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AN ECONOMIC MODEL-BASED MATCHING APPROACH BETWEEN BUYERS AND SELLERS THROUGH A BROKER IN AN OPEN E-MARKETPLACE

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Abstract

A broker in an open e-marketplace enables buyers and sellers to do business with each other. Although a broker plays an important role in e-marketplaces, theory and guidelines for matching between buyers and sellers in multi-attribute exchanges are limited. Therefore, a challenge for a broker's responsibility is how to maximize a buyer's total satisfaction degree as its goals under the consideration of trade-off between a buyer's buying quantity and price paid to a seller, and other attributes. To solve this challenge, this paper proposes an economic model-based matching approach between a buyer's requirements and a seller's offers. The major contributions of this paper are that (i) a broker can model a seller's price policy as per a buyer's buying quantity through communication between a broker and a seller; (ii) due to each buyer's different quantity demand, a broker models a buyer's satisfaction degree as per a buyer's buying quantity based on communication between a broker and a buyer; and (iii) to carry out a broker's matching processes, an objective function and a set of constraints are generated to help a broker to maximize a buyer's total satisfaction degree. Experimental results demonstrate the good performance of the proposed approach.

Keywords: E-marketplace, broker, multi-attributes, matching approach, economic model, objective function

1. Introduction

The term '*market*' refers to a place where buyers and sellers can meet together to exchange information about price, products and service offerings, to negotiate and carry out business processes (Standing et al. 2010). In some types of markets as specifications such as financial, agricultural and power markets (Ketter et al. 2012, Kuate et al. 2013, Wang et al. 2017), most of the trading processes between buyers and sellers are intermediated through brokers. In an open e-marketplace, in general, all sellers do not know buyers and vice-versa, and they depend on brokers to conduct the trading processes (Easley et al. 2010, Han et al. 2013). Thus, brokers play a significant role in maintaining market operations and bring benefits to individual participants and market efficiency.

Research on brokers or intermediaries as the third party of the trading processes in e-marketplaces has been a very active direction in recent years (Wu et al. 2013, Peters et al. 2013, Wang et al. 2015, Badidi 2016). Tiwari et al. (2013) and Srivastava et al. (2014) proposed a new approach to select cloud service providers based on users' service requirements through a cloud broker in the cloud environment. They applied the rough set to model the given services of the cloud service providers and users' requirements to find the optimal cloud service providers. Li et al. (2009) proposed a new approach to match buyers and sellers in a B2B e-marketplace through a matchmaker by using multi-objective optimization. They used a priority-based multi-objective genetic algorithm to solve their objective optimization to find out optimal matching pairs. Alpár (2010) proposed a conceptual framework of matchmaking in a B2B e-marketplace environment. Matchmaker's responsibility includes analysis, modelling, implementation and optimization. Srivastava et al. (2014) studied modelling and managing attributes in a seller's offers through a broker to select the best seller as per buyers' requirements.

Although the approaches above have focused on studying brokers as the third party in the trading process between a buyer's requirements and a seller's offers, there is little theory and few guidelines to help a broker to optimize the matching of commodity exchanges between buyers and sellers. Most current brokers in e-marketplaces only provide a buyer's or a seller's trade information and do not really carry out functions of matching between buyers and sellers. The lack of a comprehensive optimization matching approaches could not provide a solid foundation for improving exchange efficiency and market efficiency under considering buyers or sellers. Therefore, how to maximize a buyer’s total satisfaction degree under trade-off between a buyer's buying quantity and price paid to a seller as per buying quantity, and other attributes is one of the most important challenges for a broker.

In order to solve this challenge, this paper proposes an economic model-based matching approach to maximize a buyer’s total satisfaction degree. The major contributions of this paper are as follows: (i) a proposed framework is applicable to help a broker to obtain its goals; (ii) a buyer's requirements and a seller's offers are modelled based on communication between a broker and a seller, or a broker and a buyer; (iii) to carry out a broker's matching process, an objective function and a set of constraints are generated to help a broker to maximize a buyer’s total satisfaction degree; and (iv) a broker's matching algorithm is generated to seek for optimal matching solutions. Experimental results illustrate that by using the proposed approach, a broker can find out the optimal matching pairs to maximize a buyer’s total satisfaction degree.

The rest of this paper is organized as follows. The problem description is presented in Section 2. The proposed matching approach is introduced in Section 3. An experiment is presented in Section 4. Section 5 compares our approach with some related work. Section 6 concludes in this paper and points out our future work.

2. Problem Description

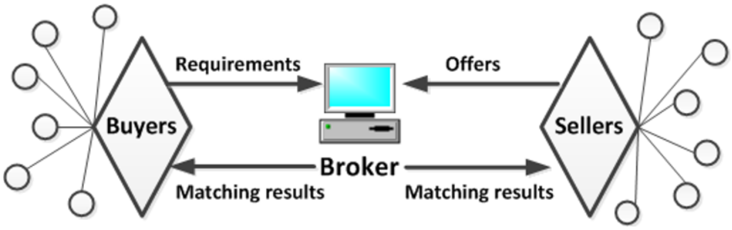


Figure 1 The trading processes through a broker in an open e-marketplace

There are three main types of members in the trading process with multi-attribute exchanges, i.e., buyers, sellers and a broker. The general trading process is shown in Figure 1.

A broker is often called a facilitator, who acts as an intermediary between a buyer and a seller in responsibility is to match n ($n \geq 1$) buyers with m ($m \geq 1$) sellers to maximize a buyer's total satisfaction degree based on the ability of broker as follows: (i) modelling a seller's different price policy as per a buyer's buying quantity and a buyer's different satisfaction degree as per buying quantity; (ii) calculating a buyer's satisfaction degree with other attributes as per a seller's offers, and (iii) carrying out matching process between a buyer's requirements and a seller's offers by solving an objective optimization model.

Assume that buyer b_i ($i=1, 2..., n$) has quantity demand of commodity with multi-attributes in e-marketplaces and seller s_j ($j=1, 2..., m$) has supply demand of commodity with multi-attributes to e-marketplaces. Multi-attributes in a buyer's requirements are divided into two categories based on their constraints including attributes with hard constraints and soft constraints. Attributes with hard constraints mean that their constraints are presented in the form of an 'equal to' notation. For example, a buyer would like to buy the exact size of jacket as the most important factor in a buyer's decision making. It means that the buyer wants to buy the jacket with a fixed size so the size of an attribute of the jacket is the hard constraint. On the other hand, attributes with soft constraints are presented in the form of 'inequality' and these constraints can be relaxed within the given scope of values (Jung et al. 2000). Soft constraints are usually classified into three categories as follows.

(i) Benefit soft constraints: it means that the bigger constraint's value offered by sellers to a buyer, the bigger a buyer's satisfaction degree. For example, the quality of goods is regarded as the attribute with benefit soft constraints.

(ii) Cost soft constraints: it means that the smaller constraint's value offered by sellers to a buyer, the bigger a buyer's satisfaction degree. For example, the price of goods is regarded as the attribute with cost soft constraints.

(iii) Interval soft constraints: it means that the constraints will be satisfied when attribute's constraint value belongs to the given interval.

After communicating with a buyer, a broker models a buyer's satisfaction degree as per a buyer's buying quantity. Other attributes in b_i's requirements are also considered to determine b_i's satisfaction degree. Thus, b_i's requirements are presented as follows.

$$\begin{pmatrix} A_1\ A_2 \dots A_z \\ C_{i1}\ C_{i2} \dots C_{iz} \\ w_{i1}\ w_{i2} \dots w_{iz} \end{pmatrix}, \tag{1}$$

where A_z indicates the z^{th} attribute name, C_{iz} is the constraint value of attribute A_z. The constraint value of attribute can be hard or benefit or cost. If the constraint value C_{iz} of attribute A_z is interval values, the constraint value C_{iz} becomes $[C_{izL}, C_{izU}]$, where C_{izL} is the lowest constraint value and C_{izU} is the largest constraint value. w_{iz} is the weight of z^{th} attribute.

Similarly, after modelling a seller's price policy as per a buyer's buying quantity, other attributes in s_j's offers are also considered to determine b_i's satisfaction degree. Thus, s_j's offers are presented as follows.

$$\begin{pmatrix} A_1\ \ A_2 \dots A_z \\ Q_{j1}\ \ Q_{j2} \dots Q_{jz} \end{pmatrix}, \tag{2}$$

where A_z indicates the z^{th} attribute name, Q_{jz} is the constraint value of attribute A_z in s_j's offers.

Based on the above analysis, the matching problem in multi-attribute exchanges can be generally presented as follows: a seller's offers are sent to a broker. Due to a seller's different price policy as per a buyer's buying quantity, a broker communicates with each seller to model a seller's price policy as per a buyer's buying quantity. Similarly, a buyer's requirements are also sent to a broker. Due to a buyer's different quantity demand, a broker communicates with each buyer to model a buyer's satisfaction degree as per buying quantity. According to a buyer and a seller's trading information, the key problem is how to help a broker to find the optimal matching pairs so that a buyer's requirements are satisfied and a buyer's total satisfaction degree is maximized. Therefore, the proposed matching approach can solve this problem and is presented in Section 3.

3. The Proposed Matching Approach

3.1 The Principle of the Whole Matching Process

A trading process between buyers and sellers is conducted through a broker to achieve the optimal matching pairs. In this paper, a broker's responsibility is how to maximize a buyer's total satisfaction degree as social goals based on a buyer's requirements and a seller's offers under multi-attribute exchanges. The principle of the whole matching process between buyers and sellers through a broker in our approach is presented in Figure 2.

Step 1 A broker receives a seller's offers in term of multi-attributes. To model a seller's price policy as per a buyer's buying quantity, a broker communicates with a seller to determine a seller's price policy such as the policy of encourage consumption or discourage consumption and so on. A broker's responsibility is to model a seller's price policy as per different buying quantity.

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

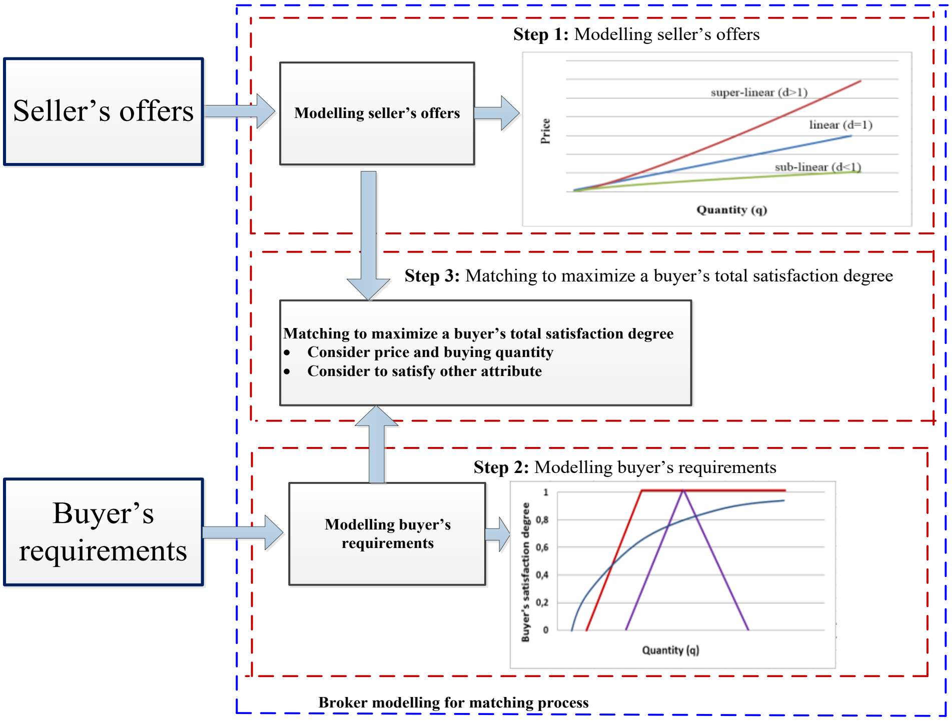


Figure 2 The conceptual framework of broker in an open e-marketplace

- Question 1: 'Is what the worst buying quantity?' → 'Everything is the worst if buying quantity is less than 10 or more than 50'.
- Question 2: 'Is what the perfect buying quantity that would give you full satisfaction level?' → 'The perfect buying quantity is between 20 and 40'.
- Question 3: 'Is what a medium satisfaction level for you with regard to buying quantity?' → 'The buying quantity is between 10 and 20, or between 40 and 50'.

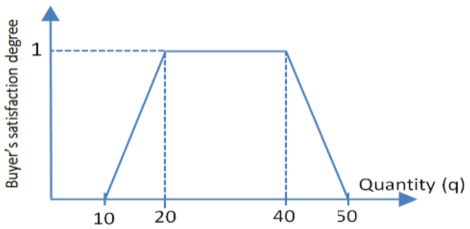
Based on a buyer's responses above, a buyer's satisfaction function as per buying quantity is presented in Figure 3.

Step 3 After modelling a seller's offers and a buyer's requirements, a broker carries out to match a seller's offers with a buyer's requirements to achieve the optimal pairs.

A broker's matching process is to maximize a buyer's total satisfaction degree under trading-off between a seller's different prices and a buyer's buying quantity, and satisfying a buyer's other attributes.

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

3.2 Modelling a Seller's Offers



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

Figure 3 For example, a buyer's satisfaction degree as per a buyer's buying quantity

3.2.1 Building a Seller's Price Functions

Each seller has different price policies corresponding to a buyer's different buying quantity. In this paper, a broker communicates with a seller to model a seller's price functions. In general, a seller's price functions are presented based on a mathematical function as follows:

$$f(q_b^d)=p.q_b^d, \tag{3}$$

where q_b^d is a quantity of commodity, which a buyer can buy from a seller; $q_b^d \le N_s$, N_s is a maximal number of commodity, which a seller can sell to buyers; p is an average unit price, which a seller offers to a buyer; $f(q_b^d)$ is a seller's turnover as per a buyer's buying quantity q_b^d. Depending on a seller's different prices, d is chosen with different values. 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 with regardless of a buyer's buying quantity (linear pricing). A seller's price function is written as follows:

$$f(q_b)=p.q_b. \tag{4}$$

(b) if d>1, it means that the more a buyer's buying quantity, the higher the average unit price (super-linear pricing). On the other word, this case is called discourage consumption.

(c) if d<1, it means that the more a buyer's buying quantity, the lower the average unit price (sub-linear pricing). On the other word, this case is called encourage consumption.

In summary, the three pricing functions above are presented in Figure 4.

3.3 Modelling a Buyer's Requirements

3.3.1 Building a Buyer's Satisfaction Function as per Buying Quantity

Each buyer has different demand of buying quantity from the market. Thus, measuring demand of a buyer's buying quantity is necessary for a broker to satisfy a buyer's requirements. In this paper, a broker communicates with a buyer to model a buyer's satisfaction function $u(q_b)$ as per buying quantity q_b, where $q_b \le N_b$ and N_b is a buyer's maximal buying quantity and $u(q_b)$ is in-between 0 and 1.

In the real world, there are different functions to model a buyer's satisfaction degrees as per buying quantity. In this paper, we present some popular functions in business environments as follows.

(a) A sigmoid function is used to express a buyer's satisfaction degree as per buying quantity (Badia et al. 2004). This satisfaction function should be a non-decreasing function of a buyer's buying quantity, i.e., we assume that the more a buyer's buying quantity, the higher a buyer's satisfaction degree. When a buyer's quantity demand is satisfied, an increase of a buyer's buying quantity would bring no improvement of a buyer's satisfaction degree. On the other hand, if a buyer's buying quantity is below some thresholds, a buyer's satisfaction degree is extremely low. Thus, a buyer's satisfaction degree is a concave function and reaches a saturation when a buyer satisfies their demand. These constraints can be presented by the following equations:

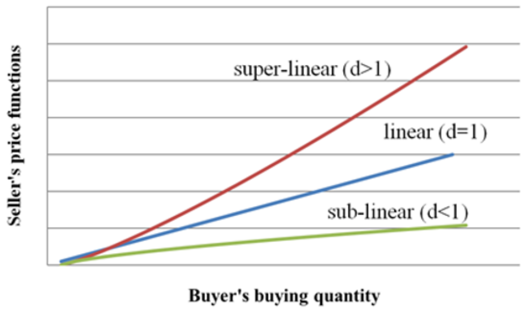


Figure 4 A seller's different price functions as per a buyer's buying quantity

$$\frac{du(q_b)}{dq_b} \geq 0 \quad (5)$$

$$\lim_{q_b \to \infty} \frac{du(q_b)}{dq_b} = 0. \quad (6)$$

Thus, the sigmoid function satisfies these constraints above so it can be used to reflect a buyer's satisfaction degrees as per buying quantity. In particular, the sigmoid function is presented in Figure 5.

The sigmoid function is presented as a title S-shaped curve that could be used to reflect the life cycles of living as human life or economical systems. It has three distinct phases including a staring phase, a maturing phase and aging phase.

(b) Triangular function can be used to express a buyer's satisfaction degrees as per buying quantity. This function is presented with three points as follows:

$$A=(a_1,a_2,a_3)$$

This presentation is interpreted as a buyer’s satisfaction degrees in Figure 6.

(c) Trapezoidal function can be used to reflect a buyer's satisfaction degrees as per buying quantity. This function is presented with four points as follows:

$$A=(a_1,a_2,a_3,a_4)$$

This presentation is interpreted as a buyer's satisfaction degree in Figure 7.

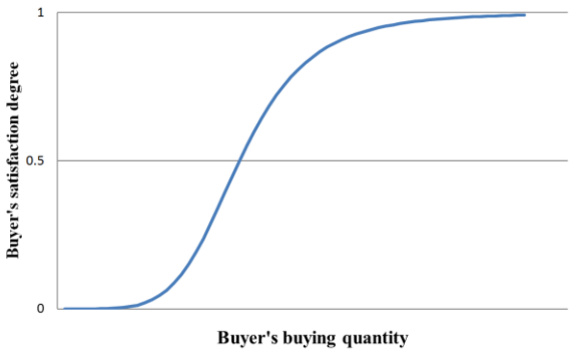
(d) Left-semi trapezoidal function can be used to express a buyer's satisfaction degrees as per buying quantity. This function is presented in Figure 8.

(e) Right-semi trapezoidal function can be used to express a buyer's satisfaction degrees as per buying quantity. This function is presented in Figure 9.

In this paper, depending on a buyer's preferences for buying quantity, a broker uses five functions, i.e., (a) − (e), to model a buyer’s satisfaction degree as per buying quantity.

3.3.2 Building a Buyer's Satisfaction Function between Price and Buying Quantity

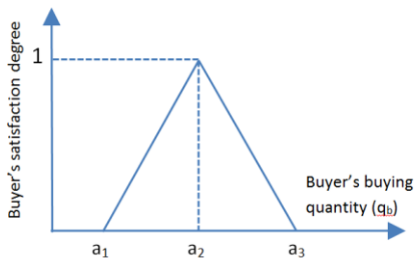
A satisfaction function of buyer b_i naming $g_{ij}^{f\leftrightarrow u}$, takes in account both a buyer's satisfaction degree $u(q_b)$ as per buying quantity and price $f(q_b)$ paid to s_j as b_i's buying quantity. For a buyer's given $u(q_b)$, $g_{ij}^{f\leftrightarrow u}$ should increase when the price paid to a seller decreases and for a given price, $g_{ij}^{f\leftrightarrow u}$ should increase when a buyer's satisfaction degree $u(q_b)$ as per buying quantity increases. Thus, these requirements are presented under mathematical conditions as follows:



$$u(q_b)=\frac{\left({}^{q_b}\!/_{\omega}\right)^z}{1+\left({}^{q_b}\!/_{\omega}\right)^z},\quad (7)$$

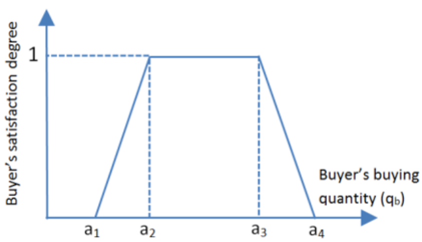
where z and ω are constants, $z\geq 2$ and $\omega>0$. Clearly, $0\leq u(q_b)\leq 1$ and $u(\omega)=\frac{1}{2}$.

Figure 5 The sigmoid function of buyer's satisfaction degree as per buying quantity



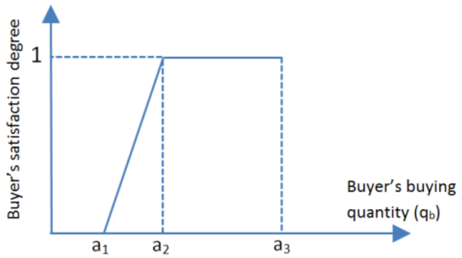
$$u(q_b)=\begin{cases} 0, & \text{for } q_b<a_1 \\ \dfrac{q_b-a_1}{a_2-a_1}, & \text{for } q_b\in[a_1,a_2] \\ \dfrac{a_3-q_b}{a_3-a_2}, & \text{for } q_b\in[a_2,a_3] \\ 0, & \text{for } q_b>a_3 \end{cases}$$

Figure 6 The triangular function of a buyer's satisfaction degree as per buying quantity



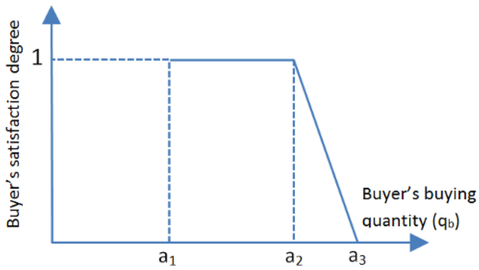
$$u(q_b)=\begin{cases} 0, & \text{for } q_b<a_1 \\ \dfrac{q_b-a_1}{a_2-a_1}, & \text{for } q_b\in[a_1,a_2] \\ 1, & \text{for } q_b\in[a_2,a_3] \\ \dfrac{a_4-q_b}{a_4-a_3}, & \text{for } q_b\in[a_3,a_4] \\ 0, & \text{for } q_b>a_4 \end{cases}$$

Figure 7 The trapezoidal function of a buyer's satisfaction degree as per buying quantity



$$u(q_b)=\begin{cases} 0 &, \text{ for } q_b<a_1 \\ \dfrac{q_b-a_1}{a_2-a_1} &, \text{ for } q_b\in[a_1,a_2] \\ 1 &, \text{ for } q_b\in[a_2,a_3] \\ 0 &, \text{ for } q_b>a_3 \end{cases}$$

Figure 8 The left semi-trapezoidal function of a buyer's satisfaction degree as per buying quantity



$$u(q_b)=\begin{cases} 0 &, \text{ for } q_b<a_1 \\ 1 &, \text{ for } q_b\in[a_1,a_2] \\ \dfrac{a_3-q_b}{a_3-a_2} &, \text{ for } q_b\in[a_2,a_3] \\ 0 &, \text{ for } q_b>a_3 \end{cases}$$

Figure 9 The right semi-trapezoidal function of a buyer's satisfaction degree as per buying quantity

$$\frac{\partial g_{ij}^{f\leftrightarrow u}}{\partial f}\leq 0 \tag{8}$$

$$\frac{\partial g_{ij}^{f\leftrightarrow u}}{\partial u}\geq 0. \tag{9}$$

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

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

(ii) For a given price $f(q_b)$, $g_{ij}^{f\leftrightarrow u}(f(q_b),u(q_b))$ approaches the minimum, i.e. 1, when $u(q_b)$ approaches infinity.

(iii) For a given a buyer's satisfaction degree $u(q_b)$, $g_{ij}^{f\leftrightarrow u}(f(q_b),u(q_b))$ approaches the minimum, i.e. 1, when $f(q_b)$ approaches 0.

(iv) For a given a buyer's satisfaction degree $u(q_b)$, $g_{ij}^{f\leftrightarrow u}(f(q_b),u(q_b))$ approaches the minimum, i.e. 0, when $f(q_b)$ approaches infinity.

These constraints are reflected as follows:

$$\forall f>0,\ \lim_{u\to 0} g_{ij}^{f\leftrightarrow u}(u,f)=0,\quad \lim_{u\to\infty} g_{ij}^{f\leftrightarrow u}(u,f)=1, \tag{10}$$

$$\forall u>0,\ \lim_{f\to 0} g_{ij}^{f\leftrightarrow u}(u,f)=1,\quad \lim_{f\to\infty} g_{ij}^{f\leftrightarrow u}(u,f)=0, \tag{11}$$

Based on Equations (10) and (11), it is easy for us to find out mathematical functions to satisfy these two constraints. However, according to theory of micro-economics (Badia et al. 2006), 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 buying quantity and the price paid to a seller as per a buyer's buying quantity. In particular, the economic model is presented as follows:

$$g_{ij}^{f\leftrightarrow u}(u,f)=1-e^{-ku^{\psi}f^{\alpha}}, \qquad (12)$$

where k, ψ and α are positive constants. The satisfaction function $g_{ij}^{f\leftrightarrow u}(u,f)$ in Equation (12) is normalized by using a reference price η. Thus $g_{ij}^{f\leftrightarrow u}(u,f)$ is written as follows:

$$g_{ij}^{f\leftrightarrow u}(u,f)=1-e^{-ku^{\psi}(f/\eta)^{-\alpha}}. \qquad (13)$$

u and f are determined based on a buyer's specific buying quantity. Thus, before a broker is based on Equation (13) to determine b_i's satisfaction degree between a buyer's buying quantity and the price paid to seller s_j as per a buyer's buying quantity, a broker is to determine a buyer's buying quantity. In this paper, after a broker models a buyer's satisfaction degree with buying quantity presented in Subsection 3.3.1, a broker can determine a buyer's buying quantity based on a buyer's target satisfaction degree τ.

For example, a buyer's satisfaction function as per buying quantity is the sigmoid in Equation (7) with a buyer's target satisfaction degree τ then a buyer's buying quantity to achieve this goal is calculated based on the inverse function as follows:

$$q_b=\frac{e^{\frac{\ln(\frac{\tau}{1-\tau})}{z}+\ln(\omega)}}{2} \qquad (14)$$

3.3.3 Calculating a Buyer's Satisfaction Function with Other Attributes

Alongside calculating a buyer's satisfaction degree between a buyer's buying quantity and price paid to a seller as per a buyer's buying quantity presented in Subsubsection 3.3.2, a broker determines a buyer's satisfaction degree with other attributes in a buyer's requirements. In particular, these attributes are divided to two categories based on their constraints referred to Section 2. The calculation method of a buyer's satisfaction degree with other attributes is presented in detail as follows:

Let $\boldsymbol{S_i}$ be a set of seller $\{s_1, s_2,\dots,s_m\}$ which is qualified to match bi, $\boldsymbol{S_{it}}$ denotes a set of values for attribute A_t in $\boldsymbol{S_i}$ ($t\in(h+k=z)$), h is a number of attributes with hard constraints, k is a number of attributes with soft constraints, $g_{ij}^{t}\in[-1,1]$ is defined as a buyer's satisfaction degree for the A_t^{th} attribute between b_i and s_j. In particular, a buyer's satisfaction degree is computed to attributes with hard constraints and soft constraints called $g_{ij}^{g'}(g'\in h)$ and $g_{ij}^{g}(g\in k)$, respectively as follows:

(i) For an attribute type with hard constraints:

$$g_{ij}^{g'}=\begin{cases}-1 & \text{if } C_{ig'}\neq Q_{jg'}\\ 1 & \text{if } C_{ig'}=Q_{jg'}\end{cases} \qquad (15)$$

$g_{ij}^{g'}$=-1 means that a seller s_j does not match with a buyer b_i for attribute g' and $g_{ij}^{g'}$=1 means that a seller s_j matches with a buyer b_i for attribute g'.

(ii) For an attribute type with benefit soft constraints: if $C_{ig}>Q_{jg}$ then g_{ij}^{g}=-1. It means that a seller s_j does not satisfied a buyer b_i. If $C_{ig}\leq Q_{jg}$, then g_{ij}^{g} is calculated as follows:

$$g_{ij}^{g}=\left(\frac{Q_{jg}\text{-}Q_{min\text{-}g}+\emptyset}{Q_{max\text{-}g}\text{-}Q_{min\text{-}g}+\emptyset}\right)^{t'}, \quad (16)$$

where $t'=C_{ig}/Q_{min\text{-}g}$, $Q_{min\text{-}g}$ is the minimal value of a seller in the set of values for the attribute A_g and $Q_{max\text{-}g}$ is the maximal value of a seller in the set of values for the attribute A_g. A value $t'\in(0,1]$ helps a broker to carry out comparing a buyer's satisfaction degree when t' is used to calculate g_{ij}^{g}. $\emptyset=Q_{min\text{-}g}/2$, $\emptyset$ helps a broker to solve some special cases such as only one seller in an e-marketplace or $Q_{max\text{-}g}=Q_{min\text{-}g}$. g_{ij}^{g} increases when Q_{ig} increases or C_{ig} decreases.

g_{ij}^{g} means that a seller s_j matches with a buyer b_i for attribute g with a buyer's satisfaction degree $\left(\frac{Q_{jg}\text{-}Q_{min\text{-}g}+\emptyset}{Q_{max\text{-}g}\text{-}Q_{min\text{-}g}+\emptyset}\right)^{t'}$. g_{ij}^{g} is in-between 0 and 1. If g_{ij}^{g} is near 1, it means that b_i is highly satisfied by s_j for attribute g.

(iii) For an attribute type with cost soft constraints: if $C_{ig}<Q_{jg}$ then g_{ij}^{g}=-1. It means that a seller s_j does not satisfied a buyer b_i. If $C_{ig}\geq Q_{jg}$, then g_{ij}^{g} is calculated as follows:

$$g_{ij}^{g}=\left(\frac{Q_{max\text{-}g}\text{-}Q_{jg}+\emptyset}{Q_{max\text{-}g}\text{-}Q_{min\text{-}g}+\emptyset}\right)^{\frac{1}{t'}}, \quad (17)$$

g_{ij}^{g} means that a seller s_j matches with a buyer b_i for attribute g with a buyer's satisfaction degree $\left(\frac{Q_{max\text{-}g}\text{-}Q_{jg}+\emptyset}{Q_{max\text{-}g}\text{-}Q_{min\text{-}g}+\emptyset}\right)^{\frac{1}{t'}}$. g_{ij}^{g} is in-between 0 and 1. If g_{ij}^{g} is near 1, it means that b_i is highly satisfied by s_j for attribute g.

g_{ij}^{g} in this case increases when Q_{jg} deceases or C_{ig} increases.

(iv) For an attribute type with benefit interval constraints

$$g_{ij}^{g}=\begin{cases} -1 & \text{if } Q_{jg}<C_{igL} \\ \dfrac{Q_{jg}-C_{igL}}{C_{igU}-C_{igL}} & \text{if } C_{igL}\leq Q_{jg}<C_{igU} \\ 1 & \text{if } Q_{jg}\geq C_{igL} \end{cases} \quad (18)$$

(v) For an attribute type with cost interval constraints

$$g_{ij}^{g}=\begin{cases} -1 & \text{if } Q_{jg}>C_{igL} \\ \dfrac{C_{jgU}-Q_{jg}}{C_{igU}-C_{igL}} & \text{if } C_{igL}\leq Q_{jg}<C_{igU} \\ 1 & \text{if } Q_{jg}\leq C_{igL} \end{cases} \quad (19)$$

In summary, a broker considers b_i's satisfaction degree based on s_j's offers under multi-attribute exchanges. Attributes with hard constraints are necessary conditions in trading processes and must be satisfied. Thus, attributes with hard constraints do not need their weight. If attributes with hard constraints are not satisfied, then b_i cannot match with s_j. On the other hand, attributes with soft constraints are necessary for using the weight because these attributes can be relaxed within the given scope of values. In particular, b_i's total satisfaction degree based on s_j's offers related to all attributes are calculated as follows:

$$\sum_{g=1}^{k} w_{ig}g_{ij}^{g}+w_i^{u\leftrightarrow f}g_{ij}^{u\leftrightarrow f}, \quad (20)$$

where w_{ig} is a weight value of attribute A_g for b_i's requirements, $w_i^{u\leftrightarrow f}$ is a weight value of attribute's buying quantity related to a seller's price and $\sum_{g=1}^{k} w_{ig}+w_i^{u\leftrightarrow f}$=1.

3.4 Broker's Matching Method

3.4.1 Framework of Matching Method

The framework of matching method

presented in Figure 10 helps a broker to solve the matching problem between a buyer's requirements and a seller's offers with multi-attribute exchanges. The framework includes four main phases as follows:

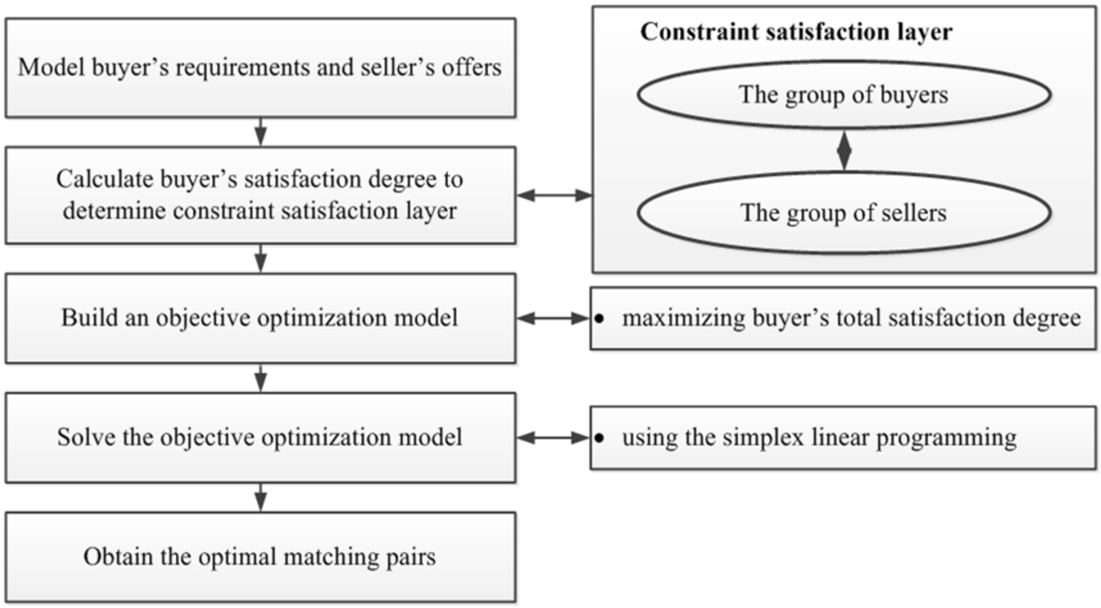


Figure 10 The framework of a broker's matching method

Step 1 Model a seller's offers and a buyer's requirements presented in Subsections 3.2 and 3.3, respectively.

Step 2 Calculate a buyer's satisfaction degree presented in Subsubsections 3.3.2 and 3.3.3 to determine a constraint satisfaction layer. The constraint satisfaction layer includes the group of buyers which satisfy at least a seller's offer and the group of sellers which satisfy at least a buyer's requirements.

Step 3 Based on a buyer's satisfaction degree, a broker builds an objective function and a set of constraints to maximize a buyer's total satisfaction degree.

Step 4 Solve the objective function by well-known linear programming methods (Fletcher 2013) to obtain the optimal matching pairs to satisfy a buyer's requirements and maximize a buyer's total satisfaction degree.

3.4.2 Building a Broker's Objective Function

An objective function for a broker's matching processes between a buyer's requirements and a seller's offers is established to maximize a buyer's total satisfaction degree as goals. Based on the above definition of buyers and sellers, a broker's objective function is presented as follows:

$$\sum_{i=1}^{n}\sum_{j=1}^{m}(\sum_{g=1}^{k} w_{ig}g_{ij}^{g} + w_i^{u\leftrightarrow f}g_{ij}^{u\leftrightarrow f})x_{ij} \quad (21)$$

$$\text{s.t.} \sum_{i=1}^{n} x_{ij} \leq 1, \quad \forall j \in m \quad (22)$$

$$\sum_{j=1}^{m} x_{ij} \leq 1, \quad \forall i \in n \quad (23)$$

$$x_{ij}=1,0, \forall i \in n, \forall j \in m \quad (24)$$

$$\sum_{g=1}^{k} w_{ig} + w_i^{u\leftrightarrow f}=1, \forall i \in n \quad (25)$$

$$x_{ij}=0 \text{ if } g_{ij}^{g'}=-1 \text{ or } g_{ij}^{g}=-1 \text{ or } N_{b_i}>N_{s_j}, \forall g' \in h, \forall g \in k, \quad (26)$$

where h is a number of attributes with hard constraints in a buyer's requirements and k is a number of attributes with soft constraints in a buyer's requirements; objective function (21) is to maximize the weighted sum of a buyer's satisfaction degree; constraints (22) and (23) are that each buyer (seller) can buy (sell) commodities from each other buyer (seller) at most; constraint (24) is decision variable constraint, if buyer b_i matches with seller s_j, then $x_{ij}=1$; otherwise $x_{ij}=0$; constraint (25) denotes the weight information of each buyer; and constraint (26) determines a constraint satisfaction layer. Furthermore, the objective function (21) can be efficiently solved by well-known linear programming methods such as simplex or interior point method (Fletcher 2013).

3.4.3 Broker's Algorithm for Matching Processes

Broker's algorithm for matching process between a buyer's requirements and a seller's offers is presented in Algorithm 1.

Algorithm 1 shows the broker's matching process between a buyer's requirements and a seller's offers. Firstly, a broker receives a buyer's requirements and a seller's offers (Line 1). The output of the algorithm returns the optimal matching pairs between buyers and sellers (Line 2).

To carry the matching process, a broker calculates each buyer's satisfaction degree for all attributes as follows: Based on a buyer's target satisfaction degree, a broker determines a buyer's buying quantity to satisfy a buyer's requirements as per buying quantity (Line 5). Based on a buyer's determined buying quantity and a seller's price policy as per buying quantity, a broker calculates a buyer's satisfaction degree between buying quantity and price paid to a seller by using Equation (13) (Line 6). After that, a broker calculates a buyer's satisfaction degree for other attributes. If an attribute in a buyer's requirements is hard constraints, a buyer's satisfaction degree for this attribute is calculated in Equation (15) (Line 9); If an attribute in a buyer's requirements is benefit soft constraints, b_i's satisfaction degree for this attribute is calculated in Equation (16) (Line 11); If an attribute in a buyer's requirements is cost soft constraints, b_i's satisfaction degree for this attribute is calculated in Equation (17) (Line 13); If an attribute in a buyer's requirements is benefit interval constraints, b_i's satisfaction degree for this attribute is calculated in Equation (18) (Line 15); If an attribute in a buyer's requirements is cost interval constraints,

Algorithm 1: Broker's matching algorithm

```
1  Input: a set of buyer's requirements B = {b_1, b_2, ..., b_n} and a set of seller's offers S = {s_1, s_2, ..., s_m};
2  Output: Return the optimal matching pairs between buyers and sellers;
3  begin
4      for each buyer b_i in S do
5          determine b_i's buying quantity so that b_i's u(q_b) = τ;
6          identify b_i's satisfaction degree between b_i's buying quantity and price paid to a seller with b_i's buying
           quantity by using Equation (13);
7          for each attribute in b_i's requirements do
8              if an attribute belongs to hard constraints then
9                  b_i's satisfaction degree for this attribute is calculated in Equation (15);
10             if an attribute belongs to benefit soft constraints then
11                 b_i's satisfaction degree for this attribute is calculated in Equation (16);
12             if an attribute belongs to cost soft constraints then
13                 b_i's satisfaction degree for this attribute is calculated in Equation (17);
14             if an attribute belongs to benefit interval constraints then
15                 b_i's satisfaction degree for this attribute is calculated in Equation (18);
16             if an attribute belongs to cost interval constraints then
17                 b_i's satisfaction degree for this attribute is calculated in Equation (19);
18
19     build the objective function in Equation (21) and a set of constraints in Equation (22-26);
20     solve the objective function in Equation (21) to achieve the optimal matching pairs to maximize buyer's total
       satisfaction degree.
```

b_i 's satisfaction degree for this attribute is calculated in Equation (19) (Line 17). After calculating a buyer's satisfaction degree for all attributes, a broker builds the objective function in Equation (21) and a set of constraints in Equations (22-26) (Line 19). Finally, a broker solves the objective function in Equation (21) to achieve the optimal matching pairs to maximize a buyer's total satisfaction degree (Line 20). There are many difficult computations in a broker's proposed matching approach, and computational cost is one of them. In particular, the computational complexity of the proposed approach is analyzed in Algorithm 1. According to Algorithm 1, a broker's matching process is related to a set of buyer's requirements $\boldsymbol{B}=\{b_1,b_2,...,b_n\}$, a set of seller's offers $\boldsymbol{S}=\{s_1, s_2, ..., s_m\}$ and a set of attributes $\boldsymbol{A}=\{A_1, A_2,..., A_z\}$ for a buyer's requirements and a seller's offers. Therefore, the computational complexity of the proposed approach is $\Theta(n\times m\times z)$. In the real world, the number of attributes in a buyer's requirements and a seller's offers is usually limited number because the number of attributes is properties of products so the computational complexity of the Algorithm 1 is considered as $\Theta(n\times m)$. Furthermore, a broker's matching process is only carried out based on a set of buyers and sellers for the same commodities so the number of buyers and sellers are not large. Based on the analysis above, the proposed approach can be potential to achieve the matching results for large-scale examples based on personal computers (Jiang et al. 2016).

4. Experiments

In this section, we present our experimental results and analyse the performance of our matching approach. The experiments mainly focus on testing maximizing a buyer's total satisfaction degree through matching between buyers and sellers. The rest of this section is divided into two subsections. Section 4.1 describes the experimental setting that have been applied in the experiments. Section 4.2 shows the experimental results and performance analysis in the three different experiments.

4.1 Experimental Setting

In the experiments, an artificial dataset of 10 buyers related to jacket's demand is generated. Each buyer contains seven attributes, i.e., brand, size, colour, gender, quantity, delivery time and warranty time. Each buyer would like to buy certain quantity from e-marketplaces but in some special cases, the sale quantity can be limited in e-marketplaces. Thus, a broker interacts with each buyer to determine a buyer's satisfaction degree function as per buying quantity. Assume that a buyer's satisfaction degree as per buying quantity in the experiments is expressed based on the triangular function preferred to Subsubsection 3.3.1. Based on a buyer's satisfaction degree function as per buying quantity, a broker can find out a potential seller to satisfy a buyer's requirements. As per a buyer's view, brand, size, colour and gender are regarded as the attributes with hard constraints while quantity, delivery time and warranty time are regarded as the attributes with soft constraints. Similarly, an artificial dataset of 50 sellers providing jackets to e-marketplaces is generated. Each seller contains eight attributes, i.e., brand, size, colour, gender, price, delivery time and warranty time, quantity. Each seller offers different price policies based on a buyer's buying quantity referred to Equation (3) in Subsection 3.2. More specifically, based on the artificial dataset of buyers and sellers, a broker use the proposed matching approach to maximize a buyer's total satisfaction degree through allocations between buyers and sellers under three different experiments in e-marketplaces in Table 1.

In our experiment, we compare a buyer's total satisfaction degrees in our proposed approach with that in Jiang's approach (Jiang et al. 2011) because experimental settings in our approach are similar to experimental settings in Jiang's approach (Jiang et al. 2011). However, a seller's price policies as per buying quantity through different price functions are considered in our proposed approach while price attribute in Jiang's approach is considered as other attribute and a buyer's satisfaction degree for price attribute is calculated based on formula for attribute with cost soft constraints.

4.2 Experimental Results and Analysis

Table 1 Experiments

Experiment	Test purpose
1	To maximize a buyer's total satisfaction degree under selecting a number of different sellers.
2	To maximize a buyer's total satisfaction degree under different ratio of a buyer's satisfied requirements.
3	To maximize a buyer's total satisfaction degree under considering a seller's different price policies with d between 0 and 2.

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

4.2.1 Experiment 1: Evaluation of a Buyer’s Total Satisfaction Degree under Selecting a Number of Different Sellers

The purpose of Experiment 1 is to maximize a buyer’s total satisfaction degree under selecting a number of different sellers. Based on the artificial dataset of 50 sellers above, a broker randomly chooses a number of sellers to carry out allocations between buyers and sellers. Both of our proposed approach and Jiang's approach, the weight vector is assigned to the attributes with soft constraints.

Two approaches in Figure 11 show the impact of the number of sellers on a buyer’s total satisfaction degree. It can be seen that when the number of seller varies from 10 sellers to 50 sellers, a buyer’s total satisfaction degree of the two approaches always increases from 10 sellers to 50 sellers. The reason is that a broker has many opportunities to select a seller's offers which satisfy a buyer's requirements and increase a buyer’s total satisfaction degree. It means that when supply is more than demand, a buyer’s total satisfaction degree is able to increase. Furthermore, a buyer’s total satisfaction degree in the proposed approach is always higher than a buyer’s total satisfaction degree in Jiang's approach. The reason is that Jiang's approach does not consider a seller's price policies to satisfy a buyer's requirements while the proposed approach in this paper utilizes a seller's price policies as per buying quantity to satisfy a buyer's requirements.

4.2.2 Experiment 2: Evaluation of a Buyer’s Total Satisfaction Degree under Different Ratio of a Buyer's Satisfied Requirements

The purpose of Experiment 2 is to maximize a buyer’s total satisfaction degree under different ratio of a buyer's satisfied requirements. Based on the artificial dataset of 50 sellers and 10 buyers above, a broker carries out to allocations between buyers and sellers under different ratio of a buyer's satisfied requirements. We use a combination formula to determine different committees for the specific ratio of a buyer's satisfied requirements. A buyer’s total satisfaction degree is calculated based on different committees for the specific ratio of a buyer's satisfied requirements. Then, based on results of different committees, a buyer’s average total satisfaction degree is calculated for each specific ratio of a buyer's satisfied requirements. In particular, different committees for specific ratio of a buyer’s satisfied requirements is calculated as follows:

$$C_n^r = \frac{n!}{r!(n-r)!}, \tag{27}$$

where C_n^r is a number of different committees for specific ratio of a buyer's satisfied requirements from a set of 10 buyers, n is 10 buyers and r is the specific ratio of a buyer's satisfied requirements, i.e., 2 buyers, 4 buyers, 6 buyers, 8 buyers, and 10 buyers. Similarly, the weight vector is set for the attributes with soft constraints for two approaches.

Two approaches in Figure 12 show the impact of the ratio of a buyer's satisfied requirements on a buyer’s total satisfaction degree. In particular, when the ratio of a buyer's satisfied requirements as per the number of current buyers in the market decreases, a buyer's total satisfaction degree increases in two approaches. The reason is that a broker has many opportunities to choose the potential

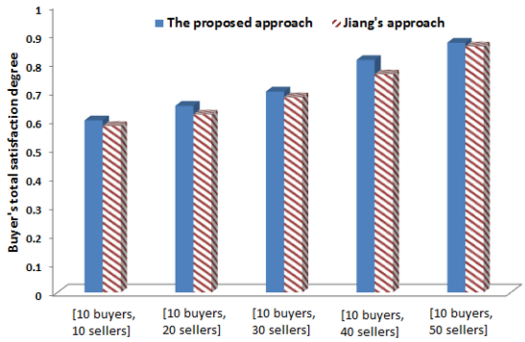


Figure 11 Buyer's total satisfaction degree compared with other approach

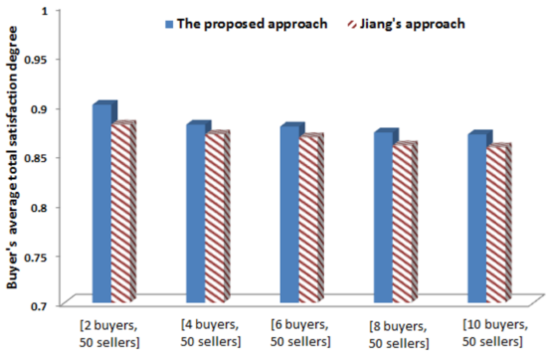


Figure 12 Buyer's total satisfaction degree under considering different ratio of a buyer's satisfied requirements

sellers to increase a buyer's total satisfaction degree. Furthermore, a buyer's total satisfaction degree of the proposed approach is always higher than a buyer's total satisfaction degree in Jiang's approach. The reason is that Jiang's approach does not consider a seller's price policies to satisfy a buyer's requirements while the proposed approach in this paper accepts a seller's different price policies including sub-linear, super-linear and linear as per buying quantity to satisfy a buyer's requirements.

4.2.3 Experiment 3: Evaluation of a Buyer's Total Satisfaction Degree under Considering a Seller's Different Price Policies

Based on the artificial dataset of 50 sellers and 10 buyers above, a broker uses the proposed matching approach to maximize a buyer's total satisfaction degree under considering a seller's different price policies with d between 0 and 2 through finding out allocations between buyers and sellers. Based on general principle of markets, when a seller's price policies are differently offered to e-marketplaces as per a buyer's buying quantity, the matching results and a buyer's total satisfaction degree are affected by a seller's different price policies. In particular, a buyer's total satisfaction degree in a seller's sub-linear price policies as per buying quantity is higher than a buyer's total satisfaction degree in a seller's linear price policies and a seller's super-linear policies as per buying quantity. Furthermore, a buyer's total satisfaction degree in a seller's linear price policies as per buying quantity is higher than a buyer's total satisfaction degree in a seller's super-linear policies as per buying quantity. Based on the results shown in Figures 13, 14 and 15, it is clear that a seller's price policies directly affect a buyer's total satisfaction degree. On the other hand, a buyer's the best total satisfaction degree in Figure 13 is different from a buyer's the best total satisfaction degree in Figures 14 and 15 because a weight value of attribute's buying quantity in Figure 13 is different from a weight value of attribute's buying quantity in Figures 14 and 15.

Although sellers offer the sub-linear price policies to buyers in Figure 13, a buyer's the best total satisfaction degree is the highest value (0.94). A buyer's the best total satisfaction degree cannot achieve 1 because a weight value of attribute's buying quantity is 0.5. Furthermore, although sellers offers the super-linear price policies to a buyer, a buyer's the worst total satisfaction degree cannot achieve 0.

In particular, a buyer's the best total satisfaction degree is the lowest value (0.45) in Figure 13. Similarly, when a weight value of attribute's buying quantity is 1, a seller's price policies totally affects to a buyer's total satisfaction degree. The evidence is demonstrated through the results in Figure 15. When sellers offer the sub-linear price policies to buyers, a buyer's the best total satisfaction degree achieves 1. Furthermore, when sellers offer the super-linear price policies to buyers, a buyer's the best total satisfaction degree achieves 0.

It is clear that the proposed approach determines a buyer's total satisfaction degree under a seller's different price policies through value d between 0 and 2. If value d is less than 1, a buyer's total satisfaction degree is relative high. It means that buyers receive the discounted prices from sellers. Otherwise, a buyer's total satisfaction degree is relative low because there are no any a seller's discounted price policies for buyers. Jiang's approach does not consider a seller's different price policies. It means that a buyer's satisfaction degree in Jiang's approach is not changed under a seller's different policies. Thus, a buyer's total satisfaction degrees of Jiang's approach in Figures 13, 14 and 15 are not changed although a seller's price policies have been changed through value d.

In summary, our proposed approach helps a broker to find out allocations between buyers and sellers to maximize a buyer's total satisfaction degree. Depending on a seller's price policies as per buying quantity, a number of sellers in e-marketplaces, different ratio of a buyer's satisfied requirements as well as selecting weights of attributes, a broker can determine the potential parameters to satisfy a

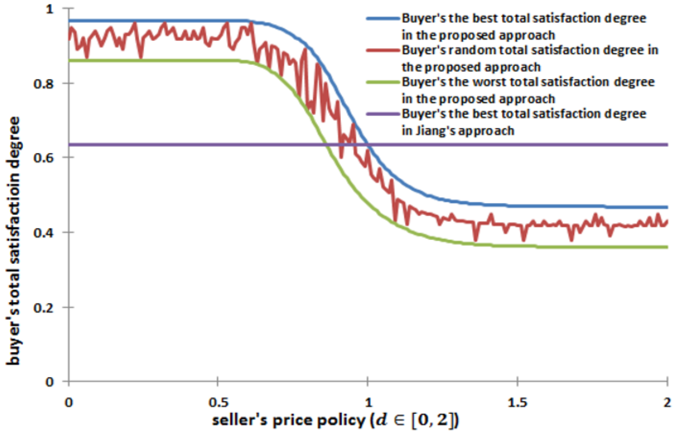


Figure 13 A weight value of attribute's buying quantity $w_i^{u\leftrightarrow f}$ is 0.5

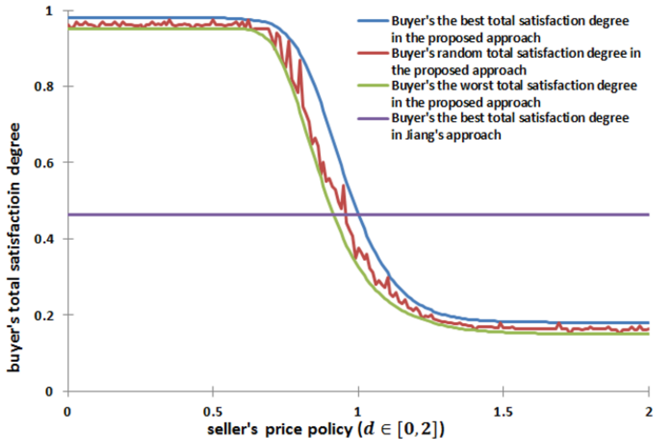


Figure 14 A weight value of attribute's buying quantity $w_i^{u\leftrightarrow f}$ is 0.8

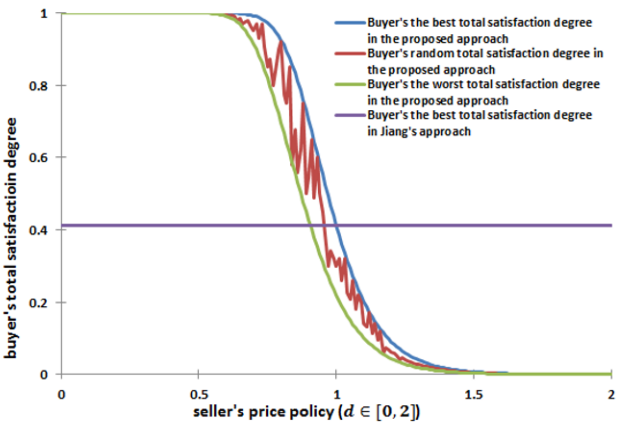


Figure 15 A weight value of attribute's buying quantity $\boldsymbol{w_i^{u\leftrightarrow f}}$ is 1

a buyer's requirements and maximize a buyer's total satisfaction degree.

5. Related Work and Discussions

In this section, we introduce some related work and give discussions on the proposed approach. Jiang et al. (2016) proposed an optimal allocation approach for a multi-attribute trading through a broker under simultaneously considering fuzzy information and indivisible demand. They firstly used 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 proposed a method to calculate the matching degree based on the improved fuzzy information axiom. Finally, based on calculation results of the matching degree, they generated a multi-objective model under a multi-attribute trading with indivisible demand and developed a new algorithm to solve their model. However, the limitation of their approach is that a seller's price policies and a buyer's satisfaction degree as per buying quantity are not considered in their multi-objective model.

Le, Zhang and Ren (2015) proposed a broker-based optimal matching approach based on predicting buyers and sellers' behaviour by using Bayes' rule to maximize a broker's profit under the consideration of buyers and sellers' total satisfaction. Also, Le, Ren and Zhang (2016) proposed membership function based matching approach through a broker. Specially, a buyer's attribute weight with soft constraints in the proposed matching approach is determined by using association rule mining. In addition, Le and Zhang and Ren (2016) proposed the matching approach through a broker in open e-marketplaces based on modelling a buyer's requirements for attributes with fuzzy information. Specially, a broker's allocation strategy was proposed based on a buyer's feedbacks from determined matching results. However, a broker's matching process in the above approaches does not consider a seller's price discount policy and a buyer's satisfaction degree as per buying quantity. In this paper, we propose a broker's matching approach based on the economic model under the consideration of a seller's price discount policy and a buyer's satisfaction degree as per buying quantity, and other attributes.

Jiang, Lp, Lau and Fan (2011) also proposed a multi-objective optimization model to optimize the trade matching in multi attribute exchanges with quantity discounts. This model is to maximize the trade volume and the matching degree. In their paper, they introduced a new conception of matching degree and some properties of matching degree to build their model. Furthermore, they proposed a novel hybrid multi-objective meta-heuristic algorithm to solve their multi-objective optimization model with quantity discounts. However, the limitation of their approach is that it does not consider a buyer's satisfaction degree as per buying quantity in their approach.

Jiang, Fan et al. (2011) proposed a bi-objective optimization model for brokers to optimize the trade matching in multi attribute exchanges. In particular, this model is to maximize the matching degree and trading volume based on a buyer's requirements and a seller's offers. Furthermore, their model considers the incomplete weight information to carry out a broker's matching process. Although their approach is effectively demonstrated in the market environment, their approach does not consider a seller's different price policies, which is offered to a buyer based on a buyer's buying quantity in their model.

Li and Murata (2009) 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, their approach does not consider a buyer's satisfaction degree as per buying quantity.

To compare with the above approaches, the proposed approach in this paper addresses these limitations including (i) modelling a buyer's satisfaction degree as per buying quantity; (ii) modelling a seller's price policy as per buying quantity; and (iii) building the objective function to maximize a buyer's total satisfaction degree with multi-attributes.

6. Conclusion and Future Work

This paper proposes the optimal matching method in an open e-marketplace through matching between a buyer's requirements and a seller's offers based on an economic model. The proposed approach is novel because (i) the design of the broker-based matching approach is general so it can be applied into broad domains to support a broker's decisions; (ii) we propose a novel framework of matching between buyers and sellers based on a broker through three steps. The first step is to model a seller's offers, the second step is to model a buyer's requirements and the last step is to match between buyers and sellers to maximize a buyer's total satisfaction degree; (iii) the proposed approach presents a formula system to calculate a buyer's satisfaction degree in multi-attribute exchanges; and (iv) the objective function and a set of constraints are generated to maximize a buyer's total satisfaction degree based on economic model through a broker. The experimental results demonstrate the good performance in the proposed approach in aspects of satisfying a buyer's requirements and maximizing a buyer's total satisfaction degree.

Future research includes extending the proposed approach to solve competition environments between brokers and we intend to design a decision support system for a broker based on a web-based environment, in which the proposed matching model is applied. Furthermore, alongside price and other attributes' satisfaction degree in a buyer's requirements as per a seller's offers, a broker needs to consider a certain value domain probability for special attributes with soft constraints in a broker's proposed matching approach. For example, delivery time of 2 days for products can be guaranteed with a probability of 95% and in 5% of the cases, delivery time is delayed.

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