Decision-Making Based on Fuzzy Estimation of Quality Level for Cargo Delivery

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Abstract This chapter presents the proposed approach and algorithms for designing hierarhical decision support systems (DSS) based on fuzzy logic with flexible rule base. Special case of changing the structure of the input data's vector for DSS in transport logistics is considered by authors. The main idea is a correction of fuzzy rule base of fuzzy DSS when different decision-makers can decrease dimension of the vector of DSS's input coordinates according to their own priorities and criteria. Simulation results confirm the effectiveness and appropriateness of editing fuzzy knowledge bases rules for DSS which solve the problems of transport logistics.

1 Introduction

Decision support systems (DSSs) are widely used in economics, enterprise organization, medicine, agriculture, technical diagnostics and others [1–3] for improving significantly the quality of decision-maker's (DM) choice of optimal decision from a set of alternative variants in difficult or extreme situations.

One of the important areas of DSS appliance is transport logistics [2, 4, 5]. Formation and organization of work of cargo delivering chains is connected with intense and operational information exchange between participants of transport process, fast reaction and high demands to the quality of cargo delivering [6]. The process of making effective decisions is to choose the best alternative variant

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among the existing ones on a particular system of criteria and preferences, and set of evaluative dimensions (input system coordinates).

Customers of transport services often are not satisfied with the quality of services, as there take place violations of delivery terms, spoiling and loosing cargo, problems with flow of documents, considering a difficult cooperation process of big amount of forwards, carriers and logistic companies, complexity of building rational routes of cargo transportation, absence of universal program systems, that accompany processes of cargo transportation in real time [5, 7].

Particularly acute are problems of designing fuzzy DSS with flexible structure, i.e. systems, the amount of input parameters of which can change during the decision-making process by DM [6].

2 General Problem Statement

Last decade in control systems and DSS that functioning in conditions of uncertainty are widely used intellectual technologies, in particular, based on fuzzy logic [8, 9]. For different DM the part of input coordinates can be not important according to their own priorities [6, 9]. For example, for DSS which can support the process of sensor choosing from a set of alternative sensors the 5 input coordinates are mostly important: power consumption, price, embedded functionality, size and noise $(N = 5)$. But in some cases a specific DM may be interested in and he can only ask, for example, just 3 input signals $(N_r = 3)$, and other 2 input signals $(N_{NI} = 2)$ are not interested (not important) for DM. That is the dimension of the vector of the input coordinates reduces from 5 to 3. In this case the correction of the fuzzy rule bases is needed in the interactive DSS's modes.

This research deals with automatic correction of fuzzy DSS's rules base for variable structure of input coordinates vector and modeling of actual situations to approve working ability and effectiveness of proposed method of antecedents and consequents correction. Main focus is concentrated on the modern DSS that will provide choice of optimal decisions when solving problems of transport logistics with big amount of input parameters, multicriterion structure, the lack in many cases of sufficiently complete prior information [2, 4, 5].

3 The Analysis of Related Publications

Improvement of cargo delivering quality by different companies-carriers is done by means of collecting the consolidated cargo from several shippers, developing optimal routes of cargo transferring, and also connecting more efficient type of transport on certain stage of transportation [1, 2]. Irrational transportations lead to increase of logistic and first of all transport expenses, and also additional workload of transport routs.

Today there exist a lot of publications on the research of DSS based on the fuzzy logic [6, 9, 10], which examine methods of the theory of fuzzy sets for modeling, analysis and synthesis of intelligent systems. Researches, which are conducted in different countries, have proved that for many subjects to management, parameters of which change in the process of operation, it is appropriate to use fuzzy computerized automatic control systems [3, 9, 11]. Learning procedure of the fuzzy Mamdani-type model presents a nonlinear optimization problem, within a framework of which the main attention is paid to achieving the maximum accuracy of learning of the fuzzy DSS [11].

Own priorities of DM essentially influence on formation in each actual situation of the input coordinates vector's dimension. Herein some of input coordinates for one DM can be important, and for another DM—non important. Among famous approaches to correction in such cases rules bases of fuzzy DSS is usage of weighting coefficients for fuzzy rules. A change of weighting coefficients vector for corresponding rules of fuzzy knowledge bases allows reducing the influence of input parameters, which by the choice of DM in some situations may not participate in the process of decision-making, on the result of system work. However, at the same time there appears a need to re-configure corresponding coefficients at each change of the input data structure [9].

The work [12] considers the problem of developing effective methods and algorithms for optimization of fuzzy rules bases of Sugeno-type fuzzy controllers that can be applied to control of dynamic objects, including objects with non-stationary parameters. Proposed in [12] approach based on calculating the coefficient of influence of each of the rules on the formation of control signals for different types of input signals provides optimization of a linguistic rule bases by using exclusion mechanism for rules with negligible influence. The publications [9, 13–16] also deals with solving problem of fuzzy rule base reduction which based on the different approach.

The main difficulty in the process of setting multidimensional fuzzy models is the large number of parameters of such systems. Moreover, their number rapidly increases with enlargement of the number of inputs and fuzzy linguistic terms needed to assess the relative values. One of the ways of its effective solution is to move from the regular division of input space to irregular [9], which consists of rectangular segments. Another way is to avoid a grid partitioning of input space and to use a non-grid partitioning, in particular, rectangular (k-d tree partition) and quadratic partition (quad tree partition). The purpose of a non-grid partitioning is to reduce the number of fuzzy segments [9].

Based on publications [9, 17] devoted to the study of simplification of fuzzy models proved the feasibility and effectiveness of the method of local models.

Considered methods for correcting fuzzy rule bases can't be directly applied for optimizing fuzzy hierarchical DSS with flexible structure of input vector that caused the feasibility researches authors in this direction.

4 Fuzzy DSS's Multi-level Structure

Let's consider a fuzzy system which modeling dependence:

$$y = F(x_1, x_2, \ldots, x_N), \tag{1}$$

where x_i, $i = 1\ldots N$—input linguistic variables; y—output variable.

Fuzzy systems by hierarchic properties are divided into one-level and multi-level. To simulate multidimensional fuzzy dependences (1) should be used hierarchical approach to building DSS based on fuzzy logical derivation [7]. In such systems, the output of one subsystem is given to the input of another with a higher level of hierarchy. The experience of creating such systems shows that their efficiency is achieved in that case when the number of separate subsystem inputs does not exceed five ($N \leq 5$). Therefore, with a large number of input variables is needed their hierarchical structuring by the general (common in the frames of subsystem) properties [8].

Let's consider, for example, fuzzy single-level system, which models the dependence (1), while the number of input parameters is $N = 9$. Relations between input variables and output variable are described by fuzzy rules of a knowledge base F. As a result of hierarchic structuring fuzzy one-level system can be represented as, for example, three-level hierarchic system. Each of subsystems f_1, f_2, f_3, f_4, f_5 of this system represents corresponding fuzzy dependences: $y_1 = f_1(x_1, x_2, x_3, x_4)$, $y_2 = f_2(y_1, y_3)$, $y_3 = f_3(x_5, x_6)$, $y_4 = f_4(x_7, x_8, x_9)$ and $y = f_5(y_2, y_4)$.

The results of the research [9, 12] of fuzzy hierarchical organized systems proved that in the process of developing fuzzy DSS with hierarchical structuring of the input parameters, the number of rules is greatly reduced, and consequently takes place a reduction of fuzzy knowledge base (rules).

Method of actual correction of fuzzy DSS rule bases (RB) by levels of hierarchy can simplify RB, reducing the number of rules with decreasing the dimension of the input signal vector X. This is achieved by reducing the number of rules at appropriate levels when excluding the least important for the DM input parameters, on the basis of which subsystems of each hierarchical level are pre-formed. Lack of interest of DM, for example, in the input parameters $\{x_1, x_2, x_3, x_4\}$ of the subsystem f_1 will significantly reduce the number of rules of the system, because in the future they will not take part in the process of decision-making $y_1 = f_1(x_1, x_2, x_3, x_4) = NI$.

5 Rule Base of Fuzzy DSS for Estimation of Cargo Delivery Quality

Analysis of review of the transport logistics tasks and a method of evaluation of the quality of cargo delivery using fuzzy DSS are presented in the article [7]. For fuzzy DSS of such type (with 19 input coordinates) particularly actual is a problem

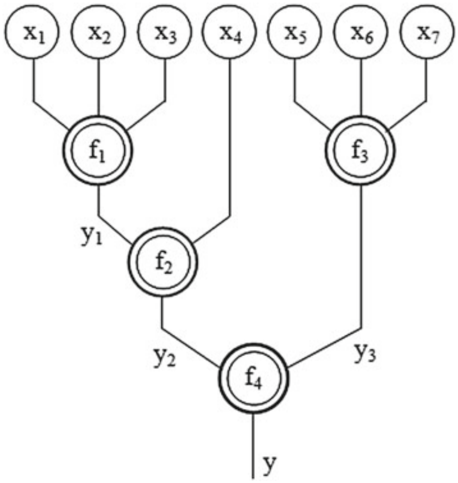

Fig. 1 Hierarchical structure of fuzzy DSS with 7 inputs

of automatic adjustment of fuzzy RB in situations when a specific DM is interested in real N_r input coordinates, herewith $N_r < N$. Hereinafter we will in more detail way observe an proposed approach that allows with the help of DSS of aforementioned class providing a creation of optimal decisions (according to the content of previously selected criteria) by correction of the RB at a prior uncertainty of input information, that is $N_r < N$.

For illustration of the proposed approach as an example we will observe fuzzy DSS that has one output y and 7 input parameters x_i, $i = 1, \ldots, 7$; $N = 7$. Among them are x_1—tracking cargo in process of cargo transferring, x_2—level of cargo security protection, x_3—insurance of cargo, x_4—monitoring of flow of traffic, x_5—price of transport services, x_6—assortment of cargo for delivery, x_7—alignment of freight participants actions, y—evaluation of the quality of transport services.

As a result of structuring of the input data as a part of the three-level DSS 4 fuzzy subsystems were formed that implement the following dependences [6, 7]:

$$y_1 = f_1(x_1, x_2, x_3);\ y_3 = f_3(x_5, x_6, x_7);$$
$$y_2 = f_2(y_1, x_4);\ y = f_4(y_2, y_3).$$

The structure of the hierarchical fuzzy DSS, that consists of 7 input linguistic variables $\{x_1, x_2, \ldots, x_7\}$, 4 RB with fuzzy rules $\{f_1, f_2, f_3, f_4\}$ and one output linguistic variable y, is presented in Fig. 1.

In the process of structuring the input variables are combined by common characteristics that are principal (important) for a particular fuzzy subsystem. Such hierarchical approach allows reducing the amount of fuzzy rules of the RB and thus increasing the sensitivity of the system to the operations of the input variables (factors) [3, 18, 19].

Table 1 Rules for the first subsystem $y_1 = f_1(x_1, x_2, x_3)$

No of rule	1	2	3	4	5	6	7	8	9
x_1	L								
x_2	L			M			H		
x_3	L	M	H	L	M	H	L	M	H
y_1	L	L	LM	L	LM	M	LM	M	MH
No of rule	10	11	12	13	14	15	16	17	18
x_1	M								
x_2	L			M			H		
x_3	L	M	H	L	M	H	L	M	H
y_1	L	LM	M	LM	M	MH	M	MH	H
No of rule	19	20	21	22	23	24	25	26	27
x_1	H								
x_2	L			M			H		
x_3	L	M	H	L	M	H	L	M	H
y_1	LM	M	MH	M	MH	H	MH	H	H

While describing the linguistic variables for DSS that was presented in Fig. 1, a diapason of variation values, the number of terms and the form of the MF (triangular) were defined. Corresponding the structure of DSS (Fig. 1) the authors has created three fuzzy RB with fuzzy rules of production of "IF—THEN" type, the first one of which $y_1 = f_1(x_1, x_2, x_3)$ will be further observed in more detail.

A set of rules from the RB of the first subsystem $y_1 = f_1(x_1, x_2, x_3)$ of fuzzy DSS is presented in Table 1. Herewith for evaluation of all input variables $\{x_1, x_2, \ldots, x_7\}$ in three linguistic terms are used (L—"low", M—"medium", H—"high"), and for evaluation of output variable—5 corresponding terms (L—"low", LM—"lower than mean", M—"medium", MH—"higher than mean", H—"high").

The project of hierarchically organized DSS for the evaluation of the quality of cargo delivery, whose structure is presented in Fig. 1, can be synthesized, for example, in computing environment MatLab or in a computing environment FuzzyTECH [8, 20, 21].

6 Preliminary Fuzzy Rules Reducing

The purpose of non-grid partitioning is to reduce the number of fuzzy segments. Partition of the input space will be denser in areas where the simulated system for surface display changes more rapidly and less dense in areas with a smooth surface. Within each segment is only one rule, so here it is advisable to use the Takagi-Sugeno model. In these models, the output of each rule is not a fuzzy set. It is the function (usually linear). An example of such a rule may be an expression of the next form [22]:

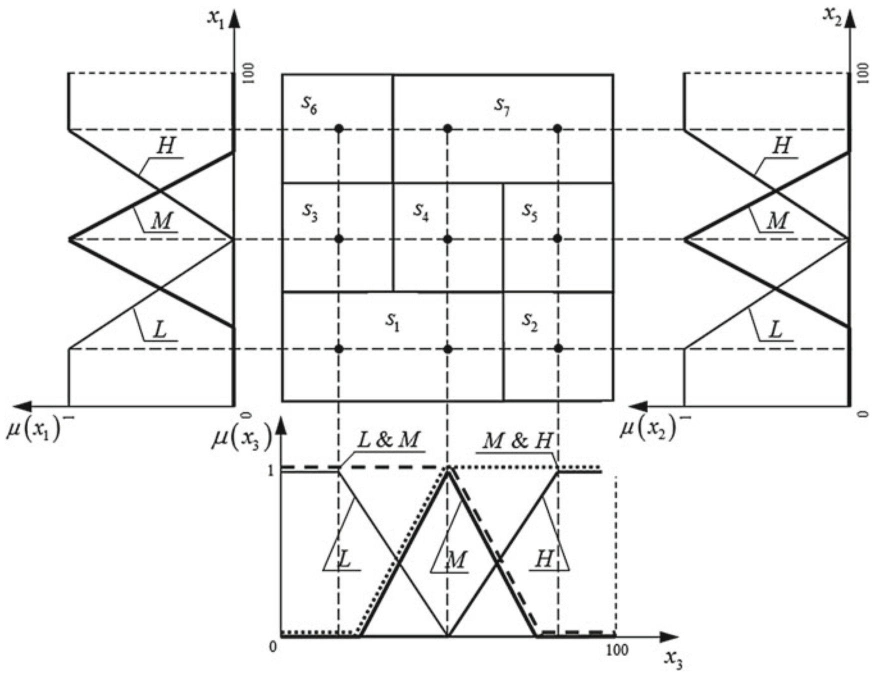

Fig. 2 The non-grid partitioning the input space to the first fuzzy subsystem $y_1 = f_1(x_1, x_2, x_3)$

$$\text{IF } x_1 = A_{11} \text{ AND } x_2 = A_{21} \quad \text{THEN y} = a_{11}x_1 + a_{21}x_2 + a_{01},$$

where A_{11}, A_{12} C {L, M, H}; a_{11}, a_{21}, a_{01}-consequent coefficients

Nevertheless can be used the model of Mamdani-type [23].

In research [9] is considered an example of non-grid partitioning of the input space into three segments using Gaussian membership functions of fuzzy sets.

Let's consider the approach of non-grid partitioning the input space to the first fuzzy subsystem $y_1 = f_1(x_1, x_2, x_3)$. Graphical representation of non-grid partitioning in seven segments $s_1, \ldots, s_7$ is presented in Fig. 2.

Each segment can match the one rule that specifies the portion of the surface model associated with this sector. Thus, instead of 27 rules, the model contains 25 rules (two of which are modified). Some of them are presented below.

$$\text{R1:IF } x_1 = L \quad \text{AND } x_2 = L \quad \text{AND } x_3 = L\&M \quad \text{THEN } \text{y}_1 = L(s_1),$$
$$\text{R3:IF } x_1 = L \quad \text{AND } x_2 = L \quad \text{AND } x_3 = H \quad \text{THEN } \text{y}_1 = LM(s_2),$$

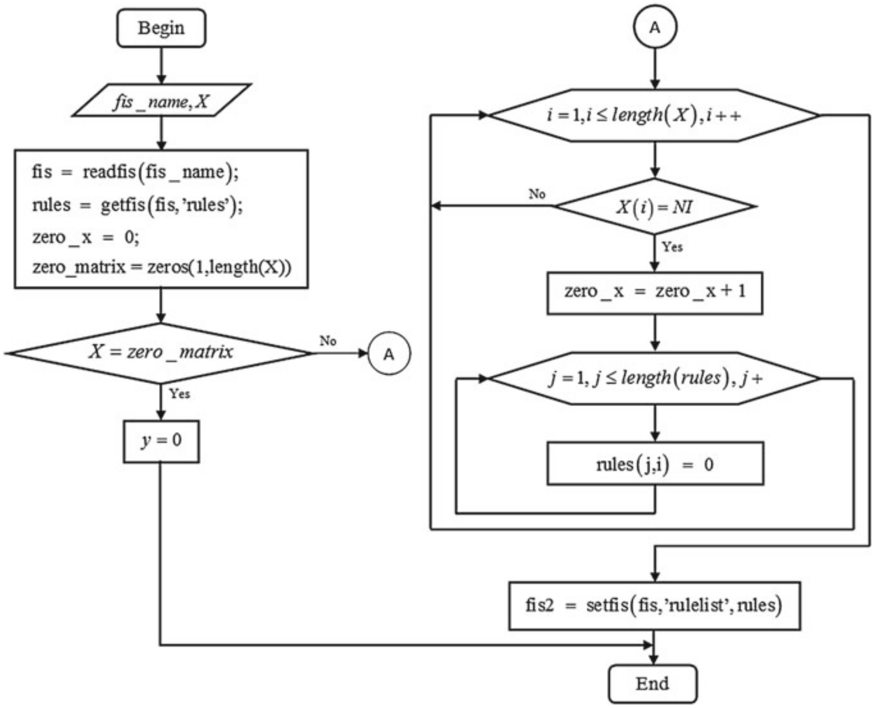

Fig. 3 Block-diagram of the editing algorithm of rules antecedents of DSS

$$
\begin{aligned}
&\text{R13:IF } x_1 = M \quad \text{AND } x_2 = M \quad \text{AND } x_3 = L \quad \text{THEN } \mathrm{y}_1 = LM(s_3),\\
&\text{R14:IF } x_1 = M \quad \text{AND } x_2 = M \quad \text{AND } x_3 = M \quad \text{THEN } \mathrm{y}_1 = M(s_4),\\
&\text{R15:IF } x_1 = M \quad \text{AND } x_2 = M \quad \text{AND } x_3 = H \quad \text{THEN } \mathrm{y}_1 = MH(s_5),\\
&\text{R25:IF } x_1 = H \quad \text{AND } x_2 = H \quad \text{AND } x_3 = L \quad \text{THEN } \mathrm{y}_1 = MH(s_6),\\
&\text{R26:IF } x_1 = H \quad \text{AND } x_2 = H \quad \text{AND } x_3 = M\&H \quad \text{THEN } \mathrm{y}_1 = H(s_7)
\end{aligned}
$$

Ability to define segments of the input space (Fig. 2) due to the fact that it uses a membership functions «*L&M*» and «*M&H*». Their kernels by the length cover practically the whole of the segment length [9]. The use of these membership functions is possible only if the consequents of two or more rules are the same. In this case, the antecedents of the rules differ only in one coordinate.

In our example, the consequents of rules No 1 and No 2 are the same. In this case, the antecedents of coordinates x_1 and x_2 corresponds to linguistic term «-L» and coordinate x_3 changes from linguistic term «L» to «M». Therefore, we can specify an additional term «*L&M*», which combines two linguistic terms «L» and «M» input coordinate x_3. The same thing happens with the rules No 26 and No 27 with using additional linguistic term «*M&H*». The use of such membership functions is one of the methods to reduce the number of rules.

In some cases [9] it is appropriate to use the compression method for fuzzy rule processing. The number of fuzzy rules of each subsystem can be reduced using an approach based on the compression rules. According to this principle, as example for first fuzzy subsystem (Fig. 1), rule No 1 and No 10 (Table 1) can be combined to one resulting rule, the structure of which is as follows:

$$\text{IF } x_1 = L \quad \text{AND } x_2 = L \quad \text{AND } (x_3 = L \text{ OR } x_3 = M) \quad \text{THEN } y_1 = L$$

7 Method of Antecedents and Consequents Correction for Variable Structure of the DSS Inputs

In the process of fuzzy DSS work with a fixed structure of the RB and at a variable structure of the vector of input data $N_r < N$, the results of making decisions y undergo deformation. This is due to the fact that the values of the input parameters (signals) that do not take part in modeling of fuzzy DSS $(x_i = 0, i \in \{1, 2, \ldots, N\})$, carry out negative impact on the result y through the appropriate fuzzy rules. To solve this problem the authors have developed an approach (based on two algorithms of editing of rules antecedents and consequents), which consists in correction of the rules of fuzzy RB at variation of input parameters that allows not to take into account the values of input signals $x_i = NI$, $i \in \{1, 2, \ldots, N\}$, which are not important for DM in the process of decision making.

A block-diagram of the editing algorithm of rules antecedents of fuzzy DSS is presented in Fig. 3.

With the implementation [20] of the algorithm (Fig. 3) all the rules of RB of the first subsystem $y_1 = f_1(x_1, x_2, x_3)$ are processed (27 rules from Table 1). If one of the input signals (x_1, x_2, x_3) is not interesting for DM, for example, $x_1 = NI$, then the algorithm of editing antecedent of rules will change the value of input coordinate x_1 terms to the value of zero signal. Since the input parameter x_1 will not take part in decision-making process, then the value of its antecedent is also excluded from consideration. Herein the values of coordinates antecedents x_2 and x_3 remain unchanged in 27 rules (Table 1), but all possible situations (complete fuzzy model [9]) of values of their antecedents have been considered in rules 1–9 and are repeated in blocks of rules 10–18, 19–27.

Therefore, if the antecedents are repeated, then only one rule with the appropriate antecedent is left that indicates about reduction in the RB from 27 (Table 1) to 9 rules.

A block-diagram of the editing algorithm of rules consequents of fuzzy DSS is presented in Fig. 4.

These algorithms can be applied in the process of designing of fuzzy DSS with a variety structure of the input data.

After correcting the antecedents of RB of fuzzy DSS it is needed to edit the consequent of RB according to modified antecedents. This is necessary because the value of coordinate antecedents, for example x_1, with zero meaning $x_1 = 0$ through appropriate fuzzy rules undermine the result of the output variable y_1 (Table 1). The value of the zero signal $x_1 = 0$ corresponds to term «L» of antecedent of each rule (rules from the Table 1). In addition, let's consider, for example, the situation when the value of antecedents coordinates x_2 and x_3 correspond to term «M», then the value of consequent output variable y_1 will respond to term «LM» (rule number 5 from the Table 2). If we exclude from consideration antecedent coordinate x_1, i.e. $x_1 = NI$, then the rule number 5 will simplify to a single variable, the formula takes the following form IF $x_2 = M$ AND $x_3 = M$ THEN $\mathrm{y}_1 = LM$ that does not correspond to reality. The value of consequent of output coordinate in such situation should meet the term «M», as input variables x_2 and x_3 correspond to term «M». So setting to zero the input coordinate $x_1 = 0$ leads to deformation of results of fuzzy DSS work, unlike actual correction of consequents of rules RB.

Let's illustrate realization of method on different actual sets of values: I—$y_1 = f_1(x_1, x_2, x_3)$; II—$y_1 = f_1(x_1, x_3)$; III—$y_1 = f_1(x_1)$; IV—$y_1 = f_1(x_2, x_3)$; V—$y_1 = f_1(x_2)$. Here in, the actual sets of values characterize different-type actual situations, for example, for the first subsystem $y_1 = f_1(x_1, x_2, x_3)$(Fig. 1, Table 1), which can appear in the process of decision making.

For abovementioned actual sets of values when implementing the first stage of editing rules on the basis of algorithms, which is presented in Fig. 3, RB of the first subsystem $y_1 = f_1(x_1, x_2, x_3)$ (Table 1) is transformed into reduced by the amount of RB rules. At the I set of values, the rules with number 1 to 27 are remained in RB, at the II set—rules No 1, 2, 3, 10, 11, 12, 19, 20, 21, at the III set—rules No 1, 10, 19, at the IV set—rules No 1–9, at the V set—rules No 1, 4, 7.

Let's consider in more detail a stage of editing consequents of reduced RB rules (Fig. 4) for fours actual set of values. Evaluation and correction of consequent of output coordinate's rules y_1 of the first subsystem $y_1 = f_1(x_1, x_2, x_3)$ for IV actual set of values we will consider on the example of the 3rd rule (Fig. 4). For presented in Table 1 third rule the value of antecedent of input (x_1, x_2, x_3) and consequent of output y_1 coordinates can be represented as follows:

$$\text{IF } x_1 = L \quad \text{AND } x_2 = L \quad \text{AND } x_3 = H \quad \text{THEN } \mathrm{y}_1 = LM,$$

where (L, LM, H) are linguistic terms of corresponding subsystem coordinates. For the fourth actual situation (IV) in the decision making process two input variables take part, i.e. $y_1 = f_1^{\mathrm{IV}}(x_2, x_3)$.

In this case, antecedent of coordinate x_2 corresponds to linguistic term «L», and of coordinate x_3—«H», at the same time, with the consequent of output variable y_1 remains unchanged and corresponds to term «LM» (Table 1). The actual situation requires correction of consequent value as according to expert evaluation for $x_2 = L$ and $x_3 = H$ the value of consequent of output variable y_1 has to match term «M».

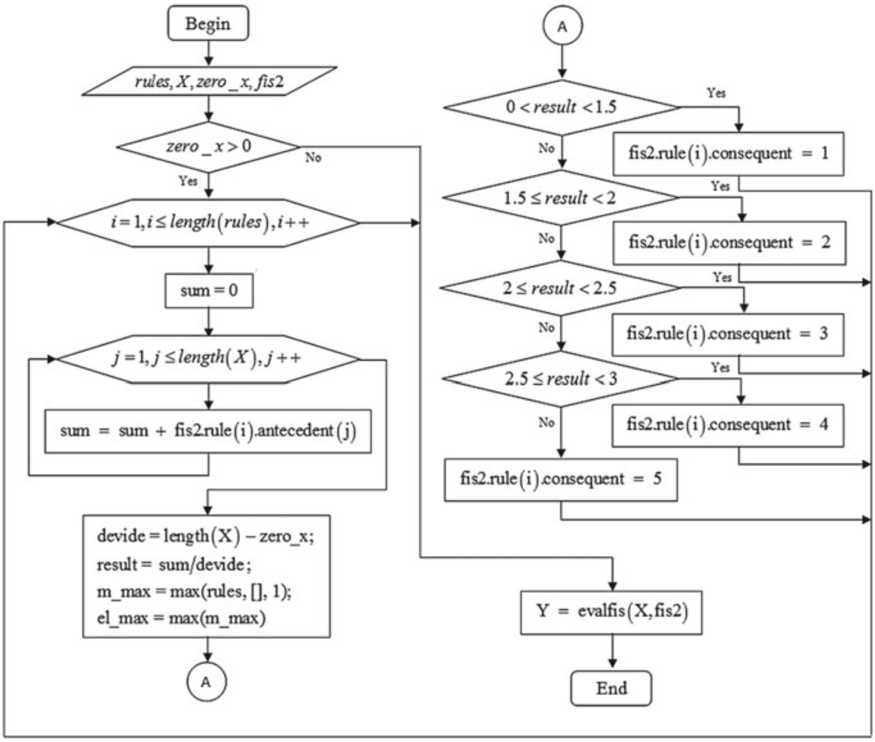

Fig. 4 Block-diagram of the editing algorithm of rules consequents of DSS

Table 2 Modeling Results of the Fuzzy DSS

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	y
I	30	NI	60	90	1,200	NI	30	40,1
II	50	NI	35	70	5,700	NI	80	65,7
III	90	NI	85	85	10,000	NI	90	77,1

Thus for all relevant sets of input values I–V, RB of second subsystem $y_2 = f_2(y_1, x_4)$ (Table 1) remains the same as with any dimension of input vector X the component y_1 will be formed. Editing of RB (Table 1) should be done only in case when $x_4 = NI$.

8 Modeling Results

Modeling results of fuzzy DSS for different types of sets (I, II, III) of input data $\{x_1, \ldots, x_7\}$ are presented in Table 2.

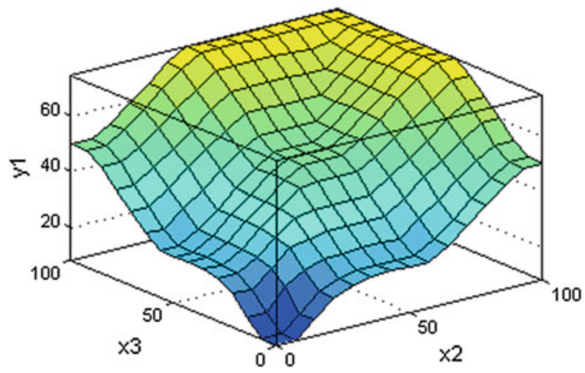

Fig. 5 Characteristic surface of the subsystem $y_1 = f_1(x_1, x_2, x_3)$

In Fig. 5 there is shown characteristic's surface for the rule base of the first subsystem $y_1 = f_1(x_1, x_2, x_3)$ for two components: x_2—level of cargo security protection, x_3—insurance of cargo, when $x_1 = const$.

From the simulation results it is obvious that changing the values of one or a group of input parameters (factors) $\{x_1, \ldots, x_7\}$ of hierarchical fuzzy DSS in different degrees qualitatively and quantitatively impact on the output variable y, which proves the efficiency of the entire system and all its subsystems with the corresponding fuzzy rule bases. In Table 2 there is highlighted one of the relevant sets of input values $x_1 = 30$, $x_2 = NI$, $x_3 = 60$, $x_4 = 90$, $x_5 = 1200$, $x_6 = NI$, $x_7 = 30$, to which will be applied algorithm of editing RB rules. According to this set there will be held a comparative evaluation of the effectiveness of using the algorithm of editing fuzzy DSS rules with flexible hierarchical structure.

Therefore, we can conclude that the indicators value x_2 and x_6 almost does not influence on the result of the system work with application of the editing algorithm of the rules.

9 Conclusions

As a result of the research, authors proposed antecedent/consequent method of current correction of RB rules of fuzzy DSS, which allow increasing of the decision-making effectiveness when solving different problems, including problems of transport logistics.

Synthesized on the basis of the method of actual correction of fuzzy rule bases the intellectual information model of DSS can be widely used for evaluation of the level of quality and efficiency of cargo delivery for variable structure of input factors in the rail, marine and air sectors of cargo transportation. Proposed by authors approach for rule base correction allows to structure and to configure developed DSS to solve different specific problems of transport logistics.

The approach of editing the rule base of fuzzy DSS can be used without limits to the number of DSS inputs and number of linguistic terms for each input and output coordinates.

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