisfaction degree \(\left(\frac{C_{ig} - C_{\min-g} + \varphi}{C_{\max-g} - C_{\min-g} + \varphi}\right)^z\). \(\delta_{ijg}\) is in-between 0 and 1. If \(\delta_{ijg}\) is near 1, it means that \(S_j\) is highly satisfied by \(B_i\) for the attribute \(A_{g}\).

(iii) For attribute type with cost soft constraints: if \(Q_{jg} < C_{ig}\) then \(\beta_{ijg} = \)}
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

It means that \( B_i \) does not satisfy \( S_j \). If \( C_{ig} \leq Q_{jg} \) then \( \delta_{ijg} \) is computed as follows:

\[
\delta_{ijg} = \left( \frac{C_{\text{max}-g} - C_{ig} + \varphi}{C_{\text{max}-g} - C_{\text{min}-g} + \varphi} \right)^\frac{1}{z} \tag{3.26}
\]

\( \delta_{ijg} \) means that \( S_j \) matches with \( B_i \) for the attribute \( A_g \) with a seller’s satisfaction degree \( \left( \frac{C_{\text{max}-g} - C_{ig} + \varphi}{C_{\text{max}-g} - C_{\text{min}-g} + \varphi} \right)^\frac{1}{z} \). \( \delta_{ijg} \) is in-between 0 and 1. If \( \delta_{ijg} \) is near 1, it means that \( S_j \) is highly satisfied by \( B_i \) for the attribute \( A_g \). In this case, \( \delta_{ijg} \) increases when \( C_{ig} \) decreases or \( Q_{jg} \) increases.

3.1.2.5 Behavior prediction for trading agents

The proposed method based on Bayes’ rules predicts the probabilities of buyers’ behaviors \( \Pr^B \) and the probabilities of sellers’ behaviors \( \Pr^S \). The principle of the proposed method is presented in Figure 3.3

**Step 1:** Trading agent’s requirements are sent to a broker agent. The requirements include one or many attributes, which trading agents are required to satisfy. Based on the historical data of trading agents, the broker agent retrieves the data of each attribute to predict trading agents’ behaviors.

**Step 2:** Once the broker agent retrieves the data of each attribute, the broker agent checks whether the data of each attribute is quantitative or qualitative. If it is qualitative, the principle of group generation is that each category in the attribute forms each group and then the broker agent groups the observations of the attribute according to each category. Otherwise, the broker agent needs to generate groups [20] in the following steps:

**Step 2.1** The broker agent calculates the highest and lowest value of the quantitative attribute.

**Step 2.2** The broker agent calculates the range. The range is defined as the
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

Figure 3.3: The principle of behavior prediction for trading agents

difference between the largest and smallest data values as follows:

\[
\text{range} = x_{\text{max}}^{\text{Quantitative}} - x_{\text{min}}^{\text{Quantitative}},
\]

(3.27)

where \(x_{\text{max}}^{\text{Quantitative}}\) is the maximal value of the quantitative attribute and \(x_{\text{min}}^{\text{Quantitative}}\) is the minimal value of the quantitative attribute.

**Step 2.3** The broker agent identifies the number of groups. Based on Sturges’s Rule [22], the number of groups \(n'\) is computed as follows.

\[
n' = 1 + 3.322\log_2 \theta,
\]

(3.28)
where $\theta$ is the total number of observations of the quantitative attribute.

**Step 2.4** The broker agent calculates the group width $k'$ as follows.

$$k' = \frac{\text{range}}{n} \quad (3.29)$$

**Step 2.5** Based on the group width $k'$, a particular number of groups with equal width is generated. The principle of generating group is that the $j^{th}$ group $G_j$ ($j' \leq n'$) is $(x_{\text{min}}^{Q} + (j' - 1) \times k', x_{\text{min}}^{Q} + j' \times k').$

**Step 2.6** The broker agent organizes observations of the quantitative attribute into groups.

**Step 3:** Once the observations of each attribute in trading agents’ requirements are organized into groups, the broker agent employs the theory of Bayes’ rules [72] to predict the probabilities of trading agents’ behaviors as follows:

$$\text{Bayes’ rule }: P(h'|E) = \frac{P(E|h')P(h')}{P(E)}, \quad (3.30)$$

where $h'$ is a hypothesis in hypothesis space $H$ that the broker agent is interested in testing and $E$ represents evidence that seems to reject or not reject the hypothesis.

Predicting the probabilities of trading agents’ behaviors using Bayes’ rules involves the following steps:
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

Step 3.1 The broker agent builds a hypothesis for prediction. Assume there are \( t' \) input attributes from the requirements of the trading agent \( TA_n \) called \( X = (X_1, \ldots, X_{t'}) \). The hypothesis space \( H \) includes two hypotheses, the first hypothesis \( h' \) is that \( TA_n \) accepts its requirements, which \( TA_n \) sent to the broker agent, and the second hypothesis \( \neg h' \) is that \( TA_n \) does not accept its requirements, which \( TA_n \) sent to the broker agent, and the evidence \( E \) is the specific value of each attribute in \( TA_n \)'s requirements \( (X_1 = x_1, \ldots, X_{t'} = x_{t'}) \).

Step 3.2 The broker agent calculates conditional probabilities based on these hypotheses in Step 3.1. In particular, the broker agent calculates, in addition to the prior probability \( P(h') \) and \( P(\neg h') \), two further conditional probabilities indicating how probable \( TA_n \)'s requirements with \( t' \) input attributes are depending on whether the broker agent’s hypothesis is or is not true. These conditional probabilities are presented as \( P(X_1 = x_1, \ldots, X_{t'} = x_{t'} | h') \) and \( P(X_1 = x_1, \ldots, X_{t'} = x_{t'} | \neg h') \).

Term \( P(X_1 = x_1, \ldots, X_{t'} = x_{t'} | h') \) means that when the given hypothesis \( h' \) is hold, the probability \( TA_n \)'s requirements with \( X_1 = x_1, \ldots, X_{t'} = x_{t'} \) are sent to the broker agent. Let \( \lambda \) represent the number of transactions under the condition of a given hypothesis \( h' \) for a group including \( X_1 = x_1, \ldots, X_{t'} = x_{t'} \), \( \phi \) represents the number of transactions under the condition of a given hypothesis \( \neg h' \) for a group including \( X_1 = x_1, \ldots, X_{t'} = x_{t'} \) and \( l \) represents the total number of transactions in the historical trading data of the trading agent.

The conditional probability \( P(X_1 = x_1, \ldots, X_{t'} = x_{t'} | h') \) is computed as:

\[
P(X_1 = x_1, \ldots, X_{t'} = x_{t'} | h') = \frac{\lambda}{l} \tag{3.31}
\]

The conditional probability \( P(X_1 = x_1, \ldots, X_{t'} = x_{t'} | \neg h') \) is computed as:

\[
P(X_1 = x_1, \ldots, X_{t'} = x_{t'} | \neg h') = \frac{\phi}{l} \tag{3.32}
\]
3.1. Broker-Based Trade Allocation through Prediction of Buyers' and Sellers' Behaviors

Step 3.3 The broker agent is to predict the probability of trading agent’s behavior $P_{rTA_n}$. In particular, the Bayes’ rules should be used to calculate the posterior probability that $h'$ is true supposing that $TA_n$ accept $TA_n$’s requirements with $t'$ input attributes are sent to the broker agent. The calculation of the probability of trading agent’s behavior is defined as follows:

$$P_{rTA_n} = P(h'|X_1 = x_1, \ldots X_{t'} = x_{t'})$$

$$= \frac{P(X_1 = x_1, \ldots X_{t'} = x_{t'}|h')P(h')}{P(X_1 = x_1, \ldots X_{t'} = x_{t'}|h')P(h') + P(X_1 = x_1, \ldots X_{t'} = x_{t'}|\neg h')P(\neg h')},$$

(3.33)

where $P(h'|X_1 = x_1, \ldots X_{t'} = x_{t'})$ represents the posterior probability of hypothesis $h'$ given the condition that $TA_n$’s requirements with $X_1 = x_1, \ldots X_{t'} = x_{t'}$ are sent to the broker agent. The process of prediction of trading agents’ behaviors is shown by Algorithm 1.

In Algorithm 1, the inputs are trading agents $TA$’s requirements and the historical trading data of trading agents $H^{TA}$ (Line 1). The outputs are the probabilities of trading agents’ behaviors $P_{rTA}$ (Line 2). A broker agent receives the trading agent’s requirements and then the broker agent retrieves the data of all attributes from the historical trading data (Lines 5-6). Then, the broker agent checks whether the data of each attribute is quantitative or qualitative. If the attribute data is quantitative, the broker agent identifies its highest and lowest value, calculates the range using Equation (3.27), calculates the number of groups $n'$ using Equation (3.28) and calculates the group width $k'$ using Equation (3.29) (Lines 9-10). Then, the broker agent groups the observations of the attribute (Line 11). Otherwise, the broker agent organizes the attribute data into groups (Line 13). After the data of all attributes are organized into groups, the broker agent applies Equation (3.31) to calculate $P(X_1 = x_1, \ldots X_{t'} = x_{t'}|h')$ for hypothesis $h'$ and Equation (3.32) to calculate $P(X_1 = x_1, \ldots X_{t'} = x_{t'}|\neg h')$ for hypothesis $\neg h'$ (Line 16). Finally, the broker agent applies the Bayes’ rules to calculate the posterior probability $P_{rTA_n} = P(h'|X_1 = x_1, \ldots X_{t'} = x_{t'})$ for $TA_i$ using
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

**Algorithm 1**: The process of prediction of trading agents’ behaviors

<table>
<thead>
<tr>
<th>Line</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td><strong>Input</strong>: TA = {TA_i, i ∈ (1, μ)}, Bi = TA, H_{TA};</td>
</tr>
<tr>
<td>2</td>
<td><strong>Output</strong>: Pr_{TA} = {Pr_{TA_i}, i ∈ (1, μ)};</td>
</tr>
<tr>
<td>3</td>
<td><strong>begin</strong></td>
</tr>
<tr>
<td>4</td>
<td><strong>foreach</strong> TA_i in TA <strong>do</strong></td>
</tr>
<tr>
<td>5</td>
<td>BR ← send(TA_i’s requirements with t’ attributes</td>
</tr>
<tr>
<td>6</td>
<td>(X_1 = x_1, ... X_{t'} = x_{t'}));</td>
</tr>
<tr>
<td>7</td>
<td>Bi ← retrieve-data(TA_i’s requirements);</td>
</tr>
<tr>
<td>8</td>
<td><strong>foreach</strong> each attribute in TA_i’s requirements <strong>do</strong></td>
</tr>
<tr>
<td>9</td>
<td>if <strong>check</strong>(each attribute) <strong>then</strong></td>
</tr>
<tr>
<td>10</td>
<td>BR identifies the highest and lowest value of the quantitative attribute and calculates the range by Equation (3.27);</td>
</tr>
<tr>
<td>11</td>
<td>BR calculates the number of groups n’ by Equation (3.28) and the group width k’ by Equation (3.29);</td>
</tr>
<tr>
<td>12</td>
<td>BR ← organize-group(each attribute, n’, k’);</td>
</tr>
<tr>
<td>13</td>
<td><strong>else</strong></td>
</tr>
<tr>
<td>14</td>
<td>BR ← organize(each attribute);</td>
</tr>
<tr>
<td>15</td>
<td><strong>end</strong></td>
</tr>
<tr>
<td>16</td>
<td>BR calculates the conditional probability with the given hypothesis h’ P(X_1 = x_1, ... X_{t'} = x_{t'}</td>
</tr>
<tr>
<td>17</td>
<td>Then BR calculates the posterior probability P(h’</td>
</tr>
<tr>
<td>18</td>
<td>Pr_{TA_i} ← P(h’</td>
</tr>
<tr>
<td>19</td>
<td><strong>end</strong></td>
</tr>
<tr>
<td>20</td>
<td><strong>end</strong></td>
</tr>
</tbody>
</table>

Equation (3.33) (Line 17). Thus, Pr_{TA} = \{Pr_{TA_i}, i ∈ (1, μ)\} is predicted by Algorithm 1.

The purpose of Algorithm 1 is to predict the probabilities of buyers’ behaviors Pr^B and the probabilities of sellers’ behaviors Pr^S. Thus, the inputs are TA ∈ \{B, S\} and H^{TA} ∈ \{H^B, H^S\}. The outputs are Pr_{TA} ∈ \{Pr^B, Pr^S\}.
3.1.3 Experiment and analysis

This subsection presents experimental results and analyses the proposed approach. The experiment is to test the maximization of a broker’s expected profit through trade allocation under different situations. Subsubsection 3.1.3.1 describes the experimental setting that has been applied in the experiment. Subsubsection 3.1.3.2 shows the experimental results and performance analysis in three different scenarios.

3.1.3.1 Experimental setting

Three scenarios are conducted in the experiment to evaluate the performance of the proposed approach, the artificially generated dataset of car markets include 100 buyers and 100 sellers. Each buyer and seller contains five attributes: make, price, warranty, model and delivery time. Weight values of attributes with soft constraints including price, warranty and delivery time are randomly assigned. 10 buyers and 10 sellers are randomly selected from 100 buyers and 100 sellers in the artificially generated dataset. In particular, buyers’ requirements and sellers’ offers are presented in Table 3.1 and Table 3.2, respectively. Based on buyers’ requirements in Table 3.1, sellers’ offers in Table 3.2 and the historical trading data of buyers and sellers from the artificially generated dataset, a broker uses Algorithm 1 (refer to Subsubsection 3.1.2.5) to predict buyers’ and sellers’ behaviors. The detail contents of the predicted probability of buyers’ and sellers’ behaviors are presented in the last column in Tables 3.1 and 3.2, respectively.
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

Table 3.1: Trading information of product in buyers’ requirements (W-Weight; BB-Buyers’ behaviors)

<table>
<thead>
<tr>
<th>Buyer</th>
<th>Make</th>
<th>Model</th>
<th>Warranty (months)</th>
<th>Delivery time (days)</th>
<th>Price ($1,000)</th>
<th>BB (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B₁</td>
<td>Toyota Camry</td>
<td>12</td>
<td>3</td>
<td>50</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td>B₂</td>
<td>Toyota Camry</td>
<td>14</td>
<td>3</td>
<td>60</td>
<td>78</td>
<td></td>
</tr>
<tr>
<td>B₃</td>
<td>Toyota Camry</td>
<td>09</td>
<td>4</td>
<td>90</td>
<td>83</td>
<td></td>
</tr>
<tr>
<td>B₄</td>
<td>Toyota Camry</td>
<td>10</td>
<td>3</td>
<td>90</td>
<td>82.5</td>
<td></td>
</tr>
<tr>
<td>B₅</td>
<td>Ford Laser</td>
<td>12</td>
<td>4</td>
<td>75</td>
<td>90</td>
<td></td>
</tr>
<tr>
<td>B₆</td>
<td>Toyota Camry</td>
<td>16</td>
<td>5</td>
<td>60</td>
<td>92.5</td>
<td></td>
</tr>
<tr>
<td>B₇</td>
<td>Toyota Camry</td>
<td>15</td>
<td>3</td>
<td>50</td>
<td>91</td>
<td></td>
</tr>
<tr>
<td>B₈</td>
<td>Toyota Camry</td>
<td>10</td>
<td>5</td>
<td>50</td>
<td>95</td>
<td></td>
</tr>
<tr>
<td>B₉</td>
<td>Toyota Camry</td>
<td>10</td>
<td>3</td>
<td>75</td>
<td>98</td>
<td></td>
</tr>
<tr>
<td>B₁₀</td>
<td>Toyota Camry</td>
<td>16</td>
<td>4</td>
<td>90</td>
<td>97</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2: Trading information of product in sellers’ offers (W-Weight; BS-Sellers’ behaviors)

<table>
<thead>
<tr>
<th>Seller</th>
<th>Make</th>
<th>Model</th>
<th>Warranty (months)</th>
<th>Delivery time (days)</th>
<th>Price ($1,000)</th>
<th>BS (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S₁</td>
<td>Toyota Camry</td>
<td>19</td>
<td>1</td>
<td>40</td>
<td>95</td>
<td></td>
</tr>
<tr>
<td>S₂</td>
<td>Toyota Camry</td>
<td>20</td>
<td>2</td>
<td>45</td>
<td>98</td>
<td></td>
</tr>
<tr>
<td>S₃</td>
<td>Toyota Camry</td>
<td>24</td>
<td>3</td>
<td>42</td>
<td>97</td>
<td></td>
</tr>
<tr>
<td>S₄</td>
<td>Toyota Camry</td>
<td>25</td>
<td>3</td>
<td>40</td>
<td>96</td>
<td></td>
</tr>
<tr>
<td>S₅</td>
<td>Toyota Camry</td>
<td>26</td>
<td>3</td>
<td>35</td>
<td>92.5</td>
<td></td>
</tr>
<tr>
<td>S₆</td>
<td>Toyota Camry</td>
<td>28</td>
<td>1</td>
<td>39</td>
<td>95</td>
<td></td>
</tr>
<tr>
<td>S₇</td>
<td>Toyota Camry</td>
<td>30</td>
<td>3</td>
<td>37</td>
<td>97</td>
<td></td>
</tr>
<tr>
<td>S₈</td>
<td>Ford Laser</td>
<td>30</td>
<td>2</td>
<td>42</td>
<td>94.5</td>
<td></td>
</tr>
<tr>
<td>S₉</td>
<td>Toyota Camry</td>
<td>36</td>
<td>3</td>
<td>46</td>
<td>96</td>
<td></td>
</tr>
<tr>
<td>S₁₀</td>
<td>Toyota Camry</td>
<td>23</td>
<td>2</td>
<td>43</td>
<td>98</td>
<td></td>
</tr>
</tbody>
</table>
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

In the experiments, a broker-based trade allocation approach in a multi-attribute trading is tested in three different scenarios shown in Table 3.3.

Table 3.3: Experimental scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Test purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>To maximize a broker’s expected profit under the consideration of the satisfaction degree of buyers ($\alpha_1 = 1$ and $\alpha_2 = 0$)</td>
</tr>
<tr>
<td>2</td>
<td>To maximize a broker’s expected profit under the consideration of the satisfaction degree of sellers ($\alpha_1 = 0$ and $\alpha_2 = 1$)</td>
</tr>
<tr>
<td>3</td>
<td>To maximize a broker’s expected profit under considering that the satisfaction degree of sellers is more than that of buyers ($\alpha_1 = 0.4$ and $\alpha_2 = 0.6$)</td>
</tr>
<tr>
<td>4</td>
<td>To maximize a broker’s expected profit under considering that the satisfaction degree of buyers is more than that of sellers ($\alpha_1 = 0.6$ and $\alpha_2 = 0.4$)</td>
</tr>
<tr>
<td>5</td>
<td>To maximize a broker’s expected profit under considering that the satisfaction degree of sellers equals to that of buyers ($\alpha_1 = 0.5$ and $\alpha_2 = 0.5$)</td>
</tr>
<tr>
<td>6</td>
<td>To maximize a broker’s expected profit without the consideration of the satisfaction degree of buyers and sellers</td>
</tr>
</tbody>
</table>

3.1.3.2 Experimental results and analysis

The proposed trade allocation approach is to maximize a broker’s expected profit in regard to the satisfaction degree of all buyers and all sellers or in regardless of the satisfaction degree of all buyers and sellers as a goal through trade allocation. The experimental results for each scenario are presented in Table 3.4.

In Scenario 1, a broker’s purpose is to maximize a broker’s expected profit in regard to the satisfaction degree of all buyers as a goal. Thus, $\alpha_1$ equals to 1 and $\alpha_2$ equals to 0. It can be seen that from Table 3.4, ten determined allocation pairs are achieved in Scenario 1. In particular, a broker’s expected profit in Scenario 1 is $241,000 and the satisfaction degree of all buyers is 0.837. Although a broker does not consider the satisfaction degree of all sellers, the satisfaction degree of all sellers is also determined based on ten determined allocation pairs and the calculation of sellers’ satisfaction degree for each pair (refer to Subsubsection 3.1.2.4). Thus, the satisfaction degree of
3.1. Broker-Based Trade Allocation through Prediction of Buyers’ and Sellers’ Behaviors

Table 3.4: Optimal allocation pairs with different scenarios (BREP: Broker’s expected profit; BSD: Buyer’s satisfaction degree and SSD: Seller’s satisfaction degree)

<table>
<thead>
<tr>
<th>No.</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>Scenario 4</th>
<th>Scenario 5</th>
<th>Scenario 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>B₁ ↔ S₂</td>
<td>B₁ ↔ S₂</td>
<td>B₁ ↔ S₂</td>
<td>B₁ ↔ S₂</td>
<td>B₁ ↔ S₂</td>
<td>B₁ ↔ S₉</td>
</tr>
<tr>
<td>2</td>
<td>B₂ ↔ S₉</td>
<td>B₂ ↔ S₉</td>
<td>B₂ ↔ S₉</td>
<td>B₂ ↔ S₉</td>
<td>B₂ ↔ S₉</td>
<td>B₂ ↔ S₃</td>
</tr>
<tr>
<td>3</td>
<td>B₃ ↔ S₁₀</td>
<td>B₃ ↔ S₅</td>
<td>B₃ ↔ S₆</td>
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<td>B₇ ↔ S₆</td>
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<td>B₉ ↔ S₄</td>
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<tr>
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<td>B₁₀ ↔ S₃</td>
<td>B₁₀ ↔ S₃</td>
<td>B₁₀ ↔ S₃</td>
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<tr>
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<td>$241,000$</td>
<td>0.837</td>
<td>0.772</td>
<td>$240,400$</td>
<td>0.83</td>
<td>0.774</td>
<td>$242,300$</td>
<td>0.832</td>
<td>0.774</td>
<td>$240,400$</td>
<td>0.83</td>
<td>0.768</td>
</tr>
</tbody>
</table>

all sellers in Scenario 1 is 0.772.

Similarly, $\alpha_1$ equals to 0 and $\alpha_2$ equals to 1 in Scenario 2 because a broker’s purpose is to maximize a broker’s expected profit in regard to the satisfaction degree of all sellers as the goal. Ten determined allocation pairs are presented in Table 3.4. A broker’s expected profit in Scenario 2 is $239,600 and the satisfaction degree of all sellers is 0.786. Furthermore, the satisfaction degree of all buyers in Scenario 2 is 0.828. The satisfaction degree of buyers (0.828) in Scenario 2 is less than the satisfaction degree of all buyers (0.837) in Scenario 1 and the satisfaction degree of all sellers (0.786) in Scenario 2 is more than the satisfaction degree of sellers (0.772) in Scenario 1 because a broker’s purpose in Scenario 2 considers the satisfaction degree of all sellers as the goal while a broker’s purpose in Scenario 1 considers the satisfaction degree of all sellers as the goal.

In Scenario 3, a broker’s purpose is to maximize a broker’s expected profit in regard to the satisfaction degree of all buyers and all sellers as the goal. A broker can select different values of $\alpha_1$ and $\alpha_2$ so that a broker’s purpose is satisfied. Assume that a
broker would like to increase the satisfaction degree of all sellers and decrease the satisfaction degree of all buyers. Thus, a broker has to choose values of $\alpha_1$ and $\alpha_2$ to test the proposed approach. Assume that $\alpha_1$ and $\alpha_2$ are assigned to 0.4 and 0.6, respectively. We can see that ten determined allocation pairs are achieved in Table 3.4. In particular, a broker's expected profit in Scenario 3 is $240,400 and the satisfaction degree of all buyers is 0.83 and the satisfaction degree of all sellers is 0.774. Results in Scenario 3 is a feasible solution for a broker because the satisfaction degree of all sellers in Scenario 3 is more than the satisfaction degree of all sellers in Scenario 1.

In Scenario 4, assume that a broker would like to increase the satisfaction degree of all buyers and decrease the satisfaction degree of all sellers. Thus, a broker has to choose values of $\alpha_1 = 0.6$ and $\alpha_2 = 0.4$ to test the proposed approach. We can see that ten determined allocation pairs are achieved in Table 3.4. In particular, a broker’s expected profit in Scenario 4 is $240,000 and the satisfaction degree of all buyers is 0.832 and the satisfaction degree of all sellers is 0.773. Results in Scenario 4 is a feasible solution for a broker because the satisfaction degree of all sellers in Scenario 4 is less than that in Scenario 3 and the satisfaction degree of all buyers in Scenario 4 is more than that in Scenario 3.

In Scenario 5, a broker chooses values of $\alpha_1 = 0.5$ and $\alpha_2 = 0.5$ to test the proposed approach. We can see that allocation results in Scenario 5 from Table 3.4 is as same as that in Scenario 3. There is not big difference between allocation results in Scenario 3 and 5 because values of $\alpha_1$ and $\alpha_2$ in Scenario 3 are as approximately as values of $\alpha_1$ and $\alpha_2$ in Scenario 5, and data set is relatively small to test in the proposed approach.

Finally, a broker’s purpose in Scenario 6 is to maximize a broker’s expected profit in regardless of the satisfaction degree of buyers and sellers. A broker’s expected profit in Scenario 6 is $242,300 and more than that in Scenarios 1, 2, 3, 4 and 5 because a broker would like to maximize a broker’s expected profit in regardless of other factors.
Furthermore, the satisfaction degree of buyers and sellers in Scenario 6 is less than that in Scenarios 1, 2, 3, 4 and 5 because a broker does not consider the satisfaction degree of buyers and sellers.

In summary, depending on market situations, a broker will focus on a broker’s specific purposes to choose optimal allocation pairs according to a broker’s goals under consideration of maximizing a broker’s expected profit in regardless to the satisfaction degree of all buyers and all sellers, or maximizing a broker’s expected profit in regard to the satisfaction degree of all buyers or the satisfaction degree of all sellers or both through changing values of $\alpha_1$ and $\alpha_2$ in Equation (3.10) rationally.

### 3.2 Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

#### 3.2.1 Problem description

In this proposed approach, a broker’s mission is to allocate $n$ buyers to $m$ sellers under a multiple attribute trading to satisfy buyers’ requirements and maximize the satisfaction degree of all buyer under the consideration of modelling uncertain information of attributes in buyers’ requirements. Assume that a buyer can only buy a unit of commodity from a seller maximally and similarly, a seller can only sell a unit of commodity to a buyer maximally.

From the buyers’ part, buyer agent $B_i (i \in n)$ has a demand to buy a unit of the multi-attribute commodity. Attributes with hard constraints in $B_i$’s requirements are presented by $REQ_H_i$ and $REQH_i$ is defined by Equation (3.1). Attributes with soft constraints are presented by $REQ_S_i$ and $REQS_i$ is defined by Equation (3.2). Due to the buyer agents’ vague knowledge regarding some attributes of commodities, it is not easy for buyer agents to determine their product feature preferences with exact
numerical values. So, attribute values in buyer agents' requirements need to be solved in this proposed approach based on expressing their product feature preferences with fuzzy or linguistic terms as inputs. In particular, a broker agent will interact with a buyer agent to build a membership function to measure a buyer agent's satisfaction degrees for attribute type with vague information.

Similarly, from the sellers' part, seller agent $S_j (j \in m)$ has a demand to sell a unit of the multi-attribute commodity. Attributes with hard constraints in $S_j$'s offers are presented by $OFFH_j$ and $OFFH_j$ is defined by Equation (3.3). Attributes with soft constraints are presented by $OFFS_j$ and $OFFS_j$ is defined by Equation (3.4). Due to seller agents' own products, it is easy for seller agents to determine the attribute level with reasonable values. Thus, the level of each attribute in the seller agents' offers is provided in detail to a broker agent.

Based on the above analysis, the key problem is to help a broker agent to (i) model buyer agents' requirements related to various attributes, i.e., attributes with hard, attributes with soft constraints and attributes with uncertain information; (ii) carry out trade allocation processes to maximize the satisfaction degree of all buyer agents; and (iii) make a decision on trade allocation based on buyer agents' feedback from determined allocation results. The proposed trade allocation approach in this section tries to solve this problem.

### 3.2.2 The principle of the proposed approach

#### 3.2.2.1 The conceptual framework of the proposed approach

In this proposed approach, a broker's mission is to maximize the satisfaction degree of all buyers as social welfare through trade allocation under a multi-attribute trading. The principle of the whole trade allocation process through a broker is presented in Figure 3.4.
3.2. Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

![Diagram of broker-based trade allocation process]

Figure 3.4: The conceptual framework of the broker-based trade allocation approach

**Step 1:** A broker receives buyers’ requirements in term of multi attributes. In addition to receiving fixed values of attributes in buyers’ requirements, a broker has to model uncertain information of attributes in buyers’ requirements. To solve this issue, a broker carries out the simplified interactive procedure with a buyer through asking questions so that a broker identifies a buyer’s reference points to build a buyer’s membership function.

**Step 2:** Sellers have their product’s own requirements. Thus, the sellers provide attribute’s fixed values to a broker and they would like to find out which buyers satisfy the sellers’ own requirements through a broker. Of course, the sellers’ offers contain
the same kinds of attributes in buyers’ requirements.

**Step 3:** After modelling uncertain information of attributes in buyers’ requirements and receiving sellers’ offers, a broker carries out allocation processes to seek the allocation results. Then a broker sends the allocation results to buyers to determine whether buyers accept the allocation results. If there exists any buyers which do not accept the results, a broker will update buyers’ requirements and the broker’s trade allocation processes are carried out again. The broker’s trade allocation processes are terminated when (i) all buyers accept allocation results or (ii) the current allocation results are as same as the previous allocation results.

### 3.2.2.2 Modelling uncertain information of attributes in buyers’ requirements

Due to the buyers’ vague knowledge regarding some attributes of products, it is difficult for buyers to express their preferences with exact numerical values. Thus, a broker employs membership functions to express buyers’ preferences for uncertain information of attributes in buyers’ requirements. The membership functions are not only used as the equivalents of utility functions over attributes of products, can but also help a broker to compare buyers’ satisfaction degrees with offers of different sellers. The fuzzy membership functions are defined as follows:

**Definition 3.2.1.** Let $X$ be a set of objectives. A fuzzy set $A$ in $X$ is defined by its membership function as follows.

$$
\mu_A : X \to [0, 1],
$$  
(3.34)

and $\forall x \in X$ is called the membership degree of $x$ in fuzzy set $A$.

There are some popular fuzzy numbers to express buyers’ satisfaction degrees through fuzzy membership functions in market environments shown in Figure 3.5. It
3.2. Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

is clear that buyers’ satisfaction degrees for uncertain information of attributes belong to \((0,1]\).

![Figure 3.5: Some popular membership functions to present uncertain information of attributes](image)

In the proposed approach, a broker determines a buyer’s membership function for each attribute with uncertain information by using the direct rating (point estimation) method [111]. In particular, a broker communicates with a buyer to determine the buyer’s preference points through questions. A broker’s questions require the buyer to select one point on the reference axis by using numerical scale that best describes this element.

For example, a broker starts the simplified interactive procedure with a buyer to build a buyer’s satisfaction degree as per capacities of a hard disk. In particular, a broker requires a buyer to answer the three following questions so that a broker identifies a buyer’s three reference points within the feasible range of a hard disk’s capacities.
3.2. Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

- Question 1: ‘What are the worst hard disk’s capacities?’ → ‘everything is the worst if a hard disk’s capacities are less than or equal to 10G, or more than or equal to 50G’.

- Question 2: ‘What are the perfect capacities of a hard disk that would give you full satisfaction level?’ → ‘the perfect capacities of a hard disk are between 20G and 40G’.

- Question 3: ‘What is a medium satisfaction level for you with regard to capacities of a hard disk?’ → ‘capacities of a hard disk are between 10G and 20G, or between 40G and 50G’.

Based on a buyer’s responses above, a buyer’s satisfaction function as per a hard disk’s capacity is presented in Equation (3.35) and Figure 3.6.

$$\mu(x) = \begin{cases} 
0 & \text{for } x \leq 10 \text{ or } x \geq 50 \\
\frac{x-10}{10} & \text{for } 10 < x < 20 \\
1 & \text{for } 20 \leq x \leq 40 \\
\frac{50-x}{10} & \text{for } 40 < x < 50 
\end{cases}$$ (3.35)

3.2.2.3 Calculating buyers’ satisfaction degrees

Based on the notations of buyers’ requirements and sellers’ offers above, the procedure of the calculation of buyers’ satisfaction degrees for all attributes in buyers’ requirements is presented as follows:

(i) **For attribute type with uncertain information:** $B_i$’s satisfaction degree as per $S_j$’s offers for attribute $A_{ij}$, denoted by $\beta_{ijg}$ is calculated based on $B_i$’s specific membership function for $A_{ij}$. $\beta_{ijg}$ has a value between 0 and 1. Assume that attribute
3.2. Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

$A_g$ is a triangular fuzzy number shown Figures 3.7 and 3.8, and $\beta_{ijg}$ is calculated as follows.

- A value $Q_{jg}$ is between $C_{ik}^1$ and $C_{ik}^2$ in Figure 3.7

$$\beta_{ijg} = (Q_{jg} - C_{ik}^1)/(C_{ik}^2 - C_{ik}^1) \text{ for } C_{ik}^1 \leq Q_{jg} < C_{ik}^2$$ (3.36)

- A value $Q_{jg}$ is between $C_{ik}^2$ and $C_{ik}^3$ in Figure 3.8

$$\beta_{ijg} = (C_{ik}^3 - Q_{jg})/(C_{ik}^3 - C_{ik}^2) \text{ for } C_{ik}^2 \leq Q_{jg} \leq C_{ik}^3$$ (3.37)

Similarly, if attribute $A_g$ is a trapezoidal fuzzy number, $\beta_{ijg}$ is calculated as follows.

$$\beta_{ijg} = (Q_{jg} - C_{ik}^1)/(C_{ik}^2 - C_{ik}^1) \text{ for } C_{ik}^1 \leq Q_{jg} < C_{ik}^2$$ (3.38)

$$\beta_{ijg} = (C_{ik}^4 - Q_{jg})/(C_{ik}^4 - C_{ik}^3) \text{ for } C_{ik}^4 \leq Q_{jg} < C_{ik}^3$$ (3.39)

$$\beta_{ijg} = 1 \text{ for } C_{ik}^2 \leq Q_{jg} \leq C_{ik}^3$$ (3.40)
(ii) For other attribute types in buyers’ requirements: calculating buyers’ satisfaction degree for other attribute types is presented in Subsubsection 3.1.2.3. In particular, \( \beta_{ijg}' \) for an attribute with hard constraint \( A_{g}' \) is determined by Equation (3.19); \( \beta_{ijg} \) for an attribute with benefit soft constraint \( A_{g} \) is determined by Equation (3.20); \( \beta_{ijg} \) for an attribute with cost soft constraint \( A_{g} \) is determined by Equation (3.21); \( \beta_{ijg} \) for an attribute with benefit interval constraint \( A_{g} \) is determined by Equation (3.22); and \( \beta_{ijg} \) for an attribute with cost interval constraint \( A_{g} \) is determined by Equation (3.23).

In summary, a broker considers \( B_{i}' \)'s satisfaction degree based on \( S_{j} \)'s offers under a multi-attribute trading. The attributes with hard constraints are necessary conditions in the trading processes and must be satisfied. Thus, the weight of attributes with hard constraints does not need to be considered. If attributes with hard constraints are not satisfied, then \( B_{i} \) cannot match with \( S_{j} \). On the other hand, the weight of attributes with soft constraints needs to be considered because buyers are willing to negotiate on these attributes. In particular, \( B_{i}' \)'s satisfaction degree based on \( S_{j} \)'s offers, related to the attributes with soft constraints, is as follows:

\[
\sum_{g=1}^{k} W_{ig} \beta_{ijg},
\]

where \( W_{ig} \) is a weight value of attribute \( A_{g} \) in \( B_{i}' \)'s requirements and \( \sum_{g=1}^{k} W_{ig} = 1 \).

In this proposed approach, each \( B_{i} \) expresses the complete weight information for attributes in \( B_{i}' \)'s requirements.

### 3.2.2.4 Building a broker’s objective function

Broker-based trade allocation is to maximize the satisfaction degree of all buyers based on modelling attributes with uncertain information in buyers’ requirements through trade allocation to satisfy buyers’ requirements. Based on a broker’s mentioned mis-
sion, an objective function and a set of constraints are built as follows.

\[ f = \sum_{i=1}^{n} \sum_{j=1}^{m} (\sum_{g=1}^{k} W_{ig} \beta_{ijg} x_{ij}) \]  
(3.42)

\[ s.t. \sum_{i=1}^{n} x_{ij} \leq 1, j = 1, 2, \ldots, m \]  
(3.43)

\[ \sum_{j=1}^{m} x_{ij} \leq 1, i = 1, 2, \ldots, n \]  
(3.44)

\[ x_{ij} = 1, 0, (i = 1, 2, \ldots, n; j = 1, 2, \ldots, m) \]  
(3.45)

\[ \sum_{g=1}^{k} W_{ig} = 1, (i = 1, 2, \ldots, n; g = 1, 2, \ldots, k) \]  
(3.46)

\[ x_{ij} = 0 \text{ if } \beta_{ijg} = -1 (g = 1, 2, \ldots, k) \]

or \( \beta_{ijg'} = -1 (g' = 1, 2, \ldots, h) \)  
(3.47)

where the objective function in Equation (3.42) seeks to maximize the weight sum of the satisfaction degree of all buyers; constraints in Equation (3.43) are that each seller only sells one unit of a commodity to a buyer maximally; constraints in Equation (3.44) are that each buyer only buys one unit of a commodity from a seller maximally; constraints in Equation (3.45) are constraints of decision variable, if \( B_i \) matches with \( S_j \), then \( x_{ij} = 1 \) and otherwise, \( x_{ij} = 0 \). Constraints in Equation (3.46) indicate \( B_i \)'s attribute weight; and constraints in Equation (3.47) indicate a constraint satisfaction layer to work in a broker's trade allocation processes.
### 3.2. Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

#### 3.2.2.5 A broker’s strategy for trade allocation

After a broker’s allocation process between buyers’ requirements and sellers’ offers is carried through an objection function, allocation pairs between buyers and sellers are found. The allocation pairs help to a broker to maximize the satisfaction degree of all buyers as goals but they cannot help a broker to evaluate whether buyers will accept the determined allocation results. Thus, to solve the issue, a broker’s strategy for making decisions to gain the final allocation pairs between buyers’ requirements and sellers’ offers is presented in Algorithm 2 as follows.

**Algorithm 2:** A broker’s trade allocation based on buyers’ feedback

1. **Input:** a set of buyer $B_1 = \{B_1, B_2, \ldots, B_n\}$, a set of seller $S_1 = \{S_1, S_2, \ldots, S_m\}$, a set of buyers’ constraints $C(B_1)$ and a set of sellers’ constraints $C(S_1)$;
2. **Output:** Return the final allocation pairs between buyers and sellers, which are accepted by buyers;
3. **begin**
   4. $i \leftarrow 1$;
   5. $\{M_{BS}\} \leftarrow \text{match}(B_i, S_i, C(B_i), C(S_i))$;
   6. $\{B_{ac}^i, S_{ac}^i, M_{BS}^i\} \leftarrow \text{check}(M_{BS})$;
   7. $C(B_i) \leftarrow \text{update}(C(B_i))$;
   8. **while** ($\neg \text{stopCriterion()}$) **do**
   9. $i \leftarrow i + 1$;
   10. $B_i \leftarrow B_{i-1} \setminus \{B_{ac}^i\}$;
   11. $S_i \leftarrow S_{i-1} \setminus \{S_{ac}^i\}$;
   12. $C(B_i) \leftarrow C(B_{i-1} \setminus B_{ac}^i)$;
   13. $C(S_i) \leftarrow C(S_{i-1} \setminus S_{ac}^i)$;
   14. $\{M_{BS}\} \leftarrow \text{match}(B_i, S_i, C(B_i), C(S_i))$;
   15. $\{B_{ac}^i, S_{ac}^i, M_{BS}^i\} \leftarrow \text{check}(M_{BS})$;
   16. $M_{BS}^i \leftarrow \text{update}(M_{BS})$;
   17. $C(B_i) \leftarrow \text{update}(C(B_i))$;
18. **return** $M_{BS}^i$

Algorithm 2 shows a broker’s allocation process between buyers’ requirements and sellers’ offers to seek the final allocation pairs based on buyers’ feedback from the determined allocation results. The input of Algorithm 2 is trading information in buyers’ requirements and sellers’ offers (Line 1). The output of Algorithm 2 returns the final allocation pairs between buyers and sellers (Line 2). Based on buyers’ requirements...
3.2. Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

and sellers’ offers, a broker carries out the allocation of buyers’ requirements to sellers’ offers by using the objective function in Equation (3.42) and a set of constraints in Equation (3.43)-(3.47) to achieve allocation results (Lines 4-5). Then, a broker sends allocation results to buyers to determine whether buyers accept the allocation results by using ‘check’ function (Line 6). If buyers exist who do not accept the results, a broker will update the buyers’ requirements through ‘update’ function (Line 7). The function ‘stopCriterion’ (Line 8) will terminate a broker’s allocation process when (i) all buyers accept allocation results or (ii) the allocation results of previous loop are as same as that of current loop. If the function ‘stopCriterion’ returns ‘false’, a broker continues to carry out its allocation process. At the stage, before a broker carries out its allocation process, a broker has to remove all the buyers and sellers who accepted allocation results in the previous stage (Lines 9-13). After determining allocation results again using ‘match’ function (Line 14), a broker sends the allocation results to buyers to determine whether the buyers accept them. If they do then, a broker will update the allocation results (Line 16). If buyers exist who do not accept the allocation results, a broker will update buyer’s constraints to carry out a broker’s next allocation process (Line 17). If the function ‘stopCriterion’ returns ‘true’, a broker terminates its allocation process and return final allocation results (Line 18).

3.2.3 Experiments

This subsection presents experimental results and analyses the proposed approach’s performance. The three experiments focus mainly on the test of the maximization of the satisfaction degree of all buyers through trade allocation in market environments. Subsubsection 3.2.3.1 describes the experimental setting that has been applied in the experiments. Subsubsection 3.2.3.2 shows the experimental results and performance analysis in three different experiments.
3.2. Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

3.2.3.1 Experimental setting

In three experiments, the artificial data of 10 buyers and 30 sellers related to demands for cars in Australia are generated. Trading information of car in buyers’ requirements and sellers’ offers contains five attributes, i.e., *make* \((a_1)\), *model* \((a_2)\), *price* \((a_3)\), *warranty time* \((a_4)\), *delivery time* \((a_5)\). As per buyers’ view, *make* attribute \((a_1)\), *model* attribute \((a_2)\) are attributes with hard constraints because their constraints must be satisfied while two attributes with soft constraints are *warranty time* \((a_4)\), *delivery time* \((a_5)\) and an attribute with uncertain information is *price* \((a_3)\).

Assume that *price* \((a_3)\) is right semi-trapezoidal fuzzy number, which is generated through communications between a broker and a buyer. Buyers’ target satisfaction degree for *price* attribute is randomly generated to support their decision. In particular, each buyer accepts a broker’s allocation results based on a seller’s offered price. If a buyer’s satisfaction degree, determined by a buyer’s membership function as per a seller’s offered price, is more than a buyer’s target satisfaction degree for *price* attribute in buyers’ requirements, a buyer accepts a broker’s allocation results. Otherwise, a buyer sends a buyer’s requirements to a broker so that a broker can seek other sellers to satisfy a buyer’s requirements. Furthermore, trading information and weights of attributes in a buyer’s requirements and a seller’s offers for experiments were automatically generated based on trading information from website of car sales (www.carsales.com.au).

In the experiments, the proposed approach is evaluated under a various number of sellers in market environments so the three different experiments include a different number of sellers. More specifically, a broker’s allocation approach is tested in three different experiments presented in Table 3.5 to maximize the satisfaction degree of all buyers under a different number of sellers.
3.2. Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

Table 3.5: Different experiments

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Test purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>To maximize the satisfaction degree of all buyers with 10 buyers and 10 sellers</td>
</tr>
<tr>
<td>2</td>
<td>To maximize the satisfaction degree of all buyers with 10 buyers and 20 sellers</td>
</tr>
<tr>
<td>3</td>
<td>To maximize the satisfaction degree of all buyers with 10 buyers and 30 sellers</td>
</tr>
<tr>
<td>4</td>
<td>To maximize the satisfaction degree of all buyers with 10 buyers and 40 sellers</td>
</tr>
</tbody>
</table>

3.2.3.2 Experimental results and analysis

In Experiment 1, a broker uses the proposed trade allocation approach to maximize the satisfaction degree of all buyers through trade allocation under considering that the number of buyers (10 buyers) equals to the number of sellers (10 sellers) in the markets. In the general principle of markets, when the number of buyers equals to a number of sellers, it is difficult for a broker to find sellers to satisfy the requirements of all buyers. Furthermore, it is difficult for buyers to obtain their high satisfaction degrees because a broker has a fewer opportunities to choose sellers’ offers to satisfy buyers’ requirements. The results of buyers’ satisfaction degrees in Experiment 1 are presented in Figure 3.9 and the allocation results are presented in Table 3.6.

From Figure 3.9 and Table 3.6, we can see that there are eight satisfied buyers including $B_1$, $B_2$, $B_3$, $B_4$, $B_6$, $B_8$, $B_9$ and $B_{10}$ while two remaining buyers are not satisfied. The proposed approach through a broker helps eight buyers to accept the allocation results. However, each buyer’s satisfaction degree is not high. In particular, the buyer’s minimal satisfaction degree is 0.7 and the maximal satisfaction degree is 0.95. Furthermore, the normalized satisfaction degree of all buyers in Experiment 1 is not high (0.856) because the number of sellers equals to the number of buyers in the markets.
3.2. Broker-Based Trade Allocation through Modelling Uncertain Information of Attributes

Table 3.6: Optimal allocation pairs with the four different experiments

<table>
<thead>
<tr>
<th>Experiment 1</th>
<th>Experiment 2</th>
<th>Experiment 3</th>
<th>Experiment 4</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>$B_1 \leftrightarrow S_1$</td>
<td>$B_1 \leftrightarrow S_{19}$</td>
<td>$B_1 \leftrightarrow S_{25}$</td>
</tr>
<tr>
<td>2</td>
<td>$B_2 \leftrightarrow S_{10}$</td>
<td>$B_2 \leftrightarrow S_{11}$</td>
<td>$B_2 \leftrightarrow S_{28}$</td>
</tr>
<tr>
<td>3</td>
<td>$B_3 \leftrightarrow S_3$</td>
<td>$B_3 \leftrightarrow S_{14}$</td>
<td>$B_3 \leftrightarrow S_{23}$</td>
</tr>
<tr>
<td>4</td>
<td>$B_4 \leftrightarrow S_2$</td>
<td>$B_4 \leftrightarrow S_{12}$</td>
<td>$B_4 \leftrightarrow S_{27}$</td>
</tr>
<tr>
<td>5</td>
<td>$B_6 \leftrightarrow S_4$</td>
<td>$B_5 \leftrightarrow S_{16}$</td>
<td>$B_5 \leftrightarrow S_{15}$</td>
</tr>
<tr>
<td>6</td>
<td>$B_8 \leftrightarrow S_9$</td>
<td>$B_6 \leftrightarrow S_{17}$</td>
<td>$B_6 \leftrightarrow S_{26}$</td>
</tr>
<tr>
<td>7</td>
<td>$B_9 \leftrightarrow S_7$</td>
<td>$B_7 \leftrightarrow S_8$</td>
<td>$B_7 \leftrightarrow S_{22}$</td>
</tr>
<tr>
<td>8</td>
<td>$B_{10} \leftrightarrow S_3$</td>
<td>$B_8 \leftrightarrow S_{15}$</td>
<td>$B_8 \leftrightarrow S_{21}$</td>
</tr>
<tr>
<td>9</td>
<td>$B_9 \leftrightarrow S_{18}$</td>
<td>$B_{10} \leftrightarrow S_{18}$</td>
<td>$B_9 \leftrightarrow S_{24}$</td>
</tr>
<tr>
<td>10</td>
<td>$B_{10} \leftrightarrow S_{20}$</td>
<td>$B_{10} \leftrightarrow S_{18}$</td>
<td>$B_9 \leftrightarrow S_{25}$</td>
</tr>
</tbody>
</table>

$f = 0.856$  $f = 0.915$  $f = 0.976$  $f = 0.978$

Figure 3.9: Buyer’s satisfaction degree in Experiments 1, 2, 3 and 4

Similarly, in Experiment 2, a broker considers that the number of sellers (20) is double the number of buyers (10). From Figure 3.9 and Table 3.6, it can be seen that 10 buyers are also satisfied and the allocation results are also found for each buyer. More specifically, the buyer’s minimal satisfaction degree is 0.8 and the buyer’s maximal satisfaction degree is 0.99. Furthermore, the normalized satisfaction degree
of all buyers in Experiment 2 is relatively high (0.915) and is higher than the normalized satisfaction degree of all buyers (0.856) in Experiment 1 because a broker has many opportunities to select sellers’ offers which satisfy buyers’ requirements and increase buyers’ satisfaction degree.

The number of sellers (30) is triple the number of buyers (10) in Experiment 3. From Figure 3.9 and Table 3.6, it can be seen that in addition to buyers’ satisfied requirements, the normalized satisfaction degree of all buyers is very high (0.976) and it is higher than the normalized satisfaction degree of all buyers (0.856) in Experiment 1 and the normalized satisfaction degree of all buyers (0.915) in Experiment 2 because a broker in Experiment 3 has more opportunities to select sellers’ offers which satisfy buyers’ requirements than that in Experiments 1 and 2.

Finally, there are 40 sellers and 10 buyers in Experiment 4. From Figure 3.9 and Table 3.6, it can be seen that in addition to buyers’ satisfied requirements, the normalized satisfaction degree of all buyers is very high (0.978) and it is higher than that of all buyers in Experiment 1, 2, and 3 because a broker in Experiment 4 has more opportunities to select sellers’ offers which satisfy buyers’ requirements than that in Experiments 1, 2, and 3.

In summary, the proposed approach performed well under different situations in market environments. In general, if the number of sellers are more than the number of buyers in a market, a broker has many opportunities to choose sellers’ offers to satisfy buyers’ requirements and increase each buyer’s satisfaction degrees as well as the satisfaction degree of all buyers.

3.3 Summary

Two broker-based buyer modelling approaches for trade allocation in market environments were proposed with different goals in this chapter. The most distinguishing
3.3. Summary

The contribution of the first proposed approach (refer to Section 3.1) is that broker-based trade allocation processes are based on prediction of buyers' and sellers' behaviors, in order to achieve the Objective 2 of this thesis. The evaluation results proved that the first proposed approach achieved good performances in terms of satisfying buyers' requirements and maximizing a broker's expected profit through trade allocation. The most distinguishing contribution of the second proposed approach (refer to Section 3.2) is that broker-based trade allocation processes are based on modelling uncertain information of attributes in buyers' requirements, to achieve the Objective 1 of this thesis. The experimental results demonstrated the good performance for the second proposed approach in terms of satisfying buyers' requirements and maximizing the satisfaction degree of all buyers.
Chapter 4

Broker-Based Seller Modelling for Trade Allocation in Market Environments

Seller modelling is one of challenges for broker-based trade allocation in market environments. Specially, modelling sellers’ price offers as per trade volume through a broker plays an important role in allocating buyers’ requirements to sellers’ offers. It can help a broker measure sellers’ price behaviors as per trade volume before broker-based trade allocation processes are carried out to find the allocation pairs to maximize the satisfaction degree of all buyers as social welfare.

A broker-based seller modelling approach is proposed for trade allocation in this chapter. The outline is organized as follows. Problem description is presented in Section 4.1 and the proposed broker-based trade allocation approach based on seller modelling is introduced in Section 4.2. In Section 4.3, the proposed approach is experimentally evaluated, and a brief discussion is given in Section 4.4. This chapter is summarised in Section 4.5.
4.1 Problem Description

In this chapter, the mission of the broker agent is to allocate \( n \) (\( n \geq 1 \)) buyer agents to \( m \) (\( m \geq 1 \)) seller agents to maximize the satisfaction degree of all buyer agents under the consideration of seller agents’ different price offers as per trade volume, buyer agents’ different satisfaction degree as per trade volume and buyer agents’ satisfaction degree with other attributes. Buyer agent \( B_i \) (\( i = 1, 2, \ldots n \)) has volume demands of multi-attribute commodities in market environments and seller agent \( S_j \) (\( j = 1, 2, \ldots m \)) has supply demands of multi-attribute commodities to market environments. Multiple attributes in buyer agents’ requirements and seller agents’ offers are divided into two categories based on their constraints including attributes with hard constraints and attributes with soft constraints (refer to Subsection 3.1.1).

A broker agent needs to model \( S_j \)’s price offers as per trade volume (presented in Subsection 4.2.2) because \( S_j \) offers price as per trade volume. Furthermore, other attributes in \( S_j \)’s offers are also considered to determine \( B_i \)’s satisfaction degree. Attributes with hard constraints in \( S_j \)’s offers are presented by \( OFFH_j \) and \( OFFH_j \) is defined by Equation (3.3). Attributes with soft constraints are presented by \( OFFS_j \) and \( OFFS_j \) is defined by Equation (3.4).

Similarly, a broker agent needs to model \( B_i \)’s satisfaction degree as per trade volume through interactions between a broker agent and a buyer agent (presented in Subsection 4.2.3) because \( B_i \)’s satisfaction degree depends on trade volume. Furthermore, other attributes in \( B_i \)’s requirements are also considered to determine \( B_i \)’s satisfaction degree. Attributes with hard constraints in \( B_i \)’s requirements are presented by \( REQH_i \) and \( REQH_i \) is defined by Equation (3.1). Attributes with soft constraints are presented by \( REQS_i \) and \( REQS_i \) is defined by Equation (3.2).

After receiving trading information in buyer agents’ requirements and seller agents’ offers as well as modelling seller agents’ price offers and buyer agents’ satisfaction
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

4.2.1 The conceptual framework of the proposed approach

The principle of the whole trade allocation process between buyers and sellers through a broker in the proposed approach is presented in Figure 4.1.

**Step 1:** A broker receives sellers’ offers in term of its attributes. To model sellers’ price offers as per trade volume, a broker communicates with a seller to determine a seller’s price offers such as the policy of encouraging consumption or discouraging consumption and so on as per trade volume. The mission of the broker is to model a seller’s price offers as per different consumption volumes.

**Step 2:** A broker receives buyers’ requirements in term of its attributes. Similarly, a broker communicates with a buyer to model the buyer’s satisfaction function as per trade volume. Depending on a buyer’s volume demand, a broker can use different functions such as sigmoid, triangular and so on to model a buyer’s satisfaction degree. For example, a broker starts the simplified interactive procedure with a buyer to build the buyer’s satisfaction degree as per trade volume. In particular, a broker requires a buyer to answer the following three questions so that a broker can identify a buyer’s three reference points within the feasible range of trade volume.

- **Question 1:** ‘what is the worst trade volume?’ → ‘everything is the worst if trade volume is less than 10 or more than 50’.

degree as per trade volume, the key problem is to help a broker agent to find the optimal allocation pairs so that buyer agents’ requirements are satisfied and the satisfaction degree of all buyer agents is maximized. The proposed broker-based trade allocation approach is presented in Section 4.2.
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

Figure 4.1: The conceptual framework of broker-based trade allocation in market environments

- Question 2: ‘what is the perfect trade volume that would give you full satisfaction level?’ → ‘the perfect trade volume is between 20 and 40’.
- Question 3: ‘what is a medium satisfaction level for you with regard to trade volume?’ → ‘the trade volume is between 10 and 20, or between 40 and 50’.

To the above questions, the buyer’s satisfaction function, namely \( u(q) \), as per trade volume, namely \( q \), is presented in Figure 4.2 and Equation (4.1) as follows.
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

Figure 4.2: For example, a buyer’s satisfaction degree as per trade volume

\[
\begin{align*}
    u(q) = \begin{cases} 
    0 & \text{for } q < 10 \\
    \frac{q-10}{10} & \text{for } q \in (10, 20) \\
    1 & \text{for } q \in (20, 40) \\
    \frac{50-q}{10} & \text{for } q \in (40, 50) \\
    0 & \text{for } q > 50
    \end{cases}
\end{align*}
\]

(4.1)

Step 3: A broker carries out to allocate sellers’ offers to buyers’ requirements to seek the optimal trade allocation pairs. A broker’s trade allocation processes are to maximize the satisfaction degree of all buyers under the consideration of sellers’ price offers and buyers’ satisfaction degree as per trade volume, and buyers’ satisfaction degree with other attributes.

The three major components of the proposed approach, which are (i) modelling sellers’ offers, (ii) modelling buyers’ requirements, and (iii) trade allocation, are introduced in detail in the following three subsections, respectively.

4.2.2 Modelling sellers’ offers

4.2.2.1 Building sellers’ price functions as per trade volume

Each seller has different price offers corresponding to buyers’ different trade volume. In this chapter, a broker communicates with a seller to model a seller’s price behavior as per trade volume. In general, a seller’s price behavior is presented based on a mathematical function as follows:

\[
f(q_B^d) = p_s \cdot q_B^d,
\]

(4.2)
where $q_B$ is trade volume of commodities, which a buyer wants to buy from a seller; $q_B \leq q_S$, $q_S$ is a maximal volume of commodity, which a seller can sell to buyers; $p_S$ is price as per unit of commodity, which a seller offers to a buyer; $f(q_B^d)$ is a seller’s turnover as per trade volume $q_B$. Depending on a seller’s different price offers as per trade volume, $d$ is chosen with different values. Thus, a new price as per unit of commodity, namely $p'_S$, which is offered to a buyer based on a buyer’s trade volume and a value $d$, is calculated as follows.

$$p'_S = \frac{p_S \cdot q_B^d}{q_B}. \quad (4.3)$$

In the real world, the particular pricing functions are generated with the three different values $d$ as follows:

(a) if $d = 1$, it means that the price per unit is constant regardless of trade volume (linear pricing). A seller’s price function is written as follows:

$$f(q_B) = p_S \cdot q_B. \quad (4.4)$$

(b) if $d > 1$, it means that if buyers buy the trade volume more and more, the price per unit will be higher and higher (super-linear pricing). In the other words, this case is called discouraging consumption.

(c) if $d < 1$, it means that if buyers buy trade volume more and more, the price per unit will be lower (sub-linear pricing). In the other words, this case is called encouraging consumption.

In summary, the above three pricing functions can be presented in Figure 4.3.
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

4.2.3 Modelling buyers’ requirements

4.2.3.1 Building buyers’ satisfaction function as per trade volume

Each buyer has different demands of trade volume from market environments. Thus, measuring demand of trade volume is necessary for a broker to satisfy buyers’ requirements. In this chapter, a broker communicates with a buyer to model a buyer’s satisfaction function \( u(q_B) \) as per trade volume \( q_B \) and \( u(q_B) \) is between 0 and 1.

In the real world, there are different functions to model a buyer’s satisfaction degrees as per trade volume. In this chapter, some popular functions to model a buyer’s satisfaction degrees as per trade volume are presented as follows.

(a) A sigmoid function is used to express buyers’ satisfaction degrees as per trade volume [8]. This function indicates that if buyers buy trade volume more and more, buyers’ satisfaction degrees will be higher and higher. However, when buyers’ trade volume is satisfied, increasing trade volume for buyers will not improve buyers’ satisfaction degrees any more. On the other hand, if trade volume is below some thresholds, buyers’ satisfaction degrees are extremely low. Thus, buyers’ satisfaction degrees are a concave function and reach a saturation when buyers satisfy their demands. These
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

\[ u(q_B) = \frac{(q_B/\omega)^z}{1 + (q_B/\omega)^z}, \quad (4.7) \]

where \( z \) and \( \omega \) are constants, \( z \geq 2 \) and \( \omega > 0 \). Clearly, \( 0 \leq u(q_B) \leq 1 \) and \( u(\omega) = \frac{1}{2} \).

Figure 4.4: The sigmoid function of buyers’ satisfaction degrees as per trade volume.

Constraints can be presented by the following equations:

\[ \frac{du(q_B)}{dq_B} \geq 0 \quad (4.5) \]

\[ \lim_{q_B \to \infty} \frac{du(q_B)}{dq_B} = 0. \quad (4.6) \]

Thus, the sigmoid function satisfies these constraints above so it can be used to reflect buyers’ satisfaction degrees as per trade volume. In particular, the sigmoid function is presented in Figure 4.4 and Equation (4.7).

(b) Triangular function can be used to express buyers’ satisfaction degrees as per trade volume. This function is presented with three points as follows:

\[ A = (a_1, a_2, a_3) \]
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

\[ u(q_B) = \begin{cases} 
0 & \text{for } q_B < a_1 \\
\frac{q_B - a_1}{a_2 - a_1} & \text{for } q_B \in (a_1, a_2) \\
\frac{a_3 - q_B}{a_3 - a_2} & \text{for } q_B \in (a_3, a_2) \\
0 & \text{for } q_B > a_3 
\end{cases} \] (4.8)

Figure 4.5: The triangular function of buyers’ satisfaction degrees as per trade volume.

\[ u(q_B) = \begin{cases} 
0 & \text{for } q_B < a_1 \\
\frac{q_B - a_1}{a_2 - a_1} & \text{for } q_B \in (a_1, a_2) \\
1 & \text{for } q_B \in (a_2, a_3) \\
\frac{a_4 - q_B}{a_4 - a_3} & \text{for } q_B \in (a_3, a_4) \\
0 & \text{for } q_B > a_4 
\end{cases} \] (4.9)

Figure 4.6: The trapezoidal function of buyers’ satisfaction degrees as per trade volume.

This presentation is interpreted as buyers’ satisfaction degrees in Figure 4.5 and Equation (4.8).

(c) Trapezoidal function can be used to reflect buyers’ satisfaction degrees as per trade volume. This function is presented with four points as follows:

\[ A = (a_1, a_2, a_3, a_4) \]

This presentation is interpreted as buyers’ satisfaction degrees in Figure 4.6 and Equation (4.9).
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

(d) Left-semi trapezoidal function can be used to express buyers’ satisfaction degrees as per trade volume. This function is presented in Figure 4.7 and Equation (4.10).

(e) Right-semi trapezoidal function can be used to express buyers’ satisfaction degrees as per trade volume. This function is presented in Figure 4.8 and Equation (4.11).

In this chapter, depending on buyers’ preferences as per trade volume, a broker can use 5 types of functions, i.e., (a) - (e), to model buyers’ satisfaction degrees as per corresponding trade volume.
4.2.3.2 Building buyers’ satisfaction function between price and trade volume

A satisfaction function of buyer $B_i$, namely $g^{f \leftrightarrow u}_{ij}$, takes in account both $B_i$’s satisfaction degree $u(q_B)$ as per trade volume and price $f(q_B)$ paid to $S_j$ as per $B_i$’s trade volume. For a buyer’s given $u(q_B)$, $g^{f \leftrightarrow u}_{ij}$ should increase when the price paid to a seller decreases and for a given price, $g^{f \leftrightarrow u}_{ij}$ should increase when a buyer’s satisfaction degree $u(q_B)$ as per trade volume increases. Thus, these requirements are presented under mathematical conditions as follows:

$$\frac{\partial g^{f \leftrightarrow u}_{ij}}{\partial f} \leq 0.$$  
(4.12)

$$\frac{\partial g^{f \leftrightarrow u}_{ij}}{\partial u} \geq 0.$$  
(4.13)

Furthermore, if $g^{f \leftrightarrow u}_{ij}$ is normalized then $g^{f \leftrightarrow u}_{ij}$ should satisfy four conditions as follows:

(i) **For a given price** $f(q_B)$, $g^{f \leftrightarrow u}_{ij}(f(q_B), u(q_B))$ approaches the minimum, i.e. 0, when $u(q_B)$ approaches 0.

(ii) **For a given price** $f(q_B)$, $g^{f \leftrightarrow u}_{ij}(f(q_B), u(q_B))$ approaches the maximum, i.e. 1, when $u(q_B)$ approaches infinity.

(iii) **For a given buyers’ satisfaction degree** $u(q_B)$, $g^{f \leftrightarrow u}_{ij}(f(q_B), u(q_B))$ approaches the maximum, i.e. 1, when $f(q_B)$ approaches 0.

(iv) **For a given buyers’ satisfaction degree** $u(q_B)$, $g^{f \leftrightarrow u}_{ij}(f(q_B), u(q_B))$ approaches the minimum, i.e. 0, when $f(q_B)$ approaches infinity.

These constraints are reflected as follows:

$$\forall f > 0, \lim_{u \to 0} g^{f \leftrightarrow u}_{ij}(u, f) = 0, \lim_{u \to \infty} g^{f \leftrightarrow u}_{ij}(u, f) = 1.$$  
(4.14)
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

\[ \forall u > 0, \lim_{f \to 0} g_{ij}^{f+u}(u, f) = 1, \lim_{f \to \infty} g_{ij}^{f+u}(u, f) = 0. \] (4.15)

Based on constraints in Equations (4.14) and (4.15), it is easy to find a mathematical function to satisfy these two constraints. However, according to the theory of micro-economics [9], the following model is popularly used to measure a buyer’s satisfaction probability, which depends on the trade-off between a buyer’s satisfaction degree as per trade volume and the price paid to a seller as per trade volume. In particular, the economic model is presented as follows:

\[ g_{ij}^{f+u}(u, f) = 1 - e^{-ku^u f^{-\alpha}}, \] (4.16)

where \( k, \psi \) and \( \alpha \) are positive constants. The satisfaction function \( g_{ij}^{f+u}(u, f) \) in Equation (4.16) is normalized by using a reference price \( \eta \). Thus \( g_{ij}^{f+u}(u, f) \) is written as follows:

\[ g_{ij}^{f+u}(u, f) = 1 - e^{-ku^u (f/\eta)^{-\alpha}}, \] (4.17)

where \( u \) and \( f \) are determined based on a buyer’s specific trade volume. Thus, before a broker determines \( B_i \)'s satisfaction degree between the trade volume and the price paid to seller \( S_j \) as per trade volume using Equation (4.17), the broker is to determine trade volume. In this chapter, after a broker models a buyer’s satisfaction degrees with trade volume presented in Subsection 4.2.3, a broker can determine trade volume based on the buyer’s target satisfaction degree \( \tau \). For example, a buyer’s satisfaction function as per trade volume is the sigmoid in Equation (4.7) with a buyer’s target satisfaction degree \( \tau \). Then trade volume to achieve this goal is calculated based on inverse function as follows:

\[ q_B = e^{\frac{ln(\frac{\tau}{\omega})}{2} + ln(\omega)} \] (4.18)
4.2.3.3 Calculating buyers’ satisfaction degrees with other attributes

In addition to calculating buyers’ satisfaction degree as per trade volume and price paid to a seller as per trade volume presented in Subsubsection 4.2.3.2, a broker determines buyers’ satisfaction degree with other attributes in buyers’ requirements. In particular, these attributes are divided into two categories based on their constraints (refer to Subsection 3.2.1). The calculation method of buyers’ satisfaction degree with other attributes is presented in detail as follows:

$\beta_{ijh}$ and $\beta_{ijk}$’s values are referred to Subsection 3.1.2.3. In particular, $B_i$’s satisfaction degree for an attribute with hard constraint $A_{g'}(g' \in h)$, called $\beta_{ijg'}$, is determined by Equation (3.19); $B_i$’s satisfaction degree for an attribute with benefit soft constraint $A_g(g \in k)$, called $\beta_{ijg}$, is determined by Equation (3.20); $B_i$’s satisfaction degree for an attribute with cost soft constraint $A_g$, called $\beta_{ijg}$, is determined by Equation (3.21); $B_i$’s satisfaction degree for an attribute with benefit interval constraint $A_g$, called $\beta_{ijg}$, is determined by Equation (3.22); and $B_i$’s satisfaction degree for an attribute with cost interval constraint $A_g$, called $\beta_{ijg}$, is determined by Equation (3.23).

In summary, a broker considers $B_i$’s satisfaction degree based on $S_j$’s offers under a multi-attribute trading. Attributes with hard constraints are necessary conditions in trading processes and must be satisfied. Thus, the weight of attributes with hard constraints does not need to be considered. If attributes with hard constraints are not satisfied, then $B_i$ cannot match with $S_j$. On the other hand, the weight of attributes with soft constraints needs to be considered because buyers are willing to negotiate on these attributes. In particular, $B_i$’s satisfaction degree based on $S_j$’s offers related to all attributes are calculated as follows:

$$\sum_{g=1}^{k} W_{ig} \beta_{ijg} + W_{i}^{u+} f_{ij}^{u+},$$

(4.19)
where \( W_{ig} \) is a weight value of attribute \( A_g \) in \( B_i \)'s requirements, \( W_{u_i^f} \) is a weight value of price attribute as per trade volume and \( \sum_{g=1}^{k} W_{ig} + W_{u_i^f} = 1 \).

4.2.4 A broker’s trade allocation method

4.2.4.1 Framework of trade allocation method

The framework of trade allocation method presented in Figure 4.9 helps a broker to solve the trade allocation problem between buyers’ requirements and sellers’ offers under a multi-attribute trading. The framework includes four main phases as follows:

**Step 1:** Model sellers’ price offers and buyers’ satisfaction degrees as per trade volume presented in Subsections 4.2.2 and 4.2.3, respectively.

**Step 2:** Calculate buyers’ satisfaction degrees presented in Subsubsections 4.2.3.2 and 4.2.3.3 to determine a constraint satisfaction layer to work in broker’s trade allocation processes. The constraint satisfaction layer includes the group of buyers, which satisfy at least a seller’s offers and the group of sellers, which satisfy at least a buyer’s requirements.

**Step 3:** Based on buyers’ satisfaction degrees, sellers’ price offers as per trade volume and buyers’ satisfaction degrees as per other attributes, a broker builds an objective function and a set of constraints to maximize the satisfaction degree of all buyers.

**Step 4:** Solve the objective function by well-know linear programming methods [36] to obtain the optimal allocation pairs to satisfy buyers’ requirements and maximize the satisfaction degree of all buyers.
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

4.2.4.2 Building a broker’s objective function

An objective function for broker-based trade allocation processes between buyers’ requirements and sellers’ offers is established to maximize the satisfaction degree of all buyers as a goal. Based on the above definition of buyers and sellers, a broker’s objective function is presented as follows:

$$\sum_{i=1}^{n} \sum_{j=1}^{m} (\sum_{g=1}^{k} W_{ig} \beta_{ijg} + W_{i}^{u+}f_{ij}^{g+}f^{+})x_{ij}$$  \hspace{1cm} (4.20)$$

$$s.t. \sum_{i=1}^{n} x_{ij} \leq 1, \forall j \in m$$  \hspace{1cm} (4.21)

$$\sum_{j=1}^{m} x_{ij} \leq 1, \forall i \in n$$  \hspace{1cm} (4.22)
4.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

\[ x_{ij} = 1, 0, \forall i \in n, \forall j \in m \]  \hspace{1cm} (4.23)

\[ \sum_{g=1}^{k} W_{ig} + W_{ij}^{u+\delta} = 1, \forall i \in n \]  \hspace{1cm} (4.24)

\[ x_{ij} = 0 \text{ if } \beta_{ijg'} = -1 \text{ or } \beta_{ijg} = -1, \text{ or } q_{Bi} > q_{Sj}, \text{ or } p_{Sj}^{f} > p_{Bi}, \forall g', h, g \in k, \]  \hspace{1cm} (4.25)

where \( h \) is a number of attributes with hard constraints in buyers’ requirements and \( k \) is a number of attributes with soft constraints in buyers’ requirements; \( p_{Bi} \) is price as per a unit of a commodity, which \( B_i \) accepts to pay to a seller \( S_j \); values of \( \beta_{ijg} \) and \( g_{ij}^{u+\delta} \) are \((0,1]\); the objective function in Equation (4.20) is to maximize the weight sum of the satisfaction degree of all buyers; constraints in Equation (4.21) mean that each seller only matches with each buyer maximally; constraints in Equation (4.22) mean that each buyer only matches each seller maximally; constraints in Equation (4.23) are constraints of decision variable, if \( B_i \) matches with \( S_j \), then \( x_{ij} = 1 \); otherwise, \( x_{ij} = 0 \); constraints in Equation (4.24) denote the weight information of attributes in buyers’ requirements; and constraints in Equation (4.25) determine a constraint satisfaction layer.

4.2.4.3 Building a broker’s algorithm for trade allocation processes

Broker-based trade allocation processes between buyers’ requirements and sellers’ offers are presented by Algorithm 3 as follows:
Algorithm 3: A broker's trade allocation

1. **Input**: a set of buyers' requirements $B = \{B_1, B_2, \ldots, B_n\}$ and a set of sellers' offers $S = \{S_1, S_2, \ldots, S_m\}$;
2. **Output**: Return the allocation pairs between buyers and sellers;

```
begin
for each buyer $B_i$ in $S$ do
  determine $B_i$'s trade volume so that $B_i$'s $u(q_B) = \tau$;
  identify $B_i$'s satisfaction degree between $B_i$'s trade volume and price paid to a seller with $B_i$'s trade volume by using Equation 4.17;
  for each attribute in $B_i$'s requirements do
    if an attribute belongs to hard constraints then
      $B_i$'s satisfaction degree for this attribute is calculated in Equation (3.19);
    if an attribute belongs to benefit soft constraints then
      $B_i$'s satisfaction degree for this attribute is calculated in Equation (3.20);
    if an attribute belongs to cost soft constraints then
      $B_i$'s satisfaction degree for this attribute is calculated in Equation (3.21);
    if an attribute belongs to benefit interval constraints then
      $B_i$'s satisfaction degree for this attribute is calculated in Equation (3.22);
    if an attribute belongs to cost interval constraints then
      $B_i$'s satisfaction degree for this attribute is calculated in Equation (3.23);
  build the objective function in Equation (4.20) and a set of constraints in Equation (4.21)-(4.25);
solve the objective function in Equation (4.20) to achieve the allocation pairs to maximize the satisfaction degree of all buyers.
end
```

Algorithm 3 shows a broker's trade allocation process between buyers' requirements and sellers' offers. The input of Algorithm 3 is trading information in buyers' requirements and sellers' offers (Line 1). The output of Algorithm 3 returns the allocation pairs between buyers and sellers to maximize the satisfaction degree of all buyers (Line 2).

To carry out the trade allocation process, a broker calculates buyers' satisfaction degrees for all attributes as follows. Based on buyers' target satisfaction degree, a broker determines the trade volume to satisfy buyers' requirements as per trade volume
4.3 Experiments

This section presents an experimental evaluation of proposed broker-based trade allocation approach under the consideration of modelling sellers’ price offers and buyers’ satisfaction degrees as per trade volume, and buyers’ satisfaction degrees as per other attributes. Three experiments are conducted and the experiments focus mainly on the test of the maximization of the satisfaction degree of all buyers through trade allocation. The rest of this section is divided into two subsections. Subsection 4.3.1 describes the experimental setting that has been applied in the experiments. Sub-
4.3. Experiments

Section 4.3.2 shows the experimental results and performance analysis in the three different experiments.

4.3.1 Experimental setting

In the experiments, an artificial dataset of 10 buyers related to demand for jackets is generated. The comparison approach is Jiang’s approach [62]. Trading information in buyers’ requirements contains eight attributes, i.e., brand, size, colour, gender, price, volume (quantity), delivery time and warranty time. Each buyer would like to buy a certain volume of commodities from the market but in some special cases, a volume of commodities from sellers is limited in the market and sellers would like to sell their commodities to multiple buyers. Thus, a broker interacts with a buyer to model the buyer’s specific satisfaction degree function as per trade volume. Some functions used to express buyers’ satisfaction degrees as per trade volume are presented in Subsection 4.2.3. In the experiments, we assume that buyers’ satisfaction degrees as per trade volume are expressed by a triangular function. The triangular function is built through an interaction between a broker and a buyer. As per buyers’ view, brand, size, colour and gender are regarded as the attributes with hard constraints while a price attribute as per trade volume, delivery time and warranty time are regarded as the attributes with soft constraints. Similarly, an artificial dataset of 50 sellers providing jackets to the market is generated. Trading information in sellers’ offers contains eight attributes, i.e., brand, size, colour, gender, price, delivery time and warranty time, volume of commodity. Sellers’ different price functions corresponding different trade volume are presented in Subsection 4.2.2. In particular, sellers’ specific price offers as per trade volume are expressed through a value $d$ and $d$ is set for each specific experiments presented in Subsection 4.3.2. Furthermore, the weight values of the attributes with soft constraints in buyers’ requirements, i.e., a price attribute as per trade volume,
4.3. Experiments

delivery time and warranty time are set in both the proposed approach and Jiang’s approach [62]. Based on the artificial dataset of buyers and sellers, a broker uses the proposed approach to maximize the satisfaction degree of all buyers through trade allocation under different experiments in the market environments.

In the experiments, the average satisfaction degree of buyers in the proposed approach is used to compare with that in Jiang’s approach [61] because experimental settings in the proposed approach are similar to experimental settings in Jiang’s approach [61]. However, sellers’ price offers as per trade volume are considered in the proposed approach while price attribute in Jiang’s approach is fixed without price discount as per trade volume.

4.3.2 Experimental results and analysis

The results of the three experiments are demonstrated and analyzed in details in the following subsubsections.

4.3.2.1 Experiment 1: the evaluation of the satisfaction degree of all buyers under selecting a different number of sellers

The purpose of Experiment 1 is to maximize the satisfaction degree of all buyers by selecting a different number of sellers and assuming that sellers’ price offers as per trade volume are sub linear pricing (\(d=0.85\)). In particular, based on the artificial dataset of 50 sellers, a different number of sellers is selected to engage in broker-based allocation processes as follows: the first 10 sellers, the first 20 sellers, the first 30 sellers, the first 40 sellers and 50 sellers.

Two approaches in Figure 4.10 show the impact of the different number of sellers on the average satisfaction degree of buyers. We can see that the larger the number of sellers in market environments, the higher the average satisfaction degree of buyers.
4.3. Experiments

Figure 4.10: The average satisfaction degree of buyers compared with other approach in the two approaches. The reason is that a broker has many opportunities to select sellers’ offers which satisfy buyers’ requirements and increase buyers’ satisfaction degrees. It means that when the number of sellers are more than the number of buyers in market environments, the average satisfaction degree of buyers is able to increase. Furthermore, the average satisfaction degree of buyers in the proposed approach is always higher than that in Jiang’s approach. The reason is that Jiang’s approach does not consider sellers’ discount price offers as per trade volume to satisfy buyers’ requirements while the proposed approach considers sellers’ discount price offers as per trade volume to satisfy buyers’ requirements.

4.3.2.2 Experiment 2: the evaluation of the satisfaction degree of all buyers under different number of buyers

The purpose of Experiment 2 is to maximize the satisfaction degree of all buyers when a different number of buyers works in market environments and assumes that sellers’ price offers as per trade volume are sub linear pricing ($d=0.85$). Based on the artificial
4.3. Experiments

Figure 4.11: The average satisfaction degree of buyers under considering a different number of buyers

dataset of 50 sellers and 10 buyers above, a broker carries out trade allocation under a
different number of buyers to engage in market environments. A combination formula
is used to determine different outcomes corresponding to the specific number of buyers
who work in broker’s trade allocation processes. Then, the average satisfaction degree
of buyers is calculated from results of different outcomes. In particular, a number
of different outcomes corresponding to the specific number of buyers is calculated as
follows:

\[ C_r^n = \frac{n!}{r!(n-r)!}, \]  \hspace{1cm} (4.26)

where \( C_r^n \) is a number of different outcomes corresponding to the specific number of
buyers; \( r \) is the specific number of buyers in this experiment, i.e., 2 buyers, 4 buyers,
6 buyers, 8 buyers, and 10 buyers; and \( n \) is the number of buyers from the artificial
dataset (10 buyers).

Two approaches in Figure 4.11 show the impact of a different number of buyers
in market environments on the average satisfaction degree of buyers. In particular,
when the number of buyers engaging in a broker’s trade allocation processes decreases, the average satisfaction degree of buyers increases in two approaches. The reason is that a broker has many opportunities to choose the potential sellers to increase the satisfaction degree of all buyers. Furthermore, the average satisfaction degree of buyers in the proposed approach is always higher than that in Jiang’s approach. The reason is that Jiang’s approach does not consider sellers’ discount price offers as per buyers’ trade volume to satisfy buyers’ requirements while the proposed approach accepts sellers’ discount price offers as per trade volume to satisfy buyers’ requirements.

4.3.2.3 Experiment 3: the evaluation of the satisfaction degree of all buyers under the consideration of sellers’ different price offers

Based on the artificial dataset of 50 sellers and 10 buyers above, a broker uses the proposed trade allocation approach to maximize the satisfaction degree of all buyers under the consideration of sellers’ different price offers with \( d \) between 0 and 2 through allocating buyers’ requirements and sellers’ offers. Based on the general principle of markets, when sellers’ price offers are differently offered to the markets as per buyers’ trade volume, the trade allocation results and the satisfaction degree of all buyers are affected by sellers’ different price offers. In particular, the satisfaction degree of all buyers in sellers’ sub-linear price offers as per trade volume is higher than the satisfaction degree of all buyers in sellers’ linear price offers and sellers’ super-linear offers as per trade volume. Furthermore, the satisfaction degree of all buyers in sellers’ linear price offers as per trade volume is higher than the satisfaction degree of all buyers in sellers’ super-linear offers as per trade volume. Based on the results shown in Figures 4.12, 4.13 and 4.14, we can see that sellers’ price offers directly affect the average satisfaction degree of buyers. On the other hand, the best average satisfaction degree of buyers in Figure 4.12 is different from the best average satisfaction degree of buyers in Figures 4.13 and 4.14 because a weight value of price attribute as per trade
4.3. Experiments

volume in Figure 4.12 is different from a weight value of price attribute as per trade volume in Figures 4.13 and 4.14.

Figure 4.12: A weight value of price attribute as per trade volume $W_i^{w+e}$ is 0.3

Figure 4.13: A weight value of price attribute as per trade volume $W_i^{w+e}$ is 0.6
Although sellers offer the sub-linear price offers to buyers in Figure 4.12, the highest average satisfaction degree of buyers in the curve of the best average satisfaction degree of buyers is 0.96 and cannot achieve 1 because a weight value of price attribute as per trade volume is 0.3. Similarly, although sellers offer the super-linear price offers to buyers, the lowest average satisfaction degree of buyers in the curve of the worst average satisfaction degree of buyers cannot achieve 0 and is 0.54 in Figure 4.12 because a weight value of price attribute as per trade volume is 0.3. Furthermore, the highest average satisfaction degree of buyers in the curve of the best average satisfaction degree of buyers (0.98) in Figure 4.13 is higher than the highest average satisfaction degree of buyers in the curve of the best average satisfaction degree of buyers (0.96) in Figure 4.12 because a weight value of price attribute as per trade volume in Figure 4.13 is 0.6. Finally, when a weight value of price attribute as per trade volume is 1, sellers’ price offers totally affects the satisfaction degree of all buyers. The evidence is demonstrated through the results in Figure 4.14. When sellers offer the sub-linear price offers to buyers, the highest average satisfaction degree of buyers in the curve of the best average satisfaction degree of buyers is 1. Furthermore, when sellers offer
the super-linear price offers to buyers, the lowest average satisfaction degree of buyers in the curve of the worst average satisfaction degree of buyers achieves 0. It is clear that the proposed approach determines the satisfaction degree of all buyers under the consideration of sellers’ different price offers through value $d$ between 0 and 2. If value $d$ is less than 1, the average satisfaction degree of buyers is relatively high. It means that buyers receive the discount prices from sellers. Otherwise, the average satisfaction degree of buyers is relatively low because there are no seller’s discount price offers for buyers. Jiang’s approach does not consider sellers’ different price offers so a value $d$ is 1. It means that the average satisfaction degree of buyers in Jiang’s approach cannot be changed under sellers’ different price offers. Thus, the average satisfaction degree of buyers of Jiang’s approach in Figures 4.12, 4.13 and 4.14 remains unchanged although sellers’ price offers have been changed through value $d$.

In summary, the proposed approach helps a broker to maximize the satisfaction degree of all buyers through trade allocation. Depending on sellers’ price offers as per trade volume, and the number of sellers and the number of buyers to work in a broker’s trade allocation processes, a broker can determine the potential parameters to satisfy buyers’ requirements and maximize the satisfaction degree of all buyers.

4.4 Discussion

A broker’s main mission in the proposed approach is to maximize the satisfaction degree of all buyers as social welfare under the consideration of trade volume, price paid to sellers as per trade volume, and buyers’ requirements in other attributes. The good performance of the proposed broker-based trade allocation approach to maximize the satisfaction degree of all buyers based on seller modelling has been demonstrated through experimental results. The reasons the good performances are achieved are (i) a broker can model a seller’s price offers as per trade volume through communications
between a broker and a seller; (ii) due to each buyer’s different trade volume, a broker models a buyer’s satisfaction degree as per trade volume through communications between a broker and a buyer; (iii) to carry out allocating buyers’ requirements to sellers’ offers through a broker, an objective function and a set of constraints are generated to help a broker to maximize the satisfaction degree of all buyers.

4.5 Summary

In this chapter, the broker-based trade allocation approach to maximize the satisfaction degree of all buyers based on seller modelling in market environments was proposed. Firstly, the problem description of a broker-based trade allocation approach was given. Then, the framework, the main steps, and three components of the proposed approach were introduced in detail. Finally, the experiments comparing with another approach to evaluate the performance of broker-based trade allocation based on modelling seller, were demonstrated and analysed so as to achieve Objective 3 of this thesis.
Chapter 5

A Broker-Based Multi-Objective Function for Trade Allocation in Market Environments

In this chapter, a broker-based multi-objective function approach for trade allocation under a multi-attribute trading in market environments is proposed. The proposed broker-based approach is to maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit under a multi-attribute trading through trade allocation. This chapter is organised as follows. Problem description and definitions are introduced in Section 5.1, and the proposed broker-based multi-objective function approach for trade allocation is introduced in Section 5.2. A case study is illustrated in Section 5.3. In Section 5.4, the proposed approach is experimentally evaluated. A discussion is given in Section 5.5, and Section 5.6 summarises this chapter.
5.1 Problem Description and Definitions

In this chapter, a broker agent is to allocate multiple buyer agents to multiple seller agents under a multi-attribute trading to maximize the satisfaction degree of all buyer agents, a broker agent’s turnover and a broker agent’s benefit. Each buyer agent (each seller agent) only matches with one seller agent (each buyer agent) maximally and there are no any limitations of trade volumes for buyer agents and seller agents. The trade allocation process is that trading information in buyer agents’ requirements and seller agents’ offers is submitted to a broker agent and then a broker agent will carry out trade allocation in a given time interval. The problem for the broker agent to solve is how to allocate buyer agents’ requirements to seller agents’ offers to seek the optimal allocation pairs in a given time interval so that the satisfaction degree of all buyer agents, a broker agent’s turnover and a broker agent’s benefit are maximized.

Before the detail contents of the proposed approach are presented, it is necessary to define the scope of the proposed approach and provide some necessary definitions.

A buyer agent is considered as a buyer who would like to buy a particular commodity from market environments to satisfy a buyer’s requirement and is defined in Subsection 3.1.1. A seller agent is considered as a company or an organization which has resources to provide to market environments and is also defined in Subsection 3.1.1.

A broker agent acts as a third party in a trading process between multiple buyer agents and multiple seller agents. Seller agents would like to sell their commodities to buyer agents through a broker agent. Thus, seller agents offer reward programs to a broker agent if their commodities are successfully sold, so a broker agent is defined as follows.
5.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

Definition 5.1.1. A broker agent $BR$ is defined as a 3-tuple $BR = \langle B, S, r \rangle$, where $B$ is a set of buyer agents, $S$ is a set of seller agents and $r$ is a set of rewards that $BR$ can get from seller agents (see definition 5.1.2).

Definition 5.1.2. A set of rewards $r$ is defined as follows.

$$ r = \{r_{S_1}^{S_1}, r_{S_2}^{S_2}, \ldots, r_{S_m}^{S_m}\}, \quad (5.1) $$

where $r_{S_m}^{S_m}$ is a reward which seller agent $S_m$ offers to a broker agent if $S_m$’s commodities are bought by a certain buyer agent through a broker agent.

Based on trading information of buyer agents’ requirements and seller agents’ offers submitted to a broker agent, the problem is that a broker agent is to allocate buyer agents’ requirements to seller agents’ offers under the consideration of seller agents’ price discount offers as per trade volume and rewards seller agents offer to a broker agent so that the satisfaction degree of all buyer agents, a broker agent’s turnover, and a broker agent’s benefit are maximized. The broker-based trade allocation approach using a multi-objective function is proposed and presented in Section 5.2.

5.2 The Principle of the Proposed Broker-Based Trade Allocation Approach

5.2.1 Framework of the proposed broker-based trade allocation approach

The framework of the proposed approach to help a broker to solve the trade allocation problem under a multi-attribute trading is presented in Figure 5.1 as follows.
5.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

Obtain trade information in buyers’ requirements and sellers’ offers

Model sellers’ offers

Calculate buyers’ satisfaction degree to determine a constraint satisfaction layer

Build a multi-objective function

Solve the multi-objective function

Obtain a Pareto optimal solution

Buyers’ requirements and sellers’ offers related to multi-attributes. Specially, sellers’ price discount offers as per trade volume.

Based on communication between a seller and a broker, a broker models sellers’ price discount offers as per trade volume.

A constraint satisfaction layer

A group of buyers

A group of sellers

There are three objective functions. The first one is to maximize the satisfaction degree of all buyers; the second one is to maximize a broker’s turnover; and the last one is to maximize a broker’s benefit.

The ideal point method

Figure 5.1: The framework of the broker-based trade allocation approach

In the framework, trading information related to multi-attribute commodities in buyers’ requirements and sellers’ offers is submitted to a broker. Furthermore, a broker interacts with a seller to model a seller’s price discount offers as per trade volume.

From trading information of buyers and sellers, a broker carries out the calculation of buyers’ satisfaction degree to determine a constraint satisfaction layer including a group of buyers and sellers to work in broker’s trade allocation processes. A group of buyers includes any buyer to satisfy at least a seller’s offers. Similarly, a group of sellers includes any seller to satisfy at least a buyer’s requirements. After that, a multi-objective function is generated based on calculating the satisfaction degree of all buyers, a broker’s turnovers, and a broker’s benefits. Finally, the multi-objective function is solved by the ideal point method to find a Pareto optimal allocation so-
5.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

In the following subsections, the main issues of the proposed approach, i.e.,
modelling sellers’ price function as per trade volume, calculating buyers’ satisfaction
degrees, building the multi-objective function and solving the multi-objective function
are presented in detail.

5.2.2 Modelling sellers’ price function as per trade volume

In reality, a seller usually offers price discount as per trade volume to a buyer so that a
seller would like to encourage a buyer to a large number of commodities from a seller.
It means that a price per unit for a buyer will be decreased when its trade volume
increases. In this chapter, the functional relationship between $B_i$’s trade volume,
namely $C_{iv}$, and $S_j$’s price unit, namely $Q_{jp}$, can be presented in Equation 5.2 as
follows.

$$
Q_{jp} = \begin{cases} 
R_1 Q_{ipv}^1 \leq C_{iv} < Q_{ipv}^2, \\
R_2 Q_{ipv}^2 \leq C_{iv} < Q_{ipv}^3, \\
\cdots \cdots \\
R_z Q_{ipv}^{z-1} \leq C_{iv} < Q_{ipv}^z
\end{cases} \tag{5.2}
$$

where $Q_{ipv}^1$ is a seller’s minimal trade volume, which is offered to a buyer and $Q_{ipv}^z$
is a seller’s maximal trade volume, which is offered to a buyer. Due to a seller’s
price discount offers as per trade volume, Equation (5.2) indicates that $R_1 > R_2 >
\ldots R_{z-1} > R_z$ and $0 \leq Q_{ipv}^1 < Q_{ipv}^2, \ldots Q_{ipv}^{z-1} < Q_{ipv}^z$. It means that the larger the trade
volume, the lower price as per one unit of a commodity. In particular, Figure 5.2
illustrates the relationship between a buyer’s trade volume and a seller’s price unit.
5.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

5.2.3 Building the calculation of buyers’ satisfaction degree

The calculation of buyers’ satisfaction degree plays an important role in a multi-attribute trading between buyers and sellers through a broker. It helps a broker to determine a constraint satisfaction layer, i.e., a group of buyers and sellers, to engage in a broker’s allocation processes. \( \beta_{ijq} \in [-1, 1] \) is defined as a buyer’s satisfaction degree for the \( q^{th} \) attribute between \( B_i \) and \( S_j \). In particular, \( B_i \)’s satisfaction degree for an attribute with hard constraints \( A_{g'}(g' \in h) \), called \( \beta_{ijg'} \), is determined by Equation (3.19), \( B_i \)’s satisfaction degree for an attribute with benefit soft constraints \( A_g(g \in k) \), called \( \beta_{ijg} \), is determined by Equation (3.20), \( B_i \)’s satisfaction degree for an attribute with cost soft constraints \( A_g \), called \( \beta_{ijg} \), is determined by Equation (3.21), \( B_i \)’s satisfaction degree for an attribute with benefit interval constraints \( A_g \), called \( \beta_{ijg} \), is determined by Equation (3.22), and \( B_i \)’s satisfaction degree for an attribute with cost interval constraints \( A_g \), called \( \beta_{ijg} \), is determined by Equation (3.23).
5.2.4 Building a multi-objective function

A broker’s decision making for a trade allocation process is driven by multi-objectives. Based on the definitions of buyers and sellers (refer to Section 5.1), and the proposed approach’s the goal, a multi-objective function, namely Model A, is presented by the following three objectives \( f_1, f_2, \text{ and } f_3 \) and a set of constraints as follows.

\[
f_1 = \sum_{i=1}^{n} \sum_{j=1}^{m} \left( \sum_{g=1}^{k} W_{ig} \beta_{ijg} x_{ij} \right) \tag{5.3}
\]

\[
f_2 = \sum_{i=1}^{n} \sum_{j=1}^{m} C_{iv} Q_{jp} x_{ij} \tag{5.4}
\]

\[
f_3 = \sum_{i=1}^{n} \sum_{j=1}^{m} Q_{jp} r_{ij}^{s_i} C_{iv} x_{ij} \tag{5.5}
\]

\[
s.t. \sum_{i=1}^{n} x_{ij} \leq 1, \forall j \in m \tag{5.6}
\]

\[
\sum_{j=1}^{m} x_{ij} \leq 1, \forall i \in n \tag{5.7}
\]

\[
x_{ij} = 1, 0, \forall i \in n, \forall j \in m \tag{5.8}
\]

\[
\sum_{g=1}^{k} W_{ig} = 1, \forall i \in n \tag{5.9}
\]
5.2. The Principle of the Proposed Broker-Based Trade Allocation Approach

\[ \sum_{i=1}^{n} C_{iv}x_{ij} \leq Q_{jv}, \forall j \in m \]  
\hspace{1cm} (5.10)

\[ x_{ij} = 0 \text{ if } \beta_{ijg} = -1, \beta_{ijg'} = -1, Q_{jv} < C_{iv}, Q_{jp} > C_{ip} \forall g \in k, \forall g' \in h, \]  
\hspace{1cm} (5.11)

where the objective function in Equation (5.3) is established to maximize the satisfaction degree of all buyers; the objective function in Equation (5.4) is established with the maximization of a broker’s turnover; and the objective function in Equation (5.5) is established with the maximization of a broker’s benefit where \( C_{ip} \) is a price unit of a commodity represented by \( B_i \). Constraints in Equation (5.6) are that each seller only matches with each buyer maximally; constraints in Equation (5.7) are that each buyer only matches with each seller maximally; constraints in Equation (5.8) are constraints of decision variable, if \( B_i \) matches with \( S_j \), then \( x_{ij} = 1 \); otherwise, \( x_{ij} = 0 \). Constraints in Equation (5.9) denote the weight information of attributes with soft constraints in buyers’ requirements; constraints in Equation (5.10) denote that \( S_j \)’s supply volume is more than or equal to \( B_i \)'s volume demand and constraints in Equation (5.11) determine a constraint satisfaction layer.

5.2.5 Solving Model A

Model A can be solved by different approaches to find out Pareto optimal solutions such as a multi-objective genetic algorithm [56, 78, 6], the weight sum method [138], the goal programming method [26], the ideal point method [87] and so forth. However, the ideal point method is a common and effective method to solve a multi-objective function [84]. Thus, Model A in this chapter is solved by the ideal point method.

Since three objective functions \( (f_1, f_2 \text{ and } f_3) \) in Model A have different units \( (f_1 \)
is the satisfaction degree of all buyers, $f_2$ is a broker’s turnover and $f_3$ is a broker’s benefit). Thus, the three objective functions need to be normalized to compare them together. In order to carry out normalization, Model A is converted to a single-objective function, namely Model B, as follows:

$$
\text{Min} F = \alpha_1 \frac{f_1^* - f_1}{f_1^*} + \alpha_2 \frac{f_2^* - f_2}{f_2^*} + \alpha_3 \frac{f_3^* - f_3}{f_3^*},
$$

(5.12)

s.t. (5.6) - (5.11),

where the ideal point of the objective function in Equation (5.12) is $(f_1^*, f_2^*, f_3^*)$; $\alpha_1$ the weight value of the objective function in Equation (5.3), $\alpha_2$ the weight value of the objective function in Equation (5.4) and $\alpha_3$ the weight value of the objective function in Equation (5.5).

The objective function in Equation (5.12) helps a broker to find a Pareto optimal allocation solution for Model A with the given value of $\alpha_1, \alpha_2$ and $\alpha_3$. The procedure of solving the objective function in Equation (5.12) by using the ideal point method is presented as follows.

**Step 1:** the simplex linear program technique is used to solve the objective function in Equation (5.3) and constraints (5.6) - (5.11) to find the optimal allocation pairs and achieve the ideal point $f_1^*$ of the objective function.

**Step 2:** the simplex linear program technique is used to solve the objective function in Equation (5.4) and constraints (5.6) - (5.11) to find the optimal allocation pairs and achieve the ideal point $f_2^*$ of the objective function.

**Step 3:** the simplex linear program technique is used to solve the objective function in Equation (5.5) and constraints (5.6) - (5.11) to find the optimal allocation pairs and achieve the ideal point $f_3^*$ of the objective function.
Step 4: after $f_1^*$, $f_2^*$ and $f_3^*$ are found, the objective function in Equation (5.12) and constraints (5.6) - (5.11) are solved by the simplex linear program to find a Pareto optimal allocation solution for Model A.

5.3 A Case Study

This section presents a case study to show how to apply the proposed allocation approach with the artificial data related to second-hand computer markets of Dell company with model - Optiplex 960. This case study not only shows the procedure of using the proposed approach in the specific example, but also demonstrates the performance of the proposed approach in the real life situations.

In this section, experimental results are illustrated to maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit through a broker. Subsection 5.3.1 introduces the case study setting. The procedure of generating multi-objective function applied on the specific example is described step by step in Subsection 5.3.2.

5.3.1 Case study setting

The case study includes settings of buyer agents, seller agents and a broker agent.

**Buyer setting:** The simulation contains 10 buyer agents and each buyer agent considers buying a computer model - Optiplex 960 with five attributes, i.e., price, quantity (trade volume), payment method, delivery time and warranty time. The detail contents of 10 buyers’ requirements are presented in Table 5.1.

**Seller setting:** The simulation contains 10 seller agents and each seller agent considers selling a computer model - Optiplex 960 with six attributes, i.e., price, quantity (trade volume), payment method, delivery time, warranty time and discount rate. The detail contents of 10 sellers’ offers are presented in Table 5.2.
5.3. A Case Study

Table 5.1: Trading information of product in buyers’ requirements

<table>
<thead>
<tr>
<th>Buyer</th>
<th>Price (AUD)</th>
<th>Quantity</th>
<th>Payment Method</th>
<th>Delivery time</th>
<th>Weight</th>
<th>Warranty time</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_1$</td>
<td>200</td>
<td>20</td>
<td>PayPal</td>
<td>4</td>
<td>0.3</td>
<td>30</td>
<td>0.7</td>
</tr>
<tr>
<td>$B_2$</td>
<td>180</td>
<td>5</td>
<td>BPay</td>
<td>5</td>
<td>0.4</td>
<td>35</td>
<td>0.6</td>
</tr>
<tr>
<td>$B_3$</td>
<td>190</td>
<td>15</td>
<td>PayPal</td>
<td>4</td>
<td>0.7</td>
<td>32</td>
<td>0.3</td>
</tr>
<tr>
<td>$B_4$</td>
<td>185</td>
<td>15</td>
<td>PayPal</td>
<td>5</td>
<td>0.45</td>
<td>26</td>
<td>0.55</td>
</tr>
<tr>
<td>$B_5$</td>
<td>210</td>
<td>11</td>
<td>PayPal</td>
<td>4</td>
<td>0.6</td>
<td>25</td>
<td>0.4</td>
</tr>
<tr>
<td>$B_6$</td>
<td>220</td>
<td>15</td>
<td>PayPal</td>
<td>4</td>
<td>0.75</td>
<td>29</td>
<td>0.25</td>
</tr>
<tr>
<td>$B_7$</td>
<td>195</td>
<td>10</td>
<td>PayPal</td>
<td>5</td>
<td>0.65</td>
<td>28</td>
<td>0.35</td>
</tr>
<tr>
<td>$B_8$</td>
<td>190</td>
<td>4</td>
<td>PayPal</td>
<td>6</td>
<td>0.4</td>
<td>24</td>
<td>0.6</td>
</tr>
<tr>
<td>$B_9$</td>
<td>210</td>
<td>20</td>
<td>PayPal</td>
<td>4</td>
<td>0.3</td>
<td>28</td>
<td>0.7</td>
</tr>
<tr>
<td>$B_{10}$</td>
<td>220</td>
<td>2</td>
<td>PayPal</td>
<td>5</td>
<td>0.65</td>
<td>27</td>
<td>0.35</td>
</tr>
</tbody>
</table>

**Broker setting:** All seller agents agree that if their product is sold through a broker, the broker will receive a discount rate, namely $r$, from seller agents. The contents of discount rates from sellers are presented in the last column in Table 5.2. A broker’s turnover and a broker’s benefit is calculated as follows.

- A broker’s turnover with each allocation pair between $B_i$ and $S_j$ is calculated as follows:
  \[
  \text{a broker’s turnover} = C_{iv} \times Q_{jp} \quad (5.13)
  \]

- A broker’s benefit with each allocation pair between $B_i$ and $S_j$ is calculated as follows:
  \[
  \text{a broker’s benefit} = Q_{jp} \times r_j^S \times C_{iv} \quad (5.14)
  \]
Table 5.2: Trading information of product in sellers’ offers

<table>
<thead>
<tr>
<th>Buyer</th>
<th>Price (AUD)</th>
<th>Quantity</th>
<th>Payment Method</th>
<th>Delivery time</th>
<th>Warranty time</th>
<th>Rate of discount ($r$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>(180,170,150)</td>
<td>(0,18,22,40)</td>
<td>PayPal</td>
<td>3</td>
<td>37</td>
<td>10%</td>
</tr>
<tr>
<td>$S_2$</td>
<td>(170,150,140)</td>
<td>(0,12,18,30)</td>
<td>BPay</td>
<td>4</td>
<td>38</td>
<td>1%</td>
</tr>
<tr>
<td>$S_3$</td>
<td>(160,150,140)</td>
<td>(0,8,15,25)</td>
<td>PayPal</td>
<td>4</td>
<td>39</td>
<td>3%</td>
</tr>
<tr>
<td>$S_4$</td>
<td>(165,160,155)</td>
<td>(0,9,13,25)</td>
<td>PayPal</td>
<td>4</td>
<td>40</td>
<td>7%</td>
</tr>
<tr>
<td>$S_5$</td>
<td>(175,170,160)</td>
<td>(0,15,20,25)</td>
<td>PayPal</td>
<td>4</td>
<td>41</td>
<td>3.5%</td>
</tr>
<tr>
<td>$S_6$</td>
<td>(168,160,155)</td>
<td>(0,12,16,22)</td>
<td>PayPal</td>
<td>3</td>
<td>40</td>
<td>8%</td>
</tr>
<tr>
<td>$S_7$</td>
<td>(175,170,160)</td>
<td>(0,20,30,35)</td>
<td>PayPal</td>
<td>3</td>
<td>42</td>
<td>11%</td>
</tr>
<tr>
<td>$S_8$</td>
<td>(180,175,160)</td>
<td>(0,15,20,28)</td>
<td>PayPal</td>
<td>3</td>
<td>40</td>
<td>12%</td>
</tr>
<tr>
<td>$S_9$</td>
<td>(160,160,155)</td>
<td>(0,16,18,25)</td>
<td>PayPal</td>
<td>3</td>
<td>35</td>
<td>2.5%</td>
</tr>
<tr>
<td>$S_{10}$</td>
<td>(180,180,175)</td>
<td>(0,8,15,25)</td>
<td>PayPal</td>
<td>3</td>
<td>38</td>
<td>9%</td>
</tr>
</tbody>
</table>

5.3.2 Generation of a concrete multi-objective function from the specific data of the case study

This subsection illustrates the procedure of creating a concrete function and using the concrete function to find the optimal allocation pairs.

**Step 1: Obtaining trading information in buyers’ requirements and sellers’ offers.**

Table 5.1 in the previous subsection already presented buyers’ requirements with five attributes from 10 buyers. Four attributes from buyers’ requirements including price, quantity, delivery time and warranty time are the attributes with soft constraints and payment method is an attribute with a hard constraint. Due to sellers’ price offers as per quantity (trade volume), weights of the two attributes, i.e. price and quantity do not need to be considered while delivery time and warranty time need to be expressed weight (or preference) information. Based on buyers’ viewpoint, delivery time is considered as the attribute with cost soft constraints and warranty time is considered as the attribute with benefit soft constraints. Similarly, as for sellers, Table 5.2 in the previous subsection already presented sellers’ offers with five attributes from
10 sellers and discount rates from sellers are offered to a broker if the sellers’ product is sold to buyers through a broker.

**Step 2: Calculating buyers’ satisfaction degrees to determine a constraint satisfaction layer.**

Buyers’ satisfaction degree $\beta_{ijq}$ is calculated based on the formula system presented in Subsubsection 3.1.2.4. The results of buyers’ satisfaction degree are presented in Table 5.3. Furthermore, the results of a broker’s turnovers and benefits are presented in Tables 5.4 and 5.5, respectively.

### Table 5.3: Buyers’ satisfaction degree $\beta_{ijq}$ for allocation pairs

<table>
<thead>
<tr>
<th></th>
<th>$S_1$</th>
<th>$S_2$</th>
<th>$S_3$</th>
<th>$S_4$</th>
<th>$S_5$</th>
<th>$S_6$</th>
<th>$S_7$</th>
<th>$S_8$</th>
<th>$S_9$</th>
<th>$S_{10}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_1$</td>
<td>0.875</td>
<td>-1</td>
<td>0.830</td>
<td>0.855</td>
<td>0.879</td>
<td>0.950</td>
<td>1</td>
<td>0.950</td>
<td>0.824</td>
<td>0.900</td>
</tr>
<tr>
<td>$B_2$</td>
<td>-1</td>
<td>0.796</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
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<tr>
<td>$B_3$</td>
<td>0.943</td>
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<td>0.743</td>
<td>0.754</td>
<td>0.765</td>
<td>0.997</td>
<td>1</td>
<td>0.977</td>
<td>0.920</td>
<td>0.954</td>
</tr>
<tr>
<td>$B_4$</td>
<td>0.914</td>
<td>-1</td>
<td>0.830</td>
<td>0.84</td>
<td>0.864</td>
<td>0.966</td>
<td>1</td>
<td>0.966</td>
<td>0.878</td>
<td>0.931</td>
</tr>
<tr>
<td>$B_5$</td>
<td>0.939</td>
<td>-1</td>
<td>0.773</td>
<td>0.785</td>
<td>0.797</td>
<td>0.976</td>
<td>1</td>
<td>0.976</td>
<td>0.914</td>
<td>0.952</td>
</tr>
<tr>
<td>$B_6$</td>
<td>0.956</td>
<td>-1</td>
<td>0.735</td>
<td>0.744</td>
<td>0.752</td>
<td>0.982</td>
<td>1</td>
<td>0.982</td>
<td>0.939</td>
<td>0.965</td>
</tr>
<tr>
<td>$B_7$</td>
<td>0.941</td>
<td>-1</td>
<td>0.793</td>
<td>0.805</td>
<td>0.816</td>
<td>0.976</td>
<td>1</td>
<td>0.976</td>
<td>0.917</td>
<td>0.953</td>
</tr>
<tr>
<td>$B_8$</td>
<td>0.913</td>
<td>-1</td>
<td>0.858</td>
<td>0.875</td>
<td>0.892</td>
<td>0.965</td>
<td>1</td>
<td>0.965</td>
<td>0.876</td>
<td>0.930</td>
</tr>
<tr>
<td>$B_9$</td>
<td>0.883</td>
<td>-1</td>
<td>0.835</td>
<td>0.858</td>
<td>0.881</td>
<td>0.953</td>
<td>1</td>
<td>0.953</td>
<td>0.934</td>
<td>0.906</td>
</tr>
<tr>
<td>$B_{10}$</td>
<td>0.943</td>
<td>-1</td>
<td>0.794</td>
<td>0.806</td>
<td>0.817</td>
<td>-1</td>
<td>1</td>
<td>0.977</td>
<td>0.919</td>
<td>0.955</td>
</tr>
</tbody>
</table>

### Table 5.4: A broker’s turnovers for allocation pairs

<table>
<thead>
<tr>
<th></th>
<th>$S_1$</th>
<th>$S_2$</th>
<th>$S_3$</th>
<th>$S_4$</th>
<th>$S_5$</th>
<th>$S_6$</th>
<th>$S_7$</th>
<th>$S_8$</th>
<th>$S_9$</th>
<th>$S_{10}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_1$</td>
<td>3400</td>
<td>0</td>
<td>2800</td>
<td>3100</td>
<td>3200</td>
<td>3100</td>
<td>3400</td>
<td>3200</td>
<td>3100</td>
<td>3500</td>
</tr>
<tr>
<td>$B_2$</td>
<td>2700</td>
<td>0</td>
<td>2100</td>
<td>2325</td>
<td>2550</td>
<td>2400</td>
<td>2625</td>
<td>2625</td>
<td>2550</td>
<td>2625</td>
</tr>
<tr>
<td>$B_3$</td>
<td>2700</td>
<td>0</td>
<td>2100</td>
<td>2325</td>
<td>2550</td>
<td>2400</td>
<td>2625</td>
<td>2625</td>
<td>2550</td>
<td>2625</td>
</tr>
<tr>
<td>$B_4$</td>
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<td>1650</td>
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<td>1925</td>
<td>1848</td>
<td>1925</td>
<td>1980</td>
<td>1870</td>
<td>1980</td>
</tr>
<tr>
<td>$B_5$</td>
<td>2700</td>
<td>0</td>
<td>2100</td>
<td>2325</td>
<td>2550</td>
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<td>2625</td>
</tr>
<tr>
<td>$B_6$</td>
<td>1800</td>
<td>0</td>
<td>1500</td>
<td>1600</td>
<td>1750</td>
<td>1680</td>
<td>1750</td>
<td>1800</td>
<td>1700</td>
<td>1800</td>
</tr>
<tr>
<td>$B_8$</td>
<td>720</td>
<td>0</td>
<td>640</td>
<td>660</td>
<td>700</td>
<td>672</td>
<td>700</td>
<td>720</td>
<td>680</td>
<td>740</td>
</tr>
<tr>
<td>$B_{10}$</td>
<td>3400</td>
<td>0</td>
<td>2800</td>
<td>3100</td>
<td>3200</td>
<td>3100</td>
<td>3400</td>
<td>3200</td>
<td>3100</td>
<td>3500</td>
</tr>
</tbody>
</table>
Table 5.5: A broker’s benefits for allocation pairs

<table>
<thead>
<tr>
<th></th>
<th>$S_1$</th>
<th>$S_2$</th>
<th>$S_3$</th>
<th>$S_4$</th>
<th>$S_5$</th>
<th>$S_6$</th>
<th>$S_7$</th>
<th>$S_8$</th>
<th>$S_9$</th>
<th>$S_{10}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_1$</td>
<td>340</td>
<td>0</td>
<td>84</td>
<td>217</td>
<td>112</td>
<td>248</td>
<td>374</td>
<td>384</td>
<td>77.5</td>
<td>315</td>
</tr>
<tr>
<td>$B_2$</td>
<td>0</td>
<td>8.5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$B_3$</td>
<td>270</td>
<td>0</td>
<td>63</td>
<td>162.75</td>
<td>89.25</td>
<td>192</td>
<td>288.75</td>
<td>315</td>
<td>63.75</td>
<td>236.25</td>
</tr>
<tr>
<td>$B_4$</td>
<td>270</td>
<td>0</td>
<td>63</td>
<td>162.75</td>
<td>89.25</td>
<td>192</td>
<td>288.75</td>
<td>315</td>
<td>63.75</td>
<td>236.25</td>
</tr>
<tr>
<td>$B_5$</td>
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<td>0</td>
<td>49.5</td>
<td>123.2</td>
<td>67.375</td>
<td>147.84</td>
<td>211.75</td>
<td>237.6</td>
<td>46.75</td>
<td>178.2</td>
</tr>
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<td>$B_6$</td>
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<td>0</td>
<td>63</td>
<td>162.75</td>
<td>89.25</td>
<td>192</td>
<td>288.75</td>
<td>315</td>
<td>63.75</td>
<td>236.25</td>
</tr>
<tr>
<td>$B_7$</td>
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<td>0</td>
<td>45</td>
<td>112</td>
<td>61.25</td>
<td>134.4</td>
<td>192.5</td>
<td>216</td>
<td>42.5</td>
<td>162</td>
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<tr>
<td>$B_8$</td>
<td>72</td>
<td>0</td>
<td>19.2</td>
<td>46.2</td>
<td>24.5</td>
<td>53.76</td>
<td>77</td>
<td>86.4</td>
<td>17</td>
<td>66.6</td>
</tr>
<tr>
<td>$B_9$</td>
<td>340</td>
<td>0</td>
<td>84</td>
<td>217</td>
<td>112</td>
<td>248</td>
<td>374</td>
<td>384</td>
<td>77.5</td>
<td>315</td>
</tr>
<tr>
<td>$B_{10}$</td>
<td>36</td>
<td>0</td>
<td>9.6</td>
<td>23.1</td>
<td>12.25</td>
<td>26.88</td>
<td>38.5</td>
<td>43.2</td>
<td>8.5</td>
<td>33.3</td>
</tr>
</tbody>
</table>

Step 3: Generating a multi-objective function related to the satisfaction degrees of all buyers, a broker’s turnovers and a broker’s benefits, and then solve the multi-objective function using the ideal point method.

According to the ideal point method, the maximal satisfaction degree of all buyers ($f_1^*$) is 9.184, a broker’s maximal turnover ($f_2^*$) is AUD 20,210 and a broker’s maximal benefit ($f_3^*$) is AUD 1,686.65. To maximize a broker’s turnover, the satisfaction degree of all buyers and a broker’s profit, a broker generates a single-objective function (refer to Subsection 5.2.5) as follows:

$$\text{Min} F = \alpha_1 \frac{9.184 - f_1}{9.184} + \alpha_2 \frac{20,210 - f_2}{20,210} + \alpha_3 \frac{1,686.65 - f_3}{1,686.65}$$  \hspace{1cm} (5.15)

Depending on the specific purposes, the broker will assign $\alpha_1$, $\alpha_2$ and $\alpha_3$ with different values. Assume that there are three different objective vectors $\vec{\alpha}_A$, $\vec{\alpha}_B$ and $\vec{\alpha}_C$ (named as Case A, Case B, and Case C). The optimal allocation pairs between buyers and sellers are obtained by using the proposed approach shown in Table 5.6.
5.3. A Case Study

<table>
<thead>
<tr>
<th>No.</th>
<th>Case A</th>
<th>Case B</th>
<th>Case C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$B_1 \leftrightarrow S_7$</td>
<td>$B_1 \leftrightarrow S_7$</td>
<td>$B_1 \leftrightarrow S_7$</td>
</tr>
<tr>
<td>2</td>
<td>$B_2 \leftrightarrow S_2$</td>
<td>$B_2 \leftrightarrow S_2$</td>
<td>$B_2 \leftrightarrow S_2$</td>
</tr>
<tr>
<td>3</td>
<td>$B_3 \leftrightarrow S_8$</td>
<td>$B_3 \leftrightarrow S_1$</td>
<td>$B_3 \leftrightarrow S_8$</td>
</tr>
<tr>
<td>4</td>
<td>$B_4 \leftrightarrow S_5$</td>
<td>$B_4 \leftrightarrow S_8$</td>
<td>$B_4 \leftrightarrow S_6$</td>
</tr>
<tr>
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<td>$B_5 \leftrightarrow S_6$</td>
<td>$B_5 \leftrightarrow S_4$</td>
</tr>
<tr>
<td>6</td>
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<td>$B_6 \leftrightarrow S_9$</td>
<td>$B_6 \leftrightarrow S_1$</td>
</tr>
<tr>
<td>7</td>
<td>$B_7 \leftrightarrow S_6$</td>
<td>$B_7 \leftrightarrow S_5$</td>
<td>$B_7 \leftrightarrow S_5$</td>
</tr>
<tr>
<td>8</td>
<td>$B_8 \leftrightarrow S_3$</td>
<td>$B_8 \leftrightarrow S_4$</td>
<td>$B_8 \leftrightarrow S_3$</td>
</tr>
<tr>
<td>9</td>
<td>$B_9 \leftrightarrow S_4$</td>
<td>$B_9 \leftrightarrow S_{10}$</td>
<td>$B_9 \leftrightarrow S_{10}$</td>
</tr>
<tr>
<td>10</td>
<td>$B_{10} \leftrightarrow S_9$</td>
<td>$B_{10} \leftrightarrow S_3$</td>
<td>$B_{10} \leftrightarrow S_9$</td>
</tr>
<tr>
<td></td>
<td>$f_1 = 9.184$</td>
<td>$f_1 = 9.016$</td>
<td>$f_1 = 8.984$</td>
</tr>
<tr>
<td></td>
<td>$f_2 = 19.865$</td>
<td>$f_2 = 20.210$</td>
<td>$f_2 = 19.965$</td>
</tr>
<tr>
<td></td>
<td>$f_3 = 1.614$</td>
<td>$f_3 = 1.611.1$</td>
<td>$f_3 = 1.686.65$</td>
</tr>
</tbody>
</table>

Based on the results from Table 5.6, ten optimal allocation pairs are found in Case A ($\alpha_A = (0.8, 0.1, 0.1)$), Case B ($\alpha_B = (0.1, 0.8, 0.1)$) and Case C ($\alpha_C = (0.1, 0.1, 0.8)$). A broker’s benefit ($f_3 = AUD1,686.65$) in Case C are more than a broker’s benefit in Case B ($f_3 = AUD1,611.1$) and Case A ($f_3 = AUD1,614$) because weight in Case C ($\alpha_3 = 0.8$) is more than weight in Case B ($\alpha_3 = 0.1$) and Case C ($\alpha_3 = 0.1$). It means that a broker’s purpose in Case C focuses on a broker’s benefit. Similarly, the satisfaction degree of all buyers in Case A ($f_1 = 9.184$) is more than that in Case B ($f_1 = 9.016$) and Case C ($f_1 = 8.984$) because weight in Case A ($\alpha_1 = 0.8$) is more than weight in Case B ($\alpha_1 = 0.1$) and Case C ($\alpha_1 = 0.1$). In addition, a broker’s turnover in Case B ($f_2 = 20.210$) is more than a broker’s turnover in Case A ($f_2 = 19.865$) and Case C ($f_2 = 19.965$) because weight in Case B ($\alpha_2 = 0.8$) is more than weight in Case A ($\alpha_2 = 0.1$) and Case C ($\alpha_2 = 0.1$). In summary, a Pareto optimal allocation solution is achieved based on weight of three objective functions ($f_1$, $f_2$ and $f_3$). Thus, depending on specific situations in market environments, a broker should consider selecting the weight of each objective function reasonably to achieve a broker’s goals.
5.4 Experiment

The experiment with four scenarios is conducted from different perspectives. Experimental results in this section are presented and analysed to evaluate the proposed allocation approach’s performance. The experiment mainly focuses on the test of the maximization of the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit through trade allocation. The experimental setting is presented in Subsection 5.4.1 and the experimental results are evaluated and analyzed in four different experimental scenarios in Subsection 5.4.2.

5.4.1 Experimental setting

In this experiment, the artificially generated dataset include 100 buyers and 100 sellers. Each buyer considers buying computers with model-ctpplex 960 with five attributes, i.e., price, quantity, payment method, delivery time and warranty time. Similarly, each seller considers selling computers with six attributes, i.e., price, quantity, payment method, delivery time, warranty time and discount rates. Based on the artificial dataset, 25 times are carried out by choosing randomly from 100 buyers and 100 sellers. Each time includes 25 buyers and 25 sellers. Four different scenarios in Table 5.7 are tested through the proposed allocation approach. A broker is to maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit in Scenario 1, 2 and 3, respectively. In Scenario 4, a broker is to maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit.
Table 5.7: Experimental scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Test purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>To maximize the satisfaction degree of all buyers</td>
</tr>
<tr>
<td>2</td>
<td>To maximize a broker’s turnover</td>
</tr>
<tr>
<td>3</td>
<td>To maximize a broker’s benefit</td>
</tr>
<tr>
<td>4</td>
<td>To maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit</td>
</tr>
</tbody>
</table>

5.4.2 Experimental results and analysis

In Scenario 1, a broker uses the proposed approach to maximize the satisfaction degree of all buyers through trade allocation. Based on general principle, the satisfaction degree of all buyers from maximizing the satisfaction degree of all buyers is more than that from maximizing a broker’s turnover and maximizing a broker’s benefit. The test results are shown in Table 5.8. From the table, we can see that the average satisfaction degree of buyers from maximizing the satisfaction degree of all buyers is 17.925, which is more than that from maximizing a broker’s turnover (17.209) and maximizing a broker’s benefit (17.109). The results demonstrate the good performance of the proposed approach. Furthermore, the maximal satisfaction degree of buyers from maximizing the satisfaction degree of all buyers is 20.126 and the minimal satisfaction degree of buyers from maximizing the satisfaction degree of all buyers is 14.174. The standard deviation of the satisfaction degrees of buyers from maximizing the satisfaction degree of all buyers is 1.19, which is less than that from maximizing a broker’s turnover and maximizing a broker’s benefit. The results indicate that the satisfaction degrees of buyers from maximizing the satisfaction degree of all buyers is less changeable than that from maximizing a broker’s turnover and maximizing a broker’s benefit through 25 times selected from the artificial dataset.
Table 5.8: Results of Scenario 1 (STD-Standard deviation)

<table>
<thead>
<tr>
<th></th>
<th>The satisfaction degree of all buyers from maximizing the satisfaction degree of all buyers</th>
<th>The satisfaction degree of all buyers from maximizing a broker’s turnover</th>
<th>The satisfaction degree of all buyers from maximizing a broker’s benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>17.925</td>
<td>17.209</td>
<td>17.109</td>
</tr>
<tr>
<td>Min</td>
<td>14.174</td>
<td>13.32</td>
<td>13.139</td>
</tr>
<tr>
<td>Max</td>
<td>20.126</td>
<td>19.638</td>
<td>19.557</td>
</tr>
<tr>
<td>STD</td>
<td>1.19</td>
<td>1.20</td>
<td>1.22</td>
</tr>
</tbody>
</table>

In Scenario 2, a broker uses the proposed approach to maximize a broker’s turnover through trade allocation. Based on the general principle, a broker’s turnover from maximizing a broker’s turnover is normally more than that from maximizing the satisfaction degree of all buyers and maximizing a broker’s benefit. Based on the results of Table 5.9, a broker’s average turnover from maximizing a broker’s turnover is AUD 35,484, which is more than that from maximizing the satisfaction degree of all buyers (AUD 30,601) and maximizing a broker’s benefit (AUD 33,721). The results demonstrate the good performance of the proposed approach. Furthermore, a broker’s maximal turnover from maximizing a broker’s turnover is AUD 41,524 and a broker’s minimal turnover from maximizing a broker’s turnover is AUD 28,099. The standard deviation of a broker’s turnover from maximizing a broker’s turnover is AUD 3,231, which is more than that from maximizing a broker’s benefit and is also less than that from maximizing the satisfaction degree of all buyers. This also indicates that a broker’s turnover from maximizing a broker’s turnover is more changeable than that from maximizing a broker’s benefit through 25 times selected from the artificial dataset.
In Scenario 3, a broker uses the proposed approach to maximize a broker’s benefits through trade allocation. From the general principle, a broker’s benefit from maximizing a broker’s benefit should be more than that from maximizing the satisfaction degree of all buyers and maximizing a broker’s turnover. Based on the results of Table 5.10, a broker’s average benefit from maximizing a broker’s benefit is AUD 4,319, which is more than that from maximizing the satisfaction degree of all buyers (2,968) and maximizing a broker’s turnover (AUD 3,537). The results demonstrate the good performance of the proposed approach. Furthermore, a broker’s maximal benefit from maximizing a broker’s benefit is AUD 6,673 and a broker’s minimal benefit from maximizing a broker’s benefit is AUD 2,571. The standard deviation of a broker’s benefit from maximizing a broker’s benefit is AUD 939.44, which is more than that from maximizing the satisfaction degree of all buyers and maximizing a broker’s benefit. The results also approve that a broker’s benefit from maximizing a broker’s benefit is more changeable than that from maximizing the satisfaction degree of all buyers and maximizing a broker’s turnover through 25 times selected from the artificial dataset.

<table>
<thead>
<tr>
<th></th>
<th>A broker’s turnover from maximizing a broker’s turnover</th>
<th>A broker’s turnover from maximizing the satisfaction degree of all buyers</th>
<th>A broker’s turnover from maximizing a broker’s benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>35,484</td>
<td>30,601</td>
<td>33,721</td>
</tr>
<tr>
<td>Min</td>
<td>28,099</td>
<td>22,210</td>
<td>26,665</td>
</tr>
<tr>
<td>Max</td>
<td>41,524</td>
<td>39,069</td>
<td>39,867</td>
</tr>
<tr>
<td>STD</td>
<td>3,231</td>
<td>3,518</td>
<td>3,223</td>
</tr>
</tbody>
</table>
Finally, a broker uses the proposed approach to allocate buyers’ requirements to sellers’ offers so that a broker can maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit. Assume that \( \alpha_1, \alpha_2 \) and \( \alpha_3 \) are equally chosen and equal to 0.333. The normalized results of the average, min, max, range and standard deviation are presented in Table 5.11. The experimental results are suitable for the proposed approach. In this case, a broker cannot know who will achieve maximal utility because \( \alpha_1, \alpha_2 \) and \( \alpha_3 \) are equally chosen. In reality, the broker can change values of \( \alpha_1 \) or \( \alpha_2 \) or \( \alpha_3 \) to achieve a broker’s the goals.

### Table 5.10: Results of Scenario 3 (STD-Standard deviation)

<table>
<thead>
<tr>
<th></th>
<th>A broker’s benefit from maximizing a broker’s benefit</th>
<th>A broker’s benefit from maximizing the satisfaction degree of all buyers</th>
<th>A broker’s benefit from maximizing a broker’s turnover</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>4,319</td>
<td>2,968</td>
<td>3,537</td>
</tr>
<tr>
<td>Min</td>
<td>2,571</td>
<td>1,979</td>
<td>1,790</td>
</tr>
<tr>
<td>Max</td>
<td>6,673</td>
<td>4,681</td>
<td>5,632</td>
</tr>
<tr>
<td>STD</td>
<td>939.44</td>
<td>719.93</td>
<td>870.54</td>
</tr>
</tbody>
</table>

### Table 5.11: Normalized results of Scenario 4 (STD-Standard deviation)

<table>
<thead>
<tr>
<th></th>
<th>The satisfaction degree of all buyers</th>
<th>A broker’s turnover</th>
<th>A broker’s benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>0.97</td>
<td>0.96</td>
<td>0.98</td>
</tr>
<tr>
<td>Min</td>
<td>0.94</td>
<td>0.90</td>
<td>0.91</td>
</tr>
<tr>
<td>Max</td>
<td>0.99</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>STD</td>
<td>0.016</td>
<td>0.037</td>
<td>0.024</td>
</tr>
</tbody>
</table>

In summary, the proposed approach can help a broker to allocate buyers’ requirements to sellers’ offers to achieve a broker’s the goals. Depending on market situations, a broker will use the proposed model to achieve its specific goals such as maximizing the satisfaction degree of all buyers or a broker’s turnover or a broker’s benefit.
5.5 Discussion

The proposed approach in this chapter was proved to be a useful approach for trade allocation in market environments through the case study and the experimental evaluations. The reasons for this include (i) a formula system, proposed to calculate buyers’ satisfaction degrees, a broker’s turnovers and a broker’s benefits; (ii) a multi-objective function and a set of constraints, generated to maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit; and (iii) the ideal point method, used to solve the multi-objective function to a Pareto optimal allocation solution.

5.6 Summary

In this chapter, the broker-based multi-objective function approach for trade allocation in market environments was proposed. In particular, the multi-objective function related to the satisfaction degree of all buyers, a broker’s turnovers and a broker’s benefits was defined. The multi-objective function can help a broker to maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit through trade allocation. The performance of the proposed approach was demonstrated and analysed through the case study and experiments so as to achieve Objective 4 of this thesis.
Chapter 6

A Broker-Based Relaxation Method for Buyer’s Constraints in Trade Allocation in Market Environments

Rapid growth of Internet and network technologies made many sellers arise across the globe to satisfy the needs of buyers in market environments. The increasing number of sellers in market environments results in difficulties for a buyer to select a potential seller based on a buyer’s requirements. To solve the above difficulties, a broker-based approach is proposed in this chapter to select a potential seller from different sellers to satisfy a buyer’s requirements by using a buyer’s constraint relaxation when a broker cannot find any seller to satisfy a buyer’s requirements. This approach includes three components: a seller selection, a constraint relaxation, and a decision making.

This chapter is organized as follows. The problem description and definitions are presented in Section 6.1, and a broker-based trade allocation approach to select a potential seller is introduced in Section 6.2. In Section 6.3, the proposed approach is experimentally evaluated, and a brief discussion is given in Section 6.4. This chapter is summarised in Section 6.5.
6.1 Problem Description and Definitions

In this chapter, the main purpose of trade allocation through a broker agent is to select a potential seller agent to satisfy a buyer agent’s requirements with assuming that seller agents cannot make any concession to a buyer agent. Furthermore, a buyer agent’s constraint relaxation in the buyer agent’s requirements is employed when a broker agent cannot seek any seller agent to satisfy the buyer agent’s requirements.

There are multiple attributes in a buyer agent’s requirements and seller agents’ offers but the attributes do not need to divide into two categories, i.e., attributes with hard constraints and attributes with soft constraints. Furthermore, we assume that a buyer agent and multiple seller agents work in a broker agent’s trade allocation processes and the priority level of attributes in the buyer agent’s requirements needs to be considered. Thus, the buyer agent’s requirements are defined again as follows.

Definition 6.1.1. A buyer agent $B$ is defined as a 3-tuple $B = <REQ, \alpha, \lambda>$, where $REQ$ indicates $B$’s requirements, $\alpha$ is the acceptability threshold of $B$, and $\lambda$ is the concession threshold of $B$.

Definition 6.1.2. $B$’s requirements are represented by $REQ$ and are defined by the following format.

$$REQ = \begin{pmatrix} A_1 & A_2 & \ldots & A_q \\ C_1 & C_2 & \ldots & C_q \\ W_1 & W_2 & \ldots & W_q \end{pmatrix},$$

(6.1)

where $A_q$ indicates the $q^{th}$ attribute name, $C_i \ (i = 1, 2, \ldots, q)$ is a constraint value of $A_i$ and $W_i$ is a priority value of $A_i$, $1 \leq W_i \leq q$. $W_i = 1$ indicates the lowest priority and $W_i = q$ indicates the highest priority.

Seller agents in this chapter offer a bonus program to buyer agents so that seller agents would like to encourage buyer agents to buy their commodities. Thus, a seller agent is defined again as follow.
Definition 6.1.3. A seller agent $S_j (j = 1, 2, \ldots, m)$ is defined as a 3-tuple $S_j =$\< $\langle ID_j, OFF_j, BO_j \rangle$, where $ID_j$ is $S_j$'s identification, $OFF_j$ indicates $S_j$'s offers and is presented by Definition 3.3, and $BO_j$ is a bonus value which $S_j$ offers to a buyer agent.

Seller agents offer a reward program to a broker agent if seller agents' commodities are bought by a buyer agent through a broker agent. Thus, a broker agent is presented by Definitions 5.1.1 and 5.1.2.

Based on trading information of a buyer agent's requirements and seller agents' offers submitted to a broker agent, the problem is that a broker agent is to find the potential seller agent to satisfy a buyer agent's requirements under the consideration of seller agents' reward and bonus program, and a buyer agent's constraint relaxation. The broker-based trade allocation approach is proposed and presented in Section 6.2.

6.2 A Proposed Broker-Based Trade Allocation Approach

Trade allocation in this proposed approach includes the three main components: (i) the seller selection; (ii) the relaxation with constraints; and (iii) the decision making. In this section, the principle of the whole trade allocation process is introduced in Subsection 6.2.1. Then the three main components are presented in details in other three subsections, respectively.

6.2.1 The principle of the whole trade allocation process

6.2.1.1 Background

A trade allocation process between a buyer agent and seller agents is conducted through a broker agent to achieve an agreement by using certain strategies. In this
6.2. A Proposed Broker-Based Trade Allocation Approach

The proposed approach, a buyer agent utilizes the relaxation with constraints to change its requirements when a broker agent cannot find out any seller to satisfy a buyer’s requirements. The broker agent relies on a reward from seller agents to select the most suitable seller agent as per the buyer agent’s requirements. Seller agents use a bonus program to attract the buyer agent to purchase their commodities. The principle of the whole trading process between a buyer agent and seller agents through a broker agent in the proposed approach is presented in Figure 6.1.

**Figure 6.1: Diagram of the principle**

**Step 1:** The buyer agent selects a constraint of attributes with the highest priority from its requirements and sends the constraint to the broker agent. Based on the buyer agent’s constraints, the broker agent searches seller agents as per the buyer’s requirements. If the broker agent cannot find any seller agent, the broker agent checks whether the constraints of the buyer can be relaxed. If the relaxation is not applied, the...
trading process is terminated. Otherwise, the buyer agent selects a relaxed constraint and sends it to the broker agent again. This procedure will be repeated until the broker agent finds seller agents to satisfy the constraints of the buyer or the trading is terminated.

**Step 2:** Once the broker agent finds suitable seller agents, it will select the most suitable seller agent based on the rewards of the suitable seller agents and send the selected seller agent to the buyer agent. The buyer agent checks whether the most suitable seller agent satisfies the buyer agent's other constraints. If there still exists constraints, the buyer agent selects the next highest priority constraints and sends it to the broker agent again, and the process goes to Step 1. Otherwise, the buyer agent evaluates whether the most suitable seller agent is acceptable.

**Step 3:** If the buyer agent accepts the most suitable seller agent, the trading makes a deal. Otherwise, the buyer agent requires the broker agent to check whether the most suitable seller agent can offer a bonus. If the most suitable seller agent does not offer a bonus, the trading process between the buyer agent and the broker agent is terminated. Otherwise, the buyer agent evaluates the most suitable seller agent with a bonus again to make a decision.
6.2.1.2 Formal description

A formal representation of a broker’s trade allocation processes for a potential seller selection is described by Algorithm 4.

Algorithm 4: A broker’s trade allocation processes for a potential seller selection

Input: \( S = \{ S_j \mid j = 1, m \} \), \( B = < ID, REQ, \alpha, \lambda > \). Threshold \( \alpha, \lambda \in [0, 1] \);

Output: Return the decision of making a deal or fail;

Initialization: Initialize submitted-constraint-set \( C^* \) and constraint set \( C \) to \( \emptyset \);

begin

for \( \forall i (i = 1, q) \) in \( REQ \) do

\( C_i \leftarrow \) determine(\( f(C_i) \geq \alpha \));

\( C \leftarrow C \cup \{ C_i \} \);

\( C_{\text{new}} \leftarrow \text{argmax}_C(W_i) \);

\( BR \leftarrow \text{send}(C_{\text{new}}) \);

while \( \neg \text{stopCriterion()} \) do

\( C^* = C^* \cup \{ C_{\text{new}} \} \);

\( S' \leftarrow \text{find}(C^*, S) \);

if \( S' \neq \text{Null} \) then

\( B \leftarrow \text{send}(S') \);

if check(\( C^*, S' \)) and evaluate(\( C^*, S', 0 \)) then

success();

else if check(\( C^*, S' \)) and \( \neg \) evaluate(\( C^*, S', 0 \)) then

else if \( B \leftarrow \text{offer-bonus}(S') \) and evaluate(\( C^*, S', BO \)) then

success();

else fail();

else

\( C_{\text{new}} \leftarrow \text{argmax}_{C \setminus C_{\text{new}}}(W_i) \);

\( BR \leftarrow \text{send}(C_{\text{new}}) \);

else

if \( B \leftarrow \text{relax}(C^*) \) then

\( B \leftarrow \text{update}(REQ) \);

Go to line 5;

else fail();

end

Algorithm 4 shows a broker’s trade allocation processes between a buyer agent \( B \) and a set of seller agents \( S \) to select a potential seller agent to satisfy \( B \)'s requirements. The input of Algorithm 4 is a set of seller agents \( S \), \( B \)'s requirements, an acceptability threshold and a concession threshold (Line 1). The output of Algorithm 4 can be either ‘deal’ or ‘fail’ (Line 2).
First, $B$ uses its acceptability threshold to determine each constraint value of an attribute in $REQ$ (Lines 6-7). Then $B$ selects a constraint of an attribute in $REQ$ with the highest priority and sends it to $BR$ (Lines 8-9). $BR$ finds the most suitable seller agent to satisfy $B$'s requirements (Line 12) by using ‘find’ function described in Subsection 6.2.2. The results from $BR$ are presented as follows.

If $BR$ finds the most suitable seller agent, $BR$ sends the most suitable seller agent to $B$ (Line 14). Then, $B$ verifies whether the most suitable seller agent satisfies $B$’s requirements and evaluation (Line 15) by using ‘evaluation’ function described in Subsection 6.2.4. There are three cases in this situation. (i) If $B$’s requirements and evaluation are acceptable, a deal is made (Line 16). (ii) If $B$’s requirements are satisfied but $B$’s evaluation is not acceptable, $B$ verifies whether the most suitable seller agent offers a bonus. If the most suitable seller agent offers the bonus and $B$’s evaluation with a bonus is acceptable, the trading process between $B$ and $BR$ makes a deal (Lines 17-18). Otherwise, the trading process between $B$ and $BR$ is terminated (Line 19). (iii) If $B$’s requirements are not satisfied, $B$ selects a constraint of attributes with the next highest priority in the $REQ$ and sends it to $BR$ (Lines 21-22). Thus, $BR$ has to find suitable sellers again with the new constraints.

If $BR$ does not find any suitable seller agent, which satisfies $B$’s requirements, $B$ has to relax its constraints in its requirements (Line 24) by using ‘relaxation’ function described in Subsection 6.2.3. In particular, if a constraint of an attribute is relaxed by $B$, $B$ has to update its $REQ$ and the algorithm runs again with the updated $REQ$ (Lines 25-26). Otherwise, the trading process is terminated (Line 27).

The three major components of the proposed approach are introduced in detail in the following three subsections, respectively.
6.2.2 Seller selection

When a broker agent receives the buyer agent’s requirements, the broker agent starts to find the most suitable seller agent for the buyer agent. The ‘find’ function, displayed in Line 12 of Algorithm 4, is shown in Algorithm 5 as follows.

<table>
<thead>
<tr>
<th>Algorithm 5: Find($C^*$, $S$)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1</strong> Input: $S = {S_j \mid j = 1, m}$, a set of constraints $C^*$;</td>
</tr>
<tr>
<td><strong>2</strong> Output: return the most suitable seller or null;</td>
</tr>
<tr>
<td><strong>3</strong> begin</td>
</tr>
<tr>
<td><strong>4</strong> foreach $S_j$ in $S$ do</td>
</tr>
<tr>
<td><strong>5</strong> add ← true;</td>
</tr>
<tr>
<td><strong>6</strong> foreach $C_i$ in $C^*$ do</td>
</tr>
<tr>
<td><strong>7</strong> if $f(S_j, C) \leq f(C_i)$ then</td>
</tr>
<tr>
<td><strong>8</strong> add ← false;</td>
</tr>
<tr>
<td><strong>9</strong> if add = true then</td>
</tr>
<tr>
<td><strong>10</strong> $SS \leftarrow SS \cup {S_j}$;</td>
</tr>
<tr>
<td><strong>11</strong> if $SS$ is not $\emptyset$ then</td>
</tr>
<tr>
<td><strong>12</strong> return $\text{argmax}_{S_j \in SS}(S_j.r)$;</td>
</tr>
<tr>
<td><strong>13</strong> else</td>
</tr>
<tr>
<td><strong>14</strong> return Null;</td>
</tr>
</tbody>
</table>

Algorithm 5 shows how to select the most suitable seller agent based on a set of sellers $S$, a set of constraints called $C^*$. The input of Algorithm 5 is a set of sellers and a set of constraints, which are submitted to $BR$ during the selection stage (Line 1). The output of the algorithm can be either ‘the most suitable seller’ or ‘null’ (Line 2). First, $BR$ selects suitable sellers, which satisfy $B$’s requirements (Lines 4-10). Then, the most suitable seller agent is selected from the suitable sellers based on a maximal reward value from seller agents. If $BR$ finds the most suitable seller agent, $BR$ sends it to $B$ (Line 12). Otherwise, $BR$ cannot find any seller agent which satisfies $B$’s requirements (Line 14).
6.2.3 A constraint relaxation

If $BR$ cannot find any $S_j$ to satisfy $B$’s requirements, $BR$ requests $B$ to consider relaxing its constraints. The ‘relaxation’ function, displayed in Line 24 of Algorithm 4, will be activated. The relaxation function is shown in Algorithm 6.

Algorithm 6 shows how to carry out the relaxation based on a set of constraints called $C^*$. The input of Algorithm 6 is a set of constraints and the concession threshold $\lambda$, which are submitted to $BR$ (Line 1).

\begin{algorithm}
\caption{Relax($C^*$)}
\begin{algorithmic}[1]
\State \textbf{Input:} a set of constraints $C^*$, the concession threshold $\lambda$;
\State \textbf{Output:} return a selected constraint for a relaxation or null ;
\begin{algorithmic}[1]
\State \textbf{begin}
\State \quad $k \leftarrow \text{argmax}_{REQ}(W_i)$;
\State \quad $l \leftarrow \infty$;
\State \quad $C^k \leftarrow \text{Null}$;
\State \quad \textbf{foreach} $C$ in $C^*$ \textbf{do}
\State \quad \quad \textbf{if} $f(C^R) \geq \lambda$ \textbf{then}
\State \quad \quad \quad $d \leftarrow f(C_i) - f(C^R)$;
\State \quad \quad \quad $p \leftarrow W_i/k$;
\State \quad \quad \quad \textbf{if} $d*p < l$ \textbf{then}
\State \quad \quad \quad \quad $l \leftarrow d*p$;
\State \quad \quad \quad \quad $C^k \leftarrow C_i$;
\State \quad \quad \quad \textbf{return} $C^k$;
\end{algorithmic}
\State \quad \textbf{end};
\end{algorithmic}
\end{algorithm}

The output of the algorithm can be either ‘a selected constraint for the relaxation’ or ‘false of the relaxation’ (Line 2). After determining the highest priority in $REQ$ (Line 4), $B$ checks whether each constraint of an attribute in $C^*$ is satisfied for the relaxation. This means that $B$ determines the degrees of satisfaction for the relaxation of each constraint. When constraint $C$ of an attribute is decreased to the next highest satisfaction degree, the decreased constraint is named $C^R$. If a satisfaction degree of a relaxed constraint $f(C^R)$ is less than its concession threshold $\lambda$, the relaxation of the constraint is not permitted. Otherwise, the constraint is considered for a relaxation. The process of the relaxation is illustrated as follows. First, $B$ calculates a decreased
satisfaction degree (Line 9) and a relative priority degree (Line 10) for each constraint of an attribute in $C^*$. Then, a lost benefit value for each constraint after relaxation is calculated from a decreased satisfaction degree and a relative priority degree. Based on a lost benefit value for each relaxed constraint, $B$ selects a constraint for a relaxation with the smallest lost benefit to $B$ (Lines 12-13).

### 6.2.4 Decision making

The ‘evaluation’ function, displayed in Line 15 of Algorithm 4, is shown in Algorithm 7. Algorithm 7 permits $B$ to evaluate the most suitable seller agent based on a set of constraints in $B$’s requirements. The input of Algorithm 7 is trading information of the most suitable seller agent, $B$’s updated requirements and the bonus from the most suitable seller agent (Line 1).

**Algorithm 7: Evaluate($C^*, S', BO$)**

1. **Input**: constraint set $C^*$, the most suitable seller $S'$, and a bonus $BO$;
2. **Output**: return true if satisfaction or false if unsatisfaction;
3. begin
4. $k \leftarrow \text{argmax}_{REQ}(W_i)$;
5. $\delta \leftarrow \text{inf}$;
6. **foreach** $C_i$ in $C^*$ **do**
7. $p \leftarrow W_i/k$;
8. $t \leftarrow (f(C_i) - 1) * p + 1$;
9. **if** $t < \delta$ **then**
10. $\delta \leftarrow t$;$
11. \Delta_{ap} \leftarrow \Delta(\alpha, \gamma, \delta)$;
12. return $(\Delta_{ap} > \alpha)$;

The output of Algorithm 7 can be either ‘acceptability’ or ‘unacceptability’ (Line 2). $B$ calculates an acceptability degree called $\Delta_{ap}$ to compare to $\alpha$. The acceptability degree is related to three parameters $\delta$, $\gamma$, and $\alpha$ [80]. Parameter $\delta \in [0, 1]$ is called the overall satisfaction degree and is calculated from $B$’s updated $REQ$. To calculate $\delta$ value, corresponding suitable degree $t_i$ is calculated for each constraint $C_i$ (Lines 7-8).
Then, $\delta$ value is $\min\{t_i\}$ (Line 10). Parameter $\gamma \in [0, 1]$ is the satisfactory degree of a bonus from $S'$. Parameter $\alpha$ is the acceptability threshold of $B$. Based on $\delta$, $\gamma$, and $\alpha$, $\Delta_{ap}$ is calculated from Equation (6.2) (Line 11) as follows.

$$
\Delta_{ap}(\alpha, \gamma, \delta) = \frac{(1 - \alpha)\delta((1 - \alpha)\gamma + \alpha)}{(1 - \alpha)\delta((1 - \alpha)\gamma + \alpha) + \alpha(1 - \delta)(1 - ((1 - \alpha)\gamma + \alpha))}
$$

(6.2)

If $\Delta_{ap}$ is more than $\alpha$, the most suitable seller agent is acceptable. Otherwise, the most suitable seller agent is unacceptable (Line 12).

6.3 Experiments

This section presents an evaluation of the proposed broker-based trade allocation approach to select the potential seller as per a buyer’s requirements in the power market. Subsection 6.3.1 introduces the experimental setting. Subsection 6.3.2 demonstrates the experimental results.

6.3.1 Experiment setting

The experiment settings include the settings for a buyer agent, multiple seller agents and a broker agent.

6.3.1.1 Seller setting

The simulation contains six seller agents and each seller agent’s offers consider four attributes, i.e., price, electricity usage on weekdays, electricity usage on weekends and early withdrawal penalty. The detail contents of each seller’s offers are presented in Table 6.1. Seller agents use a bonus to attract a buyer agent to purchase their electricity. In particular, five of the six seller agents offer a bonus for the buyer agent and the satisfaction degrees of a bonus for ‘gift’ and ‘free sign up fee’ are set as 80% and 10%, respectively.
Table 6.1: Trading information of electricity sellers (WD—Electricity usage on weekdays; WK—Electricity usage on weekends)

<table>
<thead>
<tr>
<th>Seller</th>
<th>Price (AUD/KW)</th>
<th>WD (KW)</th>
<th>WK (KW)</th>
<th>Early withdrawal penalty</th>
<th>Sale off</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1.40</td>
<td>270</td>
<td>360</td>
<td>No</td>
<td>No bonus</td>
</tr>
<tr>
<td>S2</td>
<td>0.70</td>
<td>200</td>
<td>290</td>
<td>Yes</td>
<td>Gift</td>
</tr>
<tr>
<td>S3</td>
<td>0.71</td>
<td>240</td>
<td>400</td>
<td>No</td>
<td>Free sign up fee</td>
</tr>
<tr>
<td>S4</td>
<td>0.80</td>
<td>245</td>
<td>320</td>
<td>No</td>
<td>Free sign up fee</td>
</tr>
<tr>
<td>S5</td>
<td>0.89</td>
<td>229</td>
<td>350</td>
<td>No</td>
<td>Gift</td>
</tr>
<tr>
<td>S6</td>
<td>0.98</td>
<td>248</td>
<td>420</td>
<td>No</td>
<td>Free sign up fee</td>
</tr>
</tbody>
</table>

6.3.1.2 Broker setting

All seller agents agree that if their electricity is bought by $B$ through $BR$, $BR$ will receive a reward value, namely $r$, from seller agents. In this experiment, the reward is calculated as follows.

$$r = \text{price} \times 10\%$$  \hspace{1cm} (6.3)

If there are more than one seller agent, which satisfy $B$’s requirements, $BR$ will choose a seller with the largest reward.

6.3.1.3 Buyer setting

$B$’s concession threshold $\lambda$ is set to a value (50%) and $B$’s acceptability threshold is as 95%. Four attributes in $B$’s requirements are price, electricity usage on weekdays, electricity usage on weekends and early withdrawal penalty. Satisfaction degrees as per constraint values of price, electricity usage on weekdays, electricity usage on weekends and early withdrawal penalty are displayed in Tables 6.3, 6.4, 6.5, 6.6, respectively. In addition, the priority degrees of price, electricity usage on weekdays, electricity usage on weekends and early withdrawal penalty in $B$’s requirements are set to 3, 2, 1, and 4, respectively and are presented in Table 6.2. Furthermore, $B$’s requirements for each
attribute are also presented in detail in Table 6.2.

Table 6.2: A buyer’s requirements

<table>
<thead>
<tr>
<th>Price (AUD/KW)</th>
<th>Electricity usage on weekdays</th>
<th>Electricity usage on weekends</th>
<th>Early withdrawal penalty</th>
</tr>
</thead>
<tbody>
<tr>
<td>under 0.7</td>
<td>under 200</td>
<td>under 300</td>
<td>no</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>1</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 6.3: Satisfaction degree of price

<table>
<thead>
<tr>
<th>Price (AUD/KW)</th>
<th>Satisfaction degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>under 0.7</td>
<td>100%</td>
</tr>
<tr>
<td>0.7-1.0</td>
<td>90%</td>
</tr>
<tr>
<td>1.0-1.3</td>
<td>80%</td>
</tr>
<tr>
<td>1.3-1.6</td>
<td>70%</td>
</tr>
<tr>
<td>1.6-1.9</td>
<td>60%</td>
</tr>
<tr>
<td>1.9-2.2</td>
<td>50%</td>
</tr>
<tr>
<td>above 2.2</td>
<td>40%</td>
</tr>
</tbody>
</table>

Table 6.4: Satisfaction degree of electricity usage on weekdays

<table>
<thead>
<tr>
<th>Electricity usage on weekdays</th>
<th>Satisfaction degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>under 200</td>
<td>100%</td>
</tr>
<tr>
<td>200-220</td>
<td>90%</td>
</tr>
<tr>
<td>220-240</td>
<td>85%</td>
</tr>
<tr>
<td>240-260</td>
<td>80%</td>
</tr>
<tr>
<td>260-280</td>
<td>70%</td>
</tr>
<tr>
<td>280-300</td>
<td>60%</td>
</tr>
<tr>
<td>above 300</td>
<td>50%</td>
</tr>
</tbody>
</table>

Table 6.5: Satisfaction degree of electricity usage on weekends

<table>
<thead>
<tr>
<th>Electricity usage on weekends (KW)</th>
<th>Satisfaction degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>under 300</td>
<td>100%</td>
</tr>
<tr>
<td>300-400</td>
<td>70%</td>
</tr>
<tr>
<td>above 400</td>
<td>30%</td>
</tr>
</tbody>
</table>
Table 6.6: Satisfaction degree of early withdrawal penalty

<table>
<thead>
<tr>
<th>Early withdrawal penalty</th>
<th>Satisfaction degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>100%</td>
</tr>
<tr>
<td>Yes</td>
<td>0%</td>
</tr>
</tbody>
</table>

6.3.2 Experiment results

The experimental results are illustrated on the trading process between a buyer agent and seller agents through a broker agent for seller selection in the power market. In the experiment, $B$'s acceptability threshold is set at a high value (95%). This means that it is difficult for the trading process between $B$ and $S$ through $BR$ to achieve an agreement without a constraint relaxation in $B$'s requirements. Thus, the proposed approach is useful to overcome this difficulty. In particular, $B$ uses a constraint relaxation when $BR$ cannot find any seller agent, which satisfies $B$'s requirements. Seller agents offer a bonus program to attract $B$ to purchase their electricity and $BR$ selects the most suitable seller as per $B$'s requirements.

The experimental results are illustrated in Figure 6.2. From Figure 6.2, it is clear that the agreement was achieved through 8 rounds. The constraint relaxation was applied in rounds 2, 4, and 5 because $BR$ could not find any seller agent to satisfy $B$'s requirements. After the constraint relaxation was used in round 5, $BR$ found that $S_5$ could meet $B$'s requirements and required $B$ to verify whether $S_5$ was acceptable. Although $S_5$ satisfied all constraints of $B$, the agreement was not achieved because $B$'s acceptability degree was 92.5% for $S_5$ which was less than $B$'s required acceptability threshold of 95% in round 6. So, $B$ required $BR$ to find other seller agent. Then, $BR$ found $S_5$ again with offered bonus and required $B$ to verify whether $S_5$ could be acceptable in round 7. $B$ calculated the acceptability degree for $S_5$ with the offered bonus. The acceptability degree of $S_5$ was acceptable and the agreement was achieved in round 8.
6.4 Discussion

The explanation of such results is as follows. (i) The buyer agent used a constraint relaxation three times to achieve an agreement with the acceptability threshold $\alpha=95\%$. If $B$’s constraint relaxation was not carried out, the trading process was terminated in round 2. (ii) Seller agents used a bonus program to attract the buyer agent to purchase their electricity in round 7. In summary, to achieve the agreement between a buyer agent and multiple seller agents through a broker agent, the buyer agent’s constraint relaxation, seller agents’ bonus and reward programs and the broker agent’s seller selection strategy need to be carried out combinations to find a potential seller to satisfy a buyer’s requirements.

![Figure 6.2: The experimental results](image)

6.4 Discussion

Experimental results demonstrated the good performance of the proposed approach to find a potential seller as per a buyer’s requirements. The reasons the good performances of the proposed approach achieve are that (i) due to the increasing number of sellers in market environments, it is difficult for a buyer to select a potential seller under a multi-attribute trading. Thus, the trade processes between a buyer and sellers
in market environments need to be carried out through a broker; (ii) the proposed broker-based trade allocation approach uses priority orders of attributes in a buyer’s requirements to present a buyer’s preferences and priority orders indicate how a buyer’s constraint relaxation should be made; (iii) a buyer utilizes a constraint relaxation to change a buyer’s requirements when a broker cannot find any seller to satisfy a buyer’s requirements; and (iv) sellers only offers a bonus program to a buyers and cannot make any concession to a buyer.

6.5 Summary

In this chapter, the broker-based trade allocation approach to find a potential seller to satisfy a buyer’s requirements in market environments was proposed. Firstly, the problem description and definitions of the broker-based trade allocation approach in market environments were given. Then, the broker-based trade allocation process to find a potential seller, including a seller selection, a constraint relaxation and a decision making, was introduced in detail. Finally, experiments to evaluate the performance of broker-based trade allocation to find a potential seller were demonstrated and analysed so as to achieve Objective 3 of this thesis.
Chapter 7
Conclusion and Future Work

In this thesis, the challenging issues of allocating buyers’ requirements to sellers’ offers through a broker under a multi-attribute trading in market environments were investigated. In order to solve these challenging issues to achieve broker-based trade allocation efficiently in market environments, five agent-based approaches are proposed. This chapter summarizes contributions of the thesis and points out future directions of the research.

7.1 Contributions of the Thesis

This thesis focused on investigating challenging issues of broker-based trade allocation under a multi-attribute trading in market environments and proposed multi-agent approaches to address broker-based trade allocation efficiently in market environments. The contributions of this thesis include:

1. A behavior prediction approach for broker-based trade allocation in market environments

A broker-based approach to predict buyers’ and sellers’ behaviors was proposed to help a broker to carry out allocating buyers’ requirements to sellers’ offers in market environments. In the proposed approach, firstly, a broker receives trade information from buyers and sellers. Based on the collected trade informa-
7.1. Contributions of the Thesis

tion from buyers and sellers, a broker calculates buyers’ satisfaction degrees to
determine a constraint satisfaction layer to work in a broker’s trade allocation
processes. Then, based on historical data and trade information from buyers and
sellers, a broker predicts buyers’ and sellers’ behaviors by using Bayes’ rules. Fi-
nally, a broker’s trade allocation processes are carried out to find the optimal
allocation pairs to maximize a broker’s expected profit under the consideration
of buyers’ and sellers’ satisfaction degrees. Experimental results demonstrated
the good performance of the proposed approach in terms of satisfying buyers’
requirements and maximizing a broker’s expected profit.

2. A broker-based approach for modelling uncertain information of attributes in trade allocation in market environments

A broker-based approach to model uncertain information of attributes was pro-
posed for trade allocation in market environments. In the proposed approach, in
addition to receiving trade information from buyers and sellers, a broker firstly
interacts with a buyer to model uncertain information of attributes using mem-
bership functions. After modelling uncertain information of attributes, a broker
calculates buyers’ satisfaction degrees as per sellers’ offers for attributes with
uncertain information and other attributes. Then, a broker’s trade allocation
processes are carried out to find the results of allocation pairs and a broker
sends the results of allocation pairs to buyers to check whether buyers accept
the allocation results. Finally, a broker’s strategy is proposed to allocate buyers’
requirements to sellers’ offers based on buyers’ feedback. Experimental results
demonstrated the good performance of the proposed approach in terms of satis-
fying buyers’ requirements and maximizing the satisfaction degree of all buyers.
3. A broker-based buyer’s constraint relaxation approach for trade allocation in market environments

A broker-based buyer’s constraint relaxation approach for trade allocation was proposed to find a potential seller to satisfy a buyer’s requirements. The proposed approach consists of three components: a seller selection, a constraint relaxation and a decision making. A trading process between a buyer and sellers is conducted through a broker to find a potential seller as per a buyer’s requirements. A buyer’s constraint relaxation is carried out when the broker cannot find any seller to satisfy a buyer’s requirements. The experimental results demonstrated the good performance for discovering a potential seller in market environments.

4. A broker-based multi-objective optimization approach for trade allocation in market environments

A broker-based multi-objective optimization approach was proposed for trade allocation in market environments. In this proposed approach, a formula system is proposed to calculate buyers’ satisfaction degrees, a broker’s turnovers and a broker’s benefits. Then, a multi-objective function and a set of constraints are generated to help a broker to maximize the satisfaction degree of all buyers, a broker’s turnover and a broker’s benefit under a multi-attribute trading. Three experiments and a case study were carried out to demonstrate the performance of the proposed approach.

5. A broker-based approach for seller modelling in trade allocation in market environments

A broker-based approach for seller modelling was proposed for trade allocation in market environments. In this approach, in addition to receiving trade information from buyers and sellers, a broker firstly interacts with a seller to model
sellers’ price offers as per trade volume and then interacts with a buyer to model buyers’ satisfaction degrees as per trade volume. Finally, a broker carries out allocating buyers’ requirements to sellers’ offers under the consideration of sellers’ price offers as per trade volume, buyers’ satisfaction degrees as per trade volume and buyers’ satisfaction degrees as per other attributes to maximize the satisfaction degree of all buyers. The proposed approach was evaluated by comparing with other approaches in the experiments and the results were encouraging.

7.2 Future Work

Although the proposed approaches in this thesis can solve some challenging issues of allocating buyers’ requirements to sellers’ offers under different considerations in market environments, there is still some room for the improvement of the proposed approaches in the future.

1. A broker-based trade allocation in dynamic market environments

A broker-based trade allocation in market environments in this thesis was carried out in static market environments because allocating buyers’ requirements to sellers’ offers through a broker can be fulfilled during a given time period without any changes. In reality, however, during a given time period, new buyers or sellers can enter or leave market environments, or buyers’ requirements or sellers’ offers can also be changed. The proposed approach is limited to handle these changes and will be extended to solve this limitation in future work.

2. A broker-based multi-objective optimization for trade allocation in market environments

The proposed approach in this thesis only considered that each buyer can buy commodities from each seller maximally and each seller can sell its commodities
to each buyer maximally. In reality, however, each buyer may buy commodities from one or many different sellers and each seller may sell its commodities to one or to many different buyers. This limitation will be studied in more detail in the future work. In addition, a prototype system is needed to be built by embedding the proposed model and should be applied to organizations or companies with more complicated situations in order to evaluate and improve the proposed model in complex market environments.

3. A broker-based trade allocation in competition market environments

A competition market is a type of market in which brokers compete with each other to buy commodities from sellers and sell commodities to buyers in the given time period to satisfy buyers’ requirements and to maximize a broker’s utility. Currently, a broker’s decision making in the proposed approaches only considered trade information from buyers and sellers without paying attention to opponent’s behaviors in competition market environments. In the future, we are planning to solve this limitation.

4. A broker-based buyer’s constraint relaxation for trade allocation in market environments

The proposed approach in this thesis is to find a potential seller as per a buyer’s requirements through a broker. A buyer’s constraint relaxation is carried out when a broker cannot find any seller to satisfy a buyer’s requirements. In reality, in some cases, if a broker cannot find any seller to satisfy a buyer’s requirements, a broker should use a negotiation strategy with sellers to help a buyer to make a deal. In the future, we will employ negotiation strategies during the allocation process to help a broker to find a potential seller to satisfy a buyer’s requirements.
References


References


International Conference on Industrial and Information Systems (ICIIS), pages 1–6, 2014.


