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# A MATCHING APPROACH FOR ONE-SHOT MULTI-ATTRIBUTE EXCHANGES WITH INCOMPLETE WEIGHT INFORMATION IN E-BROKERAGE

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Abstract. *Electronic brokerages (E-brokerages) are Internet-based organizations that enable buyers and sellers to do business with each other. While E-brokerage has become a significant sector of E-commerce, theory and guidelines for matching the multi-attribute exchange in E-brokerage are sparse. This paper proposes a matching approach to optimize the trade matching in one-shot multi-attribute exchanges with incomplete weight information. Firstly, the new definition of matching degree from both buyers' and sellers' points of view in multi-attribute exchanges is presented. Secondly, based on the definition of matching degree and the representation of incomplete weight information, a bi-objective optimization model is built to maximize the matching degree and trading volume. Then, according to the characteristics of the model which belongs to a class of multi-objective mixed 0-1 integer quadratic programming models, the ideal point method is used to solve it. Finally, an example is employed to illustrate the application of the proposed matching approach.*

**Keywords:** Electronic brokerage (e-brokerage), Multi-attribute exchanges, Trade matching, Incomplete weight information

## 1. Introduction.

The information revolution is dramatically reshaping the business model and pushing traditional commerce toward electronic commerce (E-commerce). More and more people are getting involved in business activities based on Internet (or electronic) markets. It not only promotes the rapid development of E-commerce, but also brings about new challenges for E-commerce [1,2].

For example, due to the vast amount of information on the Internet, it is not easy for a buyer or seller to locate and process relevant information, and to distinguish between useful and not useful material for a specific market transaction, even with the help of the search engines on the Web (such as Google, Yahoo, etc.). This has created the opportunity for new Internet intermediaries to enter the electronic marketplace [3]. These new Internet intermediaries are called *electronic brokerages* (*E-brokerages*), also named *electronic intermediaries* [4] or *cybermediaries* [5]. With the use of information communication technology (ICT), E-brokerages can facilitate exchanges between buyers (consumers) and sellers (producers) by meeting their needs [6]. Compared with traditional brokerages, E-brokerages have the advantage of not being bound by time and space constraints and the advantage of being able to provide more real-time and effective information for commodity exchanges. As a result, E-brokerages are very popular on the Internet; for instance, a not-for-profit project funded by the trade promotion organizations of various countries, provides a non-exhaustive directory of over 642 active electronic marketplaces around the world (www.emarketservices.com, Jan., 2010), which includes various brokerage patterns, such as real estate E-brokerages, automotive E-brokerages, IT product E-brokerages, etc.

However, as a significant sector of E-commerce, E-brokerage is still a relatively new and poorly understood type of business [4]. There is little theory and few guidelines to help E-brokerages optimize the trade matching between buyers and sellers, although there is a growing literature on E-brokerage that is contributing to fill the gap. Most of current E-brokerages only release the trade information, which is derived from buyers and sellers, on the Internet, however, do not really serve the function of matching buyers with sellers. In this respect, one may say that E-brokerages provide no matchmaking assistance: the matchmaker is the buyer (or the seller) herself [7]. Especially in a one-shot multi-attribute exchange where commodities use multiple attributes, such as *price*, *quality* and *delivery time* in specifications of buy and sell orders (bids) collected over a given time interval, it makes trade matching more complicated since multiple attributes of the commodity are needed to be considered. Moreover, in reality, due to the complexity of multi-attribute exchanges and the inherent subjective nature of human thinking [8], the buyer (or the seller) may not be confident in providing precise values for attribute weights. Instead, they may only possess partial knowledge about attribute weights, that is to say, the information about attribute weights is usually incomplete [9]. For example, suppose that three main attributes of a house, i.e., *price*, *location* and *building size*, are considered in the real estate exchange, a buyer may argue that the *location* is the most important, the *price* is the second, and the *building size* is the third. In this situation, the information about attribute weights is incomplete and can be described with the corresponding weights of these three attributes only in the form of weak or strict orders but not in the form of precise values. Consequently, in the absence of a comprehensive trade matching theory for one-shot multi-attribute exchanges with incomplete weight information, E-brokerages cannot become the real matchmakers between buyers and sellers, and may also lose solid foundation to improve trading efficiency and profits. Thus, effective approaches should be investigated to achieve the optimal matching pairs between buyers and sellers in one-shot multi-attribute exchanges with incomplete weight information.

The aim of this paper is to propose a matching approach for E-brokerages to optimize the trade matching in one-shot multi-attribute exchanges with incomplete weight information. Firstly, the new definition of matching degree is presented from both buyers' and sellers' points of view in multi-attribute exchanges. Then, based on the definition of matching degree and the representation of incomplete weight information, a bi-objective optimization model is built to maximize the matching degree and trading volume. This model belongs to a class of multi-objective mixed 0-1 integer quadratic programming models, and the ideal point method is used to solve it. Finally, an example is employed to illustrate the application of the proposed matching approach.

The remainder of this paper is organized as follows: Section 2 reviews some relevant literature. In Section 3, we describe the matching problem in one-shot multi-attribute exchanges with incomplete weight information. Section 4 proposes a matching approach to solve the matching problem described in Section 3. Section 5 provides an example in the real estate E-brokerage to illustrate the application of the proposed matching approach. The conclusion and some suggestions for further research are given in Section 6.

2. **Literature Review.** Exchanges (also called *double auctions* [10]) are double-sided marketplaces where both buyers and sellers submit their requirements (bids) for trading [11]. The exchanges differ in functionality with respect to timing of clearing, number of bid submissions, pricing, aggregation and the varieties of commodities traded [12]. In this paper, our interest is to determine the trade matching in one-shot exchanges based on E-brokerage, because they often enjoy liquidity and efficiency advantages over other exchanges [13]. In one-shot exchanges, buyers and sellers submit their bids once during the specified bidding interval and the market is cleared by the broker (i.e., the E-brokerage firm or the decision maker) after the termination of the bidding time. This is similar to call markets or clearing house [14], however, the bids may have multiple attributes, in this case, the exchanges are regarded as one-shot multi-attribute exchanges. Thus, in this section, we mainly review the literature on one-shot multi-attribute exchanges (also named multi-attribute call double auctions).

Only a small but steadily growing number of academic papers have considered one-shot multi-attribute exchanges so far. Ryu [15] proposed a computable mechanism of trading intermediaries for commodity auction markets, supporting not only ordinary trading constraints of prices and quantities but also other qualitative and quantitative constraints on the commodity properties and trading conditions. Jung and Jo [16] introduced *Constraint Satisfaction Problems* (CSP) to find an optimal solution by the brokerage to satisfy various preferential requirements for buyers and sellers, and implemented a prototype of a brokerage system for dealing in real estate on the Internet. Kameshwaran and Narahari [12] addressed the trade determination issue for one-shot multi-attribute exchanges that trade multiple units of the same good. They model trade determination as mixed integer programming problems for different possible bid structures. Wang et al. [17] investigated the trade matching problem in the electronic market based on a brokerage agent, but the proposed model and algorithm are only suitable in the view of either buyers or sellers, not both of them. Zhang [18] presented the model and algorithm for a single unit of multi-attribute commodity trade matching, and which have been applied in second-hand real estate and car E-brokerages. Dani et al. [19] and Engel et al. [20] discussed the optimal matching problem in two-sided multi-attribute auctions that involved multiple buyers and sellers. Some exact algorithms or CPLEX software techniques are proposed to solve the matching problem. Kim et al. [21], Placek and Buyya [22] and Schnizler et al. [23] studied multi-attribute trade matching models in goods distribution brokerage, storage services brokerage and grid services brokerage, respectively. Gujo [24] introduced an approach for multi-attribute inter-enterprise exchange of logistics services, which is based on combinatorial auction and multi-attribute bid formation.

Nevertheless, most of the existing literature related to the trade matching in one-shot multi-attribute exchanges is based on optimization models that assume the objective function is only relative to the price, such as maximizing trading surplus or profits, while other non-price attributes are regarded as the constraints. In fact, other non-price attributes, such as "*quality*, *delivery time*, *warranty*", should not only subject to the constraints, but also be considered in the objective function. For example, as far as the *quality* of the commodity is concerned, the higher its value, the keener a buyer would be to buy it. In this case, the quality is needed to be considered in the objective function to satisfy the buyer's requirements as possible. Another widely used assumption in one-shot multi-attribute exchanges is to have the precise values of attribute weights. However, this assumption is probably unrealistic when the precise values of attribute weights are not known. On the contrary, as mentioned in Introduction, the information about attribute weights is usually incomplete in the real world. Therefore, current approaches in the existing literature cannot be used to optimize the trade matching in one-shot multi-attribute exchanges with

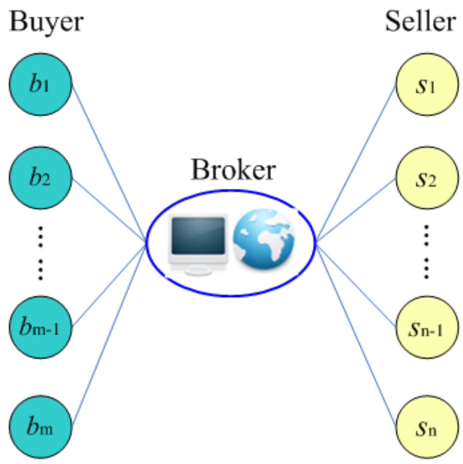


FIGURE 1. One-shot multi-attribute exchange based on E-brokerage

incomplete weight information, making it necessary to develop a novel matching approach to consider multiple attributes in the objective function of optimization models and also handle the incomplete weight information in one-shot multi-attribute exchanges.

3. **Problem Description.** There are three principal roles played by actors in a one-shot multi-attribute exchange based on E-brokerage, that is, buyer, seller and broker, as shown in Figure 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, we consider the broker is to match $m$ ($m > 1$) buyers and $n$ ($n > 1$) sellers for the same multi-attribute commodity in order to satisfy their requirements. Buyer $b_i$ ($i \in I = \{i = 1, \ldots, m\}$) and seller $s_j$ ($j \in J = \{j = 1, \ldots, n\}$) have a single unit of the commodity with multiple attributes $a_k$ ($k \in K = \{k = 1, \ldots, l\}$) to buy or sell.

From the buyer's point of view, buyer $b_i$ can represent his requirements for the attribute $a_k$, where, $k \in K_b$ and $K_b \subseteq K$. We define the buyer's requirements as the constraints. These constraints are divided into two kinds of constraints: *hard constraints* and *soft constraints*. Hard constraints are represented in the form of an "equal to" notation. Soft constraints are represented in the form of inequality and they can be relaxed within the given scope of values. There are also three kinds of soft constraints as follows:

(1) *Benefit soft constraints*, such as the quality of the commodity. The higher its value, the keener a buyer would be to buy it. Correspondingly, the quality is regarded as the benefit soft attribute.

(2) *Cost soft constraints*, such as the price of the commodity. The lower its value, the keener a buyer would be to buy it. Correspondingly, the price is regarded as the cost soft attribute.

(3) *Interval soft constraints*. This constraint will be satisfied when the attribute value is within the given interval. And this attribute is regarded as the interval soft attribute.

As far as buyer $b_i$ is concerned, $c_{ik}$ is the threshold of the attribute $a_k$ with respect to benefit or cost soft constraints; $[c_{ikL}, c_{ikU}]$ is the interval of the attribute $a_k$ with respect to interval soft constraints; $w_{ik}$ is the weight of the attribute $a_k$, which satisfies: $\sum_{k \in K_b} w_{ik} = 1$, $w_{ik} \geq 0$. As for seller $s_j$, $p_{jk}$ is used to represent the value of the attribute $a_k$.

Similarly, from the seller's point of view, seller $s_j$ can represent his requirements for the attribute $a_k$, where, $k \in K_s$ and $K_s \subseteq K$. We also define the seller's requirements as two kinds of constraints: hard constraints and soft constraints (including benefit soft constraints, cost soft constraints and interval soft constraints).

As far as seller $s_j$ is concerned, $d_{jk}$ is the threshold of the attribute $a_k$ with respect to benefit or cost soft constraints; $[d_{jkL}, d_{jkU}]$ is the interval of the attribute $a_k$ with respect to interval soft constraints; $w_{jk}$ is the weight of the attribute $a_k$, which satisfies: $\sum_{k \in K_s} w_{jk} = 1$, $w_{jk} \geq 0$. As for buyer $b_i$, $q_{ik}$ is used to represent the value of the attribute $a_k$.

Additionally, buyers and sellers also need to set the preference (or weight) on each attribute of the commodity. As we discussed in the previous sections, it is usually unrealistic for buyers or sellers to give the precise values of attribute weights. Instead, they can intuitively represent these attribute weights in the form of incomplete information. Hence, it makes the incomplete weight information necessary to be considered in one-shot multi-attribute exchanges.

Based on the above analysis, the matching problem in one-shot multi-attribute exchanges with incomplete weight information can be generally described thus: buyers and sellers submit their trade information (bids) to the broker within the given time interval. The trading information or bids include buyers' and sellers' requirements and incomplete attribute weights. Then, according to the trading information, the broker matches buyers with sellers in order to find the optimal matching pairs. In brief, the key issue of the problem is how to help the broker achieve the optimal trade matching between buyers and sellers in one-shot multi-attribute exchanges with incomplete weight information. Therefore, in the next section, a matching approach is proposed to solve the problem.

## 4. The Proposed Matching Approach.

### 4.1. Framework of the proposed matching approach.

The framework of proposed matching approach for solving the matching problem in one-shot multi-attribute exchanges with incomplete weight information is presented graphically in Figure 2.

In the framework, the trading information, including the requirements of multi-attribute commodity and the incomplete weight information, is firstly obtained from buyers and sellers. Then, the requirements are classified into four kinds of constraints, i.e., hard constraints, benefit soft constraints, cost soft constraints and interval soft constraints. According to these constraints, the matching degree of each attribute is calculated. At the same time, the incomplete weight information is represented by linear constraints. After that, a bi-objective optimization model is built, in which the first objective function is to maximize the matching degree, and the second function is to maximize the trading volume. Finally, the model is solved by the ideal point method, and the optimal matching pairs are obtained. In the following subsections, the main issues of the proposed matching approach, i.e., matching degree, incomplete weight information, bi-objective optimization model and ideal point method, are discussed in detail.

### 4.2. Matching degree.

The matching degree plays an important role in one-shot multi-matching relationship of each attribute as possible according to buyers' and sellers' requirements. However, in the existing research, the matching degree about the price is mostly addressed, while the matching degree about the non-price attributes has seldom been a focus. Only Zhang [18] used a simple relative ratio to define the matching degree of multiple attributes (including the price and non-price attributes), but this method is not reasonable in some cases, which will be illustrated later by an example. Thus, based on the previous concepts and notations, this paper presents a new definition of matching degree to overcome the limitations in the exiting research. Furthermore, some properties of matching degree are also given below.

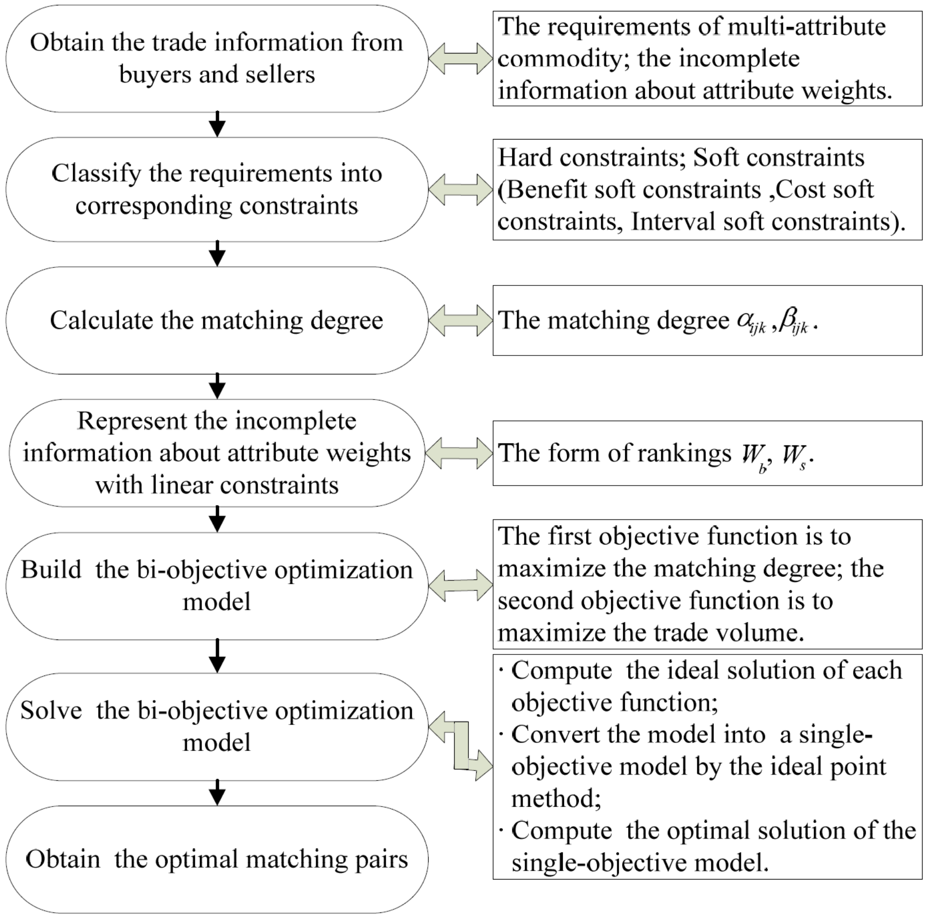


FIGURE 2. The framework of the proposed matching approach

**Definition 4.1.** *$s_j$ is qualified to match $b_i$, ① to hard constraints, if it satisfies $p_{jk} = c_{ik}$; ② to benefit soft constraints, if it satisfies $p_{jk} \geq c_{ik}$; ③ to cost soft constraints, if it satisfies $p_{jk} \leq c_{ik}$; ④ to interval soft constraints, if it satisfies $p_{jk} \in [c_{ikL}, c_{ikU}]$.*

**Definition 4.2.** *$b_i$ is qualified to match $s_j$, ① to hard constraints, if it satisfies $q_{ik} = d_{jk}$; ② to benefit soft constraints, if it satisfies $q_{ik} \geq d_{jk}$; ③ to cost soft constraints, if it satisfies $q_{ik} \leq d_{jk}$; ④ to interval soft constraints, if it satisfies $q_{ik} \in [d_{jkL}, d_{jkU}]$.*

**Definition 4.3.** *Let $S_i$ be the set of $s_j$ which is qualified to match $b_i$, $\alpha_{ijk} \in [0, 1]$, $p_{\max\_k}$, $p_{\min\_k} \in S_{ik}$, where $S_{ik}$ denotes the set of values for the attribute $a_k$ in $S_i$, $p_{\max\_k}$ and $p_{\min\_k}$ are the maximum and minimum values of $p_{jk}$ in $S_{ik}$, respectively. We define $\alpha_{ijk}$ as the matching degree of the attribute $a_k$ between $b_i$ and $s_j$. If $s_j \notin S_i$, then $\alpha_{ijk} = 0$; otherwise, if $s_j \in S_i$, then, ① to hard constraints and interval soft constraints, we have $\alpha_{ijk} = 1$; ② to benefit soft constraints, we have $\alpha_{ijk} = \left(\frac{p_{jk} - p_{\min\_k} + \varepsilon}{p_{\max\_k} - p_{\min\_k} + \varepsilon}\right)^t$; ③ to cost soft constraints, we have $\alpha_{ijk} = \left(\frac{p_{\max\_k} - p_{jk} + \varepsilon}{p_{\max\_k} - p_{\min\_k} + \varepsilon}\right)^{1/t}$; here, $t = \frac{c_{ik} + \left(\frac{p_{\max\_k} + p_{\min\_k}}{2}\right)}{p_{\max\_k} + p_{\min\_k}}$, $\varepsilon = \frac{p_{\min\_k}}{2}$.*

**Property 4.1.** *If $s_j \in S_i$, then, to benefit soft attributes, the matching degree $\alpha_{ijk} \in (0, 1]$; moreover, $\alpha_{ijk}$ is increasing in $p_{jk}$ and decreasing in $c_{ik}$.*

**Property 4.2.** *If $s_j \in S_i$, then, to cost soft attributes, the matching degree $\alpha_{ijk} \in (0, 1]$; moreover, $\alpha_{ijk}$ is decreasing in $p_{jk}$ and increasing in $c_{ik}$.*

Properties 4.1 and 4.2 imply that if one of the conditions in Definition 4.1 is satisfied, then $\alpha_{ijk}$ is greater than 0. Furthermore, $\alpha_{ijk}$ is not only the function of $p_{jk}$, but also the function of $c_{ik}$; that is, to benefit (cost) soft attributes, the greater $c_{ik}$ is, the less (greater) $\alpha_{ijk}$ is, and vice versa. These properties coincide with the actual situation. For example, suppose $c_{i1}$ is the threshold of the price attribute $a_1$ represented by $b_i$, and $p_{j1}$ is the value of the price attribute $a_1$ represented by $s_j$. Now let $p_{j1} = 10$ and $c_{i1}$=20; according to Definition 4.1, $s_j$ is qualified to match $b_i$. If we increase $c_{i1}$ from 20 to 30, i.e., $c_{i1} = 30$, it is clear that $s_j$ is more qualified to match $b_i$ than before, hence, in this situation, the matching degree $\alpha_{ij1}$ would increase according to Definition 4.3. However, if we use the definition of matching degree presented in Zhang [18], the matching degree $\alpha_{ij1}$ remains unchanged since $c_{i1}$ is not taken into account in $\alpha_{ij1}$. Obviously, it is not reasonable in the real world.

**Definition 4.4.** *Let $B_j$ be the set of $b_i$ which is qualified to match $s_j$, $\beta_{ijk} \in [0,1]$, $q_{\max\_k}$, $q_{\min\_k} \in B_{jk}$, where $B_{jk}$ denotes the set of values for the attribute $a_k$ in $B_j$. $q_{\max\_k}$ and $q_{\min\_k}$ are the maximum and minimum values of $q_{ik}$ in $B_{jk}$, respectively. We define $\beta_{ijk}$ as the matching degree of the attribute $a_k$ between $s_j$ and $b_i$. If $b_i \notin B_j$, then $\beta_{ijk} = 0$; otherwise, if $b_i \in B_j$, then, ① to hard constraints and interval soft constraints, we have $\beta_{ijk} = 1$; ② to benefit soft constraints, we have $\beta_{ijk} = \left(\frac{q_{ik}-q_{\min\_k}+\varepsilon}{q_{\max\_k}-q_{\min\_k}+\varepsilon}\right)^t$; ③ to cost soft constraints, we have $\beta_{ijk} = \left(\frac{q_{\max\_k}-q_{ik}+\varepsilon}{q_{\max\_k}-q_{\min\_k}+\varepsilon}\right)^{1/t}$; here, $t = \frac{d_{jk}+\left(\frac{q_{\max\_k}+q_{\min\_k}}{2}\right)}{q_{\max\_k}+q_{\min\_k}}$, $\varepsilon = \frac{q_{\min\_k}}{2}$.*

**Property 4.3.** *If $b_i \in B_j$, then, to benefit soft attributes, the matching degree $\beta_{ijk} \in (0,1]$; moreover, $\beta_{ijk}$ is increasing in $q_{ik}$ and decreasing in $d_{jk}$.*

**Property 4.4.** *If $b_i \in B_j$, then, to cost soft attributes, the matching degree $\beta_{ijk} \in (0,1]$; moreover, $\beta_{ijk}$ is decreasing in $q_{ik}$ and increasing in $d_{jk}$.*

Properties 4.3 and 4.4 imply that if one of conditions in Definition 4.2 is satisfied, then $\beta_{ijk}$ is greater than 0. Furthermore, $\beta_{ijk}$ is not only the function of $q_{ik}$, but also the function of $d_{jk}$; that is, to benefit (cost) soft attributes, the greater $d_{jk}$ is, the less (greater) $\beta_{ijk}$ is, and vice versa. These properties also coincide with the actual situation. It is easy to give similar examples from the real world.

4.3. **Incomplete weight information.** As mentioned earlier, in one-shot multi-attribute exchanges, due to the complexity of multi-attribute exchanges and the inherent subjective nature of human thinking, the buyer (or the seller) may only possess incomplete information about attribute weights. Therefore, in order to represent the incomplete weight information, the linear constraints used in multiple attribute making decision are introduced. Let $\vec{w} = (w_1, w_2, \ldots, w_l)^T \in \hat{W}$ be the weight vector of attributes, where $w_j \in [0,1]$, $j = 1, 2, \ldots, l$, $\sum_{j=1}^{l} w_j = 1$, $\tilde{W}$ is a set of the known weight information, which can be constructed by the following forms [25], for $i \neq j$.

**Form 1**. *A weak ranking*: $\{w_i \geq w_j\}$;
**Form 2.** *A strict ranking*: $\{w_i - w_j \geq \varepsilon_{ij}\ (> 0)\}$;
**Form 3**. *A ranking of differences*: $\{w_i - w_j \geq w_k - w_h\}$, for $j \neq k \neq h$;
**Form 4**. *A ranking with multiples*: $\{w_i \geq \gamma_i w_j\}$, $0 \leq \gamma_i \leq 1$;
**Form 5**. *An interval form*: $\gamma_i \leq w_i \leq \gamma_i + \varepsilon_i$, $0 \leq \gamma_i \leq \gamma_i + \varepsilon_i \leq 1$.

Forms 1 – 2 and Forms 4 – 5 are well known types of incomplete weight information, and Form 3 is ranking of differences of adjacent parameters obtained by ranking between two parameters, which can be constructed based on Form 1.

Inspired by Park [26], we also give detailed interpretations as to when incomplete weight information Forms 1 – 5 could occur in one-shot multi-attribute exchanges:

For the Forms 1 – 2, the buyer or the seller may argue that the attribute $a_i$ is the most important, the attribute $a_j$ is the second, and the attribute $a_k$ is the third. This information can be represented with the corresponding weights of these three attributes in the form of weak orders $w_i \geq w_j \geq w_k$ or strict orders $w_i - w_j \geq \varepsilon_{ij}$ and $w_j - w_k \geq \varepsilon_{jk}$ with the positive constants $\varepsilon_{ij}$ and $\varepsilon_{jk}$, i.e., the weight of the attribute $a_i$ exceeds that of the attribute $a_j$ by at least $\varepsilon_{ij}$, and the weight of the attribute $a_i$ exceeds that of the attribute $a_k$ by at least $\varepsilon_{jk}$ [27]. The difference order $w_i - w_j \geq w_k - w_h$ is possible when the preference difference between $w_i$ and $w_j$ is greater than or equal to that between $w_k$ and $w_h$, which is also referred to as strength of preference [28]. For the Form 4, the buyer or the seller may argue that the attribute $a_j$ is the most important (100%), and the attribute $a_i$ is in the level greater than or equal to $\gamma_i$, $(0 \leq \gamma_i \leq 1)$ relative to the level of the attribute $a_j$. That is to say, the weight of the attribute $a_i$ is greater than or equal to $\gamma_i$ times of that of the attribute $a_j$, which is expressed as $w_i \geq \gamma_i w_j$. Form 5 indicates that the crisp weight can not be specified but value range can be obtained, this type of weights is called interval weights. It is the most common form to describe the incomplete information about attribute weights, which can be provided by the buyer or the seller directly [29].

In a particular one-shot multi-attribute exchange, it should be noted that the incomplete information about attribute weights can be expressed as a subset of $\hat{W}$. Accordingly, in this paper, we let $\hat{W}_b$ and $\hat{W}_s$ denote the buyer's and seller's incomplete weight information, respectively.

4.4. **Bi-objective optimization model and method.** Based on the above definition of matching degree and the presentation of incomplete weight information, a bi-objective optimization model is built bellow:

***Model I*** :

$$Max\ f_1 = \sum_{i\in I}\sum_{j\in J}\left(\sum_{k\in K_b} w_{ik}\alpha_{ijk}x_{ij} + \sum_{k\in K_s} w_{jk}\beta_{ijk}x_{ij}\right) \tag{1}$$

$$Max\ f_2 = \sum_{i\in I}\sum_{j\in J}[\lambda p_{i1} + (1-\lambda)q_{j1}]x_{ij} \tag{2}$$

$$\text{s.t.} \sum_{i\in I} x_{ij} \leq 1, \quad \forall j \in J \tag{3}$$

$$\sum_{j\in J} x_{ij} \leq 1, \quad \forall i \in I \tag{4}$$

$$(w_{i1}, w_{i2}, \ldots, w_{il})^T \in \hat{W}_b, \quad \forall i \in I \tag{5}$$

$$(w_{j1}, w_{j2}, \ldots, w_{jl})^T \in \hat{W}_s, \quad \forall j \in J \tag{6}$$

$$\sum_{k\in K_b} w_{ik} = 1, \quad \forall i \in I \tag{7}$$

$$\sum_{k\in K_s} w_{jk} = 1, \quad \forall j \in J \tag{8}$$

$$x_{ij} = 1, 0, \quad \forall i \in I, \quad \forall j \in J \tag{9}$$

$$w_{ik}, w_{jk} \geq 0, \quad \forall i \in I, \quad \forall j \in J, \quad \forall k \in K \tag{10}$$

Objective function (1) seeks to maximize the weighted sum of matching degree. Objective function (2) seeks to maximize the trading volume, where $p_{i1}$ and $q_{j1}$ are the values of the price attribute $a_1$ represented by $b_i$ and $s_j$, respectively; furthermore, a $\lambda$-Pricing scheme is introduced to determine prices for a buyer and a seller on the basis of the difference between their bids, which is a practical alternative to the VCG mechanism [23]. Generally, the broker favors neither the buyer's side nor the seller's side, so we set $\lambda = 0.5$

$(0 \leq \lambda \leq 1)$. Constraints (3) and (4) ensure each buyer (seller) can buy (sell) one unit of the commodity at most. Constraints (5) and (6) denote the incomplete weight information expressed by the buyer. Constraints (6) and (8) denote the incomplete weight information expressed by the seller. Constraints (9) and (10) are decision variable constraints, if buyer $b_i$ matches with seller $s_j$, then $x_{ij} = 1$; otherwise, $x_{ij} = 0$.

The above model (namely, ***Model I***) belongs to a class of multi-objective mixed 0-1 integer quadratic programming models. Many approaches have been proposed to deal with multi-objective optimization, such as the weighted sum method [30], the goal programming method [31], the ideal point method [32], the multi-objective evolutionary algorithm [33-36], etc. However, the existing literature shows that the ideal point method is one of the most common and effective approaches for multi-objective optimization [37]. Thus, in this paper, we use the ideal point method to deal with ***Model I***. Since two objective functions ($f_1$ and $f_2$) in ***Model I*** have different units (one is the matching degree and the other is the trading volume), the objective functions should be normalized such that they are dimensionless. In order to do that, ***Model I*** is transformed into a single-objective model (namely, ***Model II***) as follows:

***Model II*** :

$$Min\ F = r_1 \frac{f_1^* - f_1}{f_1^*} + r_2 \frac{f_2^* - f_2}{f_2^*} \tag{11}$$
$$\text{s.t. } (3) - (10)$$

Here, $\vec{f}^* = (f_1^*, f_2^*)^T$ is the ideal point, $\vec{r} \in R = \{\vec{r} | r_i \geq 0, \sum_{i=1}^{2} r_i = 1\}$ is the weight vector. Objective function (11) is to minimize the weighted sum of normalized distance between the optimal solution and the ideal point.

According to the theorem about ideal point method, the optimal solution of ***Model II*** is a Pareto optimal solution of ***Model I***. That is to say, ***Model I*** can be solved through solving ***Model II***, which involves the following steps:

*Step 1*: Use branch-and-bound algorithm or an appropriate optimization software technique (such as LINGO or CPLEX) to get the optimal solution of the single-objective model (1), (3) – (11) and obtain the corresponding optimal objective function value $f_1^*$.

*Step 2*: Use branch-and-bound algorithm or an appropriate optimization software technique (such as LINGO or CPLEX) to get the optimal solution of the single-objective model (2) – (4), (9) and obtain the corresponding optimal objective function value $f_2^*$.

*Step 3*: Put the ideal point $\vec{f}^* = (f_1^*, f_2^*)^T$ into (11) and use branch-and-bound algorithm or an appropriate optimization software technique (such as LINGO or CPLEX) to solve the single-objective model (***Model II***), and then get the Pareto optimal solution of the original bi-objective model (***Model I***).

5. **An Illustrative Example.** In this section, an example is employed to illustrate the application of the matching approach proposed in this paper.

The original data of our example is derived from SouFun (www.soufun.com), which is the largest real estate E-brokerage firm in China. In accordance with SouFun, these data were slightly modified to comply with our simplifying model assumptions and ensure the non-disclosure of vital information. Generally speaking, in the real estate exchange, six attributes of a house are considered, i.e., price ($a_1$), building size ($a_2$), payment date ($a_3$), living condition ($a_4$), location ($a_5$) and floor ($a_6$). In what follows, we will illustrate how to apply the proposed matching approach with this example.

*Step 1*: Obtain the trading information from buyers and sellers. Table 1 gives the requirements on six attributes from 10 buyers and 10 sellers in the real estate E-brokerage. In Table 1, $c_{ik}$, $q_{ik}$ and $[c_{ikL}, c_{ikU}]$ denote the threshold, value and interval of the attribute

$a_k$ in the requirements represented by $b_i$, respectively; $d_{jk}$ and $p_{jk}$ denote the threshold and value of the attribute $a_k$ in the requirements represented by $s_j$, respectively. As for buyers, price ($a_1$) and living condition ($a_4$) are cost soft attributes, building size ($a_2$) and payment date ($a_3$) are benefit soft attributes, floor ($a_6$) is interval soft attribute and location ($a_5$) is hard attribute. Meanwhile, sellers only consider the price ($a_1$) and payment date ($a_3$), since other attributes of a house are usually fixed. For instance, a seller can not change the location or floor of the house that he wants to sell in the real estate exchange. Obviously, as for sellers, price ($a_1$) is benefit soft attribute and payment date ($a_3$) is cost soft attribute. In addition, the incomplete information about attributes is needed to be described by buyers and sellers. For the sake of simplicity, in this example, each buyer expresses the same incomplete weight (or preference) information on six attributes as: living condition ($a_4$) is the most important, location ($a_5$) is second, price ($a_1$) is third, building size ($a_2$) is forth, floor ($a_6$) is fifth and payment date ($a_3$) is sixth. Similarly, each seller expresses the same incomplete weight (or preference) information on two attributes as: price ($a_1$) is most important, and payment date ($a_3$) is in the level of greater than or equal to 0.5 relative to the level of price ($a_1$).

*Step 2*: Classify the requirements on six attributes into four kinds of constraints. From the buyer's point of view, the requirements on cost soft attributes ($a_1$ and $a_4$), benefit soft attributes ($a_2$ and $a_3$), interval soft attribute ($a_6$) and hard attribute ($a_5$) are regarded as cost soft constraints, benefit soft constraints, interval soft constraints and hard constraints, respectively. Also, from the seller's point of view, the requirements on benefit soft attribute ($a_1$) and cost soft attribute ($a_3$) are regarded as benefit soft constraints and cost soft constraints, respectively.

*Step 3*: Calculate the matching degree. According to Definitions 4.3 and 4.4, we can get the matching degree $\alpha_{ijk}$, $i = 1, 2, \ldots, 10$, $j = 1, 2, \ldots, 10$, $k = 1, 2, \ldots, 6$ and $\beta_{ijk}$, $i = 1, 2, \ldots, 10$, $j = 1, 2, \ldots, 10$, $k = 1, 3$. The detailed results are not listed here for lack of space.

*Step 4*: Represent the incomplete weight information with linear constraints in the form of rankings, i.e., $\hat{W}_b$: $w_{i4} \geq w_{i5} + \varepsilon$, $w_{i5} \geq w_{i1} + \varepsilon$, $w_{i1} \geq w_{i2} + \varepsilon$, $w_{i2} \geq w_{i6} + \varepsilon$, $w_{i6} \geq w_{i3} + \varepsilon$, $i = 1, 2, \ldots, 10$ and $\hat{W}_s$: $w_{j1} \geq w_{j3} + \varepsilon$, $w_{j3} \geq 0.5w_{j1} + \varepsilon$, $j = 1, 2, \ldots, 10$, here, we set $\varepsilon = 0.01$.

*Step 5*: Build the bi-objective optimization model (***Model I***) and solve it using the ideal point method. Here, two different objective weight vectors $\vec{r}_A$ and $\vec{r}_B$ (named as

Table 1. The requirements from 10 buyers and 10 sellers in the real estate E-brokerage

| $b_i$ | $c_{i1}$ (¥) | $c_{i2}$ (m$^2$) | $c_{i3}$ | $c_{i4}$ | $q_{i5}$ | $[c_{i6L}, c_{i6U}]$ | $s_j$ | $d_{j1}$ (¥) | $p_{j2}$ (m$^2$) | $d_{j3}$ | $p_{j4}$ | $p_{j5}$ | $p_{j6}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $b_1$ | 450000 | 90 | 3 | 3 | A | [3, 10] | $s_1$ | 450000 | 130 | 6 | 3 | A | 3 |
| $b_2$ | 600000 | 70 | 2 | 4 | A | [3, 6] | $s_2$ | 450000 | 70 | 5 | 1 | A | 6 |
| $b_3$ | 900000 | 70 | 4 | 2 | A | [4, 9] | $s_3$ | 300000 | 90 | 6 | 1 | A | 7 |
| $b_4$ | 900000 | 110 | 3 | 3 | A | [5, 9] | $s_4$ | 300000 | 110 | 5 | 3 | B | 7 |
| $b_5$ | 750000 | 110 | 4 | 3 | B | [5, 10] | $s_5$ | 600000 | 110 | 7 | 1 | A | 7 |
| $b_6$ | 600000 | 90 | 5 | 5 | B | [4, 9] | $s_6$ | 600000 | 50 | 5 | 1 | A | 5 |
| $b_7$ | 300000 | 90 | 3 | 5 | B | [4, 7] | $s_7$ | 300000 | 80 | 6 | 3 | A | 8 |
| $b_8$ | 450000 | 70 | 2 | 5 | A | [5, 9] | $s_8$ | 600000 | 70 | 7 | 1 | A | 6 |
| $b_9$ | 750000 | 70 | 3 | 2 | A | [3, 8] | $s_9$ | 450000 | 90 | 5 | 2 | A | 7 |
| $b_{10}$ | 900000 | 110 | 4 | 3 | B | [2, 8] | $s_{10}$ | 450000 | 70 | 7 | 4 | A | 8 |

TABLE 2. Optimal matching pairs with different objective weight vectors

| *No.* | Matching pairs | |
|---|---|---|
| | *Case A* $\vec{r}_A = (0.2, 0.8)$ | *Case B* $\vec{r}_B = (0.8, 0.2)$ |
| 1 | $b_1 \leftrightarrow s_3$ | $b_1 \leftrightarrow s_9$ |
| 2 | $b_2 \leftrightarrow s_1$ | $b_2 \leftrightarrow s_2$ |
| 3 | $b_3 \leftrightarrow s_8$ | $b_3 \leftrightarrow s_8$ |
| 4 | $b_4 \leftrightarrow s_5$ | $b_4 \leftrightarrow s_5$ |
| 5 | $b_5 \leftrightarrow s_4$ | $b_6 \leftrightarrow s_4$ |
| 6 | $b_6 \leftrightarrow s_9$ | $b_8 \leftrightarrow s_{10}$ |
| 7 | $b_8 \leftrightarrow s_{10}$ | $b_9 \leftrightarrow s_3$ |
| 8 | $b_9 \leftrightarrow s_2$ | —— |

*Case A* and *Case B*) are employed in the ideal point method. And then, we obtain the optimal matching pairs between buyers and sellers as shown in Table 2.

It can be seen from Table 2 that eight optimal matching pairs are achieved in *Case A* ($\vec{r}_A = (0.2, 0.8)$) and seven optimal matching pairs in *Case B* ($\vec{r}_B = (0.8, 0.2)$). Furthermore, the trading volume in *Case A* is 4725000¥, which is 525000¥ more than *Case B*. The reason for this is that *Case A* has greater trading volume weight (here, $r_2 = 0.8$) than *Case B* (here, $r_2 = 0.2$). In contrast, the matching degree in *Case A* (here, $f_2 = 6.0737$) is less than *Case B* (here, $f_2 = 11.0779$). Therefore, the Pareto optimal solution obtained by each different objective weight vector is a trade-off between two objective functions in ***Model I***, and the decision maker (or the E-brokerage firm) can make decisions on optimal matching pairs according to his/her own preferences on matching degree or trading volume.

6. **Conclusions.** This paper proposes a novel matching approach for E-brokerage to optimize the trade matching in one-shot multi-attribute exchanges with incomplete weight information. In the matching approach, through the definition of matching degree and the representation of incomplete weight information, a bi-objective optimization model is built to obtain the optimal trade matching in one-shot multi-attribute exchanges with incomplete weight information. Afterwards, the ideal point method is used to solve the model. The major contributions of the proposed matching approach are discussed below.

First, it is a novel idea to consider the incomplete weight information with respect to the matching problem in one-shot multi-attribute exchanges. It makes the proposed matching approach be able to solve the matching problem in one-shot multi-attribute exchanges with incomplete weight information which cannot be handled by the existing approaches.

Second, the proposed matching approach presents a new definition of matching degree in one-shot multi-attribute exchanges. Also, some properties of matching degree are discussed. And these properties show that the new definition is consistent with the actual situation and more reasonable than the existing definition.

Third, a bi-objective optimization model is built not only to maximize the trading volume between buyers and sellers but also to maximize the matching degree from both buyers' and sellers' points of view. It overcomes the current limitations that occur in the existing literature neglecting to optimize the trade matching with respect to non-price attributes. Hence, the presented model is more suitable for one-shot multi-attribute exchanges and can provide better theoretical direction and support for decision makers or E-brokerage firms.

Additionally, the ideal point method is used to solve the bi-objective optimization model. And then an example is given to illustrate the application of our proposed matching approach in the real estate E-brokerage.

In terms of future research, two directions have been identified. First, it is necessary to consider alternative multi-objective evolutionary algorithms (MOEAs) to solve the presented model, since MOEAs, such as multi-objective genetic algorithms (MOGAs), may be adequate and efficient for an application in lager-scale multi-attribute exchanges. Second, we intend to develop a decision support system based on Web, in which the proposed matching approach is embedded. The decision support system will provide practical guidelines to help E-brokerages improve trading efficiency and profits.

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## REFERENCES

[1] S. Albers and M. Clement, Analyzing the success drivers of e-business companies, *IEEE Trans. on Engineering Management*, vol.54, no.2, pp.301-314, 2007.

[2] X. P. Hu, X. Y. Wang, L. J. Sun and Z. C. Xu, A real-time intelligent system for order processing in B2C E-commerce, *International Journal of Innovative Computing, Information and Control*, vol.5, no.11(A), pp.3691-3706, 2009.

[3] J. Hands, M. Bessonov, M. Blinov, A. Patel and R. Smith, An inclusive and extensible architecture for electronic brokerage, *Decision Support Systems*, vol.29, no.4, pp.305-321, 2000.

[4] S. Muylle and A. Basu, Online support for business processes by electronic intermediaries, *Decision Support Systems*, vol.45, no.4, pp.845-857, 2008.

[5] M. Sarkar, B. Butler and C. Steinfield, Cybermediaries in electronic marketspace: Toward theory building, *Journal of Business Research*, vol.41, no.3, pp.215-221, 1998.

[6] G. M. Giaglis, K. Stefan and R. M. OKeefe, The role of intermediaries in electronic marketplaces: Developing a contingency model, *Information Systems Journal*, vol.12, no.3, pp.231-246, 2002.

[7] A. Rogone, *When Price Is Not Enough: Innovative Knowledge Based Approaches to Matchmaking and Negotiation in Electronic Markets of Goods and Services*, Ph.D. Thesis, University of Michigan, 2008.

[8] Z. S. Xu, A method for multiple attribute decision making with incomplete weight information in linguistic setting, *Knowledge-Based Systems*, vol.20, no.8, pp.719-725, 2007.

[9] Z. J. Wang, K. W. Li and W. Z. Wang, An approach to multiattribute decision making with interval-valued intuitionistic fuzzy assessments and incomplete weights, *Information Science*, vol.179, no.17, pp.3026-3040, 2009.

[10] J. E. Pinker, A. Seidmann and Y. Vakrat, Managing online auctions: Current business and research issues, *Management Science*, vol.49, no.11, pp.1457-1484, 2003.

[11] E. Fink, J. Johnson and J. Hu, Exchange market for complex goods: Theory and experiments, *Netnomics*, vol.6, no.1, pp.21-42, 2004.

[12] S. Kameshwaran and Y. Narahari, Trade determination in multi-attribute exchanges, *Proc. of the IEEE International Conference on E-Commerce*, Newport Beach, CA, pp.173-180, 2003.

[13] N. Economides and R. A. Schwartz, Electronic call market trading, *Journal of Portfolio Management*, vol.21, no.3, pp.10-18, 1995.

[14] S. Kameshwaran and Y. Narahari, A new approach to the design of electronic exchanges, *Lecture Notes in Computer Science*, vol.2455, pp.27-36, 2002.

[15] Y. U. Ryu, Hierarchical constraint satisfaction of multilateral trade matching in commodity auction markets, *Annals of Operations Research*, vol.71, no.10, pp.317-334, 1997.

[16] J. J. Jung and G. S. Jo, Brokerage between buyer and seller agents using constraint satisfaction problem models, *Decision Support Systems*, vol.28, no.4, pp.293-304, 2000.

[17] H. B. Wang, T. Y. Wang and J. Y. Xie, An intelligent communication model between buyers and suppliers, *Chinese Journal of Computers*, vol.26, no.9, pp.1190-1195, 2003.

[18] Z. H. Zhang, *Research on Trading Matching Methods of Electronic Brokerage and Its Applications*, Ph.D. Thesis, Northeastern University, China, 2005.

[19] A. R. Dani, A. K. Pujari and V. P. Gulati, Continuous call double auctions with indivisibility constraints, *IEEE International Conference on e-Technology, e-Commerce and e-Service*, Hong Kong, China, pp.32-37, 2005.

[20] Y. Engel, M. P. Wellman and K. M. Lochner, Bid expressiveness and clearing algorithms in multi-attribute double auctions, *Proc. of the 7th ACM Conference on Electronic Commerce*, Ann Arbor, pp.110-119, 2006.

[21] H. K. Kim, W. J. Chung, H. Hwang and C. S. Ko, A distributed dispatching method for the brokerage of truckload freights, *International Journal of Production Economics*, vol.98, no.2, pp.150-161, 2005.

[22] M. Placek and R. Buyya, Storage exchange: A global trading platform for storage services, *Lecture Notes in Computer Science*, vol.4128, pp.425-436, 2006.

[23] B. Schnizler, D. Neumann, D. Veit and C. Weinhardt, Trading grid services-a multi-attribute combinatorial approach, *European Journal of Operational Research*, vol.187, no.3, pp.943-961, 2008.

[24] O. Gujo, Multi-attribute inter-enterprise exchange of logistics services, *Proc. of the 10th IEEE Conference on E-Commerce Technology and the 5th IEEE Conference on Enterprise Computing, E-Commerce and E-Services*, Washington, pp.113-120, 2008.

[25] B. S. Ahn, K. S. Park, C. H. Han and J. K. Kim, Multi-attribute decision aid under incomplete information and hierarchical structure, *European Journal of Operational Research*, vol.125, no.2, pp.431-439, 2000.

[26] K. S. Park, Mathematical programming models for charactering dominance and potential optimality when multicriteria alternative values and weights are simultaneously incomplete, *IEEE Transactions on Systems, Man, and Cybernetics – Part A, Systems and Humans*, vol.34, no.5, pp.601-614, 2004.

[27] W. D. Cook and M. Kress, A multiple criteria decision model with ordinal preference data, *European Journal of Operational Research*, vol.54, no.2, pp.191-198, 1991.

[28] B. Malakooti, Ranking and screening multiple criteria alternatives with partial information and use of ordinal and cardinal strength of preferences, *IEEE Transactions on Systems, Man, and Cybernetics – Part A, Systems and Humans*, vol.30, no.3, pp.355-368, 2000.

[29] Z. S. Xu and J. Chen, An interactive method for fuzzy multiple attribute group decision making, *Information Sciences*, vol.177, no.1, pp.248-263, 2007.

[30] L. A. Zadeh, Optimality and non-scalar-valued performance criteria, *IEEE Trans. on Automatic Control*, vol.8, no.1, pp.59-60, 1963.

[31] A. Charnes and W. W. Cooper, Goal programming and multiple objective optimizations: Part 1, *European Journal of Operational Research*, vol.1, no.1, pp.39-54, 1977.

[32] K. Miettinen, *Nonlinear Multiobjective Optimization*, Kluwer Academic Publishers, 1999.

[33] D. Martin, R. D. Toro, R. Haber and J. Dorronsoro, Optimal tuning of a networked linear controller using a multi-objective genetic algorithm and its application to one complex electromechanical process, *International Journal of Innovative Computing, Information and Control*, vol.5, no.10(B), pp.3405-3414, 2009.

[34] S. Ono, Y. Hirotani and S. Nakayama, A memetic algorithm for robust optimal solution search – Hybridization of multi-objective genetic algorithm and quasi-newton method, *International Journal of Innovative Computing, Information and Control*, vol.5, no.12(B), pp.5011-5020, 2009.

[35] C. Liu and Y. Wang, A new evolutionary algorithm for multi-objective optimization problems, *ICIC Express Letters*, vol.1, no.1, pp.93-98, 2007.

[36] C. Liu, New evolutionary algorithm for multi-objective constrained optimization, *ICIC Express Letters*, vol.2, no.4, pp.339-344, 2008.

[37] R. T. Marler and J. S. Arora, Survey of multi-objective optimization methods for engineering, *Structural and Multidisciplinary Optimization*, vol.26, no.6, pp.369-390, 2004.