

Two-sided Matching Decision under Multi-granularity Uncertain Linguistic Environment

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Abstract

With respect to the two-sided matching problem, where the agents' preferences are in the format of multi-granularity uncertain linguistic terms, a matching method is proposed. Some basic concepts and definitions on uncertain linguistic term and 2-tuple are firstly given. Based on this, the two-sided matching problem with multi-granularity uncertain linguistic terms is described. Then, multi-granularity uncertain linguistic term matrixes are transformed into multi-granularity 2-tuple matrixes. Furthermore, a multi-objective optimization model is developed by using the extended 2-tuple weighted average. By using the normalization method and the linear weighted method twice, the multi-objective optimization model can be converted into a single-objective optimization model. By solving the model, the matching alternative can be obtained. Example of matching demand and supply in agricultural knowledge illustrates the feasibility and effectiveness of this method.

Keywords: *two-sided matching; multi-granularity; uncertain linguistic term; 2-tuple; optimization model*

1. Introduction

The two-sided matching problems widely exist in the real world. Examples contain the stable marriage problem [1-4], the CEOs selection problem [5-8], the college admission problem [9-12], the employee selection problem [13-15], and the personnel assignment problem [16-18]. Since the reasonable and effective matching alternative has a promoting effect for improving the efficiency of economic management activities and the satisfaction degrees of two-sided agents, studying on the two-sided matching problems has important theoretical significance and practical application value.

There are plenty of two-sided matching problems in many fields of real life, such as marriage assignment [1], college admission [2], employee selection [3], personnel assignment [4] and CEOs to companies [5], Therefore two-sided matching is a research topic with extensive application backgrounds.

At present, the two-sided matching problems with different forms of information have attracted extensively attentions. For example, Gale and Shapley initially investigate the concept, existence, optimality and algorithm of stable assignment [6]. The notions of

vonNeumann–Morgenstern (vNM) farsightedly stable sets are adopted to determine which matchings are possibly stable when agents are farsighted in one-to-one matching problems [7]. Boon and Sierksma match position with player in soccer team formation using linear optimization models, [8]. Sethuraman et al. focus on the geometric structure of fractional stable matchings in the stable admission problem [9]. Ehlers studies truncation strategies in matching markets using the deferred acceptance algorithm, and show that truncation strategies are also applicable to all priority mechanisms and all linear programming mechanisms [10]. Uetake and Watanabe propose an approach to estimate a non-transferable utility in two-sided matching models [11].

The existing studies develop the methods for solving the two-sided matching problems, and expand the actual application background. However, due to the complexity of actual problems, the ambiguity of thinking judgement, the preferences provided by agents are in the format of uncertain linguistic terms, and the granularity of the linguistic term sets is also different. The existing studies seldom consider this case. Therefore, how to consider the two-sided matching problem with multi-granularity uncertain linguistic terms is a valuable research topic. In this paper, a novel two-sided matching method is presented.

The remainder of this paper is arranged as follows: Section 2 introduces some concepts of uncertain linguistic term and 2-tuple. Section 3 formulates the two-sided matching problem with multi-granularity uncertain linguistic terms. Section 4 proposes a new method. Section 5 gives a matching example in agricultural knowledge. Section 6 summarizes the main features of the proposed method.

2. The Concepts

In this section, some concepts on uncertain linguistic term and 2-tuple are given.

Definition 1. Let S be the set of linguistic terms, and Z^+ be the set of positive integers. An uncertain linguistic term \tilde{s} is expressed by $\tilde{s} = \{s^L, s^{L+1}, \dots, s^U\}$, where $s^L, s^{L+1}, \dots, s^U \in S$, $L, U \in Z^+, L \leq U$. Here s^L and s^U are the lower bound and upper bound of \tilde{s} , respectively. Specially, if $s^L = s^U$, then \tilde{s} reduces to a linguistic term.

By Definition 1, we know that \tilde{s} is a discrete set. For simplicity, we express \tilde{s} as $\tilde{s} = [s^L, s^U]$. In the considered two-sided matching problem, if $\tilde{r} = [r^L, r^U]$ is an uncertain linguistic term, then linguistic terms $r^L, r^{L+1}, \dots, r^{U-1}$ and r^U possess the same possibility.

Definition 2. Let \tilde{r} be an uncertain linguistic term, then the probability vector on \tilde{r} is expressed by $\tilde{p}_{\tilde{r}} = (p_{\tilde{r}}^L, \dots, p_{\tilde{r}}^k, \dots, p_{\tilde{r}}^U)$, where $p_{\tilde{r}}^k = 1/(U - L + 1)$.

Definition 3 [12-15]. Let $S = \{s_0, s_1, \dots, s_g\}$ be a linguistic term set and $\beta \in [0, g]$ a value supporting the result of a symbolic aggregation operation, then the 2-tuple that expresses the equivalent information to β is obtained with the following function θ :

$$\theta : [0, g] \rightarrow S \times [-0.5, 0.5] \quad (1a)$$

$$\theta(\beta) = (s_i, \alpha) = \begin{cases} s_i, & i = \text{round}(\beta) \\ \alpha = \beta - i, & \alpha \in [-0.5, 0.5] \end{cases} \quad (1b)$$

where round is the usual *rounding* operation, and s_i has the closest index label to β , and α is the value of the symbolic translation.

Definition 4 [12-15]. Let $S = \{s_0, s_1, \dots, s_g\}$ be a linguistic term set and (s_i, α) be a 2-tuple. There is always a function θ^{-1} , such that, from a 2-tuple it returns its equivalent numerical value $\beta \in [0, g]$:

$$\theta^{-1} : S \times [-0.5, 0.5] \rightarrow [0, g] \quad (2a)$$

$$\theta^{-1}(s_i, \alpha) = i + \alpha = \beta \quad (2b)$$

Remark 1: From Definitions 3 and 4, it is obvious that the conversion of a linguistic term into a 2-tuple consists of adding a value 0 as symbolic translation, i.e., $s_i \in S \Rightarrow (s_i, 0)$.

Definition 5 [12-15]. Let $x = \{(r_1, \alpha_1), (r_2, \alpha_2), \dots, (r_f, \alpha_f)\}$ be a set of 2-tuples and $w = \{w_1, w_2, \dots, w_f\}$ be their associated weights, where $w_i \in [0, 1]$ and $\sum w_i = 1$. The 2-

tuple weighted average is defined as $\bar{r}^w = \theta \left[\frac{\sum_{c=1}^f \theta^{-1}(r_c, \alpha_c) w_c}{\sum_{c=1}^f w_c} \right]$, where θ is a symbolic

translation, and θ^{-1} is the inverse of θ .

Definition 6. Let $\tilde{r} = [r^L, r^U]$ be an uncertain linguistic term, and \tilde{p}_i be the probability vector on \tilde{r} , then by Definitions 2 and 3, the expectation of \tilde{r} (noted as $E(\tilde{r})$) is calculated by

$$E(\tilde{r}) = \theta \left[\sum_{k=r^L}^{r^U} \frac{\theta^{-1}(k, 0)}{U - L + 1} \right] \quad (3)$$

In order to deal with 2-tuples, the definition of the extended 2-tuple weighted average should be given according to Definitions 5.

Definition 7. Let $x = \{(r_1, \alpha_1), (r_2, \alpha_2), \dots, (r_f, \alpha_f)\}$ be a set of 2-tuples and $w = \{w_1, w_2, \dots, w_f\}$ be their associated weights, where $w_i \in [0, 1]$ and $\sum w_i \in [0, 1]$. The extended 2-tuple weighted average is defined by

$$\tilde{r}^w = \begin{cases} \theta \left[\frac{\sum_{c=1}^f \theta^{-1}(r_c, \alpha_c) w_c}{\sum_{c=1}^f w_c} \right], & 0 < \sum_{c=1}^f w_c \leq 1 \\ \theta \left[\sum_{c=1}^f \theta^{-1}(r_c, \alpha_c) w_c \right] = \theta(0), & \sum_{c=1}^f w_c = 0 \end{cases} \quad (4)$$

3. The Problem

This paper considers the two-sided matching problem, where the agents' preferences are in the format of multi-granularity uncertain linguistic terms. Let $A = \{A_1, A_2, \dots, A_m\}$ ($m \geq 2$) be the set of agents of side A , where A_i denotes the i th agent of side A ; $B = \{B_1, B_2, \dots, B_n\}$ ($n \geq m \geq 2$) be the set of agents of side B , where B_j denotes the j th agent of side B . Let $S_{A_i} = \{s_0, s_1, \dots, s_{p_i}\}$ be the set of satisfaction linguistic terms given by A_i , where $p_i + 1$ denotes the cardinality of set S_{A_i} ; $S_{B_j} = \{s_0, s_1, \dots, s_{q_j}\}$ be the set of satisfaction linguistic terms given by B_j , where $q_j + 1$ denotes the cardinality of set S_{B_j} . Let $\tilde{L}_A = [\tilde{l}_{ij}^A]_{m \times n}$ be the multi-granularity uncertain linguistic term matrix from side A to B , where $\tilde{l}_{ij}^A = [l_{ij}^{AL}, l_{ij}^{AU}]$ denotes the multi-granularity uncertain linguistic term for agent

A_i towards B_j , $l_{ij}^{AL}, l_{ij}^{AU} \in S_{A_i}$; $\tilde{L}_B = [\tilde{l}_{ij}^B]_{m \times n}$ be the multi-granularity uncertain linguistic term matrix from side B to A , where $\tilde{l}_{ij}^B = [l_{ij}^{BL}, l_{ij}^{BU}]$ denotes the multi-granularity uncertain linguistic term for agent B_j towards A_i , $l_{ij}^{BL}, l_{ij}^{BU} \in S_{B_j}$. Let μ be the two-sided matching or matching alternative, $\mu = \mu_T \cup \mu_O$. Here, μ_T denotes the set of matching pairs, $\mu_T = \{(A_i, B_{\sigma(i)}) \mid i = 1, \dots, m\}$, where $\sigma(1), \dots, \sigma(m)$ is the permutation of $1, 2, \dots, m$; μ_O denotes the set of single pairs, $\mu_O = \{(B_j, B_j) \mid j \in \{1, \dots, n\} \setminus \{\sigma(1), \dots, \sigma(m)\}\}$.

The considered problem is how to obtain the reasonable matching alternative based on multi-granularity uncertain linguistic term matrixes $\tilde{L}_A = [\tilde{l}_{ij}^A]_{m \times n}$ and $\tilde{L}_B = [\tilde{l}_{ij}^B]_{m \times n}$.

4. The Method

This section will present a matching method for solving the two-sided matching problem with multi-granularity uncertain linguistic terms.

Firstly, by Eqs. (1a)-(3), we transform multi-granularity uncertain linguistic term matrixes $\tilde{L}_A = [\tilde{l}_{ij}^A]_{m \times n}$ and $\tilde{L}_B = [\tilde{l}_{ij}^B]_{m \times n}$ into multi-granularity 2-tuple matrixes $L_A = [(l_{ij}^A, \alpha_{ij})]_{m \times n}$ and $L_B = [(l_{ij}^B, \beta_{ij})]_{m \times n}$, where multi-granularity 2-tuples (l_{ij}^A, α_{ij}) and (l_{ij}^B, β_{ij}) are calculated by

$$(l_{ij}^A, \alpha_{ij}) = \theta \left(\frac{\theta^{-1}(l_{ij}^{AL}, 0) + \theta^{-1}(l_{ij}^{AU}, 0)}{2} \right) \quad (5)$$

$$(l_{ij}^B, \beta_{ij}) = \theta \left(\frac{\theta^{-1}(l_{ij}^{BL}, 0) + \theta^{-1}(l_{ij}^{BU}, 0)}{2} \right) \quad (6)$$

Based on multi-granularity 2-tuple matrixes L_A and L_B , we consider to construct an optimization model for obtaining the matching alternative considering matching constraints. On the one hand, according to the characteristics of linguistic term and 2-tuple, we know that the greater l_{ij}^A or l_{ij}^B is, the greater satisfaction degree of agent A_i or B_j is. Hence, we take the maximization 2-tuple as the objective function. On the other hand, due to $m \leq n$, the matching constraints can be interpreted as follows: agent A_i has exactly one matching agent of side B (i.e., $\sum_{j=1}^n x_{ij} = 1$), and agent B_j has at most one matching agent of

side A (i.e., $\sum_{i=1}^m x_{ij} \leq 1$), where $x_{ij} = \begin{cases} 0, & \mu(A_i) \neq B_j \\ 1, & \mu(A_i) = B_j \end{cases}$. Moreover, by using the extended 2-

tuple weighted average, the following multi-objective optimization model (7) can be set up:

$$\max Z(A_i) = \theta \left(\sum_{j=1}^n \theta^{-1}(l_{ij}^A, \alpha_{ij}) x_{ij} \right), i = 1, 2, \dots, m \quad (7a)$$

$$\max Z(B_j) = \theta \left(\sum_{i=1}^m \theta^{-1}(l_{ij}^B, \beta_{ij}) x_{ij} \right), j = 1, 2, \dots, n \quad (7b)$$

$$\text{s.t.} \quad \sum_{j=1}^n x_{ij} = 1, i = 1, 2, \dots, m \quad (7c)$$

$$\sum_{i=1}^m x_{ij} \leq 1, j = 1, 2, \dots, n \quad (7d)$$

$$x_{ij} = 0 \text{ or } 1, i = 1, 2, \dots, m, j = 1, 2, \dots, n \quad (7e)$$

In order to solve model (7), considering that symbolic translation θ is a monotone increasing function, the optimal solution(s) of the following optimization model (8) is that of model (7):

$$\text{max } Z(A_i) = \sum_{j=1}^n \theta^{-1}(l_{ij}^A, \alpha_{ij}) x_{ij}, i = 1, 2, \dots, m \quad (8a)$$

$$\text{max } Z(B_j) = \sum_{i=1}^m \theta^{-1}(l_{ij}^B, \beta_{ij}) x_{ij}, j = 1, 2, \dots, n \quad (8b)$$

$$\text{s.t. } \sum_{j=1}^n x_{ij} = 1, i = 1, 2, \dots, m \quad (8c)$$

$$\sum_{i=1}^m x_{ij} \leq 1, j = 1, 2, \dots, n \quad (8d)$$

$$x_{ij} = 0 \text{ or } 1, i = 1, 2, \dots, m, j = 1, 2, \dots, n \quad (8e)$$

In order to solve model (8), considering that the cardinalities of sets S_{A_i} ($i = 1, 2, \dots, m$) may be not equal, we should normalize Eqs. (8a) and (8b) firstly. Usually, the status of each agent of one side is the same. Hence, we can suppose that each agent of one side has equal priority. Then, using the linear weighted method, model (8) can be transformed into the following bi-objective optimization model (9):

$$\text{max } Z(A) = \frac{1}{m} \sum_{i=1}^m \frac{\sum_{j=1}^n \theta^{-1}(l_{ij}^A, \alpha_{ij}) x_{ij}}{p_i + 1} \quad (9a)$$

$$\text{max } Z(B) = \frac{1}{n} \sum_{j=1}^n \frac{\sum_{i=1}^m \theta^{-1}(l_{ij}^B, \beta_{ij}) x_{ij}}{q_j + 1} \quad (9b)$$

$$\text{s.t. } \sum_{j=1}^n x_{ij} = 1, i = 1, 2, \dots, m \quad (9c)$$

$$\sum_{i=1}^m x_{ij} \leq 1, j = 1, 2, \dots, n \quad (9d)$$

$$x_{ij} = 0 \text{ or } 1, i = 1, 2, \dots, m, j = 1, 2, \dots, n \quad (9e)$$

In order to solve model (9), the linear weighted method is also used. Let w_A and w_B be the weight of objectives functions $Z(A)$ and $Z(B)$, respectively, such that $w_A, w_B \in [0, 1]$, $w_A + w_B = 1$, then model (9) can be transformed into the following single-objective optimization model (10):

$$\max Z = \left(\frac{w_A}{m} \sum_{i=1}^m \frac{\sum_{j=1}^n \theta^{-1}(l_{ij}^A, \alpha_{ij})}{p_i + 1} + \frac{w_B}{n} \sum_{j=1}^n \frac{\sum_{i=1}^m \theta^{-1}(l_{ij}^B, \beta_{ij})}{q_j + 1} \right) x_{ij} \quad (10a)$$

$$\text{s.t. } \sum_{j=1}^n x_{ij} = 1, i = 1, 2, \dots, m \quad (10b)$$

$$\sum_{i=1}^m x_{ij} \leq 1, j = 1, 2, \dots, n \quad (10c)$$

$$x_{ij} = 0 \text{ or } 1, i = 1, 2, \dots, m, j = 1, 2, \dots, n \quad (10d)$$

Model (10) can be solved by the existing mathematical optimization software. According to multiple-objective programming theory, the optimal solution of model (10) is the efficient solution of model (9). Then the matching alternative can be obtained based on the obtained optimal solution.

In sum, an algorithm is developed to solve the two-sided matching problem with multi-granularity uncertain linguistic terms as follows:

Step 1. Transform multi-granularity uncertain linguistic term matrixes $\tilde{L}_A = [\tilde{l}_{ij}^A]_{m \times n}$ and $\tilde{L}_B = [\tilde{l}_{ij}^B]_{m \times n}$ into multi-granularity 2-tuple matrixes $L_A = [(l_{ij}^A, \alpha_{ij})]_{m \times n}$ and $L_B = [(l_{ij}^B, \beta_{ij})]_{m \times n}$ by Eqs (5) and (6).

Step 2. Built the multiple-objective optimization model (7) based on multi-granularity 2-tuple matrixes L_A and L_B by Eq. (4).

Step 3. Transform model (7) into model (8).

Step 4. Transform model (8) into model (9) by using the normalization method and the linear weighted method.

Step 5. Transform model (9) into model (10) by using the linear weighted method.

Step 6. Obtain the matching alternative by solving model (10).

4. The Example

The agricultural innovation intermediary in high-tech zone of Nanchang plans to make agricultural knowledge matchings between end-users of agricultural entrepreneurs (demand side) and producers of agricultural R&D and KIBS (supply side). Four agricultural entrepreneurs A_1, A_2, \dots, A_4 and six producers B_1, B_2, \dots, B_6 participate in the process of matching. Agricultural entrepreneur A_i evaluates producers from market prospect, complexity, and price. Producer B_j evaluates agricultural entrepreneurs from income, conversion speed, and technological level. The satisfaction linguistic term sets $S_{A_1} = S_{A_2} = \{s_0 = \text{VL(Very low)}, s_1 = \text{L(Low)}, s_2 = \text{ML(Medium low)}, s_3 = \text{M(Medium)}, s_4 = \text{MH(Medium high)}, s_5 = \text{H(High)}, s_6 = \text{VH(Very high)}\}$, $S_{A_3} = S_{A_4} = \{s_0 = \text{VL(Very low)}, s_1 = \text{L(Low)}, s_2 = \text{M(Medium)}, s_3 = \text{H(High)}, s_4 = \text{VH(Very high)}\}$. The satisfaction linguistic term set $S_{B_1} = S_{B_2} = S_{B_3} = S_{B_4} = \{s_0 = \text{VL(Very low)}, s_1 = \text{L(Low)}, s_2 = \text{M(Medium)}, s_3 = \text{H(High)}, s_4 = \text{VH(Very high)}\}$, $S_{B_5} = S_{B_6} = \{s_0 = \text{L(low)}, s_1 = \text{M(Medium)},$

$s_2 = \text{H(High)}$. The multi-granularity uncertain linguistic term matrixes $\tilde{L}_A = [\tilde{l}_{ij}^A]_{4 \times 6}$ and $\tilde{L}_B = [\tilde{l}_{ij}^B]_{4 \times 6}$ are provided as follows.

$$\tilde{L}_A = \begin{bmatrix} [s_2, s_3] & [s_3, s_4] & [s_2, s_2] & [s_4, s_5] & [s_1, s_2] & [s_5, s_6] \\ [s_3, s_4] & [s_2, s_3] & [s_1, s_1] & [s_0, s_1] & [s_4, s_4] & [s_2, s_2] \\ [s_2, s_2] & [s_0, s_1] & [s_1, s_2] & [s_3, s_4] & [s_2, s_3] & [s_4, s_4] \\ [s_1, s_2] & [s_4, s_4] & [s_3, s_4] & [s_0, s_1] & [s_2, s_3] & [s_2, s_2] \end{bmatrix}$$

$$\tilde{L}_B = \begin{bmatrix} [s_2, s_3] & [s_3, s_4] & [s_2, s_2] & [s_3, s_3] & [s_1, s_1] & [s_0, s_1] \\ [s_3, s_4] & [s_2, s_3] & [s_1, s_1] & [s_2, s_3] & [s_1, s_2] & [s_2, s_2] \\ [s_2, s_2] & [s_0, s_1] & [s_2, s_3] & [s_1, s_2] & [s_0, s_1] & [s_1, s_2] \\ [s_1, s_2] & [s_2, s_2] & [s_3, s_4] & [s_4, s_4] & [s_2, s_2] & [s_1, s_2] \end{bmatrix}$$

To determine the reasonable matching alternative, a brief description of the matching process is given below. Firstly, by Eqs. (5) and (6), multi-granularity uncertain linguistic term matrixes $\tilde{L}_A = [\tilde{l}_{ij}^A]_{4 \times 6}$ and $\tilde{L}_B = [\tilde{l}_{ij}^B]_{4 \times 6}$ are transformed into multi-granularity 2-tuple matrixes $L_A = [(l_{ij}^A, \alpha_{ij})]_{4 \times 6}$ and $L_B = [(l_{ij}^B, \beta_{ij})]_{4 \times 6}$. Then, the multiple-objective optimization model (7) can be built by Eq. (4). By using the normalization method and the linear weighted method, model (7) can be transformed into model (9). Suppose $w_A = 0.6$ and $w_B = 0.4$, model (9) can be transformed into model (10), where coefficient matrix $C = (c_{ij})_{4 \times 6}$ is calculated by

$$C = \begin{bmatrix} 0.0869 & 0.1217 & 0.0695 & 0.1364 & 0.0544 & 0.129 \\ 0.1217 & 0.0869 & 0.0348 & 0.044 & 0.119 & 0.0873 \\ 0.0867 & 0.0217 & 0.0783 & 0.125 & 0.0861 & 0.1533 \\ 0.065 & 0.1467 & 0.145 & 0.0683 & 0.1194 & 0.0933 \end{bmatrix}$$

Lastly, by solving model (10), the matching alternative $\mu = \mu_T^* \cup \mu_o^*$ can be obtained, *i.e.*,

$$X^* = [x_{ij}^*]_{4 \times 6} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

According to the unique optimal solution X^* , the matching alternative μ^* can be obtained, *i.e.*, $\mu^* = \mu_T^* \cup \mu_o^*$, where $\mu_T^* = \{(A_1, B_4), (A_2, B_1), (A_3, B_6), (A_4, B_2)\}$, $\mu_o^* = \{(B_3, B_3), (B_5, B_5)\}$. Hence, entrepreneur A_1 matches with producer B_4 , entrepreneur A_2 matches with producer B_1 , entrepreneur A_3 matches with producer B_6 , entrepreneur A_4 matches with producer B_2 , producers B_3 and B_5 are single.

5. Conclusion

A matching method for solving the two-sided matching problem with multi-granularity uncertain linguistic terms is proposed. Comparing with the existing methods, the proposed method has distinct characteristics as discussed below.

Firstly, the related concepts of uncertain linguistic term and 2-tuple are given. It is a beneficial supplement of theory of linguistic term. Secondly, a multi-objective

optimization model is constructed. By solving it, it could be easier to obtain the reasonable stable matching alternative. Finally, the proposed method is theoretically sound and computationally simple which provides a new way to solve the considered two-sided matching problem and can be adopted for practical use. When the multi-granularity linguistic terms are incomplete, how to obtain the reasonable matching alternative is worth to study for us in future.

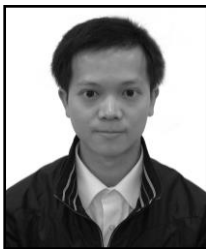
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