# Chapter 9
# Membership Function Based Matching Approach of Buyers and Sellers Through a Broker in Open E-Marketplace

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**Abstract** A broker in a market enables buyers and sellers to do business with each other and can provide many value-adding functions that cannot be replaced by direct buyer-seller dealings. Recently, some research has focused on this issue. However, broker modelling based on buyer's membership functions to carry out a matching process between buyer's requirements in fuzzy preference information and seller's offers is still sparse. Thus, this paper proposes membership function based matching approach of buyers and sellers through a broker in open e-marketplace. The major contributions of this paper are that (i) a proposed framework is applicable to help a broker to carry out the matching process between buyers and sellers; (ii) a proposed method is to determine buyer's attribute weight with soft constraints by using association rule mining; and (iii) an objective optimization function and a set of constraints are built to help a broker to maximize buyer's total utility. Experimental results demonstrate the good performance of the proposed approach in terms of satisfying buyer's requirements and maximizing buyer's total utility.

**Keywords** Matching approach · Seller's offers · Buyer's requirements · Buyer's total utility

## 9.1 Introduction

Research on brokers or intermediaries in the markets as the third party of the trading processes in e-markets has been a very active direction in recent years. Li et al. [9] developed a mathematical model to solve the multi-attribute matching problem

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through a matchmaker. Jiang et al. [7] proposed a novel matching approach for a broker to achieve the optimal trade matching in multi-attribute exchanges under consideration of the trading volume and the matching degree. Alpar [1] developed a conceptual framework of matching in B2B e-marketplaces environments and proposed the new algorithm for the implementation of the functionalities of the matchmaker. Blume et al. [2] studied the trading processes in general e-markets between buyers and sellers through a layer of intermediaries. Jung et al. [8] proposed a two-layered multi-agent framework to match between buyers and sellers through brokerage by using constraint satisfaction problems (CSP).

Although the above approaches have focused on studying brokers as a third party in the trading processes between buyers and sellers, there is little theory and few guidelines to help a broker to optimize the trading matching between buyer's requirements in fuzzy preference information and seller's offers. Therefore, following challenges for broker modelling still exist, which are (i) how to map buyer's requirements to seller's offers optimally; (ii) how to maximize buyer's total utility under consideration of buyer's requirements in fuzzy preference information and seller's offers; and (iii) how to determine buyer's attribute weight with soft constraints based on historical trading dataset to support broker's decision.

In order to solve the above challenges, this paper proposes membership function-based matching approach in multi-attribute exchanges through a broker between buyers and seller. The major contributions of this paper are as follows. (i) The design of membership function based matching approach in multi-attribute exchanges is in general level by considering general markets so that it can be applied to different types of markets; (ii) The proposed method is to derive buyer's attribute weight with soft constraints by using association rule mining; and (iii) An objective optimization function and a set of constraints are proposed to maximize buyer's total utility in regard to buyer's requirements and seller's offers. Experimental results demonstrate the good performance of the proposed approach in terms of satisfying buyer's requirements and maximizing buyer's total utility.

The rest of this paper is organized as follows. Problem description is presented in Sect. 9.2. The proposed matching approach in the markets is introduced in Sect. 9.3. An experiment is presented in Sect. 9.4. Section 9.5 compares our approach with some related work. Section 9.6 concludes in this paper and points out our future work.

## 9.2 Problem Description

There are three members in the trading process with multi-attribute exchanges, i.e., buyers, sellers and a broker. The trading process is shown in Fig. 9.1. The broker is often called the facilitator, who acts as an intermediary between the buyer and the seller in the commodity exchange. In this paper, the broker's responsibility is to match $n$ ($n \geq 1$) buyers with $m$ ($m \geq 1$) sellers for the same commodity with multi attribute exchanges in order to satisfy buyer's requirements. Buyer $b_i$ ($i = 1, 2, \ldots n$)

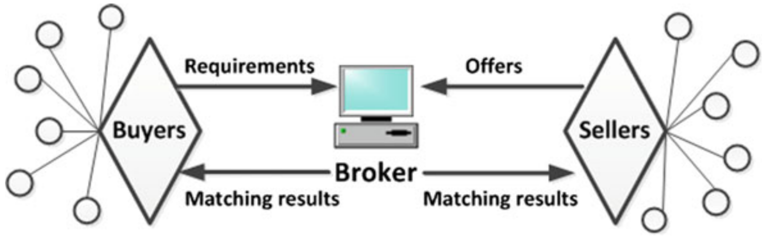


**Fig. 9.1** The trading processes through a broker in open E-marketplace

and seller $s_j$ $(j = 1, 2, \ldots m)$ have a single unit of the commodity with multiple attributes to buy or sell. Multi attributes in buyer's requirements are divided into two categories including the attributes with hard constraints and the attributes with soft constraints. The attributes with hard constraints mean that their constraints are presented in the form of an 'equal to' notation while the attributes with soft constraints are presented in the form of inequality and their constraints can be relaxed within the given scope of values [8].

From the buyer's part, buyer $b_i$ can present $b_i$'s requirements through many attributes. In general, when buyers select a certain product from the markets through a broker, buyers work with product's uncertain information or product's attribute level choices. Under these situations, it is difficult for buyers to estimate the attribute levels with exact numerical values. Thus, buyers normally express their requirements of the product features in fuzzy or linguistic terms [3]. For example in a washing machine purchasing problem, buyer's preference information related to price, popularity, comfort and maintenance cost is sent to a broker in following terms.

*Price*: The price of washing machine should be *around AUD1,000*.

*Popularity*: Popularity of washing machine *should be high*.

*Comfort*: Overall washing machine *should be comfortable*.

*Maintenance*: Maintenance cost of washing machine *should be medium*.

Fuzzy or linguistic terms are the italic words in the above example. The price attribute can be presented through fuzzy numbers while the other attributes, i.e., popularity, comfort and maintenance cost can be expressed by using the fuzzy or linguistic terms [6].

Similarly, from seller's point of view, seller $s_j$'s offer is related to many attributes. Level of each attribute in $s_j$'s offer is provided in details to a broker.

Based on the above analysis, a key problem is how to help a broker to find the optimal matching pairs so that buyer's requirements are satisfied and buyer's total utility is maximized. Therefore, the proposed matching approach is to solve this problem and presented in Sect. 9.3.

## 9.3 The Proposed Matching Approach

### *9.3.1 Framework of the Proposed Approach*

The framework of the proposed approach presented in Fig. 9.2. helps a broker to solve the matching problem between buyer's requirements in fuzzy preference information and seller's offers with multi-attribute exchanges. The proposed approach focuses on maximizing buyer's total utility through a broker under business environments.

In the framework, buyer's requirements in fuzzy preference information and seller's offers related to a multi-attribute commodity are submitted to a broker. A broker communicates with buyers by using the direct rating (point estimation) method to build buyer's membership function for each attribute. Based on buyer's membership function, a broker calculates buyer's utility for each attribute as per seller's offers to determine a constraint satisfaction layer. The constraint satisfaction layer includes sellers which satisfy at least a certain buyer's requirements. Then, a broker uses association rule mining to estimate buyer's attribute weight with soft constraints based on buyer's historical trading datasets. After that, an objective optimization function and a set of constraints are generated to maximize buyer's total utility. Finally, the objective optimization function is solved by linear programming problem (LPP) to obtain the optimal matching pairs. The main issues of the proposed approach, i.e., building the calculation of buyer's utility, calculating buyer's attribute weight with soft constraints and building the objective optimization function are presented in details in the following subsections.

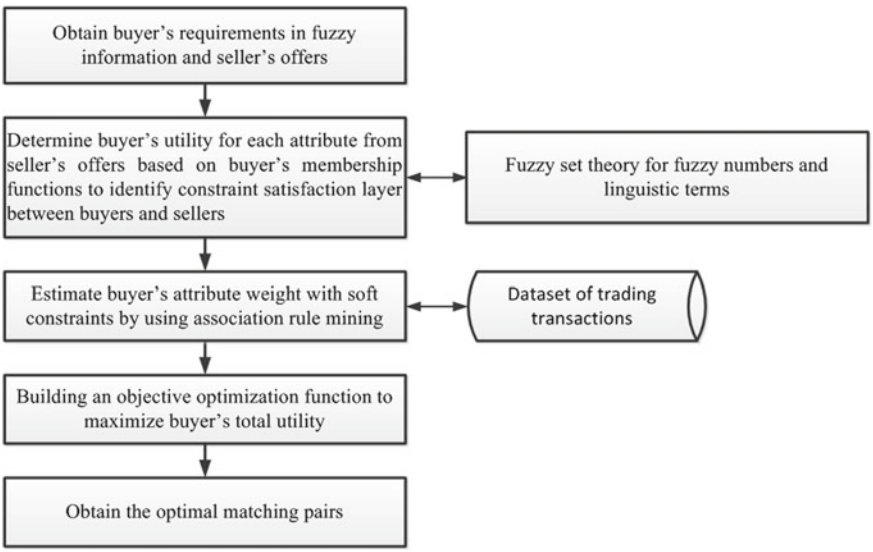


**Fig. 9.2** The framework of the broker modeling approach

### *9.3.2 Building the Calculation of Buyer's Utility*

In the majority of market settings and products, buyer's own preferences about products and their features are normally expressed in a qualitative or linguistic manner because buyer's knowledge about products is relatively vague. Thus, it is difficult for buyers to express their preferences with an exact numerical value. On the other hand, the use of words or sentences rather than numbers enables a more flexible and realistic form of adequately expressing day-to-day business terms. To estimate buyer's preferences in a qualitative or linguistic manner, fuzzy set theory is best suited to deal with the qualitatively defined terms (linguistic assessments) in a quantitative manner [12]. A precise definition of fuzzy set is as follows:

**Definition** Let X be a set of objectives. A fuzzy set A in X is defined as a set of ordered pairs $A = \{x, \mu_A(x)\}$, where $\mu_A(x)$ represents a membership function of fuzzy set A, which associates each point $x \in X$ with a real number in the interval [0,1]. The value $\mu_A(x)$ is called the grade of membership of $x$ in A.

Let a set of buyer $\mathbf{B} = \{b_1, b_2, \ldots, b_n\}$ and a set of sellers $\mathbf{S} = \{s_1, s_2, \ldots, s_m\}$, buyer's requirements and seller's offers are related to many attributes which can be split into a set of the attributes with soft constraints $\mathbf{A} = \{a_1, a_2, \ldots, a_k\}$ and a set of the attributes with hard constraints $\mathbf{H} = \{h_1, h_2, \ldots, h_z\}$ [7]. Let a set of constraint values $\mathbf{c_i} = \{c_{i1}, c_{i2}, \ldots, c_{iz}\}$ and $\mathbf{c_j} = \{c_{j1}, c_{j2}, \ldots, c_{jz}\}$ for the attributes with hard constraints in $b_i$'s requirements and $s_j$'s offers, respectively. Similarly, $a_{il}$ and $a_{jl}$ denote the attribute level $l$ with soft constraints of buyer $b_i$ and seller $s_j$, respectively. Buyer's requirements related to the attributes with hard constraints must be satisfied by seller's offers to attend broker's matching process. Furthermore, the nature of fuzzy information is related to the attributes with soft constraints and is not allowed for hard attributes. Thus, the procedure of calculating buyer's utility for the attributes with soft constraints is presented as follows:

**Step 1**: A broker receives $b_i$'s product requirements in fuzzy preference information and $s_j$'s offers in terms of its attributes. A broker determines buyer's membership function for each attribute by using the direct rating (point estimation) method [10]. In this method, a broker communicates with buyers to determine buyer's preference point through questions. Broker's questions require a buyer to select one point on the reference axis (using numerical or verbal scale) that best describes this element. For example, a broker starts the simplified interactive procedure with buyers to build a membership function for the attribute of price. It consists of 3 questions that allows to identify three reference points within the feasible range of price as follows:

- Question 1: "What is the worst option for the attribute of price?"→ "everything is the worst if price of product is more than or equal to 25 AUD".
- Question 2: "What is the perfect option for the attribute of price that would give you full satisfaction level?" → "the perfect price is less than or equal to 15 AUD".
- Question 3: "What is a medium resolution level for you with regard to price? → "an average 20 AUD".

Based on buyer's responses above, the continuous membership function of the price attribute is presented as follows:

$$\mu(x) = \begin{cases} 1 & for \ \ x \leq 15 \\ \frac{25-x}{10} & for \ \ x \in \langle 15, 25 \rangle \\ 0 & for \ \ x \geq 25 \end{cases}$$

In general, $b_i$'s membership function for each attribute is presented as follows.

$$\{a_1^i, \mu_{a_1^i}\}, \{a_2^i, \mu_{a_2^i}\}, \dots \{a_k^i, \mu_{a_k^i}\}, \tag{9.1}$$

where $a_k^i$ represents the fuzzy set of the $k$th attribute for buyer $b_i$ and $\mu_{a_k^i}$ presents the membership function of the fuzzy set corresponding to attribute $a_k$ for buyer $b_i$.

**Step 2**: A broker determines buyer's utility for each attribute based on $b_i$'s membership function and $b_i$'s requirements. It is presented as follows:

$$\{(a_1^i, \mu^i(a_{i1})), (a_2^i, \mu^i(a_{i2})), \dots (a_k^i, \mu^i(a_{ik}))\}, \tag{9.2}$$

where $\mu^i(a_{ik})$ is $b_i$'s utility for attribute $a_k$, $\mu^i(a_{ik})$ is determined from $b_i$'s requirements and $b_i$'s membership function so it means that $b_i$ expects to find out the minimal utility value $\mu^i(a_{ik})$.

**Step 3**: Based on $b_i$'s membership function for each attribute, a broker determines $b_i$'s utility for each attribute as per $s_j$'s offer. It is presented as follows:

$$\{(a_1^i, \mu^{ij}(a_{j1})), (a_2^i, \mu^{ij}(a_{j2})), \dots (a_k^i, \mu^{ij}(a_{jk}))\}, \tag{9.3}$$

where $\mu^{ij}(a_{jk})$ is $b_i$'s utility for attribute $a_k$ if $s_j$'s offer is provided to $b_i$.

**Step 4**: A broker determines a constraint satisfaction layer by comparing $\mu^{ij}(a_{jl})$ with $\mu^i(a_{il})$, and $c_{ig}$ with $c_{jg}$. More specifically, if $\mu^{ij}(a_{jl}) \geq \mu^i(a_{il})$ $(l = 1, 2, \dots, k)$ and $c_{ig} = c_{jg}$(g=1,2,...,z) then seller $s_j$'s offer satisfies $b_i$'s requirements. Otherwise, seller $s_j$ can not match with $b_i$.

### *9.3.3 Determining Buyer's Soft Attribute Weight*

When carrying out the trading process between buyers and sellers in open environments, a broker needs to understand buyer's behavior in term of their attribute weight with soft constraints. Such understanding buyer's attribute weight with soft constraints helps a broker to retrieve buyer's real preferences. This will enable the broker to better understand buyers to select seller's appropriate offers to satisfy buyer's requirements. It is not an easy job to uncover buyer's attribute weight with soft constraints from fuzzy information. Our paper follows the Analytical Hierarchy

Process [11] to derive the attribute weight with soft constraints using association rule mining.

Assume that there are the number $t$ of transactions $(\{T_1, T_2, \ldots, T_t\})$ carried out by buyer $b_i$ so far. Each transaction consists of a set of sellers who provided a product to $b_i$. A broker determines $b_i$'s soft attribute weight based on historical trading datasets as follows:

**Step 1**: For each transaction, a broker can find $b_i$'s average utility for each attribute. For example, take the transaction $T_s$ $(s \in t)$ and assume that $T_s$ includes $s_1, s_2, s_3$ and $s_4$. $b_i$'s average utility $T^i_{sl}$ of the attribute $l$ in the transaction $s$ is calculated as follows:

$$T^i_{sl} = (\mu^{i1}(a_{1l}) + \mu^{i2}(a_{2l}) + \mu^{i3}(a_{3l}) + \mu^{i4}(a_{4l}))/4 \tag{9.4}$$

**Step 2**: A broker calculates $b_i$'s average utility of the $l$th attribute $T^i_l$ in the entire business transactions as follows.

$$T^i_l = \frac{\sum\limits_{s=1}^{t} T^i_{sl}}{t} \tag{9.5}$$

**Step 3**: $b_i$'s average utility $T^i_{sl}$ of the attribute $l$ in transaction $s$ is checked to ensure that its value is at least equal to the value of $T^i_l$. If $T^i_{sl} < T^i_l$ then zero value is assigned to $T^i_{sl}$. Otherwise, $T^i_{sl}$ is taken as $T^i_{slnew}$. This is necessary, as a broker does not want to consider $b_i$'s average utility $T^i_{sl}$ in any transaction if its value is less than $b_i$'s average attribute utility of the entire business transaction.

**Step 4**: A broker calculates transaction frequency of the $l$th attribute $T^i_{lnew}$ as follows.

$$T^i_{lnew} = \sum_{s=1}^{t} T^i_{slnew} \tag{9.6}$$

**Step 5**: Using the association rule mining [5], a broker can find the degree of association of the attribute $a_l$ with any other attribute(s) $w$, where $w \in P(\mathbf{A} - a_l)$, $w \neq \varnothing$ and $P(\mathbf{A} - a_l)$ is a power set of any subset of $(\mathbf{A} - a_l)$. In particular, it is calculated as follows.

$$c^i_{lw} = \frac{\sum\limits_{s=1}^{t} [T^i_{slnew} \bigwedge T^i_{swnew}]}{T^i_{lnew}}, \tag{9.7}$$

where $c^i_{lw}$ represents the degree to which $b_i$ likes the attributes $w$ because of the presence of the $l$th attribute $(l = 1, 2, \ldots, k)$.

**Step 6**: A broker can calculate the degree of confidence of $b_i$ for attribute $a_l$ as follows:

$$c^i_l = \sum_{w \in P(\mathbf{A} - a_l), w \neq \varnothing} c^i_{lw} \tag{9.8}$$

Note that the number of non empty sets in $P(\mathbf{A} - a_l)$ is $2^{k-1} - 1$.

**Step 7**: If $rp^i_{ll'}$ $(l, l' = 1, 2, \ldots, k)$ represents $b_i$'s relative preference of $a_l$ over $a'_l$ $(rp^i_{ll'} = c^i_l / c^i_{l'})$, then the matrix is generated as follows:

$$Z^i_{k,k} = \begin{bmatrix} rp^i_{1,1} & rp^i_{1,2} & \cdots & rp^i_{1,k} \\ rp^i_{2,1} & rp^i_{2,2} & \cdots & rp^i_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ rp^i_{k,1} & rp^i_{k,2} & \cdots & rp^i_{k,k} \end{bmatrix} \tag{9.9}$$

The eigenvector calculated from the maximum eigenvalue of the matrix $Z^i_{k,k}$ in Eq. (9.9) gives a broker buyer's attribute weight with soft constraints after the eigenvector is normalized. In particular, $\sum_{l=1}^{k} w^i_l = 1$, $w^i_l \geq 0$, where $w^i_l$ is the weight of attribute $a_l$ in $b_i$'s requirements.

After determining buyer's attribute weight with soft constraints, a broker will build an objective optimization function to maximize buyer's total utility. The objective optimization function is presented in Sect. 9.3.4.

### *9.3.4 Building an Objective Optimization Function*

Broker's decision making in open environments to maximize buyer's total utility through matching process between buyers and sellers is driven by the objective optimization function. Based on the problem description and notations, the objective optimization function and a set of constraints are built as follows:

$$f = \sum_{i=1}^{n} \sum_{j=1}^{m} (\sum_{l=1}^{k} w^i_l \mu^{ij}(a_{jl}) x_{ij}) \tag{9.10}$$

$$s.t. \sum_{i=1}^{n} x_{ij} \leq 1, j = 1, 2, \ldots, m \tag{9.11}$$

$$\sum_{j=1}^{m} x_{ij} \leq 1, i = 1, 2, \ldots, n \tag{9.12}$$

$$x_{ij} = 1, 0, (i = 1, 2, \ldots, n; j = 1, 2, \ldots, m) \tag{9.13}$$

$$\sum_{l=1}^{k} w^i_l = 1, (i = 1, 2, \ldots, n; l = 1, 2, \ldots, k) \tag{9.14}$$

$$x_{ij} = 0 \; if \; \mu^{ij}(a_{jl}) < \mu^i(a_{il}) (l = 1, 2, \ldots, k) \; or \; c_{ig} \neq c_{jg} (g = 1, 2, \ldots, z) \tag{9.15}$$

where the objective optimization function in Eq. (9.10) seeks to maximize the weight sum of buyer's utility, constraints (9.11) and (9.12) are that each buyer (seller) can buy (sell) one unit of the commodity at most. Constraint (9.13) is assignment variable constraints, if $b_i$ matches with $s_j$, then $x_{ij} = 1$; otherwise $x_{ij} = 0$. Constraint (9.14) indicates $b_i$'s attribute weight with soft constraints; and constraint (9.15) indicates a constraint satisfaction layer to attend broker's matching processes. Furthermore, Eq. (9.10) can be efficiently solved by well-known linear programming methods such as simplex methods or interior point method [4].

## 9.4 Experiments

In this section, we present our experimental results and analyse our matching approach's performance. The experiments mainly focus on testing maximizing buyer's total utility through matching between buyer's requirements and seller's offers. The rest of this section is divided into two subsections. Section 9.4.1 describes the experimental setting that have been applied in the experiments. Section 9.4.2 shows the experimental results and performance analysis in three different experimental scenarios.

### *9.4.1 Experimental Setting*

In the experiments, we generate an artificial data of 10 buyers related to jacket's demand. Each buyer contains seven attributes: brand, price, delivery time, warranty time, size, colour and gender. From the buyer's point of view, brand, size, colour and gender are regarded as the attributes with hard constraints while price, delivery time and warranty time are considered as the attributes with soft constraints. Furthermore, each buyer includes 10 transactions selected from the historical trading dataset. Based on each buyer's historical trading dataset, a broker uses the association rule mining presented in Sect. 9.3.3 to determine buyer's attribute weight with soft constraints including price, delivery time and warranty time. Similarly, each seller contains seven attributes including brand, price, delivery time, warranty time, size, colour and gender. In the experiments, the proposed approach is evaluated under seller's market so the three different scenarios includes a number of different selected sellers. More specifically, a broker's matching approach is tested in three different scenarios presented in Table 9.1 to maximize buyer's total utility under different sellers.

Before the matching process is happened, a broker interacts with each buyer to determine buyer's membership function for each attribute with soft constraint by using the direct rating method presented in Sect. 9.3.2. Based on the buyer's responses, a broker is able to identify buyer's membership function for each attribute with soft constraint to carry out broker's matching process.

**Table 9.1** Experimental scenarios

| Scenario | Test purpose |
|---|---|
| 1 | To maximize buyer's total utility with 10 buyers and 5 sellers |
| 2 | To maximize buyer's total utility with 10 buyers and 10 sellers |
| 3 | To maximize buyer's total utility with 10 buyers and 20 sellers |

## *9.4.2 Experimental Results and Analysis*

In scenario 1, a broker uses the proposed matching to maximize buyer's total utility through finding out the allocations between buyers and sellers under considering that the number of buyers (10 buyers) is more than the number of sellers (5 sellers) in the markets. In general principle of markets, when buyer's demand is more than seller's supply, all buyer's requirements cannot be satisfied and it is difficult for buyers to obtain their high utility because a broker has a fewer opportunity to select seller's offers to satisfy buyer's requirements. The results of buyer's utility in scenario 1 are presented in Fig. 9.3 and the matching results are also presented in Table 9.2.

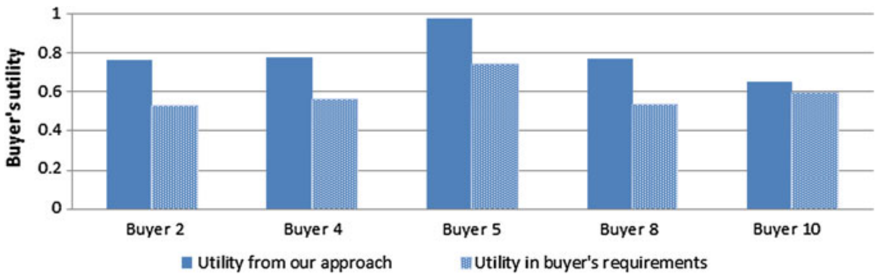


**Fig. 9.3** Buyer's utility in Scenario 1

**Table 9.2** Optimal matching pairs with the three different scenarios

| | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|
| 1 | $B_2 \longleftrightarrow S_5$ | $B_1 \longleftrightarrow S_1$ | $B_1 \longleftrightarrow S_7$ |
| 2 | $B_4 \longleftrightarrow S_3$ | $B_2 \longleftrightarrow S_5$ | $B_2 \longleftrightarrow S_{20}$ |
| 3 | $B_5 \longleftrightarrow S_2$ | $B_3 \longleftrightarrow S_4$ | $B_3 \longleftrightarrow S_2$ |
| 4 | $B_8 \longleftrightarrow S_1$ | $B_4 \longleftrightarrow S_3$ | $B_4 \longleftrightarrow S_{10}$ |
| 5 | $B_{10} \longleftrightarrow S_4$ | $B_5 \longleftrightarrow S_8$ | $B_5 \longleftrightarrow S_4$ |
| 6 | | $B_6 \longleftrightarrow S_2$ | $B_6 \longleftrightarrow S_{12}$ |
| 7 | | $B_7 \longleftrightarrow S_{10}$ | $B_7 \longleftrightarrow S_{17}$ |
| 8 | | $B_8 \longleftrightarrow S_7$ | $B_8 \longleftrightarrow S_{15}$ |
| 9 | | $B_9 \longleftrightarrow S_9$ | $B_9 \longleftrightarrow S_{19}$ |
| 10 | | $B_{10} \longleftrightarrow S_6$ | $B_{10} \longleftrightarrow S_{14}$ |
| | $f = 0.78$ | $f = 0.82$ | $f = 0.90$ |

Based on Fig. 9.3 and Table 9.2, it is clear that there are only five satisfied buyers including $B_2$, $B_4$, $B_5$, $B_8$ and $B_{10}$ while other buyers do not satisfy. Our proposed approach through a broker helps five satisfied buyers to find their utility which is higher than utility in their requirements. However, five satisfied buyer's normalized total utility in scenario 1 is not high (0.78) because a number of sellers is less than a number of buyers.

Similarly, in scenario 2, a broker considers that the number of sellers is as equal as the number of buyers. Based on Fig. 9.4 and Table 9.2, it can be seen that buyer's requirements are also satisfied and the matching results are also found for each buyer. More specifically, buyer's normalized total utility in scenario 2 is relative high (0.82) and is higher than buyer's normalized total utility in scenario 1 because a broker has many opportunities to select seller's offers which satisfy buyer's requirements and increase buyer's total utility.

Finally, the number of sellers is twice as equal as the number of buyers. Based on Fig. 9.5 and Table 9.2, it is clear that except buyer's satisfied requirements, buyer's normalized total utility is very high (0.90) and higher than buyer's normalized total utility (0.78) in scenario 1 and buyer's normalized total utility (0.82) in scenario 2 because a broker in scenario 3 is more opportunity to select seller's offers which satisfy buyer's requirements than in scenario 1 and 2.

In summary, the proposed approach is perfectly performed under different situations in business environments. In general, if seller's supply is more than buyer's demand, a broker has many opportunities to choose seller's offers to satisfy buyer's requirements and increase each buyer's utility as well as buyer's total utility.

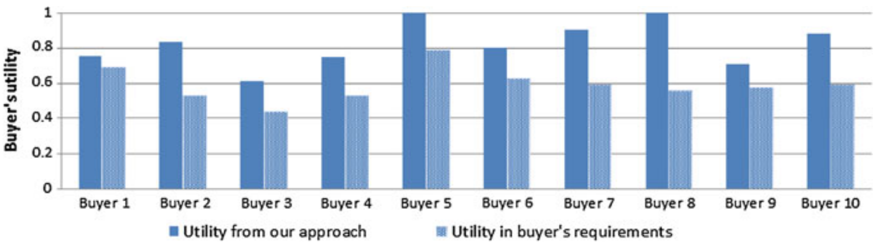


**Fig. 9.4** Buyer's utility in Scenario 2

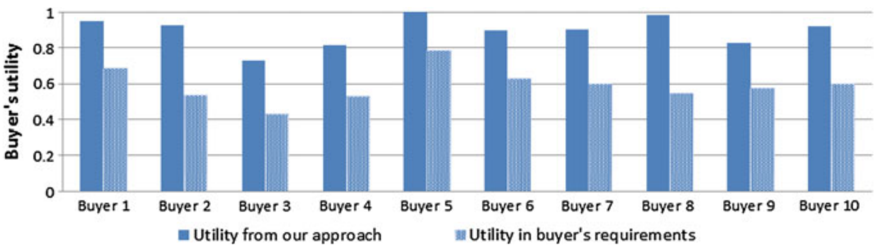


**Fig. 9.5** Buyer's utility in Scenario 3

## 9.5 Related Work

There has been a lot of previous work on regarding the indirect interaction between buyer agents and seller agents through broker agents in e-markets. Jiang et al. [7] proposed a matching approach based on a bi-objective function to optimize the trade matching in multi-attribute exchanges with incomplete weight information through electronic brokerages (E-brokerages). In particular, the bi-objective optimization function is to maximize the matching degree and trading volume. The difference between Jiang's work and our work is that a broker in our approach uses the direct rating (point estimation) method [10] to communicate with buyers to determine buyer's membership function before a broker carries out the matching process between buyers and sellers. Thus, our approach is to maximize buyer's total utility through a broker based on buyer's membership function while Jiang et al. [7] does not pay attention to buyer's utility from its membership function in Jiang's bi-objective optimization function.

Li et al. [9] proposed two objective optimization functions to match buyers and sellers in B2B e-marketplace. The first and second objective optimization function are to maximize the total satisfaction of buyer and seller, respectively. Although buyer's attribute weight is considered in Li's multi objective function, buyer's attribute weight values are chosen by buyers. The novelty of our approach is that a broker determines buyer's attribute weight with soft constraints by using association rule mining based on historical trading datasets.

Jung et al. [8] modelled the trading phenomenon in the markets in which brokerage acted as a middleman between buyers and sellers. They proposed a two-layered mult-agent framework for brokerage between buyers and sellers. Based on buyer and seller's requirements, their approach helps brokerage to find out an optimal matching solution to satisfy buyer's various preferential requirements using constraint satisfaction problems (CSP). However, the limitation of their approach is that they do not consider each buyer's utility as well as buyer's total utility.

## 9.6 Conclusion and Future Work

This paper proposes the optimal matching method based on buyer's membership function through a broker in open e-marketplace. The proposed approach is novel because (1) it is a novel idea to consider buyer's requirements in fuzzy preference information and seller's offers with multi-attribute exchanges. The proposed approach solves the matching problem with multi-attribute exchanges through a broker based on buyer's membership function; (2) the new method is proposed to estimate buyer's attribute weight with soft constraints using the association rule mining; and (3) the objective optimization function and a set of constraints are generated to maximize buyer's total utility. The experimental results demonstrate the good performance for the proposed approach in aspects of satisfying buyer's requirements and buyer's total utility.

Future research includes extending the proposed approach to solve competition environments between brokers and dynamic environments.

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