A Type-2 Fuzzy Model to Prioritize Suppliers Based on Trust Criteria in Intelligent Agent-Based Systems

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Abstract In the last two decades the intelligent agents have improved the lifestyle of human beings from different aspects of view such as life activities and services. Considering the importance of the safety and security role in the e-procurement, there have been many systems developed including trust engine. In particular, some of the first systems were modeled though trust evaluation concepts as crisp values, but now a days to adjust the systems with real world cases, the uncertainty and impreciseness parameters must be considered with the use of fuzzy sets theory. In this paper to minimize the number of exceptions related to suppliers, Trust Management Agent (TMA) is considered to prioritize candidate suppliers based on trust criteria. Due to lots of uncertainties, type-2 fuzzy sets prove to be a most suitable methodology to deal with the trust evaluation process efficiently. In this regard, a new evaluation process based on hierarchical Linguistic Weighted Averaging (LWA) sets is proposed. The solution method was then illustrated through a simple example which clarifies the suitability as well as the simplicity of the proposed method for the category of the defined problem.

Keywords Interval type-2 fuzzy · Intelligent agent-based systems
Trust evaluation · E-procurement · Prioritize suppliers

1 Introduction

The term e-Procurement refers to the use of electronic communications to deal with business process between sellers and buyers, through linking and integrating inter-organization business processes and systems with the use of Internet-based

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protocols [2]. E-Procurement has been providing more efficient trading methods as well as new trading opportunities in the supply networks.

In the last two decades the intelligent agents have improved the lifestyle of human beings from different aspects including life activities and services. There has been growing interest in the design of a distributed, intelligent society of agents in e-commerce applications in the recent years [10, 13, 21, 30].

It is crucial, in an agent based e-procurement system to protect both buyers and sellers from any possible unsatisfied condition, which is commonly due to some uncertain and vague characters. In this regard, there have been a number of systems developed using a kind of trust engine to help establish trust orientation between the firms [33]. Such trust, could positively affect firms' behaviors and performances and meantime reduce their interrelation risks.

The establishment of the trust commonly requires one party to assess the other on its past behaviors, acts and promises based on some appropriate trust criteria [7, 22, 32]. For this assessment, commonly, not crisp but vague and uncertain data are available. Further, in the agent based systems, the assessment heavily relies on the collective opinions from the agents in the community. Whilst, some early agent based systems modeled the trust evaluation process merely using crisp values, but to adjust the systems with real world cases, the uncertainty and vagueness parameters must be considered in the modelling through utilizing fuzzy based theories.

While type-1 fuzzy sets are capable to handle several kinds of uncertainties [16] these are not able to directly model uncertainties related to some particular sources, such as: uncertainty in the meanings of the words and uncertainty associated with the consequences (e.g. when the knowledge extracted from group of experts who do not all agree). Type-2 fuzzy sets are more appropriate for these situations. Type-2 fuzzy sets utilizes higher degree of freedom by a fuzzy membership functions to handle uncertainties in real world situations.

Considering uncertainty characteristics of the inter-organizational trust evaluation in an agent based e-procurement system (as detailed in the next section) and based on the capabilities outlined for type-2 fuzzy sets (in Sect. 4) this paper propose a new evaluation process based on Linguistic Weighted Averaging (LWA) sets using Interval Type-2 Fuzzy set (IT2-FSs).

The following section (Sect. 2) provides a brief review of the literature and the main subjects concerned in this paper. Section 3 describes the defined problem. The background of the solution approach is presented in Sect. 4 and the solution approach is detailed in Sect. 5. Then an illustrative example is presented in Sect. 6. Finally, conclusions are provided in Sect. 7.

2 Literature Review

This section provides brief reviews for the three main aspects concerned in this work:

- Intelligent agents in e-procurement
- Inter-organizational trust in the e-procurement intelligent agents
- The capabilities of T2-FSs in dealing with high levels of uncertainties.

2.1 Intelligent Agents in E-Procurement

E-Procurement is considered to be a strategic tool for improving the competitiveness of organizations and generating scale economies for both sellers and buyers. In this context, one critical issue is to tackle problems existing in ensuring a trustworthy environment in which business interrelationship risks can be minimized [2].

Intelligent agents reveal the capability to operate on behalf of buyers to look for requested products concerning the process of procurement [9]. Raghavan and Prabhu [19] developed a software for agent-based framework considering a typical e-procurement process by classifying the procurement process into three classes: e-negotiations, e-settlement, and reverse auctions [19]. Cheung et al. [6] proposed an agent-oriented knowledge-based system for strategic e-procurement using real time information to produce dynamic business rules [6]. Lee and his collogues [12] proposed an agent based e-procurement system, in which the intelligent agents are responsible for searching and negotiating the potential suppliers and evaluating the performance of suppliers based on the selection criteria [12, 26].

Sun and his collogues [26] proposed an agent and Web service based architecture for considering exception handling in e-procurement. In this architecture, different tasks in the e-procurement process are assigned to different agents, such as searching, negotiating, supplier selection, contracting, monitoring, and exception handling [26].

Despite the existing developments on applying intelligent agents for e-procurement, the challenge remains on how to tackle the existing problem as the legal framework that can ensure a trustworthy environment (as mentioned in this section). For this reason Inter-organizational trust in intelligent agents of e-procurement is considered in the next sub-section.

2.2 Inter-organizational Trust in the E-Procurement Intelligent Agents

Inter-organizational trust helps establish a kind of inter-firm relationship which ensures each side holding a collective trust orientation towards the other [33]. This positively affects firms' behaviors and performances and meantime reduces interrelation risks. Inter-organizational trust is conceptualized as a multi-dimensional construct, for which a list of 22 widely referred dimensions is introduced in [25].

The same paper also summarized the most commonly used dimensions as: credibility, benevolence, goodwill, predictability, reciprocity, openness and confidence.

Trust has been recognized as a key issue in multi-agent and e-commerce systems, being at the core of the interactions between agents operating in uncertain business environments [11, 20]. Bases of the trustworthiness knowledge is one main concern, for which three types are commonly agreed in the literature: individual experience, inference from other agents in the community, and a hybrid of the two [3]. Evidences used for trust evaluation, based on their source types, can also be categorized as priori evidences and experienced evidences [11, 18, 35]. Priori evidences are those mainly provided by protocols, policies, or mechanisms; while experienced evidences are obtained by the agents during their interactions. The literature reveals considerable research interest in trust decision with regard to the community based experiences. With regard to the characteristics of trust evaluation in the e-procurement environment, we refer to [1] which states the need to deal with high levels of uncertainties, vagueness and ambiguities which are commonly due to: (1) The absence of an authority to prescribe the rules for inter-organizational interaction as buyer supplier relationships, (2) Trading transactions might occur among unknown parties, which requires a collection of indirect trust experience from referee agents in the community, and (3) The use of trust experiences which are based on the feedback from buyers.

According to some studies [20, 27], for an agent to evaluate other agents' trustworthiness some models traditionally use a bi-stable value (good or bad), while this cannot generally support realistic situations. Instead, some other researches (e.g. [18, 23, 24]) attribute some fuzziness to the notion of performance and then evaluate the trustworthiness using fuzzy reasoning techniques. These authors concluded that the fuzzy reasoning is especially attractive for the trust evaluation purpose.

The above review leads to the recognition of the characteristics of trust evaluation in the e-procurement context the characteristic represent the high levels of uncertainties, vagueness and ambiguities (as detailed [1]).

2.3 A Short Review of T2-FSs Capabilities

In 1975 Zadeh introduced type-2 fuzzy sets to minimize the effect of uncertainties concerning ambiguity, vagueness and randomness [31]. While type-1 fuzzy sets are capable to handle several kinds of uncertainties, according to Mendel and his colleagues in [16] these are not able to directly model uncertainties related to the following sources: (1) Uncertainty in the meanings of the terms (for instance used in the rules), (2) Uncertainty associated with the consequences (for instance when the knowledge extracted from group Of experts who do not all agree), (3) Uncertainty in the measurements that activate type-1 fuzzy set and (4) Uncertainty in the data used to tune parameters of a type-1 fuzzy sets. These types of uncertainties all translate into uncertainties about fuzzy sets membership functions, while in the type-1 fuzzy sets membership functions are totally crisp. In this paper, it is concluded that type-2 fuzzy sets are able to model such types of uncertainties because of fuzzy membership functions. According to Castillo and his colleagues [5] five types of uncertainties emerge from imprecise knowledge natural state, which are: uncertainties related to measurement, process, model, estimate and implementation.

As discussed in [34] a type-2 fuzzy set, which is characterized by a fuzzy membership function, is capable to provide us with more degrees of freedom to represent the vagueness and the uncertainty and of the real world.

According to Mendel and his colleagues [16], there has been several application areas for fuzzy logic systems and type-2 fuzzy sets (for instance decision making, extracting knowledge from questionnaire surveys, function approximation, learning linguistic membership grades, preprocessing radiographic images and transport scheduling).

3 Problem Description

As discussed in the previous section, it is crucial in an agent based e-procurement system to protect the buyer from any possible unsatisfied condition which is commonly due the existence of uncertain and vague characters. In this regard, many research attempts have been reported in the literature including some developments which use an exception management agent to handle such undesired situations. Some research works with the inter-organizational trust orientation have been also presented in the literature. It is notable that presence of the trust in the buyer-seller relationship not only reduces uncertainty and vagueness characteristics, but significantly reduces the complexity of the inter-firm relations which could in turn enhance their trading process. These published works, however, mostly utilize T1-FSs in their solution approach, therefore, they provide limited capabilities in handling mentioned uncertainty and vagueness characteristics. As reviewed in the literature, T2-FSs utilize higher degree of freedom by a fuzzy membership function to handle uncertainties and vagueness in real world situations.

Based on the recognition of the above remarking points, the current paper aims to establish inter-organizational trust in the agent based e-procurement systems, through proposing an effecting supplier evaluation and ranking method. Considering previously mentioned characteristics inherent in the inter-organizational trust evaluation process such as; uncertainty and vagueness in the data, use of collective opinions from experts or other agent in the community, as well as using both direct and indirect sources of evidences; this paper utilizes type-2 fuzzy sets as the solution approach for the defined problem.

The paper considers an agent based e-procurement system consisting of specific agents for the required functions also including a Trust Management Agent (ATM) which is responsible to establish inter-organizational trust in the buyer-supplier relationship. One major function in this respect is to evaluate some pre-qualified candidate suppliers in order to rank them on some particular trust criteria. In this regard the paper aims to propose a solution method to determine various decision to lead to a short list of the most appropriate suppliers ranked based on their trustworthiness characteristics. It is notable that this approach utilizes linguistic weighted averaging based on interval type-2 fuzzy sets in the evaluation process.

The proposed solution is further detailed in the following sections.

4 Basic Concepts of Type-2 Fuzzy Sets

In 1975 Zadeh introduced type-2 fuzzy sets to minimize the effect of uncertainties concerning ambiguity, vagueness and randomness [31]. Comparing to an ordinary (type-1) fuzzy set which has a grade of crisp membership function, a type-2 fuzzy set has grades of fuzzy membership functions [14]. This section is organized to review theoretical definitions related to the proposed fuzzy type-2 based solution method, including: Interval Type-2 Fuzzy Sets (IT2-FSs) and Linguistic Weighted Averaging (LWA).

4.1 Interval Type-2 Fuzzy Sets

Definition 1 [16] A type-2 fuzzy set $\tilde{A}$ is characterized by a type-2 membership function $\mu_{\tilde{A}}(x,u)$, where $x \in X$, $u \in J_x \subseteq [0,1]$ and $\mu_{\tilde{A}}(x,u) \subseteq [0,1]$, i.e.,

$$\tilde{A} = \left\{ ((x,u),\ \mu_{\tilde{A}}(x,u)) \middle| \forall x \in X,\ \forall u \in J_x \subseteq [0,1] \right\} \tag{1}$$

Also $\tilde{A}$ can be presented by Eq. (2),

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{A}}(x,u)/(x,u)\ J_x \subseteq [0,1] \tag{2}$$

where $\int$ denotes union overall admissible x and u. For discrete universe of discourse x and u, $\int$ is replaced by $\sum$.

Definition 2 [17] If all $\mu_{\tilde{A}}(x,u) = 1$ then $\tilde{A}$ is an interval type-2 fuzzy sets which can be expressed as a special case of general type-2 fuzzy sets, Eq. (3):

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} 1/(x,u) \qquad J_x \subseteq [0,1]. \tag{3}$$

Note that x is the primary variable, $J_x \subseteq [0,1]$ is the primary MF of x, also u is the secondary variable, and $\int_{u \in J_x} 1/u$ is the secondary MF at x.

Definition 3 [17] A bounded region with respect to the uncertainty in the primary memberships of an IT2-FS, is called the Footprint of Uncertainty (FOU), which is the union of all primary membership functions.

$$FOU(\tilde{A}) = \bigcup_{x \in X} J_x. \tag{4}$$

So, FOU demonstrates the vertical-slice-representation to indicate the interval type-2 fuzzy sets.

Definition 4 [28] The FOU is bounded by an Upper Membership Function (UMF) $\bar{A}(x) \equiv \bar{A}$ and a Lower Membership Function (LMF) $\underline{A}(x) \equiv \underline{A}$, which are T1-FSs; So, the membership function of each element of an IT2-FS is an interval $[\underline{A}(x), \bar{A}(x)]$.

4.2 Linguistic Weighted Averaging

The linguistic weighted average, concerning IT2-FSs as inputs, is introduced by Wu and Mendel in 2007 and 2008 in [28, 29] which is an extension of the Fuzzy Weighted Average (FWA) [8] for type-1 FSs inputs. The LWA is defined:

$$\tilde{Y}_{LWA} = \frac{\sum_{i=1}^{n} \tilde{X}_i \tilde{W}_i}{\sum_{i=1}^{n} \tilde{W}_i} \tag{5}$$

where $\tilde{X}_i$ and the corresponded weight $\tilde{W}_i$ are linguistic terms. Considering that $\tilde{X}_i$ and $\tilde{W}_i$ which are modeled by IT2-FSs, the $\tilde{Y}_{LWA}$ is also IT2-FSs (Eq. (6)),

$$\tilde{Y}_{LWA} = 1/FOU(\tilde{Y}_{LWA}) = 1/[\underline{Y}_{LWA}, \bar{Y}_{LWA}] \tag{6}$$

where $\underline{Y}_{LWA}$ and $\bar{Y}_{LWA}$ are LMFs and UMFs of $\tilde{Y}_{LWA}$, respectively [28]. Considering the use of $\tilde{X}_i$ and $\tilde{W}_i$ in computing $\tilde{Y}_{LWA}$, with regard to vertical-slice-representation, Eqs. (7) and (8) are defined as below [28]:

$$\tilde{X}_i = 1/FOU(\tilde{X}_i) = 1/[\underline{X}_i, \bar{X}_i] \tag{7}$$

$$\tilde{W}_i = 1/FOU(\tilde{W}_i) = 1/[\underline{W}_i, \bar{W}_i] \tag{8}$$

where $\underline{X}_i$ and $\bar{X}_i$ ($\underline{W}_i$ and $\bar{W}_i$) are LMFs and UMFs of $\tilde{X}_i(\tilde{W}_i)$, respectively.

$\bar{Y}_{LWA}$ and $\underline{Y}_{LWA}$ will be computed using the α-cut, in which the range of the MF is discretized into m points as $\alpha_1, \alpha_2, \ldots, \alpha_m$. The α-cut on $\tilde{X}_i$ and $\tilde{W}_i$ are applied to compute the corresponding $\tilde{Y}_{LWA}$ (Figs. 1, 2 and 3) [28].

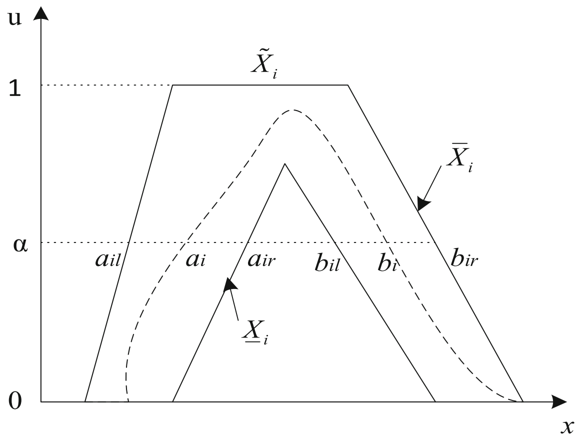

Fig. 1 $\tilde{X}_i$ and an α-cut. the dashed curve is an embedded T1 FS of $\tilde{X}_i$ [28]

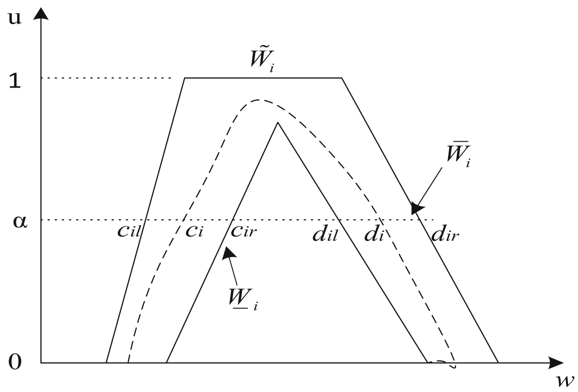

Fig. 2 $\tilde{W}_i$ and an α-cut. The dashed curve is an embedded T1 FS of $\tilde{W}_i$ [28]

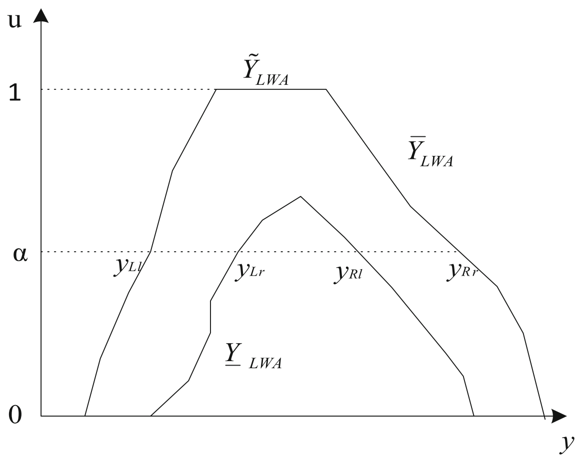

Fig. 3 $\tilde{Y}_i$ and an α-cut [28]

Noted that all UMFs are T1 FSs normal, so the height of the UMFs of $\bar{Y}_{LWA}$ is one $(h_{\bar{Y}_{LWA}} = 1)$.

And the height of $\underline{Y}_{LWA}$ which is the lower bound of MFs of FOU ($\tilde{Y}_{LWA}$) is calculated by $h_{\min}$ which is defined as the smallest height of all FWAs resulted from T1 FSs of the height of $\underline{X}_i$ as $h_{\underline{X}_i}$ and $\underline{W}_i$ as $h_{\underline{W}_i}$ in Eq. (9) [14].

$$h_{\min} = \min\{\min_{\forall i} h_{\underline{X}_i},\ \min_{\forall i} h_{\underline{W}_i}\} \tag{9}$$

Let the interval of $[a_i(\alpha),\ b_i(\alpha)]$ be an α-cut on $\tilde{X}_i$, and the interval $[c_i(\alpha),\ d_i(\alpha)]$ be an α-cut on $\tilde{W}_i$. As shown in Fig. (1), if the α-cut on $\underline{X}_i$ exists, then the interval $[a_{il}(\alpha),\ b_{ir}(\alpha)]$ is divided into three subintervals: $[a_{il}(\alpha),\ a_{ir}(\alpha)]$, $[a_{ir}(\alpha),\ b_{il}(\alpha)]$, and $[b_{il}(\alpha),\ b_{ir}(\alpha)]$.

However, if the α on $\underline{X}_i$ is larger than $h_{\underline{X}_i}$ (α-cut dose not exist), then both the value of $a_i(\alpha)$ and $b_i(\alpha)$ can be assumed in the entire interval $[a_{il}(\alpha),\ b_{ir}(\alpha)]$:

$$a_i(\alpha) = \begin{cases} [a_{il}(\alpha), a_{ir}(\alpha)] & \alpha \in [0, h_{\underline{X}_i}] \\ [a_{il}(\alpha), b_{ir}(\alpha)] & \alpha \in [h_{\underline{X}_i}, 1] \end{cases} \tag{10}$$

$$b_i(\alpha) = \begin{cases} [b_{il}(\alpha), b_{ir}(\alpha)] & \alpha \in [0, h_{\underline{X}_i}] \\ [a_{il}(\alpha), b_{ir}(\alpha)] & \alpha \in [h_{\underline{X}_i}, 1] \end{cases} \tag{11}$$

Similarly the value of $c_i(\alpha)$ and $d_i(\alpha)$ can be assumed based on Fig. 2,

$$c_i(\alpha) = \begin{cases} [c_{il}(\alpha), c_{ir}(\alpha)] & \alpha \in [0, h_{\underline{W}_i}] \\ [c_{il}(\alpha), d_{ir}(\alpha)] & \alpha \in [h_{\underline{W}_i}, 1] \end{cases} \tag{12}$$

$$d_i(\alpha) = \begin{cases} [d_{il}(\alpha), d_{ir}(\alpha)] & \alpha \in [0, h_{\underline{W}_i}] \\ [c_{il}(\alpha), d_{ir}(\alpha)] & \alpha \in [h_{\underline{W}_i}, 1] \end{cases} \tag{13}$$

In Eqs. (10)–(13), the l and r *are the left and* right indices respectively. Also the value of $a_{ir}(\alpha), b_{il}(\alpha)$, $c_{il}(\alpha)$ and $d_{il}(\alpha)$ can be defined as Eqs. (14)–(17):

$$a_{ir}(\alpha) \triangleq \begin{cases} a_{ir}(\alpha), & \alpha \le h_{\underline{X}_i} \\ b_{ir}(\alpha), & \alpha > h_{\underline{X}_i} \end{cases} \tag{14}$$

$$b_{il}(\alpha) \triangleq \begin{cases} b_{il}(\alpha), & \alpha \le h_{\underline{X}_i} \\ a_{il}(\alpha), & \alpha > h_{\underline{X}_i} \end{cases} \tag{15}$$

$$c_{ir}(\alpha) \triangleq \begin{cases} c_{ir}(\alpha), & \alpha \le h_{\underline{W}_i} \\ d_{ir}(\alpha), & \alpha > h_{\underline{W}_i} \end{cases} \tag{16}$$

$$d_{il}(\alpha) \triangleq \begin{cases} d_{il}(\alpha), & \alpha \le h_{\underline{W}_i} \\ c_{il}(\alpha), & \alpha > h_{\underline{W}_i} \end{cases} \tag{17}$$

In the LWA, the value of $a_i(\alpha)$, $b_i(\alpha)$, $c_i(\alpha)$, and $d_i(\alpha)$ can be assumed continuously in their corresponding α-cut intervals. So numerous different combinations of those values can be produced to form $y_L(\alpha)$ and $y_R(\alpha)$. By considering all $y_L(\alpha)$ and $y_R(\alpha)$, continuous intervals $[y_{Ll}(\alpha), y_{Lr}(\alpha)]$ and $[y_{Rl}(\alpha), y_{Rr}(\alpha)]$ are obtained, where $y_{Lr}(\alpha)$, $y_{Rl}(\alpha)$, $y_{Ll}(\alpha)$, and $y_{Rr}(\alpha)$ are illustrated in (Fig. 3):

$$\underline{Y}_{LWA}(\alpha) = [y_{Lr}(\alpha), y_{Rl}(\alpha)], \quad \alpha \in [0, h_{\min}] \tag{18}$$

$$\bar{Y}_{LWA}(\alpha) = [y_{Ll}(\alpha), y_{Rr}(\alpha)], \quad \alpha \in [0, 1] \tag{19}$$

Considering the fix values of $a_i(\alpha)$, $b_i(\alpha)$, $c_i(\alpha)$ and $d_i(\alpha)$, the values of $y_{Ll}(\alpha)$, $y_{Lr}(\alpha)$, $y_{Rl}(\alpha)$ and $y_{Lr}(\alpha)$ are defined as below [14, 28, 29]:

$$y_{Ll}(\alpha) = \frac{\sum_{i=1}^{L_l^*} a_{il}(\alpha) d_{ir}(\alpha) + \sum_{i=L_l^*+1}^{n} a_{il}(\alpha) c_{il}(\alpha)}{\sum_{i=1}^{L_l^*} d_{ir}(\alpha) + \sum_{i=L_l^*+1}^{n} c_{il}(\alpha)} \quad \alpha \in [0, 1] \tag{20}$$

$$y_{Lr}(\alpha) = \frac{\sum_{i=1}^{L_r^*} a_{ir}(\alpha) d_{il}(\alpha) + \sum_{i=L_r^*+1}^{n} a_{ir}(\alpha) c_{ir}(\alpha)}{\sum_{i=1}^{L_r^*} d_{il}(\alpha) + \sum_{i=L_r^*+1}^{n} c_{ir}(\alpha)} \quad \alpha \in [0, h_{\min}] \tag{21}$$

$$y_{Rl}(\alpha) = \frac{\sum_{i=1}^{R_l^*} b_{il}(\alpha) c_{ir}(\alpha) + \sum_{i=R_l^*+1}^{n} b_{il}(\alpha) d_{il}(\alpha)}{\sum_{i=1}^{R_l^*} c_{ir}(\alpha) + \sum_{i=R_l^*+1}^{n} d_{il}(\alpha)} \quad \alpha \in [0, h_{\min}] \tag{22}$$

$$y_{Rr}(\alpha) = \frac{\sum_{i=1}^{R_r^*} b_{ir}(\alpha) c_{il}(\alpha) + \sum_{i=R_r^*+1}^{n} b_{ir}(\alpha) d_{ir}(\alpha)}{\sum_{i=1}^{R_r^*} c_{il}(\alpha) + \sum_{i=R_r^*+1}^{n} d_{ir}(\alpha)} \quad \alpha \in [0, 1] \tag{23}$$

In these Equations, L_l^*, L_r^*, R_l^* and R_r^* are defined as switch points which are computed by KM or EKM algorithms discussed in [15]. $y_{Ll}(\alpha)$ and $y_{Rr}(\alpha)$ as shown in Figs. 1, 2 and 3 and Eqs. (20) and (23) only depend on the UMFs of $\tilde{X}_i$ and $\tilde{W}_i$, which are computed from the corresponding α-cuts (Expressive Eq. (24)).

$$\bar{Y}_{LWA} = \frac{\sum_{i=1}^{n} \bar{X}_i \bar{W}_i}{\sum_{i=1}^{n} \bar{W}_i} \tag{24}$$

Because all $\bar{X}_i$ and $\bar{W}_i$ are normal T1-FSs, $\bar{Y}_{LWA}$ is also normal.

Similarly, observe from Eqs. (21) and (22) and the mentioned Figures, the $y_{Lr}(\alpha)$ and $y_{Rl}(\alpha)$ only depend on the LMFs of $\tilde{X}_i$ and $\tilde{W}_i$, which are computed from the corresponding α-cuts (Expressive Eq. (25)).

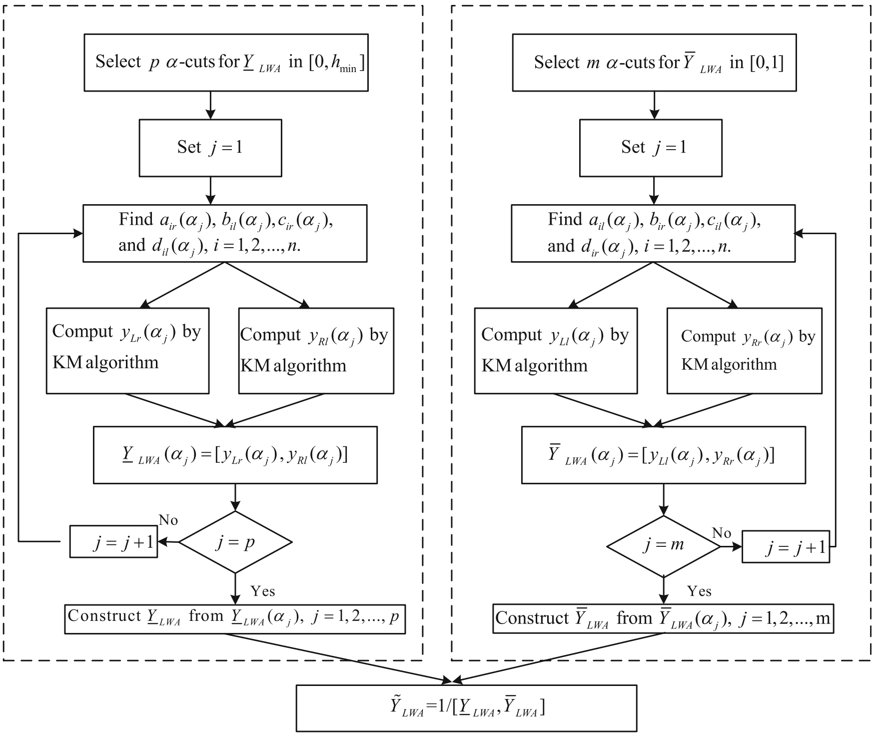

Fig. 4 The pseudo-code of computing LWA [29]

$$\underline{Y}_{LWA} = \frac{\sum_{i=1}^{n} \underline{X}_i \underline{W}_i}{\sum_{i=1}^{n} \underline{W}_i} \tag{25}$$

Noted that, unlike $\bar{Y}_{LWA}$, the height of $\underline{Y}_{LWA}$ is $h_{\min}$, which is defined by Eq. (9), as the minimum height of all $\underline{X}_i$ and $\underline{W}_i$.

A pseudo-code for computing $\bar{Y}_{LWA}$ and $\underline{Y}_{LWA}$ is given in Fig. 4.

5 Solution Approach

This section describes the proposed method of prioritizing suppliers based on trust criteria in the intelligent agent environment considering type-2 fuzzy sets.

Let $S_i = \{s_1, s_2, \ldots, s_z\}$ be a set of prequalified (candidate) suppliers. A set of agents $A_f = \{a_1, \ldots, a_m\}$ is considered to query from, also concerning their frequency of interaction with suppliers, linguistic weights $WA_f = \{wa_1, \ldots, wa_m\}$ are defined, where $\sum_{f=1}^{m} WA_f = 1$. Also $C_h = \{c_1, c_2, \ldots, c_n\}$ is a set of trust criteria with respect to their importance weights $W_h = \{w_1, w_2, \ldots, w_n\}$, defined as linguistic terms, where $\sum_{h=1}^{n} W_h = 1$.

The supplier prioritization process consists of 6 Steps, which is organized in two Stages. While, stage 1 includes three functions for the determination of: candidate suppliers, trust evaluation criteria and referee agents. This paper concentrates more on stage 2, which consists of data collection, data aggregation and supplier prioritization.

Stage 1
This is a kind of preparation stage which consists of the following 3 steps.

Step 1: Determine prequalified suppliers
Suppliers register their services in the service register center of the e-procurement system. The registration should include detailed information about the service or commodity. Based on the information, prequalified suppliers are identified for the further trust evaluation process, as presented in [18], to serve their product catalogs to the buyers through the e-procurement system

Step 2: Determine trust evaluation criteria
Inter-organizational trust is conceptualized as a multi-dimensional construct, for which a list of 22 widely referred dimensions are reviewed in [25] while the most commonly used dimensions are summarized as: credibility, benevolence, goodwill, predictability, reciprocity, openness and confidence.

This Step is concerned with the determination of those more appropriate trust dimensions considering each industry/organization situation. Furthermore, with regard to the firm's strategic aspects, an appropriate weight has also to be considered for each selected criterion.

Step 3: Determine referee agents
Multi-agent systems work autonomously and collaboratively by mean of the Internet. Each agent are focused on its own particular tasks, meanwhile cooperatively provide a specific operation or service to other agents [26]. To retrieve information from agents, a set of agents who has historical data about direct and indirect trust experience with the target suppliers is identified.

Stage 2
This stage consists of the following three steps to prioritize suppliers based on the trust criteria concerning interval type-2 fuzzy sets (both data judgment and weights).

Step 1: Data collection
When the supplier prioritization is required, the TMA queries about suppliers, concerning trust criteria, from each of the referee agent. These agents are asked to evaluate the suppliers by completing an electronic form which is provided by TMA as shown in Fig. 5.

The evaluation of the agents are based on the defined trust criteria as mentioned in Stage 1–Step 2. There are different trust assessment levels which are ranged from

Assessment	Weakly Trustable	Moderately Trustable	Strongly Trustable	Extremely Trustable
Trust criteria 1 (C_1)	( )	( )	( )	( )
Trust criteria 2 (C_2)	( )	( )	( )	( )
Trust criteria n (C_n)	( )	( )	( )	( )

Term of interaction	Never	Almost Never	Seldom	Unspecified	Often	Almost always	Always
Frequency of interaction	( )	( )	( )	( )	( )	( )	( )

Fig. 5 The trust evaluation form of *i*th supplier for the agent *f*

the worst to the best based on linguistic terms as: Weakly Trustable (WT), Moderately Trustable (MT), Strongly Trustable (ST) and Extremely Trustable (ET). Also weights of the frequency of interaction associated with agents and suppliers are concerned using linguistic terms as: Never (N), Almost Never (AN), Seldom (S), Unspecified (U), Often (O), Almost Always (AA) and Always (A). in this paper, it is assumed that each category of terms, as mentioned, has been explained as IT2 FSs $\tilde{X}$, using upper and lower fuzzy membership functions (Tables 1 and 2).

Step 2: Data aggregation

In this paper two phases of aggregation are defined as below:

- **Step 2-1**: The aggregation process with respect to agents' judgments.
  In this phase linguistic judgments of agents are aggregated for each criterion and supplier. Considering that the frequency of interaction between agents and suppliers can improve the accuracy of the collected data, the LWA operator is applied to aggregate the all agents' judgment for the *h*th criterion of the *i*th supplier with regard to the linguistic data related to frequency of interaction. The frequency of interaction of agents can be considered based on the filled form as shown in Fig. 5. So in this case, the opinion of the agent who always interact with specific supplier is taken into account by considering higher linguistic weights.
- **Step 2-2**: The aggregation process with respect to defined trust criteria.

Table 1 Fuzzy membership functions of agents' judgments based on linguistic terms

Linguistic variables	Fuzzy type 1	Fuzzy type 2	
	Membership function (MFs)	Upper membership function (UMF)	Lower membership function (LMF)
Weakly Trustable (WT)	(0, 2, 4)	(0.00, 2, 4.2)	(0.20, 2, 3.80)
Moderately Trustable (MT)	(2, 4, 6)	(1.80, 4, 6.2)	(2.20, 4, 5.80)
Strongly Trustable (ST)	(4, 6, 8)	(3.80, 6, 8.2)	(4.20, 6, 7.80)
Extremely Trustable (ET)	(6, 8, 10)	(5.80, 8, 10)	(6.20, 8, 9.80)

Table 2 Fuzzy membership functions assigned to agents' and criteria's weight based on linguistic terms

Linguistic variables of agents	Linguistic variables of criteria	Fuzzy type 1	Fuzzy type 2	
		Membership function(MFs)	Upper membership function (UMF)	Lower membership function (LMF)
Never (N)	Very Low (VL)	(0.1, 0.5, 1)	(0.06, 0.5, 1.05)	(0.14, 0.5, 0.95)
Almost Never (AN)	Low (L)	(0.5, 1, 3)	(0.45, 1, 3.2)	(0.55, 1, 2.80)
Seldom (S)	Medium Low (ML)	(1, 3, 5)	(0.80, 3, 5.2)	(1.20, 3, 4.80)
Unspecific (U)	Moderate (M)	(3, 5, 7)	(2.80, 5, 7.2)	(3.20, 5, 6.80)
Often (O)	Medium High (MH)	(5, 7, 8)	(4.80, 7, 8.1)	(5.20, 7, 7.9)
Almost always (AA)	High (H)	(7.5, 8, 9.5)	(7.45, 8, 9.65)	(7.55, 8, 9.35)
Always (A)	Very High (VH)	(9, 9.5, 10)	(8.95, 9.5, 10)	(9.05, 9.5, 9.95)

In this phase the aggregated data of previous Phase are used to aggregate them based on the trust criteria for each supplier. Considering the importance of each criterion, the TMA assigns an importance weight to each criterion based on the different assessment level that range from the lowest to the highest as defined by linguistic terms: Very Low (VL), Low (L), Medium Low (ML), Moderate (M), Medium High (MH), High (H) and Very High (VH).

In this paper assumed that each category of terms, as mentioned, has been explained as IT2 FSs $\tilde{X}$ using upper and lower fuzzy membership functions (Table 2). LWA operator is applied to aggregate the data of all criteria for each supplier based on the importance weight of the criterion.

Step 3—Suppliers prioritization

Different approaches to prioritizing/ranking interval type-2 fuzzy sets exist. In this paper, a method proposed by Asan and his colleagues in [4] is applied to rank suppliers based on α-cuts in the form of IT2-FSs in which both UMFs and LMFs are normal T1-FSs.

Let $Y_i^M(\alpha)$ in Eq. (26), denote the total mean of the end points crossing α-cuts on both LMFs and UMFs of $\tilde{Y}_i$,

$$Y_i^M(\alpha) = \frac{y_{Ll}(\alpha) + y_{Lr}(\alpha) + y_{Rl}(\alpha) + y_{Rr}(\alpha)}{4} \tag{26}$$

Also $|Y_i(\alpha)|$ in Eq. (27), considered as a weighting factor using the length of the α-cuts of the embedded average T1 FN.

$$|Y_i(\alpha)| = \frac{y_{Rl}(\alpha) + y_{Rr}(\alpha)}{2} - \frac{y_{Ll}(\alpha) + y_{Lr}(\alpha)}{2} \tag{27}$$

Then the ranking value rs_i of the supplier with respect to IT2-FSs $(\tilde{Y}_i)$ is calculated by Eq. (28) as proposed in [4]:

$$\begin{aligned} rs_i &= \frac{\int_0^1 Y_i^M(\alpha)|Y_i(\alpha)|d\alpha}{\int_0^1 |Y_i(\alpha)|d\alpha} \\ &= \frac{\int_0^1 \left(\frac{y_{Ll}(\alpha)+y_{Lr}(\alpha)+y_{Rl}(\alpha)+y_{Rr}(\alpha)}{4}\right)\left(\frac{y_{Rl}(\alpha)+y_{Rr}(\alpha)}{2} - \frac{y_{Ll}(\alpha)+y_{Lr}(\alpha)}{2}\right)d\alpha}{\int_0^1 \left(\frac{y_{Rl}(\alpha)+y_{Rr}(\alpha)}{2} - \frac{y_{Ll}(\alpha)+y_{Lr}(\alpha)}{2}\right)d\alpha} \end{aligned} \tag{28}$$

In this case higher ranking value (rs_i) indicates more suitable supplier based on trust criteria compared to others.

6 Numerical Example

This section prioritizes the suppliers concerning interval type-2 fuzzy sets, using a simplified example. Based on the description of Stage1 in the previous section, a set of prequalified suppliers $S_i = \{s_1, s_2, \ldots, s_5\}$ is candidated by TMA as well as three referee agents $\{a_1,\ a_2,\ a_3\}$. Weights considered for the referee agents, with respect to their frequency of interaction toward target supplier, are $\{\widetilde{wa}_1, \widetilde{wa}_2, \widetilde{wa}_3\}$ as shown in Table 4. Four trust criteria $\{c_1, c_2,\ c_3,\ c_4\}$ for example: credibility, confidence, benevolence and predictability (as discussed in Sect. 1) are considered

Table 3 All agents' judgments for trustworthiness of the suppliers based on linguistic terms

Criterion	Importance weight of the criterion	Agents	Suppliers (Sup)				
			Sup 1	Sup 2	Sup 3	Sup 4	Sup 5
Credibility (Cr)	H	Agent 1	MT	MT	ET	MT	MT
		Agent 2	WT	WT	ET	MT	WT
		Agent 3	WT	ST	MT	MT	MT
Confidence (Con)	MH	Agent 1	WT	ST	ET	MT	WT
		Agent 2	MT	ST	ST	ST	WT
		Agent 3	MT	WT	ET	ST	MT
Benevolence (B)	M	Agent 1	WT	MT	ET	MT	MT
		Agent 2	WT	MT	ST	WT	MT
		Agent 3	MT	ST	ET	MT	WT
Predictability (P)	ML	Agent 1	WT	MT	ET	MT	WT
		Agent 2	WT	MT	ET	MT	MT
		Agent 3	WT	MT	MT	WT	MT

Table 4 Linguistic weights of agents based on frequency of interaction

Criterion	Agents		
	(Agent 1)	(Agent 2)	(Agent 3)
Supplier 1	U	O	O
Supplier 2	O	A	U
Supplier 3	O	O	AA
Supplier 4	U	U	U
Supplier 5	S	U	U

to evaluate the candidate suppliers. Importance weights associated with for the defined criterion 1 to 4 are $\{\tilde{w}_1, \tilde{w}_2,\ \tilde{w}_3,\ \tilde{w}_4\}$ respectively.

In this method, considering Step 1 of the Stage 2, each three agent is asked to fill the electronic form to evaluate the five suppliers. The completed forms are collected by TMA and presented in Table 3. Moreover, importance weights of each trust criterion, which is assigned by TMA, are also expressed in this table.

Also the linguistic weights of agents, with respect to their frequency of interaction with suppliers, are collected by the electronic forms (Table 4).

Two phases have been defined for data aggregation. At the first Phase of aggregation, concerning the conversions of the linguistic data of agents' judgments and the frequency of interactions to IT2-FSs, the LWA operator is applied to provide an evaluation of each supplier for each of the defined trust criterion. Figure 6 demonstrates the evaluation of supplier 2 based on four trust criteria.

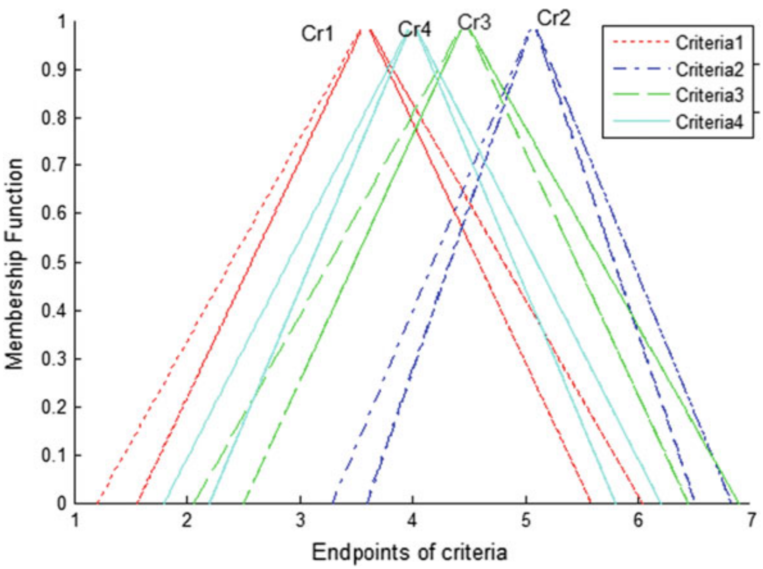

Fig. 6 Statistics endpoints of all criteria for supplier 2

Also at the second phase of this step (Step 2), another LWA operator computes the overall evaluation for each supplier concerning the importance weights of all criteria as IT2-FSs (Fig. 7). The result of the overall aggregation of each supplier is depicted in Fig. 8.

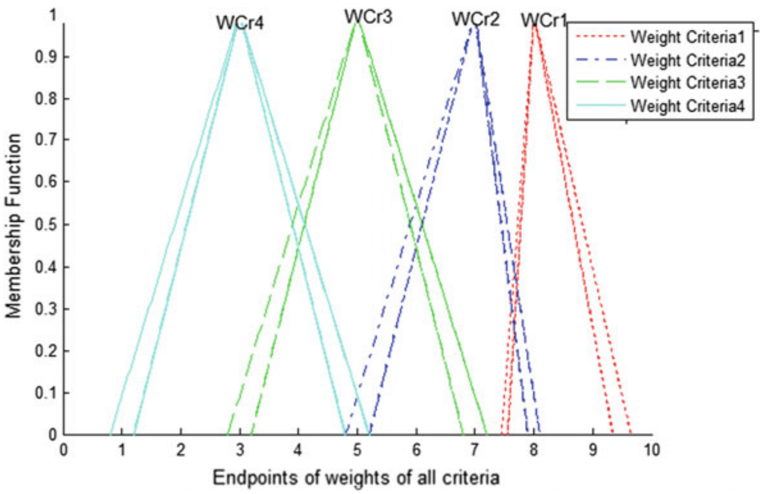

Fig. 7 Statistics endpoints of weights of all criteria for supplier 2

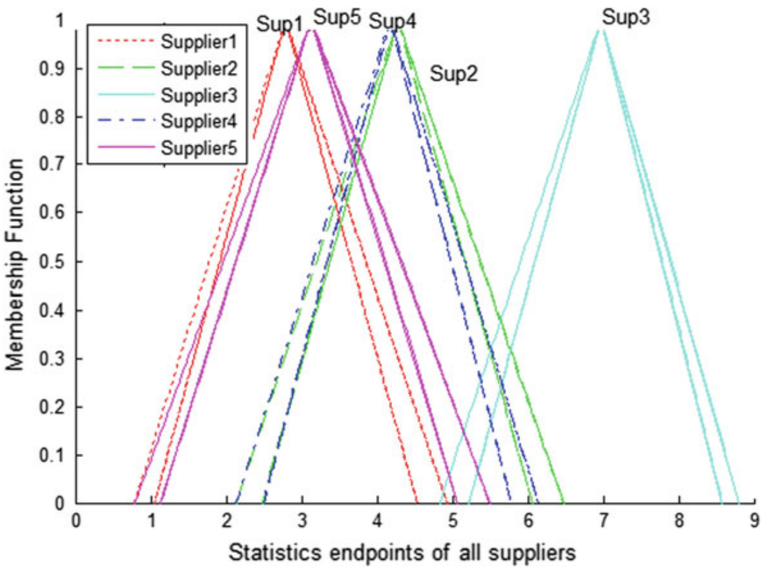

Fig. 8 Statistics endpoints of all suppliers

Table 5 The result of prioritizing suppliers based on trust criteria using type-2 fuzzy sets

Criterion	Scores	Ranks
Supplier 1	2.8103	5
Supplier 2	4.2791	2
Supplier 3	6.9003	1
Supplier 4	4.1517	3
Supplier 5	3.1316	4

Finally in the Step 3 of the Stage 2 suppliers are prioritized based on a method proposed by Asan and his colleagues in [4] using α-cuts Table 5 illustrates the result of prioritizing the suppliers based on trust criteria, using type-2 fuzzy sets. It can be seen from the Table that the most and the least trustable suppliers are supplier 3 and supplier 1 with the value of 6.9003 and 2.8103 respectively. Based on the descending order, supplier 2, supplier 4 and supplier 5 are ranked based on trustworthiness evaluation with the values of 4.2791, 4.1517 and 3.1316 respectively. Moreover, Fig. 8 confirms the result of the prioritization of suppliers in Table 5.

7 Conclusion and Future Work

E-procurement has been recognized as a strategic tool for improving the competitiveness of the firms and generating scale economies for the both sellers and buyers. In an agent based e-procurement system, intelligent agents exhibit good capability to function on behalf of the buyers to look for a most satisfying seller (or supplier). In this context, it is crucial to protect buyers from any possible unsatisfied conditions which are commonly due the existence of uncertain and vague characters in their interrelation. Presence of inter-organizational trust in the buyer-seller relationship was found not only reducing such uncertainty and vagueness characteristics, but also significantly reducing the complexity of the inter-firm relations which could in turn reduce supply risks in this context.

Based on this finding, this paper considered the utilization of inter-organizational trust concept in the agent based e-procurement environment, through proposing an effective supplier evaluation and ranking method. Considering an agent based e-procurement system consisting of specific agents for the required functions, the paper, further included a Trust Management Agent (ATM) which is responsible to establish inter-organizational trust in the buyer-supplier relationship. ATM is to evaluate some pre-qualified candidate suppliers and to rank them on some particular trust criteria. Characteristics inherent in the inter-organizational trust evaluation process, such as: uncertainty and vagueness in the data, use of collective opinions from experts or other agent in the community, were considered in the determination of the solution approach. With regard to the solution approach, Type-2 fuzzy sets proved to be most suitable in dealing trust evaluation process efficiently. In this regard, a new evaluation process based on hierarchical linguistic weighted averaging sets was proposed. The solution method was then illustrated through a simple example which clarifies the suitability as well as the simplicity of the proposed method for the category of the defined problem.

For the future work we will concentrate on changing points in the LWA, which can be estimated by heuristic methods instead of KM or EKM algorithms, also using real data that can help to validate and verify the problem.

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