# Developing a distributed linguistic decision making system

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**Abstract**

In this paper, a new approach to multi-criteria decision making is proposed based on linguistic information taken from a group of autonomous experts. This approach provides an opportunity to better analyze and find solutions for poorly structured problems with consideration of their multidimensionality and uncertainty of context. One of the key components of the proposed methodology is the hierarchy of abstractions proposed by John van Gigch, which presents the levels of alternative solutions and criteria for assessing them. By integrating this hierarchy, it is claimed that the problem situation can be comprehensively analyzed. Therefore, we call our approach multi-level multi-attribute linguistic decision making (ML–MA–LDM).

Our approach includes a methodology that is the particular sequence of steps and the mathematical model, as well as the method to automatically distribute weights of experts' assessments depending on their confidence level. Furthermore, this novel approach supports both qualitative and quantitative assessments that are strictly propagated through the complete decision making process across all hierarchical levels of abstraction. Finally, we demonstrate a prototype of a multi-agent expert system for solving poorly structured models with regard to their context uncertainty and multiple aspects. This prototype plays the role of simulation engine for competitive solutions and for verification purposes of the proposed methodology.

Capabilities of the developed approach and the prototype were demonstrated in a practical case of solving a complex conflict problem of strategic management, as well as rigorous analysis of the proposed approach strengths and weakness that defines the direction for further research.

**Key words:** linguistic decision making; multi-criteria choice; meta-decisions; multi-agent systems; fuzzy logic; poorly structured problems; decision support systems.

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## Introduction

In the modern world, there is a huge number of very complex and intricate problems, such as global warming, hunger, poverty, unemployment. These problem situations can be divided into two groups: structured and poorly structured situations [1]. The latter are characterized by uncertainty, environmental variability etc. A large subset of poorly structured problems can be characterized by a huge number of stakeholders (or experts), alternative solutions and criteria, which are used by decision makers. It is proposed that selection of one of these alternatives lets a decision maker solve a problem situation and satisfy a majority of stakeholders. Therefore, creation of new decision making models and the software design of expert systems for multi-criteria choice is a highly topical scientific and social problem.

Moreover, such problem situations frequently have multiple analysis aspects (or dimensions), like political (e.g. political tension), economical (e.g. benefit), ethical (e.g. conformity to morality) etc. In this way a case of multi-criteria decision making problem appears [2, 3].

The search for the solution of the problem that has an impact on multiple stakeholders requires mathematical models, algorithms and a methodology which allow one to analyze subjective experts' evaluations from different aspects. We may note that frequently different problems' aspects are hierarchically structured. In our approach, for multi-criteria choice we propose to use the framework of meta-decisions suggested by J. van Gigch [4]. We adopt his main idea of extracting eight abstraction levels which characterize the principal aspects of the problematic situation.

There are numerous attempts to elaborate new decision making approaches or adopt existing ones to real-life cases, like healthcare [5], performance evaluation of partnerships [6], fiber composites optimization [7], reverse logistics selection and evaluation [8], project resources scheduling [9], supplier selection [10], aircraft incident analysis [11]. Usually traditional approaches like TOPSIS, ELECTRE, VIKOR are used. The considerable drawback is that these methods rely mostly on quantitative evaluations, even given in a form of fuzzy sets [12]. On the other hand, estimations that are given by experts during problem discussion can be both quantitative and qualitative. Qualitative evaluations become more and more preferable in complex situations because compared to quantitative evaluations, qualitative ones have the serious advantage of their ability to express fuzzy information (e.g. hesitation). However, according to our rigorous analysis of the field, there is an emerging trend of combining traditional decision making approaches with methods of processing qualitative evaluations. The combination of TOPSIS methodology and 2-tuple model for analyzing qualitative assessments represents a bright example [13].

Reliable and flexible means for analysis of qualitative evaluations are provided within the scientific area of "linguistic decision making" [2, 3, 14–17] and "linguistic multi-attribute decision making" [2]. These and other methods of processing qualitative evaluations now are generally called "computing with words" [16–20]. The three most popular approaches used for calculation in linguistic terms [21] are:

✦ linguistic computational model based on membership functions;

✦ linguistic symbolic computational model based on ordinal scales;

✦ max-min operators, linguistic symbolic computational model based on convex combinations.

In many cases, information that comes from the experts is heterogeneous due to its multigranularity and there are approaches which provide methods to work with such information: the fusion approach for managing multigranular linguistic information [22], the linguistic hierarchy approach [23] and the method of extended linguistic hierarchies [14].

This paper presents results of the development of a new approach to multi-criteria linguistic decision making in the presence of multiple hierarchically ordered problem aspects. Our approach includes a methodology and prototype of a multi-agent expert system for solving poorly structured models with regards to their context uncertainty and multiple aspects. The main contribution in the development of methods of multi-criteria problem analysis is development of new scientific principles for integrating linguistic decision making and the meta-decision framework of J. van Gigch. This integration provides stakeholders with a structured method to analyze the problem from multiple aspects so that the solution found is more likely to be objective and optimal than one that is taken without considering its influence on all aspects of our life.

This paper has the following structure. In Section 1, we provide necessary background information that contains a description of basic elements of the proposed methodology. Then, in Section 2, we give a detailed description of the proposed approach which defines the process of decision making. In Section 3, we demonstrate the applicability of the proposed approach to the real case of complex conflict situation in the rice industry. Section 4 covers details on the design of a multi-agent system (MAS) that was built for demonstrating the work of the proposed methodology. Finally, the Conclusion displays the analysis of the proposed approach and potential directions of further research.

## 1. Background and related research

Modeling, analysis and solving poorly structured problems on the basis of linguistic estimation use several important mathematical structures.

**Definition 1.** The linguistic variable is characterized by the tuple:

$$(H, T(H), U, G, M),$$

where $H$ — the name of the variable;

$T(H)$ or just $T$ — a set of notions $H$, i.e. a set of names of linguistic values $H$, where each value is a variable which is denoted in general case as $X$ and gets values from the set of terms of the subject area $U$, which is denoted as $u$;

$G$ — syntax rule (often takes the form of grammar) for generation of values from $H$;

$M$ — semantic rule, which defines relation between $H$, $M(x)$ [24].

In order to use such linguistic evaluations, it is important to pick up linguistic descriptors for a set of concepts and also to define granularity of uncertainty. Usually the set of concepts is denoted as $S = \{s_0, ..., s_g\}$. The granularity degree of such a set depends on the context of the problem situation.

On the basis of the given definitions, Herrera et al. [25] proposed a classical model of analysis of linguistic evaluations using the structure which is called 2-tuple.

### 1.1. The classical model on the basis of 2-tuple structure

2-tuple includes the pair [25]:

- $s_i \in S = \{s_0, ..., s_g\}$ — a linguistic concept;
- $\alpha$ — a numeric value, or "symbolic translation", which shows the result of the member function, i.e. the nearest concept $s_i \in S = \{s_0, ..., s_g\}$, if $s_i$ is not the precise mapping of the given result.

Later multiple authors proposed a huge number of operators [3], which allows us to aggregate linguistic information.

### 1.2. The modernized 2-tuple model

The main problem of the classical model is the necessity to define the basic scale of evaluations and rules of translation of these evaluations to a single scale. The selection of the scale and translation rules in that scale becomes a separate and complex task. In their recent paper [26] researchers proposed a model which allows one to work with multiple scales without additional transformations. The significant difference between the classical model [25] and the modernized one [26] is the set of translation rules from the 2-tuple structure to the numeric representation and vice versa. It is important to emphasize that this model does not imply the fact that alternatives and criteria can vary across the time, since it is considered in a model with bipolar linguistic term sets [27]. The modernized 2-tuple model [26] is used in the approach proposed in this paper.

**Definition 2.** Translation function [26]. Let $S = \{s_0, \ldots, s_g\}$ be the set of linguistic concepts, $\mathcal{S}$ – the set of 2-tuple structures, $g = \tau + 1$ – its granularity, $\beta$ – a normalized result of the symbolic aggregation. Then the translation function can be defined as:

$$\delta_g : [0,1] \to \mathcal{S} \times [-0.5, 0.5)$$

$$\delta_g(\beta) = (s_i, \alpha) = \begin{cases} s_i, i = round(\beta, \tau) \\ \alpha = \beta\tau - i, \alpha \in [-0.5, 0.5) \end{cases}, \quad (1)$$

where *round* is a function that assigns $\beta$ to the nearest integer value $i \in \{0, 1, \ldots, g\}$ to $\beta$.

**Definition 3.** Reverse translation function [26]. Let $S = \{s_0, \ldots, s_g\}$ be the set of linguistic concepts, $\mathcal{S}$ – the set of 2-tuple structures, $g = \tau + 1$ – its granularity, $(s_i, \alpha)$ – a 2-tuple structure on $\mathcal{S}$, where $\alpha \in [-0.5, 0.5)$. Then the function $\delta_g^{-1}$ always exists, so that for the given 2-tuple structure it returns an equivalent numeric value $\alpha \in [0, 1)$:

$$\delta_g^{-1} : \mathcal{S} \times [-0.5, 0.5) \to [0,1]$$

$$\delta_g^{-1}(s_i, \alpha) = \frac{1+\alpha}{\tau} = \beta. \quad (2)$$

### 1.3. 2-tuple model for the comparative linguistic information

It is reasonable to suppose that experts are not able to estimate alternatives by a given criteria equally well. When experts are not able to give precise evaluation, they can make it comparative and even express it as a whole sentence that can have the following structure: "< > is better than | equal to | worse than < >". This idea exactly is the basis of the approach which is called HFLTS (hesitant fuzzy linguistic term sets) [28].

**Definition 4.** HFLTS [29]. Let $S = \{s_0, \ldots, s_g\}$ be a set of linguistic concepts. Then HFLTS or is an ordered finite set of consecutive linguistic concepts from $S$:

$$H_S = \{s_i, s_{i+1}, \ldots, s_j\}, S_k \in S, k \in \{1, \ldots, g\} \quad (3)$$

In order to avoid information loss when using HFLTS, another approach was proposed that is called hesitant 2-tuple set [26]. There are also operators for aggregation and comparison of hesitant 2-tuples sets entities: MTWA [26], MHTWA [26], etc.

**Definition 5.** Hesitant 2-tuple set [26]. Let $S = \{s_0, \ldots, s_g\}$ be a set of linguistic concepts, is a 2-tuple structure on $S$, $i = 1, 2, \ldots, n$. If $(b_i, \alpha_i) < (b_j, \alpha_j)$( for any $(i < j)$, $(b_1, \alpha_1)$, $(b_2, \alpha_2)$, ..., $(b_l, \alpha_l)$, which is denoted as $T_S$, is hesitant 2-tuple set for any $i < j$. Then HFLTS or $H_S$ is an ordered finite subset of consecutive linguistic concepts from $S$.

### 1.4. A meta-decision framework for analysis of problem situations from different abstraction levels

Due to the fact that during the process of finding solutions for complex problems it is important to analyze the situation from different aspects, we decided to use eight abstraction levels that were initially proposed by J. van Gigch in his meta-decision framework [26]. These levels are used as the basic set of aspects of any analyzed problem. More specifically, these levels are (in increasing order of abstraction level): managerial, economic, scientific, legal, political, epistemological, ethical, aesthetic.

**Definition 6.** Abstraction is a mental process in which representations of reality are defined on different levels of conceptualization.

**Definition 7.** An abstraction level (a logic level) – a perspective or a point of view from which stakeholders are trying to solve the problem. A chosen perspective reflects historical skills of an expert on the given abstraction level (the logic level).

## 2. Proposed multi-criteria decision making approach

In the previous chapter, basic linguistic decision making (LDM) approaches were described as well as eight levels of abstraction that are vital for analysis of complex problems. It is important to emphasize that existing approaches concentrate either on analysis of only quantitative assessments or only qualitative ones. Very few approaches focus on both types of estimations. At the same time, modern methodologies are likely to assume that there are a number of experts without capturing the area of their expertise as well as the fact that criteria also belong to different abstraction levels, like politics, economics etc. More importantly, existing methods for decision making are demonstrated on artificial cases with very few experts and alternative solutions. Finally, the demonstration is never made in the dynamics of a multi-agent system (MAS), although not only could it help to reveal drawbacks of existing approaches but also to analyze the behavior of agents and details of their interaction. For example, it is promising to also consider trust among experts. This brings us to the point to propose a new methodology which could incorporate most of the gaps described above.

In this section, we will describe the proposed approach for solving poorly structured problems that are capable of taking into consideration multiple hierarchically ordered aspects of the problem situation and process heterogeneous evaluations. We call our approach multi-level multi-attribute linguistic decision making (ML–MA–LDM).

### 2.1. Description of steps during ML–MA–LDM

The proposed approach consists of several consecutive steps starting from defining the estimation rules and finishing with the communication stage (*Figure 1*). It is important to note that these steps can be found individually in various papers describing the decision making process, for example in [30, 31], but never were fused in a consistent way. The proposed approach includes:

1. Setting up rules for providing estimations and distribution of criteria weights. In the proposed approach we make several assumptions:
   a. experts give honest evaluations;
   в. experts believe each other;

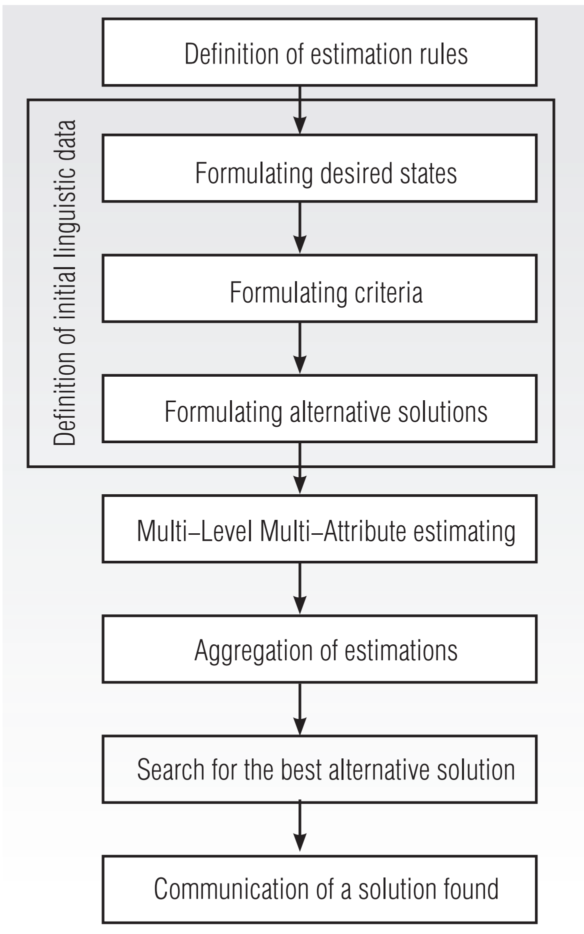


*Fig. 1.* The proposed methodology to solve poorly structured problems in conditions of uncertainty of context and fuzzy estimations

c. experts choose granularity of evaluations according to their experience and knowledge about a problem;

d. experts have the same understanding of evaluations;

2. Defining available linguistic sets, a context-free grammar and transformation function;

3. Multi-level definition of the desired state, criteria and alternatives.

a. analyzing the desired state on each level of abstraction;

b. formulating criteria for each level of abstraction;

c. formulating alternatives.

4. Giving multi-level and multi-criteria evaluations.

a. aggregating information;

b. searching for the best alternative;

c. communicating the solution found.

### 2.2. Aggregating information

After criteria and alternatives were defined, all experts start giving evaluations of each alternative for each available criterion.

Let $\mathbf{x} = \{x_1, x_2, ..., x_N\}$ is the list of alternatives, $\mathbf{c} = \{c_1, c_2, ..., c_M\}$ is the list of criteria, $\mathbf{e} = \{e_1, e_2, ..., e_T\}$ is the list of experts. We assume that each expert $e_k$ can evaluate alternatives using different linguistic scales $S_{g_k}$ with granularity $g_k$. In the case of comparative evaluations, we also have the grammar $G_H$ which can be also used for creation of linguistic evaluations. Moreover, the criteria are given for each level of abstraction in the meta-decision framework, i.e. let $\mathbf{l} = \{l_1, l_2, ..., l_Z\}$ be the list of the levels of abstraction.

The overall sequence of steps is described in *Figure 2.* These steps describe pre-processing and aggregation of evaluations collected from experts. Therefore, as a result, one evaluation for each given alternative is obtained and the best alternative can be found by sorting these evaluations according to rules of comparing hesitant 2-tuple fuzzy sets.

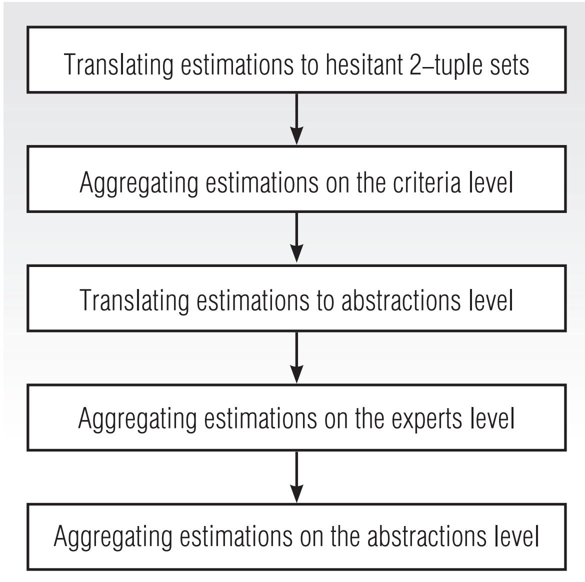


*Fig. 2.* A structure of the "Aggregating information" step of the proposed methodology

**Step 1. Formulating matrices of HFLTS evaluations.** Due to the fact that experts can give evaluations in a different form, it is important to preprocess them. More specifically, evaluations should be translated to HFLTS as this format is flexible enough to represent both precise and interval evaluations. As a result, for each expert we get a matrix of evaluations

$$\mathbf{R}_k = \left(\mathbf{T}^{ij}_{S_{gk}}\right)_{N \times M},$$

where $\mathbf{T}^{ij}_{S_{gk}}$ – an evaluation of the expert $e_k$ for the $i$-th alternative on the $j$-th criterion in the format of HFLTS on the scale $S_g$.

**Step 2. Aggregation of evaluations by criteria.** During this step, it is important to find an accumulated evaluation for combination of each alternative $i$, every level of abstraction $l$, and every expert $e_k$ by aggregating evaluations for every criterion corresponding to the given abstraction level. Then for each expert we get a following matrix:

$$\mathbf{T}_i^j = MHTWA^p_{s_{gk}}\left(\mathbf{T}^v_{s_{gk}}\right),\ \mathbf{c}_v \in \mathbf{l}_j, \tag{4}$$

where $i$ – the index of alternative;

$j$ – the index of the abstraction level;

**p** — the vector of criteria weights,

$$\mathbf{p} = (p_1, p_2, ..., p_M)^T, \ p_j \geq 0, \ \sum_{j=1}^{M} p_j = 1.$$

Here we propose to use the MHTMA operator because each criterion has its own defined weight. So, for each expert we get the following decisions matrix:

$$\mathbf{R}_k = \left(\mathbf{T}_{S_{gk}}^{ij}\right)_{N \times Z},$$

where $\mathbf{T}_{S_{gk}}^{ij}$ — the evaluation of the expert $e_k$ for $i$-th alternative for $j$-th level of abstraction in a form of HFLTS on the scale $S_{g_k}$.

**Step 3. Translation of evaluations to abstraction levels.** The next step should be aggregation of evaluations for each level of abstraction separately. From the previous step we get $T$ matrices with evaluations, each of size $N \times Z$. In order to make aggregation for each level of abstraction, we need to have $Z$ matrices with evaluations, each of the size $N \times T$, where $N$ is a number of alternatives and $T$ is a number of criteria. So, for each abstraction level we get the following decisions matrix:

$$\mathbf{R}_U = \left(\mathbf{T}_{S_{gk}}^{ij}\right)_{N \times T},$$

where $\mathbf{T}_{S_{gk}}^{ij}$ — the evaluation for $l_u$-th abstraction level from the $i$-th alternative for $j$-th expert in a form of HFLTS on the scale $S_{g_k}$.

**Step 4. Aggregation of evaluations by expert.** During this step, the total evaluation is calculated for each level of abstraction $l_u$, for each $i$-th alternative, and for each expert given. If **w** is the given vector of experts' weights,

$$\mathbf{w} = (w_1, w_2, \ldots, w_T)^T, \ w_j \geq 0, \ \sum_{j=1}^{T} w_j = 1,$$

then for each level of abstraction we get the following matrix:

$$\mathbf{T}_i^j = MHTWA_{S_{gk}}^{w}\left(\mathbf{T}_{S_{gk}}^{i_1}, \mathbf{T}_{S_{gk}}^{i_2}, \ ..., \ \mathbf{T}_{S_{gk}}^{i_t}\right), \tag{5}$$

where $i$ — the index of the alternative;

$j$ — the index of the abstraction level.

If the vector of weights is not given, the following formula should be used for their calculation:

$$m(i) = \begin{cases} w, \ i = 1 \\ \left(1 - \sum_{j=1}^{i-1} w\right) \times w, 1 \leq i \leq T \\ 1 - \sum_{j=1}^{i-1} w, i = x, \end{cases} \tag{6}$$

where $w \in [0, 1)$ — the proportion of the first expert's evaluation in the weights sum.

Therefore, we get the following decisions matrix

$$\mathbf{R}_k = \left(\mathbf{T}_{S_{gk}}^{ij}\right)_{N \times Z},$$

where $\mathbf{T}_{S_{gk}}^{ij}$ is aggregated evaluation for $i$-th alternative and for $j$-th level of abstraction in a form of HFLTS on the scale $S_{g_k}$.

**Step 5. Aggregation of evaluation by levels of abstraction.** During this step the total evaluation for each $i$-th alternative and for each level of abstraction is found:

$$\mathbf{T}_i = MHTWA_{S_{gk}}^{q}\left(\mathbf{T}_{S_{gk}}^{i_1}, \mathbf{T}_{S_{gk}}^{i_2}, \ldots, \mathbf{T}_{S_{gk}}^{i_Z}\right), \tag{7}$$

where $i$ – the index of alternative;

**q** — the vector of weights of levels of abstraction,

$$\mathbf{q} = (q_1, q_2, \ldots, q_Z)^T, \ q_j \geq 0, \ \sum_{j=1}^{Z} q_j = 1.$$

So, we get the following vector of evaluations

$$\mathbf{r} = \left(\mathbf{T}_{S_{gk}}^{i}\right)_N,$$

where $\mathbf{T}_{S_{gk}}^{i}$ is the aggregated evaluation for $i$-th alternative in a form of HFLTS on the scale $S_{g_k}$.

As a result, we get assessments that draw insights on how each alternative is measured on each level of abstraction and a decision maker can use this information to better understand the scope of alternatives and their influence on each aspect of the problem situation. It can also be possible to customize a methodology at this point; for example it is possible to select only a subset of levels of abstraction which interest the decision maker to make the final decision.

## 3. Demonstration in one case

For demonstrating our approach, we use a complex problem situation with rice production in the state Chhattisgarh (India) [32]. Rice is one of the main products in India in terms of consumption. This state is the biggest provider of paddies. The first step is to give a general description of the current situation.

### 3.1. Description of the current state

In the Chhattisgarh state, the rice industry obeys the Government. There is a huge number of farmers, the majority of whom are middle- and small-sized households. Middle- and small-sized households are very dependent on weather conditions and Government politics with respect to buying the rice left over at the end of the season for distribution among poor people. That is why they have to take loans that often bankrupt households. This in turn makes the number of working population in rice industry decline. After the rice is ready, farmers sell rice to millers. Millers do not rush to buy rice since the Government buys rice at very low prices at the end of the season. Millers clean the paddy up, produce rice and sell it via sales agents. The miller business has minimal profitability, and that is why the market is decreasing and only big players are left there. These big players define the rice price to make it as low as possible. Rice cannot be exported due to the use of several fertilizers that damage the atmosphere. The overall political atmosphere is unfavorable.

### 3.2. Description of a desired state

Households receive subsidies from the Government on their business. Rice that is left unbought at the end of the season is bought at the market price by either the Government or millers. The Government prevents the creation of miller monopolies that tend to reduce the market price. Moreover, there is an active export policy that let millers increase their profits. Moreover, innovative technologies make it possible to avoid use of polluting fertilizers, thus opening a door for export. Millers have a joint logistics union that lets them control the supply chain. The poor get rice from the Government and this, in turn, motivates them to become farmers. Low unemployment decreases chaos on the streets.

Due to the multidimensionality of the problematic situation, there are a large number of alternative solutions. Alternative solutions define the set of actions that can be later evaluated by criteria defined earlier. In order to formulate them there is a specific technique:

1. Definition of the desired state of industry for each level of abstraction;
2. Definition of criteria specific for each level;
3. Definition of concrete alternative solutions driven by the desired state on each level.

In the given case there are the following experts: the representative of the Department of Foreign and Domestic Policies (DFD), the representative of the Department of social politics (DSP), the representative of farmers (F), the owner of a mill (M), a sales agent (SA), a rice transporter (RT), an ecologist (E).

We consider the experts having experience on the following levels of abstraction (*Table 1*): managerial (MLA), economic (ELA), scientific (SLA), legal (LLA), political (PLA), epistemological (EPLA), ethical (ETLA), aesthetic (ALA).

### 3.3. Aggregating information

According to our approach, the following actions should be taken for the reasonable choice of the problem solution.

**Step 1. Formulating matrices of evaluations.** As HFLTS allows to use multiple linguistic scales and there is no need to translate evaluations to a single scale, the only needed transformation is to translate all evaluations to the form of HFLTS. Let is suppose, that

*Table 1.*

**Experience of experts participating in the evaluation**

| | MLA | ELA | SLA | LLA | PLA | EPLA | ETLA | ALA |
|---|---|---|---|---|---|---|---|---|
| **DFD** | | x | | x | x | | x | x |
| **DSP** | | | | | x | | x | x |
| **F** | x | | | | | | x | x |
| **M** | x | | | | | | x | x |
| **SA** | | x | | | | | x | x |
| **RT** | | | | | | | x | x |
| **E** | | | x | | | x | x | x |

an expert gave the evaluation ("good", "vary good"). The evaluation can be translated to the instance of Hesitant 2-tuple Set: $\{(s_6^7,0),(s_7^7)\}$, where $S^7=\{s_1^7$ – very bad, $s_2^7$ – bad, $s_3^7$– slightly fair, $s_4^7$ – fair, $s_5^7$ – slightly good, $s_6^7$ –good, $s_7^7$ – very good$\}$.

After that, all evaluations are in a united form and it is possible to start aggregating them. It is mandatory to define weights for criteria and the levels of abstraction. In this case, because there are no presuppositions on importance neither for criteria nor for alternatives, weights are equal among both the alternatives and the criteria.

**Step 2. Aggregating evaluations for criteria.** The very first step is to find the aggregated estimation for every expert, every alternative and every level of abstraction. Aggregation happens across criteria which belong to the same level of abstraction. In our example we assume, that the expert of Department of Foreign and Domestic Politics (DFD) gave following estimations for the alternative A.ETLA.1 (*Table 2*) on a political level of abstraction (PLA).

For example, we consider the weights of the criteria to be equal: **w** = (0.33, 0.33, 0.33). For calculating an aggregated evaluation, the MHTWA operator is used:

$$\text{aggreagated\_value} =$$
$$MHTWA_{S^{g7}}^{w}\left(\{(s_3^9)\},\{(s_6^9)\},\{(s_4^9)\}\right)=\{(s_4^7,0.33)\}$$

**Step 3. Translation to the levels of abstraction.** This is the technical transformation of given matrices and it is described in Step 3 of the proposed methodology.

**Step 4. Aggregation of evaluations by experts.** During this step, the accumulated evaluation for each alternative, each level of abstraction and each expert is calculated. In this case, experts' weights are distributed in a way that the expert who gives the most precise evaluation has the bigger weight.

*Table 2.*

**DFD evaluations for the alternative A.ETLA.1**

| | Criteria on PLA | | |
|---|---|---|---|
| | C.PLA.1 | C.PLA.2 | C.PLA.3 |
| **A.ETLA.1** | $\{(s_3^9)\}$ | $\{(s_6^9)\}$ | $\{(s_4^9)\}$ |

**Step 5. Aggregation of evaluations by levels of abstraction.** During this step, evaluations are accumulated by each level of abstraction to get the final evaluation for each alternative. *Table 3* shows the results of aggregation for the described case.

*Table 3.*

**The ordered list of alternatives and accumulated evaluations**

| | Alternative name | Estimation |
|---|---|---|
| A.ELA.7 | Increase crop via irrigation system implementation | $\{(s_6^7)\}$ |
| A.SLA.3 | Decrease usage of fertilizers | $\{(s_4^7)\}$ |
| A.ELA.2 | Increase taxes for farmers | $\{(s_4^7)\}$ |
| A.ELA.1 | Increase subsidies for farmers | $\{(s_4^7)\}$ |

**Step 6. Seeking the best alternative.** During this step, the best alternative is chosen. For that, the list of calculated evaluations should be ordered according to the rules of comparing instances of Hesitant 2-tuple Set. In the described case, the best alternative is the one with id A.ELA.7 "Increase crop via irrigation system implementation".

**Step 7. Communication of the solution found.** All the participants of the decision making problem are notified about the solution found. It is important to draw attention to the fact that to find the solution, multiple alternative solutions were assessed against multiple criteria and, which is more important, each alternative solution was analyzed separately on different level of abstraction representing a vital aspect of the problem situation.

## 4. Implementation details

### 4.1. MAS design and implementation

For validation of the proposed LDM multi-level model and our approach in general, an expert system was developed and tested for a relevant use case. The system was originally designed as a distributed multi-agent system (MAS) with a belief-desire-intention (BDI) architecture [33]. It is a promising set of principles for designing an MAS and has practical use in various projects, like supply chain modeling [34], transport logistics [35] and timetabling [36]. During design and implementation, we exploited advanced features of the MAS platform JASON[1] and its extension JaCaMo framework[2]. JASON provides a powerful AgentSpeak interpreter and basic communication primitives, while JaCaMo offers such environment artifacts as tasks, bids, etc. New numerical and linguistic algorithms related to our proposed LDM multi-level models were implemented in Java and then were encapsulated to the JASON coordinator agent using the Java-AgentSpeak proxy. The architecture of the MAS is presented in *Figure 3*. A detailed explanation of the level of implementation is given in *Figure 4*.

There are always two types of agents available in the system: a coordinator and an expert. While it is enough to have a single coordinator to rule the whole decision process, there are multiple expert entities that make evaluations based on the problem context. A number of experts in simulation represents one-to-one mapping to experts in the real life.

The coordinator is an agent that has two main goals: starting the decision making process and accumulation and calculation of the best alternative solution based on the evaluations provided. At the same time, coordinator activates the main goal of the expert by publishing the task in the Common Environment Artifact: giving evaluations for the given problem on the basis of alternatives and criteria provided

[1] http://jason.sourceforge.net/wp/
[1] http://jacamo.sourceforge.net/

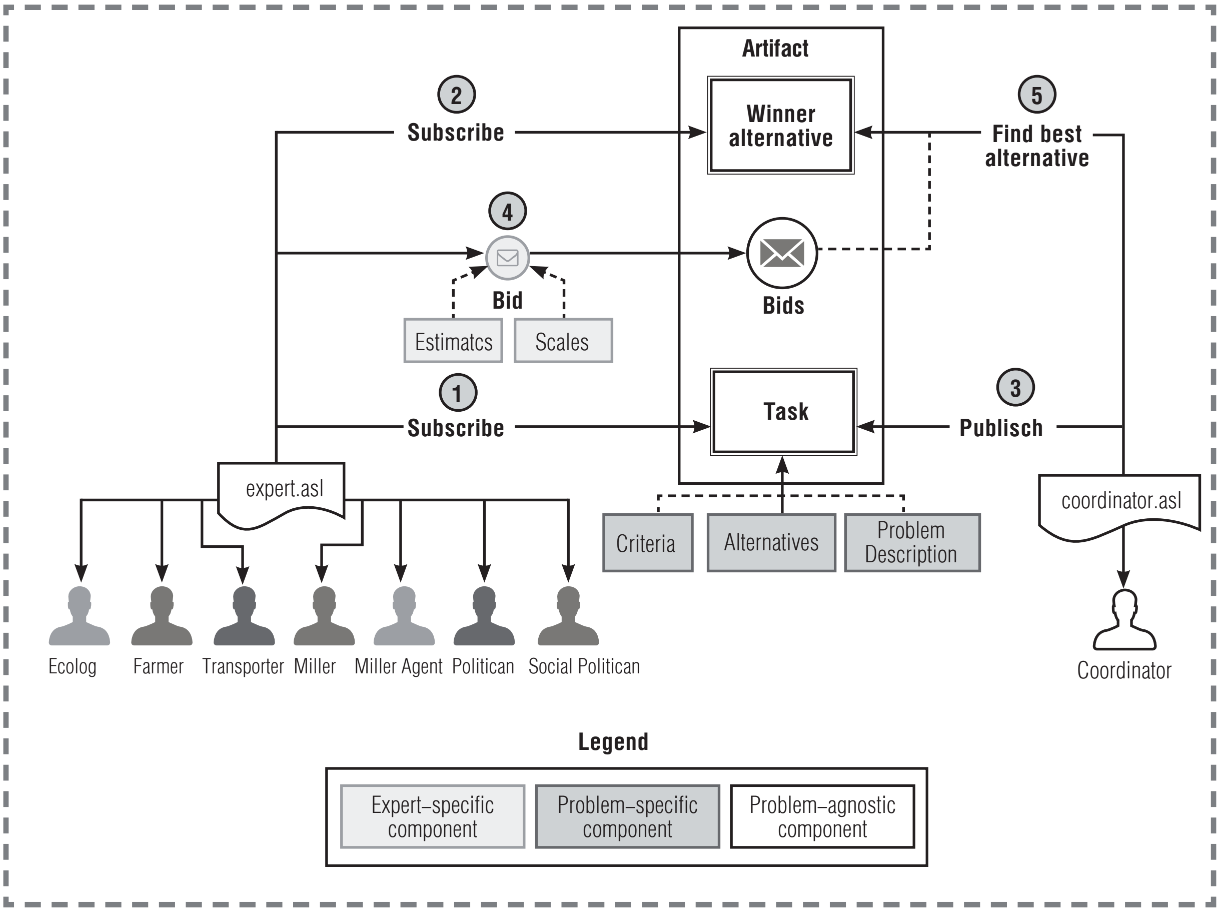


*Fig. 3.* Multi–agent architecture for multi–attribute LDM

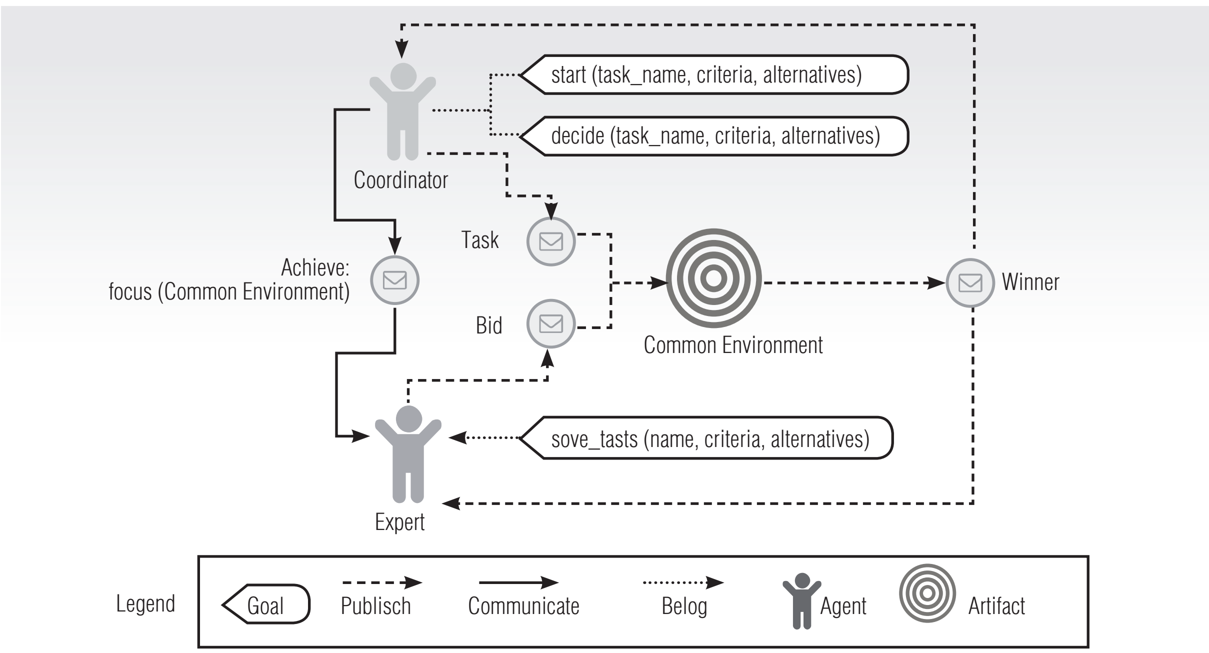


*Fig. 4.* Jason implementation of MAS

by coordinator. Once all the needed evaluations are made, the coordinator tries to achieve his second goal – finding out what alternative is best according to our LDM multi-level model. As for an expert agent, its only goal is to give evaluations by publishing in the Common Environment artifact. Both coordinator and expert agents are subscribed to the entity of the winner in the Common Environment artifact and get notified when it appears after all calculations are done.

### 4.2. Description of decision making in the MAS expert system

The algorithm of the decision making in our multi-agent expert system follows the formal methodology of our approach. During an initialization phase, the coordinator provides experts with information on the common environment (CE) where they will work together. Experts also get prepared by subscribing to the task to be notified when it is published. When experts get notification about the new task, they start providing their evaluations of the given problem situation. Moreover, experts subscribe to the winner alternative (WA) to be aware of the best alternative. It is chosen based on the evaluations of all agents. When all preparations are done and experts are waiting for the task to appear, the coordinator publishes the task. All tasks contains the problem description, alternatives and criteria – all necessary information for experts to analyze the problem and evaluate every alternative by given criteria.

After experts evaluate every alternative solution of the given problem, they publish bids that contain these evaluations alongside the description of scales that were used during the decision process. These bids are handled and stored in the common environment. The coordinator either waits for all experts to provide evaluations or waits for a certain, explicitly defined period and then closes the admission. As soon as the admission is closed, the coordinator initiates accumulation of all the evaluations that is performed according to the formal algorithm proposed in this paper. When the calculations are finished, the winning alternative (WA) is published and every expert is notified about it. This appears to be the end of the simulation, however the system can be still active and waiting for a new request.

The implementation of algorithms of aggregation of heterogeneous estimations was aligned with corporate enterprise standards of software development. Furthermore, the authors elaborated the input/output format for describing the important parameters (criteria, alternatives, levels, experts). The software implementation of the prototypes is available publicly on GitHub[3] and contains the complete system described in *Figure 3*. It can be further extended for a more general case.

## Conclusion

In the framework of current research, we have made a broad investigation of the field and aligned research with design science [37] methodology. Rigorous analysis of existing approaches to linguistic multi-criteria decision making revealed their disunity and inferiority if applied to problems with heterogeneous information and uncertainty of context. On the one hand, there are classical decision making approaches that instruct each expert to find the best alternative, however quantitative estimations are not taken into consideration. On the other hand, methods of LDM are supposed to tackle heterogeneous estimations, though they are hardly applied to real life problems due to lack of unified methodology for searching for the best alternative. More importantly, poorly structured problems are characterized by a huge number of stakeholders.

[3] https://github.com/demid5111/lingvo-dss-bdi

In our approach, we propose to extend traditional LDM methods with the meta-decision framework on the basis of the abstraction hierarchy by J. van Gigch that suggests analyzing the problem from eight different perspectives.

The proposed approach has a set of improvements compared to existing approaches in LDM. As was already stated, the considerable drawback of existing approaches is that they concentrate either on analysis of only quantitative assessments, e.g. TOPSIS, ELECTRE, VIKOR etc., or only qualitative ones [25, 26, 29]. Very few approaches focus on both types of evaluations [13] or fuzzy sets [12]. Our proposed approach relies on both types of assessments originally from the very beginning. At the same time, modern methodologies do not respect the fact that experts differ in their knowledge in different areas, like politics, economics etc. Moreover, our approach offers a reliable mechanism for selecting weights for experts' evaluations depending on how precise their evaluations are. We also proposed a format for describing poorly structured problems. Existing approaches are demonstrated on artificial cases that are far from reality. The proposed approach was demonstrated on a real life case that has an impact on huge number of stakeholders, while existing methods are demonstrated on artificial cases with very few experts and alternative solutions. In addition to that, the implementation of the proposed approach was performed as well as implementation of algorithms for aggregating heterogeneous information where there is no existing open source implementation. Finally, the implementation is made in dynamics of a multi-agent system (MAS). This allows a decision maker to analyze behavior of agents and details of their interaction. For example, it is promising to also consider trust among experts. This brings us to the point to propose a new approach which could bridge most of the gaps described above. We could not find any similar solution among existing approaches and consider it to be an important innovation in the field of decision making, because it can be used in the context of various poorly structured tasks with multiple stakeholders and alternatives – all of which is especially topical in the modern world. Our expert system demonstrated the desired outcome for the case of a complex problem situation with rice production.

An important step of any research is the definition of the further direction of study. The authors suggest the following improvement of their ideas to get rid of the drawbacks of the proposed approach:

1. Consider the trust factor among experts;

2. Consider ontologies of difference among experts. These differences are expressed in various meanings of the same linguistic concepts for multiple experts. In the proposed methodology, authors make an assumption that ontology is the same for all experts. ■

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