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# Modeling and simulation of logistic processes: risk assessment with a fuzzy logic technique

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**Abstract**

Logistic processes imply the presence of a large number of different types of risks, primarily in the fields of transport, transshipment, and storage of goods. The main reason for this fact is the presence of numerous participants of logistic systems, the existence of various interactions between large numbers of subsystems or subprocesses, which causes disturbances and uncertainties, both locally and at the system level. The initial idea of this research is to model the total risk of logistic processes based on evaluation of the significance of different risk elements, their interrelations, and their influence on total risk. This paper presents a developed fuzzy logic model based on the analytic hierarchy process (AHP) model and fuzzy analytic hierarchy process (FAHP). The model is designed to be practical, understandable, and easy to implement and maintain. The incorporated data have different forms of crisp numbers, triangular fuzzy numbers, and linguistic variables. Logistic process data are incorporated into the proposed model and validated with an example case.

**Keywords**

AHP, decision-making, FAHP, fuzzy logic, logistic processes, risk

## 1. Introduction

Logistic systems and processes are exposed to numerous risks that may occur due to various negative scenarios. The characteristic of these risks is that they often simultaneously have effect on both the goods and the environment. Selection of appropriate methods, techniques, and models in relation to the specific features and characteristics of the considered logistics system and available information and resources is a key parameter of reliability assessment. Risk modeling is a dynamic process that involves a wide range of activities and skills, including analysis of the system or process, development, testing, simulations, and application of methods and models and periodic improvements and corrections. Logistic processes often have significant uncertainty associated with their complexity, reliability of information available on present risks, and availability of various statistical parameters from the previous period. For several reasons, in defining acceptable risk models, it is required, in addition to the statistical data, to use engineering, technological and managerial knowledge, intuition and experience of experts, as well as physical laws for the purpose of a comprehensive identification, assessment, and control of risks.

Aiming at these problems, the authors developed a new fuzzy logic model combining the analytic hierarchy process (AHP) model, fuzzy analytic hierarchy process (FAHP), and fuzzy logic techniques in order to ensure more reliable risk assessment in specific logistic processes.

## 2. Literature review

The mathematical basis of criteria analysis can be described as a selection of one from the final series of $m$ alternatives $A_i$ ($i$ = 1,…,$m$) based on $n$ criteria $X\,j$ ($j$ = 1,…,$n$). Each of the alternatives is the vector $A_i$ ($x_{i1}$,…, $x_{ij}$,…,$x_{in}$) where $x_{ij}$ is a value of $j$ attribute for $i$ alternative. In order to formulate mathematically the model of multi-criteria decision-making, we need information on all the alternative embodiments of the process for which the decision is made, and on the goals to achieve. Description of the mathematical formulation of the AHP is shown in articles published by Saaty.[1–3] The main reason for using this method is the nature of the risk, as a multi-parameter,

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complex measure, which is very difficult to accurately analyze and evaluate. Critics of the AHP method indicate that significance of elements presents only some sort of arithmetic accuracy that does not reflect real or objective evaluation. Although Saaty's discrete scale has an advantage in terms of simplicity and ease of use, it does not take into account the uncertainty associated with perceptions of a decision-maker. In certain cases, the AHP method cannot present the nature of human understanding of mutual relations between risk elements. This particularly refers to situations when a decision-maker cannot accurately assess the crisp values of numerical criteria comparisons. Numerous authors have applied the AHP method with risk assessment in various areas,[4] including the transport industry.[5,6]

The objective of the fuzzy theory[7,8] is to model a situation described indistinctly and imprecisely, or one that is too complex or undefined to be analyzed using conventional methods – that is, just by theory of probability or interval mathematics.[9] Van Laarhoven and Pedrycz[10] have developed an FAHP method based on integration of fuzzy sets and AHP. Fuzzy numbers are used in this method to describe mutual significance of elements. There are different modalities of the FAHP method proposed by different authors. Chang's FAHP method[11] can be viewed as an advanced analytical method developed on the basis of a classical AHP method. The FAHP can reduce or even eliminate the ambiguity and lack of clarity that exists in complex decision-making problems and improve the accuracy of the estimate of the given situation in relation to the AHP method. An and colleagues[12] applied the FAHP method of risk assessment in the railway transport system. Vosooghi and colleagues[13] used the FAHP method for decomposition and risk quantification in supply chains for crude oil. In the paper of Tadić and colleagues,[14] FAHP is applied for obtaining the weights of the criteria defined on the basis of conflicting goals of different stakeholders. Azadeh and Zadeh presented AHP and fuzzy approaches to preclude failures in system engineering due to its fallbacks in the safety and economics of plants operation.[15]

Comparison of the AHP and FAHP methods is usually shown from different aspects: present differences in theoretical settings, the results obtained for the same problems, and the advantages and disadvantages of application in different situations in practice. The most often cited fact is that the experts who make decisions about a particular problem in the FAHP method may present a flexible evaluation, which implies a more realistic view of the observed situation. Durán and Aguilo[16] state that the disadvantage of the AHP method lies in the fact that it cannot process uncertainty and vagueness, which cannot be compared, including the perceptions of a decision-maker, on the basis of crisp numbers on the discrete scale presented by Saaty. The FAHP can reduce or even eliminate the ambiguity and lack of clarity that exists in complex decision-making problems, and improve the accuracy of the estimate of the given situation in relation to the AHP method (for more about the differences between these methods, see Durán and Aguilo,[16] Meixner[17] and Zhu and colleagues[18]). Wang and colleagues[19] describe the disadvantages of Chang's method and state three specific numerical examples. The examples show that fuzzy evaluation of criteria, subcriteria, and alternatives cannot achieve complete reliability when creating a comparison matrix, which can cause inconsistency in the output data.

Fuzzy logic[20] is often used to model complex systems where application of other methods makes determination of interdependencies between particular variables very difficult. Sii and colleagues[21,22] used a fuzzy logic-based approach to quantitative safety modeling for marine systems. A microscopic traffic simulation model with the fuzzy logic technique was developed by Errampalli and colleagues.[23] Nedeljković and Drenovac[24] proposed a possible approach for solving data envelopment analysis models with fuzzy data for determination of efficiency of postal units.

Detailed information on the methods of identification, analysis, and assessment of risk are given in numerous publications and works by Ellis,[25] Mullai,[26] Hong and Dugan,[27] Ayyub and colleagues,[28] Dhillon,[29] and Brown.[30]

Numerous papers show the possibility of applying the models from AHP, FAHP, or fuzzy logic in the areas of risk analysis, transport, and logistics. To our best knowledge, there are no papers currently available in the literature combining all three models in a single model. Moreover, in this paper input data for the fuzzy logic model are obtained from AHP and FAHP models for specific logistic processes.

## 3. Problem description

The authors analyzed the total risk in logistics processes in five datasets (basic risk elements). Each of the defined risk elements consists of numerous subelements, which individually or in interaction with other subelements determine the total risk of specific logistics processes. Considering the complexity of the risk in logistics processes, it is almost impossible to make a clear distinction between particular elements and subelements of risk, which can be classified according to different criteria and subjective perceptions. Also, there is a problem of the existence of causal links between the risk elements and subelements. Certain risk subelements lead to full or partial exclusion of others, while some subelements are often not considered because of their numerosity and/or subjective assumption of their insignificance. Given these facts, the proposed classification of risk elements refers to the largest number of different classes of logistics processes, but not to all possible scenarios that may occur in practice.

Classical theory is often an inadequate basis for the treatment of relations and events based on linguistic variables, such as "very high risk,""short-distance transport,""highly flammable dangerous material," etc. The uniqueness and peculiarity of fuzzy sets lies in modeling terms of uncertainty that otherwise cannot be fully explained or determined by the theory of probability. One such uncertainty is the ambiguity characteristic of human perception and description of phenomena. Another is making decisions on complex problems, especially combined with the human inability to undertake controlled experiments that deal with complexity.

Physical distribution presents a key part of logistic processes and includes all activities regarding transport, such as preparation of transport processes, preparation of goods for transport, loading of goods in the first transportation means, all phases until their final destination (changes of transportation means, re-loading, and warehousing), unloading of goods at the final destination, and all commercial and administrative operations. Hesse and Rodrigue[31] present characteristics and specific features of transport networks that influence performance, costs, complexity, and reliability of logistic processes and physical distribution. Based on the stated facts, it can be concluded that distribution of nodes in transport networks as well as distribution and activity of transport routes predetermine efficiency, speed, and reliability of a process.

The authors developed the model for risk assessment in one class of logistics processes – the process of physical distribution of goods from the sender to the receiver. The basic idea in developing the model was to evaluate, in a quality manner, the total risk process, so as to take into account different risk elements, their mutual relationship, relative importance and impact on the total risk.

The developed models include three parts:

1. The *analytical* part refers to the collection of available data in the previous period. Input measures of models include five risk elements:

   a. Characteristics and technological features of goods (CTG). There is almost an infinite number of goods in transport with different characteristics and specific features, which affects the level of riskiness in logistics processes realization. For the purpose of analysis and quantification of risk, it is necessary to establish a single class of logistics processes involving homogeneous groups of goods similar in characteristics – that is, the probability of loss occurrence and the expected consequences.
   b. Type of packaging and goods security (PGS). The level of riskiness of transport is significantly affected by the type of packaging (e.g., the characteristics of packaging, packaging technology, palletization, packaging standards, container type, etc.) and security of goods in transit and during storage.
   c. Technological characteristics and transport organization (TTO). Each type of transport generates specific risks inherent in the specific transport (quality and characteristics of transport infrastructure, as well as various conditions and limitations of the transport route, manner and organization of transport, characteristics of forwarding, and other).
   d. Characteristics and specificity of transport route (CTR). Physical distance of sender and receiver is an important but not essential risk component. More significant risk factors are transport and traffic infrastructure, area and destination, climate conditions, political conditions, terms and restrictions of specific transport, and other.
   e. Other logistic parameters (OLP). There are numerous logistical parameters that affect the risk level. Manipulation risks are constantly present during loading, unloading, and transshipment of goods. Warehousing risk depend on factors such as the type of goods, type of warehouse and its technologies, security of goods in a warehouse, and other. Depending on the type and natural characteristics of goods, the realization of transport risks may be associated with climate factors in the regions through which goods are transported.

2. The *processing* part includes application of the AHP (Model 1), the FAHP (Model 2) and methods based on fuzzy logic (Model 3). The output is the total risk assessment in the logistic process, which can be low, medium, and high (Models 1 and 2), or very low, low, medium, high, and very high (Model 3).
3. The *managerial* part includes analysis of output data values of total risk and impact of each element to the total risk.

Application of the three models and three different approaches to risk assessment is implemented as follows:

1. First, the model is applied based on the AHP method. Input values of models are expert estimates of the relationship between the risk elements, expressed on a scale from 1 to 9. The output of the model is the significance of each risk element for total risk, and total risk assessment of the logistics process.
2. Then, we apply the model based on the AHP method. Input values are expert estimates of the relationship between the risk elements expressed by fuzzy numbers, and output is the significance of each risk element and total risk assessment for the logistics process.

3. The third model is based on fuzzy logic and risk assessment is determined using a fuzzy system. Input parameters of the model are risk elements described by fuzzy numbers. The fuzzy system leads to the value of total risk in the logistics process, and processing and analyzing the output results leads to the significance of each risk element for the total risk.

## 4. Fuzzy model for risk assessment

The theory of fuzzy sets and fuzzy logic enables the use of subjective assessments expressed by vague terms, relations and statements to describe problems, the choice of alternatives for decision, formulation of vague descriptions using fuzzy variables, and the presentation of outputs using linguistic concepts and relations or in the form of clear quantitative recommendations. For these reasons, risk assessment methods based on fuzzy logic can be characterized as the semiquantitative and quantitative methods.

### 4.1. AHP method: Model 1

The basic idea of the AHP method is to include and apply the knowledge and experts' experience on the problem to be analyzed.[1] The method enables hierarchical decomposition and partial solution of the specific problem, and the obtained partial solutions are entirely integrated in order to obtain the solution to the initial problem. The hierarchical structure consists of aim (risk assessment in logistic process), criteria (the five risk elements and alternatives), and risk levels (low, medium, and high total risk).

The process of applying the AHP method comprises the following steps:[19,32]

**Step 1.** A hierarchical decomposition of the problem, with the aim set at the highest level, the criteria and subcriteria at lower levels, and the alternatives at the lowest level.
**Step 2.** Comparison of pairs of elements at each level of the hierarchy in relation to the elements of the higher level, by applying the Saaty. The decision-maker determines the value $a_{ij}$, of the elements $i$ and $j$, where $a_{ij} = 1/a_{ji}, \forall i, j = 1, \ldots, n, a_{ij} = 1, \forall i = j$.
**Step 3.** Setting priorities for each element in relation to a higher hierarchy level –$w_{ij}$ is a priority of the alternative $i$ in relation to the criterion $j$, where $i = 1,\ldots,m$, $j = 1,\ldots,n$, $m$ is the number of alternatives, $n$ is the number of criteria.
**Step 4.** Synthesis of all values of priorities so as to obtain the priority of each element in relation to the objective. $W_i$ is the alternative priority $i$ and is determined as:

$$W_i = \sum_{j=1}^{n} c_j w_{ij} \tag{1}$$

where $c_j$ is the criteria priority $j$, and $w_{ij}$ is the alternative priority $i$ in relation to criterion $j$.

AHP predicts an analysis of the consistency of decision-makers, with a tolerance of up to 10%. Calculated priorities present the significance of elements and alternatives, and are eligible only if the comparison matrices are consistent or approximately consistent.

In this model, the AHP method, based on the expert knowledge of the risk elements, enables the total risk assessment in logistic process $W_i$ ($i$ = 1, low total risk; $i$ = 2, medium total risk; $i$ = 3, high total risk) and quantification of priorities – the importance of each risk element $c_j$ ($j$ = 1, CTG; $j$ = 2, PGS; $j$ = 3, TTO; $j$ = 4, CTR; $j$ = 5, OLP).

### 4.2. FAHP method: Model 2

The FAHP method is an extended version of the AHP method in which the input parameters are described by fuzzy numbers.[10,11] Application of fuzzy numbers may improve the accuracy of experts' assessment and quality of output results.

**Step 1.** Comparison of pairs of elements $i$ and $j$ at every level of the hierarchy in relation to the elements at a higher level, by using fuzzy numbers that correspond to Saaty's scale. The decision-maker determines the value $b_{ij}$, for elements $i$ and $j$, where $b_{ij}$ is a triangular fuzzy number ($l_{ij}$, $m_{ij}$, $u_{ij}$).
**Step 2.** Summarizing rows of the matrix $B = (b_{ij})_{n \times n}$ to obtain the following values:

$$RS_i = \sum_{j=1}^{n} b_{ij} = \left( \sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij} \right), \ i = 1, \ldots, n \tag{2}$$

Normalization of value $RS_i$ according to Equation (3):

$$S_i = \frac{RS_i}{\sum_{j=1}^{n} RS_j} = \left( \frac{\sum_{j=1}^{n} l_{ij}}{\sum_{k=1}^{n}\sum_{j=1}^{n} u_{kj}}, \frac{\sum_{j=1}^{n} m_{ij}}{\sum_{k=1}^{n}\sum_{j=1}^{n} m_{kj}}, \frac{\sum_{j=1}^{n} u_{ij}}{\sum_{k=1}^{n}\sum_{j=1}^{n} l_{kj}} \right), i = 1, \ldots, n \tag{3}$$

**Step 3.** Probability that $S_i \geqslant S_j$ for $i, j = 1, \ldots, n$, is:

$$V(S_i \geqslant S_j) = \begin{cases} 1, & \text{if } m_i \geqslant m_j \\ \frac{u_i - l_j}{(u_i - m_i) + (m_j - l_j)}, & \text{if } l_j \leqslant u_i,\ j \neq i \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

where $S_i = (l_i, m_i, u_i)$ and $S_j = (l_j, m_j, u_j)$.

Determination of the probability that the fuzzy number $S_i$ is greater than other fuzzy numbers according to Equation (5):

$$V(S_i \geqslant S_j | j = 1, \ldots, n;\ j \neq i) = \min_{j \in \{1,\ldots,n\}, j \neq i} V(S_i \geqslant S_j),\ i = 1, \ldots, n \quad (5)$$

**Step 4.** Determination of priority vectors $W = (w_1,\ldots,w_n)^T$ of the comparison matrix of the fuzzy value $B$ as:

$$w_i = \frac{V(S_i \geqslant S_j | j = 1, \ldots, n;\ j \neq i)}{\sum_{k=1}^{n} V(S_k \geqslant S_j | j = 1, \ldots, n;\ j \neq k)},\ i = 1, \ldots, n \quad (6)$$

The output result of this model is the value of priority – significance $S_i$ of each risk element ($i$ = 1, CTG; $i$ = 2, PGS; $i$ = 3, TTO; $i$ = 4, CTR; $i$ = 5, OLP) and the total risk in the logistic process $W = w_1$, low; $w_2$, medium; $w_3$, high total risk).

Figure 1 presents the procedures of application of the Model 1 and Model 2 for the assessment of the total risk in the logistics process.

### 4.3. Fuzzy logic: Model 3

Model 3 is a fuzzy system based on the application of fuzzy logic and approximate reasoning algorithms. The fuzzy system for risk assessment in logistics process includes the following steps:

**Step 1:** Defining input variables and output variable.

Fuzzy system has five input variables (CTG, PGS, TTO, CTR, and OLP). The output variable is the total risk in the logistic process. The fuzzy system enables assessment of the total risk based on qualification of all risk elements.

**Step 2.** Defining the membership functions for selected variables.

Each risk element may be low, medium, or high, and can be described by fuzzy sets as low risk, medium risk, or high risk. Membership functions of fuzzy sets $X_L$ (low risk), $X_M$ (medium risk), and $X_H$ (high risk) are shown in Figure 2. The shape of membership functions of fuzzy sets $X_L$, $X_M$, and $X_H$ is the same for all risk elements, but values $x_1$, $x_2$, $x_3$, $x_4$, $x_5$, and $x_6$ for the left and right border, and the value with the highest level of membership of fuzzy numbers are different for each risk element.

The output value of the fuzzy system is the total risk in logistic process (*TR*), which can be very low, low, medium, high, or very high. Membership functions of fuzzy sets $Y_{VL}$ (a very low risk), $Y_L$ (low risk), $Y_M$ (medium risk), $Y_H$ (high risk), and $Y_{VH}$ (very high risk), are shown in Figure 3.

Figure 4 shows the concept of the model for risk assessment based on fuzzy logic. It consists of analytical, processing, and control parts.

**Step 3.** Determining intervals of values of input and output variable.

Using Model 1 and Model 2, for each risk element its weighting factor is obtained – that is, total risk share. For example, an element of risk of CTG weighting factors can be 0.45 and 0.41. This means that the share of CTG in the total risk is 45%, that is 41%. Based on this we can conclude that the interval of value of fuzzy sets describing the low, medium, and high risk elements of CTG is (0, 0.45), that is (0, 0.41). The output results of Model 1 and Model 2 are the values of priorities – weight $c_i$ and $S_i$ for each risk element $i$ ($i$ = 1, ..., 5). Interval of values $l_i$ of input variable $i$ of the fuzzy system is defined as the average value of the priorities obtained in the previous two models, according to the following:

$$l_i = \frac{c_i + S_i}{2} 100 \quad (7)$$

Based on the defined interval of value $l_i$ of input variables, the left and right boundaries can be set, and the value with the highest level of membership of fuzzy numbers $X_L$, $X_M$, and $X_H$, for each risk element: $x_{i1} = 0.1 l_i$, $x_{i2} = 0.3 l_i$, $x_{i3} = 0.5 l_i$, $x_{i4} = 0.7 l_i$, $x_{i5} = 0.9 l_i$, and $x_{i6} = l_i$. The output of the fuzzy system is the value of the total risk in the logistics process, and it can be in the interval (0, 100).

**Step 4.** Define the approximate reasoning algorithm.

Approximate reasoning is the process or processes by which a possible imprecise conclusion is deduced from a collection of imprecise premises.[33] This process is formulated as a compositional rule of inference which subsumes *modus ponens* as a special case. A characteristic feature of approximate reasoning is the fuzziness and non-uniqueness of consequents of fuzzy premises.[34] It includes the process of aggregation based on which the output values of all fuzzy rules compress into a single fuzzy set. This is a process obtaining the approximate solution of a system of relational assignment equations. There are two most frequently used techniques of approximate reasoning,

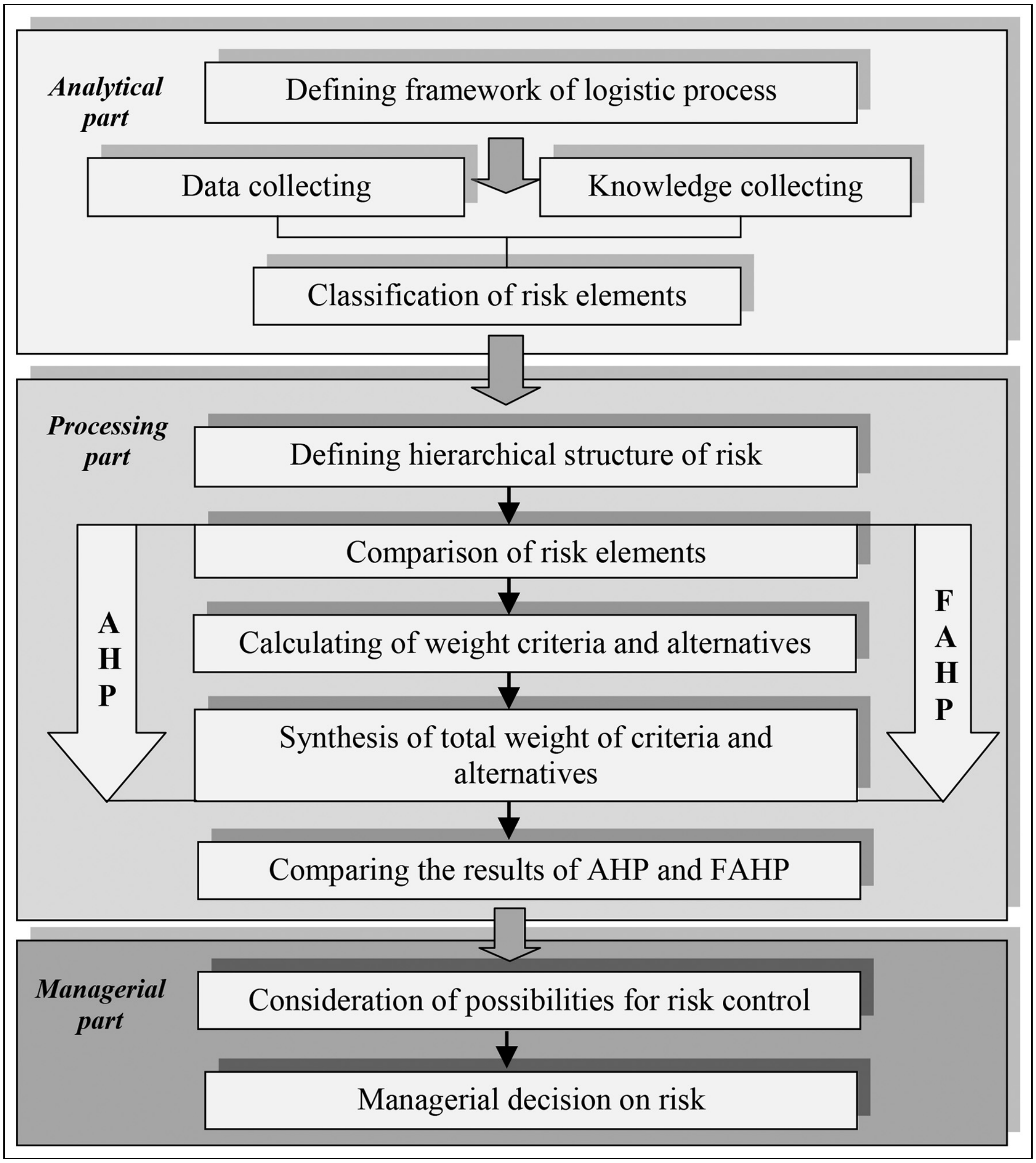


**Figure 1.** Model 1 and Model 2 structure. Adapted from Radivojević and Gajović.[32]

Takagi–Sugeno and Mamdani inference technique.[8] In this fuzzy system, the authors used the Mamdani technique.

An approximate reasoning algorithm is a set of rules with assumptions that include the input values, and in consequence output values of a fuzzy system. Rules are defined to show the relations between all possible combinations of input and output variables. Each rule represents a fuzzy phrase defined for set CTG $\times$ PGS $\times$ TTO $\times$ CTR $\times$ OLP $\times$ TR. An approximate reasoning algorithm includes 243 fuzzy rules which represent a set of variations with repetition of all risk elements and levels of risk (very low, low, medium, high, and very high). The rules are defined as follows:

$R^1$: IF CTG Low and PGS Low AND TTO Low and CTR Low and OLP Low THEN TR Very Low

$R^2$: IF CTG Low and PGS LOW and TTO Low and CTR and OLP Medium THEN TR Very Low

. . .

$R^{107}$: IF CTG Medium PGS and TTO High and CTR High and OLP Medium THEN TR High

$R^{108}$: IF CTG Medium PGS and TTO High and CTR High and OLP High THEN TR Very high

. . .

$R^{242}$: IF CTG High and PGS High and TTO High and CTR High and OLP Medium THEN TR Very high

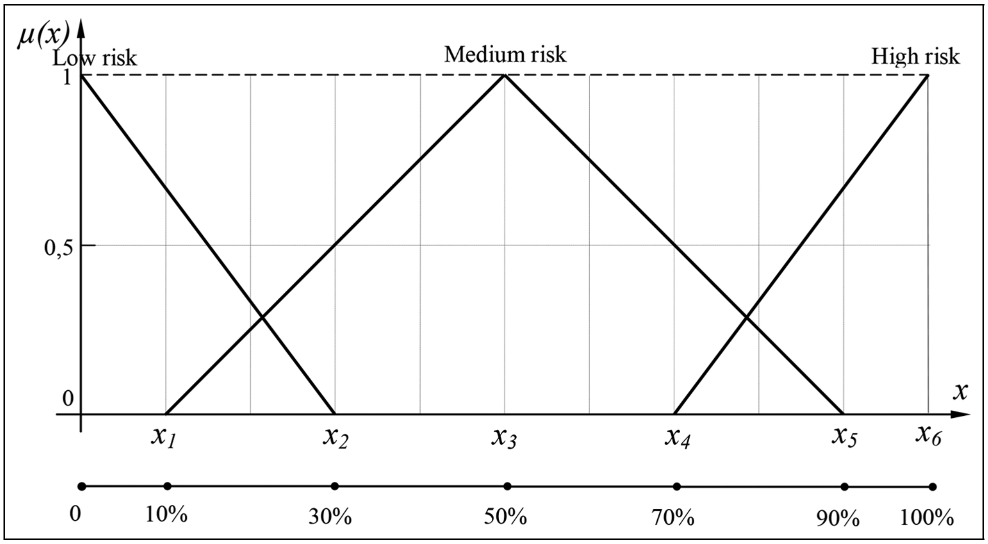


**Figure 2.** Membership functions of fuzzy sets $X_L$ (low risk), $X_M$ (medium risk), and $X_H$ (high risk).

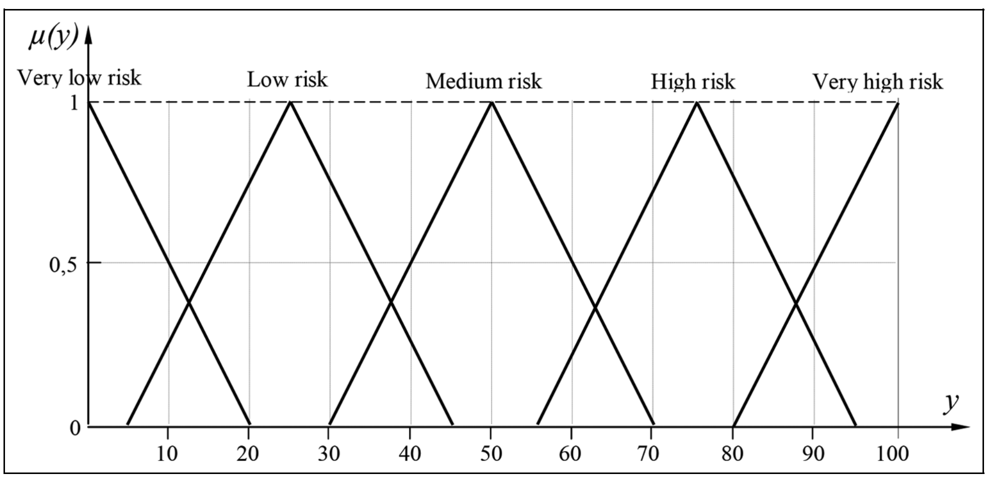


**Figure 3.** Membership functions of fuzzy sets $Y_{VL}$ (very low risk), $Y_L$ (low risk), $Y_M$ (medium risk), $Y_H$ (high risk) and $Y_{VH}$ (very high risk).

$R^{243}$: IF CTG High and PGS High and TTO High and CTR High and OLP High THEN TR Very High

**Step 5.** Defuzzification

There are several methods of defuzzification, and in this model we applied the *centroid* method. The centroid defuzzification method finds a point representing the center of gravity of the fuzzy set.[35,36]

## 5. Implementation of the model with simulation and the numerical example

According to the developed models, appropriate software packages are designed. For Model 3, MATLAB software was used. Input parameters (CTG, PGS, TTO, CTR, and OLP) were obtained by generating random numbers for each risk element in accordance with the output data of Model 1 and Model 2 from Step 3 point 3.3. Each risk element *i* is simulated as an independent variable with uniform distribution in the (0, $l_i$) interval. The output results are obtained on the basis of the approximate reasoning algorithm and defuzzification process. Testing of Model 3 was performed on a large number of hypothetical examples. The fuzzy model in MATLAB simulated 1000 input sets in order to obtain output data of a fuzzy model – that is weight risk elements.

The models are applied sequentially – Model 1, Model 2, and then Model 3. All three models use experts' knowledge implementation: in Models 1 and 2 through expert

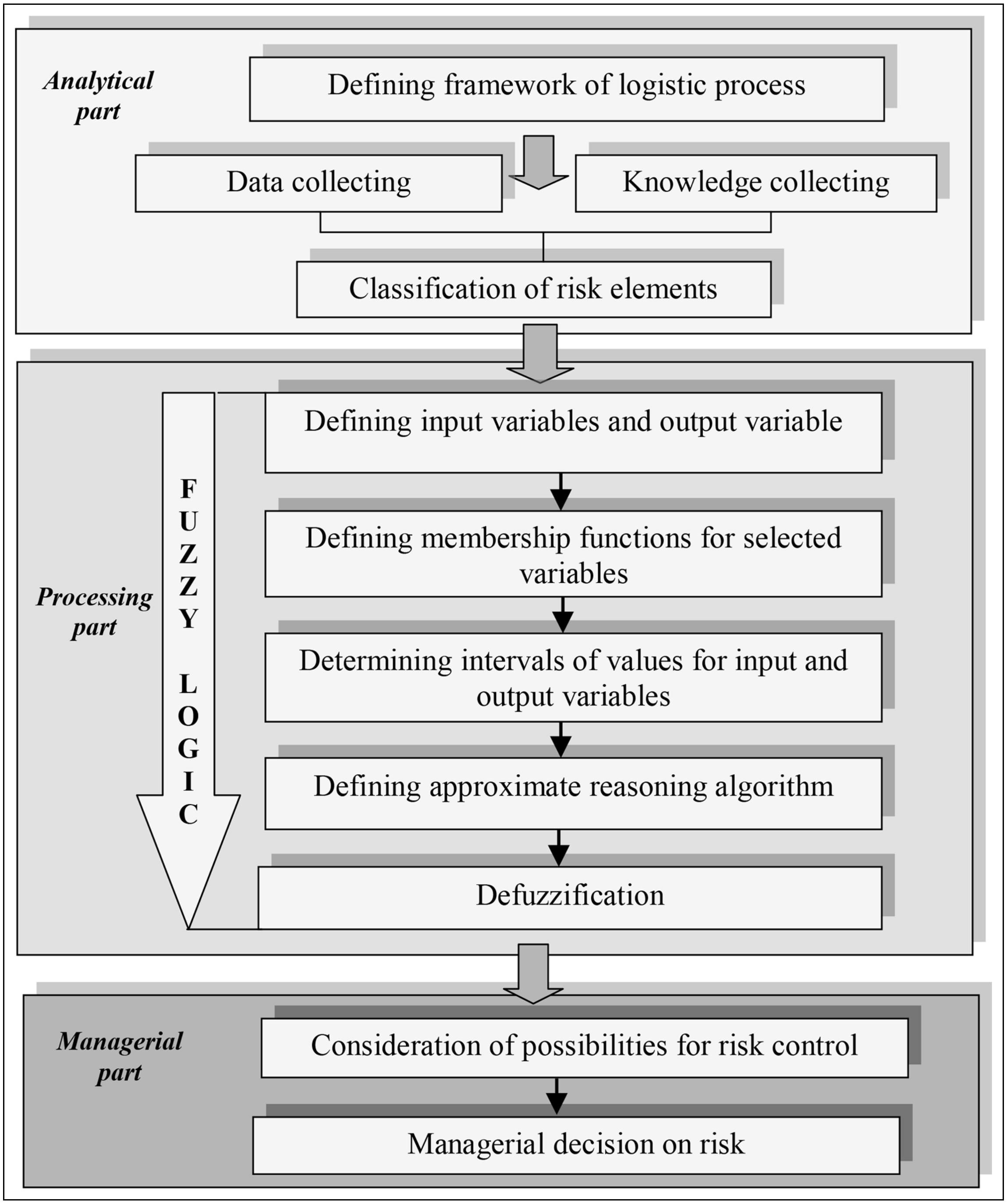


**Figure 4.** Model 3 structure.

assessment of input parameters of the model, and in Model 3 through application of the results of Model 1 and 2 and development of a set of fuzzy rules for total risk assessment.

Input parameters for Model 1 are expert assessment of comparison of pairs of risk elements using Saaty's scale from 1 to 9. In practice, various methods of expert assessment are used and can be roughly divided into individual and group assessment. In this paper, risk assessment was obtained by interviewing a group of experts. The group of selected experts comprise managers and risk managers from various logistic systems, with experience regarding risks that are present in logistics and physical distribution. They have expertise and experience regarding probability of occurrence of various types of risks, as well as experience regarding expected consequences in case of

**Table 1.** The comparison matrix of risk elements: Model 1.

| | CTG | PGS | TTO | CTR | OLP | W |
|---|---|---|---|---|---|---|
| CTG | 1 | 3 | 5 | 5 | 5 | 0.488 |
| PGS | 1/3 | 1 | 3 | 3 | 3 | 0.233 |
| TTO | 1/5 | 1/3 | 1 | 1 | 1/3 | 0.074 |
| CTR | 1/5 | 1/3 | 1 | 1 | 1 | 0.087 |
| OLP | 1/5 | 1/3 | 3 | 1 | 1 | 0.118 |
| | $\lambda$ = 5.1960 | | CI = 0.0490 | | CR = 0.0438 | |

**Table 2.** The comparison matrix of risk elements: Model 2.

| | CTG | PGS | TTO | CTR | OLP | W |
|---|---|---|---|---|---|---|
| CTG | (1,1,1) | (1,3,5) | (3,5,7) | (3,5,7) | (3,5,7) | 0.393 |
| PGS | (1/5,1/3,1) | (1, 1, 1) | (1,3,5) | (1,3,5) | (1,3,5) | 0.287 |
| TTO | (1/7,1/5,1/3) | (1/5,1/3,1) | (1,1,1 ) | (1,1,3) | (1/5,1/3,1) | 0.085 |
| CTR | (1/7,1/5,1/3) | (1/5,1/3,1) | (1/3,1,1) | (1,1,1) | (1,1,3) | 0.088 |
| OLP | (1/7,1/5,1/3) | (1/5,1/3,1) | (1,3,5) | (1/3,1,1) | (1,1,1) | 0.147 |

**Table 3.** Local and global priorities: Model 2.

| Risk level | Risk elements | | | | | Final W |
|---|---|---|---|---|---|---|
| | CTG | PGS | TTO | CTR | OLP | |
| | 0.393 | 0.287 | 0.085 | 0.088 | 0.147 | |
| Low total risks | 0.227 | 0.096 | 0.040 | 0.040 | 0.075 | 0.468 |
| Medium total risks | 0.146 | 0.096 | 0.036 | 0.040 | 0.045 | 0.377 |
| High total risks | 0.020 | 0.096 | 0.010 | 0.008 | 0.027 | 0.155 |

realization of risks. The process of posing questions, summary of opinions and corrections of obtained opinions are repeated several times until a consistency of assessments is reached or at least approximate consistency within determined tolerance of value deviation.

Table 1 shows the matrix comparisons and the calculated values of the resulting vector of priorities $W$. Vector $W$ indicates the relative priority of each risk element. The table shows values for $\lambda$ (the highest eigenvalue of the decision matrix), CI (consistency index), and CR (the ratio of consistency obtained using the AHP method). Considering that CI is less than 10%, we can accept an estimate vector of priority. In the next step, experts determined the comparison matrices for each risk level in relation to each criterion.

In Model 2 we used as input parameters expert assessments expressed by triangular fuzzy numbers (Table 2). Further, experts determine the comparison matrix elements for each risk level in relation to each risk element. Table 2 shows values of the comparison matrix and calculated value of the resulting vector of priority $W$. Local and global priorities of risk levels and final vector of priority $W$ are shown in Table 3. According to these results, the logistics process has a low total risk with 46.8% significance.

Applying relations of the FAHP method, we calculated the local priority $W$ for each risk level. The highest priority has CTG with 39.3% influence, and the lowest priority has TTO with 8.5% influence on total risk.

Comparing the results obtained using Models 1 and 2, we get high similarity. Deviations of the results obtained by applying the AHP and FAHP methods can be considered as acceptable, and they resulted from the fact that the FAHP method with greater significance acknowledges the subjectivity of experts when comparing criteria and alternatives.

Model 3 is the fuzzy system based on five inputs, which can have values of low, medium, and high risk. The output result of a model is the total risk value in the logistics process. In this model, the interval of value $l_i$ for each risk element and each risk level $i$ is determined based on the value of the priority of risk elements obtained by Models 1 and 2 and shown in Table 4. Each risk element is described by fuzzy sets as low risk, medium risk, and high risk; values $x_1$, $x_2$, $x_3$, $x_4$, $x_5$, and $x_6$ are for left and right borders of

**Table 4.** The parameters of membership functions for input variables of the fuzzy system: Model 3.

| Risk elements | CTG | PGS | TTO | CTR | OLP |
|---|---|---|---|---|---|
| Model 1 | 0.488 | 0.233 | 0.074 | 0.087 | 0.118 |
| Model 2 | 0.393 | 0.287 | 0.085 | 0.088 | 0.147 |
| Low risk | 0 | 0 | 0 | 0 | 0 |
| | 0 | 0 | 0 | 0 | 0 |
| | 13.215 | 7.8 | 2.385 | 2.625 | 3.975 |
| Medium risk | 4.405 | 2.6 | 0.795 | 0.875 | 1.325 |
| | 22.025 | 13 | 3.3975 | 4.375 | 6.625 |
| | 39.645 | 34.4 | 7.155 | 7.875 | 11.925 |
| High risk | 30.835 | 18.2 | 5.565 | 6.125 | 9.275 |
| | 44.05 | 26 | 7.95 | 8.75 | 13.25 |
| | 44.05 | 26 | 7.95 | 8.75 | 13.25 |

**Table 5.** Output results of Model 1, Model 2, and Model 3.

| Risk elements | CTG | PGS | TTO | CTR | OLP |
|---|---|---|---|---|---|
| Model 1 | | | | | |
| Low total risks | 0.309 | 0.078 | 0.034 | 0.037 | 0.071 |
| Medium total risks | 0.127 | 0.078 | 0.031 | 0.037 | 0.024 |
| High total risks | 0.052 | 0.078 | 0.009 | 0.012 | 0.024 |
| $c_i$ | 0.488 | 0.233 | 0.074 | 0.087 | 0.118 |
| Model 2 | | | | | |
| Low total risks | 0.227 | 0.096 | 0.040 | 0.040 | 0.075 |
| Medium total risks | 0.146 | 0.096 | 0.036 | 0.040 | 0.045 |
| High total risks | 0.020 | 0.096 | 0.010 | 0.008 | 0.027 |
| $S_i$ | 0.393 | 0.287 | 0.085 | 0.088 | 0.147 |
| Model 3 | | | | | |
| $(c_i + S_i)/2$ | 0.441 | 0.260 | 0.079 | 0.088 | 0.133 |
| Fuzzy system (MATLAB simulation results) | 0.432 | 0.266 | 0.081 | 0.087 | 0.134 |

triangular fuzzy numbers. The parameters of membership functions for input variables are presented in Table 4.

The output result of the model is the value of the total risk in the logistics process. Analysis of the output data included measuring the relative weighting factors of each risk element and their share in the total risk. Table 5 shows the results obtained by Models 1–3. Analysis of the results indicates the following conclusions:

1. Model 1 and Model 2 are consistent and their output results show no significant differences.
2. Model 3 gives results that correspond to results obtained by Model 1 and Model 2. If we compare the results of Model 3 with an average value obtained by Models 1 and 2, the differences are less than 2.5% for all risk elements.
3. Weighting risk element ranking is the same for all three models.
4. The highest impact on the total risk in logistic processes have characteristics and technological features of goods – CTG (39.3–48.8%); followed by packaging and security of goods – PGS (23.3–26.6%).
5. The technological characteristics and organization of transport– TTO (7.4–8.5%); the characteristics and specificity of transport route – CTR (8.7–8.8%); and other logistic parameters – OLP (11.8–14.7%) have less impact on the total risk.

The idea to minimize the subjectivity degree of decision-makers is realized by using fuzzy models. The fuzzy model suggests a ‘‘more accurate’’ approach, which means assessment of risk for different risk elements in logistic processes that are dominant, and obtaining a numerical value for the total risk of the observed logistic process according to a defined output values scale. Reduction of the level of assessment subjectivity is thus greatly affected, which is stressed as one of the more significant problems in experience and expert assessment.

The proposed fuzzy model for total risk assessment in logistics processes has many advantages:

1. Application of a single scale for expert risk assessment of individual risk elements can be adapted to assessors' practice, and enables a relatively simple evaluation without knowing the fuzzy logic model.

2. It reduces the impact of personal subjectivity and perception on definition of total risk.
3. A fuzzy logic model represents a support to risk managers in decision-making in logistics systems.
4. It offers partial treatment of various risk elements that affects the total risk, which leads to a reduction of inadequate estimations in decision-making in risk assessments. Analysis and assessment of individual risk elements instead of the total risk assessment in logistics processes will reduce the possibility of error.
5. It eliminating the risk of rough oversights and inconsistencies of decision-makers regarding the risk level.

Risk assessment of logistics processes represents a dynamic process that involves constant checking and any corrections of parameters of the established model. If the results of the fuzzy model, according to the achieved results, do not meet established reliability criteria, the entire process of formulation of experience and knowledge should be reviewed and corrected, even to the level of correction in Models 1 and 2 (AHP, FAHP), until we obtain acceptable results. If, however, the result of the fuzzy model in a defined time period led to the expected results, the application can continue by using the defined fuzzy logical rules with defined significance of risk elements.

## 6. Conclusions

The authors proposed the fuzzy logic model for risk assessment in logistics processes whose input data are from AHP and FAHP models. The stated model can have significant application when representative statistical data on the risks present in logistics systems are missing. Models based on the AHP and FAHP models were used for formulation and implementation of expert knowledge about risks for making a model based on fuzzy logic. The fuzzy model enables obtaining the level of total risk assessment in the observed logistics process based on evaluation of defined risk elements.

The proposed fuzzy logic model for analysis and risk assessment in logistic processes presents a new approach to modeling a system or a process, which can be used in different areas of science and for practical purposes. The AHP and FAHP models provide a relatively simple process of decomposition of total risk in logistics processes to defined risk elements, and obtaining of data on percentage share of each element in total risk. The fact is that these models do not have the necessary flexibility, since for every change of risk parameter of the logistics process it is necessary to change input parameters of the model, test data consistency by decision-makers, and carry out any corrections in order to obtain acceptable results. This means re-engagement of experts, implementation of new data, and repeating the process in order to obtain a new structure for the adjusted models. On the other hand, the fuzzy model is flexible, which means it enables a relatively simple correction of model parameters. Considering dynamic and changeable characteristics of logistic systems and processes, weight factors of risk elements can be simply corrected in the fuzzy model, which enables efficient implementation of new information on risks. Also, the fuzzy model ensures more precise numerical value of total risk of a specific logistic process within the observed class.

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