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A Fuzzy Model for Assessing Risk of Occupational Safety in the Processing Industry

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Managing occupational safety in any kind of industry, especially in processing, is very important and complex. This paper develops a new method for occupational risk assessment in the presence of uncertainties. Uncertain values of hazardous factors and consequence frequencies are described with linguistic expressions defined by a safety management team. They are modeled with fuzzy sets. Consequence severities depend on current hazardous factors, and their values are calculated with the proposed procedure. The proposed model is tested with real-life data from fruit processing firms in Central Serbia.

occupational safety risk assessment uncertainty fuzzy sets

1. INTRODUCTION

During the past few decades, the use of quantified risk assessment of the problems of managing occupational safety has dramatically increased especially within the processing industry. The importance of this issue is closely connected with environmental problems in developing countries, and linked with social and economic aspects, which must be considered in the development of any environmental program or regulation.

In the literature, there are numerious definitions of risk. Chia listed some common ones [1]:

- a risk is a future event that may or may not occur;
- a risk must also be an uncertain event or condition that, if it occurs, has an effect on at least one of the objectives;
- the probability of the future event occurring must be higher than zero but lower than 100%. Future events that have a zero or 100% chance of occurrence are not risks;
- the impact or consequence of the future event must be unexpected or unplanned for.

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The considered problem comprises the following phases: identifying hazardous factors, assessing values of the consequences caused by each and every identified hazardous factor and its frequencies, determining hazardous factors which influence the occurrence of a risk the most, and determining the overall risk.

Hazardous factors can be decomposed with brainstorming or a checklist. For instance, there are numerous hazardous factors in a workplace: chemical, biological, related to equipment hazards; management and human factors also act as modifiers of hazards. They greatly affect workers' occupational health and safety (OHS). Without effective health and safety management, businesses will lose not only money but also their key workers. The true cost of treating workers who have suffered an injury in the workplace can far outweigh the cost of preventing an accident [2]. However, when talking about losses, the situation could become even worse if equipment, buildings or even the whole plant were lost.

Any identified hazardous factor can result in health, property and environmental consequences or a combination of them. When determining consequences, there may be a variety of problems, e.g., incorrect identification of the types of consequences or of the interactions among those consequences. In practice, determination of frequencies is based on the number of accident outcome cases. Thus, the correctness of obtained values of frequency depends on how accurately events are selected.

In recent years, researchers made a significant effort to increase our knowledge and understanding of both consequences and frequencies of undesirable incidents. It is obvious that those parameters are characterized by the presence of different kinds and types of imprecision, randomness and ambiguity.

In its use of approximate information and uncertainty to generate decisions, the fuzzy set theory resembles human reasoning. There are numerous advantages of the fuzzy approach in modeling of uncertainties over other techniques and methods. Fuzzy approaches to treating uncertainties in real-world applications have several advantages: (a) they are conceptually easy to understand, (b) they can capture most nonlinear relations in problems of arbitrary complexity, (c) they are based on a natural language, (d) they can be built on the basis of expertise and (e) they can be combined with conventional methods and techniques for dealing and reasoning with uncertain data [3]. The most important advantage is the possibility to present expert knowledge in a natural language, which is the most advanced form of communication (in accordance with the long history of optimization) [4]. Fuzzy logic enables us to emulate the human reasoning process and make a decision on the basis of vague or imprecise data [5].

Many research papers state that consequence severities are the main cause of uncertainties existing within safety management problems. They are described with different linguistic expressions [6, 7, 8, 9]. In safety and reliability analysis, membership functions are defined with typical convex triangular and trapezoidal functions. Some papers describe frequencies with linguistic expressions which are modeled by applying the fuzzy set theory [6, 7, 9].

Identified hazardous factors do not have the same influence on, e.g., priority for risk occurrence. Zeng, An and Smith [7] use an analytic hierarchy process [10] to determine the priority of hazardous factors at each hierarchical level. Aggregate importance assessment for each pair of identified hazardous factors is calculated with the arithmetic averaging method [10]. Nieto-Morote and Ruz-Vila develop an algorithm to handle the inconsistences in the fuzzy preference of a pairwise comparison matrix [9]. Priority of hazardous factors at the first hierarchical level is obtained with the procedure developed in this paper. Sii, Ruxton and Wang determine the importance of every group of hazardous factors and hazardous factors preferability within each group with the analytic hierarchy process [6].

There are many different risk assessment procedures. Sii et al. [6] determine the value of risk for each group of identified hazardous factors with fuzzy IF–THEN rules [11]. If hazardous factors are independent, the rules are interpreted as a single fuzzy relation [11, 12]. The overall risk is calculated as a sum of the risks associated with each group of hazardous factors and its weight. Nieto-Moroto and Ruz-Vila, in the fuzzy interference step of risk analysis, convert the aggregated fuzzy numbers into a fuzzy number that represents the overall risk factor of each hazardous factor [9]. The overall risk of each hazardous factor is calculated as a product of consequence severity and frequency probability divided by risk discrimination. By applying the defuzzification method, a representative scalar of fuzzy number, which describes the overall risk factor, is obtained. This scalar value is the output of the procedure of fuzzy risk assessment. It presents a final risk rating. Zeng et al. introduce the factor index to structure and evaluate risk probability and consequence severity and to integrate them into the decision making process in risk assessment [7].

The basic requirements are to provide a method for determining the risk of occupational safety in the processing industry. The main goal of this paper is to provide a reliable method which could be used to decrease expenditure and to increase the efficiency of OHS management in the processing industry. To this end, a new method of classifying hazardous factors is developed. It helps determine hazardous factors with highest priorities; the overall risk of occupational safety management depends on hazardous factors with highest priorities. The advantage of this model over experimental research is reduced time and cost. Practical results in the environment of the processing industry should be used to determine hazardous factors which influence risk occurrence the most, the overall risk of occupational safety as well as cost reduction. The contribution of this paper is the following: values of hazardous factors are determined with the proposed fuzzified Delphi method; analysis and presentation of results in the proposed fuzzy Delphi method is close to human reasoning; a procedure for determining consequence severities for each hazardous factor depending on its value is developed; consequence severity of each hazardous factor is given by applying a fuzzy comparison procedure [13]; a new procedure for determining hazardous factors with highest priorities is developed; it is possible to determine a measure of belief that the rank of identified hazardous factors is stable. Assessing the overall risk of safety management is based on the fuzzy algebra rules [14, 15]. An illustrative example with real data of the application of the proposed method for assessing risk of OHS management problem is given.

The paper is organized as follows: section 2 presents the basis of the fuzzy set theory and the procedures for modeling uncertainties existing within the model; section 3 describes the proposed fuzzy model for classifying identified hazardous factors and for determining the overall risk of safety management in the processing industry; section 4 presents the results obtained with the newly developed fuzzy model for real-life data; the conclusion is given in section 5.

2. SOURCES OF UNCERTAINTY IN CLASSIFYING HAZARDOUS FACTORS

This section describes the basis of the fuzzy set theory and modeling of all uncertainties in the considered problem. A safety management team (SMT) does the fuzzy rating of uncertainties; its members are engineers who are experts in mechanical engineering, electroengineering, chemistry, biology, etc.

2.1. Basis of Fuzzy Set Theory

This section introduces basic definitions and notions important for understanding the fuzzy model used in this paper [16].

2.1.1. Definition 1

A fuzzy set is defined as a set of organized pairs:

$$\tilde{A} = \left\{ x, \mu_{\tilde{A}}(x) \mid x \in X,\, 0 \le \mu_{\tilde{A}}(x) \le 1 \right\}, \quad (1)$$

where fuzzy set $\tilde{A}$ is defined on the universe set $X \in R$. In general, set X can be either finite or nonfinite; $\mu_{\tilde{A}}(x)$—membership function of fuzzy set $\tilde{A}$. Each fuzzy set is completely and uniquely determined by its membership function.

2.1.2. Definition 2

A fuzzy number $\tilde{A}$ is a convex normalized fuzzy set $\tilde{A}$ of the real line R such that if there is $x_0 \in R$ such that $\mu_{\tilde{A}}(x_0) = 1$, $\mu_{\tilde{A}}(x)$ is piecewise continuous.

2.1.3. Definition 3

Fuzzy number $\tilde{A}$ on R is to be a triangular fuzzy number if its membership function R is equal to $\mu_{\tilde{A}}(x)$: R→[0, 1] is equal to

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-l}{m-l} & x \in [l, m] \\ \dfrac{x-u}{m-u} & x \in [m, u] \\ 0 & \text{otherwise} \end{cases}, \qquad (2)$$

where $l \le m \le y$; l, u—lower and upper value of the support of X, respectively; m—modal value. The triangular fuzzy number can be denoted with (l, m, u). The support of X is the set of elements $\{x \in R \mid l < x < u\}$ When $l = m = u$, it is a non-fuzzy number by convention.

2.1.4. Definition 4

The α-cut of the fuzzy number is defined as

$$\left(\tilde{A}\right)^{\alpha} = \left\{ x \mid \mu_{(\tilde{A})^{\alpha}}(x) \ge \alpha,\ x \in X \right\}, \qquad (3)$$

where $\alpha \in [0, 1]$.

The symbol $\left(\tilde{A}\right)^{\alpha}$ represents a nonempty bounded interval contained in X, which can be denoted with $\left(\tilde{A}\right)^{\alpha} = \left[l_{\tilde{A}}^{\alpha}, u_{\tilde{A}}^{\alpha}\right]$, where $l_{\tilde{A}}^{\alpha}, u_{\tilde{A}}^{\alpha}$—lower and upper bounds of the closed interval, respectively [17].

2.1.5. Definition 5

The operations of fuzzy numbers are based on Dubois and Prade's theorem [16]. Let two fuzzy numbers $\tilde{A} = \{x, \mu_{\tilde{A}}(x) \mid x \in R\}$ and $\tilde{B} = \{y, \mu_{\tilde{B}}(y) \mid y \in R\}$. The membership functions of these fuzzy numbers are monotonous and subjective from zero to one and * is a continuous binary operation. Then $\tilde{A} * \tilde{B}$ is a fuzzy number which is denoted $\tilde{C} = \tilde{A} * \tilde{B}$, such that $\tilde{C} = \{z, \mu_{\tilde{C}}(z) \mid z \in R\}$. Values in the domain of fuzzy number $\tilde{C}$ can be calculated as

$$z = x * y \text{ and } \mu_{\tilde{C}}(z) = \sup_{z = x*y} \min\left(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y)\right). \qquad (4)$$

2.1.6. Definition 6

Arithmetic defuzzification means extracting a single scalar value from the fuzzy set which most appropriately represents the fuzzy set. The moment rule is the most often used defuzzification technique. It takes as a representative scalar the projection of the centre area under membership function curve to the *x* axis [14].

2.2. Modeling Consequence Severities

This section presents the proposed method, which helps determine consequences caused by hazardous factors. The value of any type of consequence of each hazardous factor depends on the current value of the hazardous factor. The proposed method has three stages:

1. the value of every considered hazardous factor is determined with the extended fuzzy Delphi method;
2. the SMT determine the value of any type of consequence caused by a considered hazardous factor on the basis of the determined value of that factor; and
3. the highest value of a consequence is maintained.

We suggest a method for determining criteria values based on the Delphi method. The Delphi method accumulates and analyses the results of anonymous experts (the SMT in this paper) who communicate on a particular topic in written, discussion and feedback formats. Probably, the SMT should not be too large, it should have a minimum of five and a maximum of ~50 members [18]. In this study, there are six decision makers in the Delphi method. In our opinion, the Delphi method is an absolutely suitable method to aggreggate opinion of many decision makers into a unique assessment of the relative importance of criteria.

It is more natural and closer to human reasoning for decision makers to express their opinion and attitude with linguistic expressions than with numerical scales. It is assumed that each decision maker of the SMT assesses the value of each hazardous factor. Vague expressions are used to describe the values of hazardous factors: *very* *low value*, *low value*, *low medium value, medium value, high medium value, high value* and *very high value*. The meanings of the seven expressions are defined with triangular fuzzy numbers. On that basis, we used a horizontal method of estimating membership [19].

The domain of each triangular fuzzy number is defined on a [0–1] scale.

very low value	(y; 0, 0, 0.1)
low value	(y; 0, 0.15, 0.3)
low medium value	(y; 0.1, 0.25, 0.4)
medium value	(y; 0.25, 0.45, 0.65)
high medium value	(y; 0.5, 0.65, 0.8)
high value	(x; 0.7, 0.85, 1)
very high value	(y; 0.9, 1, 1)

In the literature, there are different approaches to modifying the Delphi method. In this paper, we compute a unique assessment of the relative importance of criteria with the average method (which is, according to the rules of fuzzy algebra, also a fuzzy number), which is analogous to the conventional Delphi method and the methods found in the literature, $\tilde{v}_i^I = \frac{1}{E} \cdot \sum_{e=1}^{E} \tilde{v}_i^e, e = 1, \ldots, E$. Calculating distances of the obtained fuzzy number from all previously defined fuzzy numbers which describe the values of hazardous factors follows, $d_n\left(\tilde{v}_i^I\right)$ [20]. This information is sent to decision makers. We find information presented in that way is absolutely clear and easy to understand by decison makers. They estimate the values of hazardous factors in the second iteration, on the basis of given information. The values of hazardous factors are calculated with the average method, $\tilde{v}_i$, $i = 1, \ldots, I$. The way data are processed and presented is the main difference between the proposed method and other modified Delphi methods.

A description of the procedure for determining values of the consequences of hazardous factors on the basis of the obtained values, $\tilde{v}_i$, $i = 1, \ldots, I$ which is realized in the second stage, follows.

In this paper, we suppose that consequence severities are the SMT's subjective judgments and they are described with linguistic expressions. The following linguistic expressions can be used: *low severity*, *moderate severity* and *high severity.* The membership functions of the corresponding triangular fuzzy numbers are given on a [0–1] scale (Figure 1). Zero indicates that the consequence severity caused by the considered hazardous factor is the lowest, whereas one indicates the highest consequence severity.

low severity	(0, 0, 0.3)
moderate severity	(0.2, 0.5, 0.8)
high severity	(0.7, 1, 1)

For each $\tilde{v}_i$, $i = 1, \ldots, I$ and for every consequence type t, $t = 1, \ldots, T$, the distance $d_{it}\left(\tilde{v}_i\right)$ from linguistic expressions which describe values of consequence is calculated. Consequence severity caused by hazardous factor i, $i = 1, \ldots, I$ is calculated on the basis of the relation $\tilde{c}_i = \max_{t=1,\ldots,T} \tilde{c}_{s_t}\left(y; l_s, m_s, u_s\right)$, $s = 1, \ldots, S$; $t = 1, \ldots, T$; $i = 1, \ldots, I$ [13, 16].

2.3. Estimating Frequency of Hazardous Factor

The frequency of the occurrence of a hazardous factor is determined on the basis of the SMT's estimates. They base their estimation on evidence, experience and knowledge. In this paper, the following linguistic expressions describe frequency values:

very low frequency	(0, 0, 0.2)
low frequency	(0.1, 0.2, 0.3)
medium frequency	(0.3, 0.5, 0.7)
high frequency	(0.7, 0.8, 0.9)
very high frequency	(0.8, 1, 1)

Triangular fuzzy numbers define the meanings of the five expressions. On that basis, we use a horizontal method of estimating membership [19]. The domains of those triangular fuzzy numbers are defined on a real line. Zero denotes no influence of a hazardous factor, whereas one denotes the greatest influence of a hazardous factor on occupational risk in the processing industry.

3. PROPOSED FUZZY MODEL

This section presents the proposed method of assessing fuzzy risk. Firstly, we give the notation used in the developed model.

3.1. Notation

i—identified hazardous factor, $i = 1, \dots, I$

I—total number of identified hazardous factors

$\tilde{v}_i$—a triangular fuzzy number $(x; l_i, m_i, u_i)$ describing consequence severity value influenced by hazardous factor i, decision maker e, $i = 1, \dots, I$; $e = 1, \dots, E$

$\tilde{v}_i$—a triangular fuzzy number $(x; L_i, M_i, U_i)$ describing aggregated value of consequence severity influenced by hazardous factor i, $i = 1, \dots, I$

$\tilde{c}_{it} = (y; l_{it}, m_{it}, u_{it})$—a triangular fuzzy number $(y; l_{it}, m_{it}, u_{it})$ describing value of consequence severity of type t influenced by hazardous factor i, $i = 1, \dots, I$; $t = 1, \dots, T$

$\tilde{c}_i = (y; l_i, m_i, u_i)$—a triangular fuzzy number $(y; l_i, m_i, u_{it})$ describing value of consequence severity influenced by hazardous factor i, $i = 1, \dots, I$; $t = 1, \dots, T$

3.2. Proposed Model

Hazardous factors are the major cause of accidents and occupational injuries in any industrial branch, especially in the processing industry. In this paper, they are indexed with $i = 1, \dots, I$. The proposed model is realized in the following phases.

In the first phase, the SMT identify hazardous factors. For each hazardous factor, a current value is determined in the second phase. These values are the basis for calculating the severity of any type of consequence caused by the influence of the treated hazardous factor. In this paper, fuzzy rating of the value of each hazardous factor by each decision maker e, $e = 1, \dots, E$ is described with one of five linguistic expressions modeled with triangular fuzzy numbers $\tilde{v}_i^e = (x; l_i, m_i, u_i)$, $i = 1, \dots, I$, where l_i, u_i—lower, upper bounds, respectively; m_i—modal value. Triangular number domains $\tilde{v}_i$, $i = 1, \dots, I$ are defined on a set of real numbers in the [0–1] interval. Zeri denotes the lowest value of a hazardous factor, whereas one denotes the highest one. Aggregated fuzzy rating of the value of a hazardous factor $\tilde{v}_i$, $i = 1, \dots, I$ is obtained with the fuzzified Delphi method developed in this paper.

In this paper, the value of any consequence type t, $t = 1, \dots, T$ caused by the influence of hazardous factor i, $i = 1, \dots, I$ can be adequately described with one of the three previously defined linguistic expressions modeled with triangular fuzzy numbers $\tilde{c}_{it} = (y; l_{it}, m_{it}, u_{it})$, where l_{it}, u_{it}—lower and upper bounds, respectively; m_{it}—modal value. Triangular fuzzy number domains are defined in the [0–1] interval. Zero denotes that the severity consequence is the lowest; one that is it the highest. The value of severity consequence caused by the influence of hazardous factor i, $i = 1, \dots, I$, $\tilde{c}_i = (y; l_i, m_i, u_i)$ is obtained from the relation $\tilde{c}_i = \max_{t=1,\dots,T} \tilde{c}_{it} = (y; l_{it}, m_{it}, u_{it})$, $t = 1, \dots, T$; $i = 1, \dots, I$. First, $\tilde{c}_{it}{*}$ with the highest modal value is found and fuzzy elements of matrix $\tilde{c}_{ist}$ are ranked in decreasing order of their modal values m_{it}, $i = 1, \dots, I$. $\tilde{c}_i{*}_t$ is the first in this sequence. The rank of fuzzy numbers, $i = 1, \dots, I$, corresponds to the rank of consequences of different types caused by the influence of hazardous factor i, $i = 1, \dots, I$.

In a similar way, the frequency of each hazardous factor is described with a triangular fuzzy number $\tilde{f}_i = (z; a_i, b_i, c_i)$, where a_i, c_i—lower and upper bounds, respectively; b_i—modal value. Triangular fuzzy number $\tilde{f}_i$ is selected from the set of five linguistic expressions defined in section 3.2. In this way, each hazardous factor i, $i = 1, \dots, I$, is characterized with fuzzy pair $(\tilde{c}_i, \tilde{f}_i)$, which represents its fuzzy consequence and fuzzy frequency.

The values of the considered hazardous factors and, therefore, the values of the consequences caused by the influence of those factors as well as the values of frequency can change with time due to changes in the environment or in the workplace. All those changes lead to changes in the importance of hazardous factors which may cause a risk.

The third phase of the proposed model comprises classifying identified hazardous factors with respect to severity consequences and their frequencies. The main goal of the classification can be defined in the following way: the SMT undertake necessary management activities for the highest priority hazardous factors, which leads to more efficient OHS management. Namely, this provides a higher degree of occupational safety in a shorter time, with less effort and invested money, which again has a critical effect on increasing the competitive advantage of fruit growing and processing companies. This paper develops and presents a new classification method.

Crisp value 1, with membership degree 1, represents the highest consequence. Similarly, crisp value 1, with membership degree 1, represents the highest frequency. Thus, the reference point *refA* according to which risk assessment is determined is given with the pair of two crisp values (1, 1). To determine the rank of hazardous factor i, i = 1, … , I, the Euclidian distance of hazardous factor i, represented as $\left(\tilde{c}_i, \tilde{f}_i\right)$ from the reference point *refA*, is determined:

$$\text{dist (i, } refA) = \sqrt{\left(1-\tilde{c}_i\right)^2 + \left(1-\tilde{f}_i\right)^2}.$$

As $\tilde{c}_i$ and $\tilde{f}_i$ are fuzzy numbers, their distance to *refA* is also a fuzzy number. The supports of $\tilde{c}_i$ and $\tilde{f}_i$ can be described in discrete forms with discrete points c_{ij_i}, $j_i = 1, \dots, J_i$ and f_{ik_i}, $k_i = 1, \dots, K_i$. Then, *dist*(i, *refA*) has the value

$\sqrt{\left(1-\cdot c_{ij_i}\right)^2 + \left(1-f_{ik_i}\right)^2}$ with membership degree $\min\left(\mu_{\tilde{c}_i}\left(c_{ij_i}\right), \mu_{\tilde{f}_i}\left(f_{ik_i}\right)\right)$.

Once the fuzzy distances of all hazardous factors from *refA* are calculated, they are ranked in ascending order, using a fuzzy number ranking procedure given in the Appendix (p. 126).

Then, we determine the measure of belief that a lower rank hazardous factor ranks first. According to the calculated measures of belief, the SMT determine the number of hazardous factors with the greatest influence on occupational risk assessment.

In the last phase of the proposed model, the value of overall risk is determined. This risk is caused by the influence of hazardous factors which influence the risk occurrence to the highest degree, $\tilde{R}$:

$$\tilde{R} = \bigcup_m \tilde{c}_m \cdot \tilde{f}_m, \ m \in I\ I = \{1, \dots, i, \dots, I\}.$$

Let us determine representative scalar fuzzy number $\tilde{R}$: $R = \text{defuzz } \tilde{R}$.

4. CASE STUDY

This section tests the proposed model on real data from fruit processing factories in Central Serbia. The fruit processing sector is part of the food processing industry, one of the largest manufacturing sectors. Therefore, it is crucial for the economic development of every country (this is Europe's second largest manufacturing sector). For numerous reasons, the fruit industry has become a very interesting research area in the past decade. There are standards which control food safety (HACCP [21] and Standard No. ISO 22000:2005 [22]). However, not enough attention is paid to the safety of workers in the fruit processing industry. Thus, it is necessary to look into this problem more thoroughly, primarily because it could negatively affect the health and safety of numerous fruit industry workers [23]. The hazardous factors considered in this paper result from experimental research of the

TABLE 1. Checklist for Identifying Hazardous Factors

Hazardous Factor		Description
h = 1	uneven or slippery surfaces	The condition of floors must not cause slips, trips, falls, etc.
h = 2	moving vehicles and machines	Paths should be defined for moving devices and apparatus.
h = 3	moving parts of machines	It is necessary to define the danger zones near devices.
h = 4	objects and parts with dangerous surface	There are sharp edges on devices, unsecured parts, etc.
h = 5	fire	There is fire hazard.
h = 6	lifting and carrying loads	Manual material handling is poor.
h = 7	biological hazards	Dangerous biological substances are used in the work process.

TABLE 2. Hazardous Factors: Consequence Severity and Frequency

Hazardous Factor	Consequence Severity	Frequency
h = 1	*moderate severity*	*high frequency*
h = 2	*high severity*	*very low frequency*
h = 3	*moderate severity*	*moderate frequency*
h = 4	*high severity*	*very high frequency*
h = 5	*low severity*	*very low frequency*
h = 6	*high severity*	*high frequency*
h = 7	*moderate severity*	*low frequency*

TABLE 3. Hazardous Factors: Rank

Hazardous Factor	*dist* (i, *refA*)	Rank	Degree of Belief That Hazardous Factor Ranks First
h = 1	{(0.22, 0), … , (0.54, 1), … , (0.85, 0)}	3	0.21
h = 2	{(0.8, 0), … , (0.9, 1), … , (1.04, 0)}	5	0
h = 3	{(0.36, 0), … , (0.71, 1), … , (1.06, 0)}	4	0
h = 4	{(0, 1), … , (0.36, 0)}	1	1
h = 5	{(1.06, 0), … , (1.41, 1)}	7	0
h = 6	{(0.1, 0), … , (0.2, 1), … , (0.42, 0)}	2	0.56
h = 7	{(0.73, 0), … , (0.94, 1), … , (1.2, 0)}	6	0

Notes. dist (i, *refA*)—Euclidian distance of hazardous factor i from the reference point *refA.*

Health and Safety Executive (HSE) [24] in berry growing and processing. Their research was based on data on numerous irregularities in factories for berry growing and processing, and estimates of the situation in factories visited during that study. A list of hazardous factors which influenced occupational safety in those factories was defined on the basis of the obtained data (Tables 1–3).

Hazardous factor h = 4 (Objects and parts with a dangerous surface) has the greatest influence on occupational risk assessment in the considered fruit processing companies in Central Serbia. Hazardous factor h = 6 (Lifting and carrying loads) comes second. According to the calculated measures of belief that hazardous factors can rank first, the SMT can decide that occupational risk is caused by the influence of those two factors.

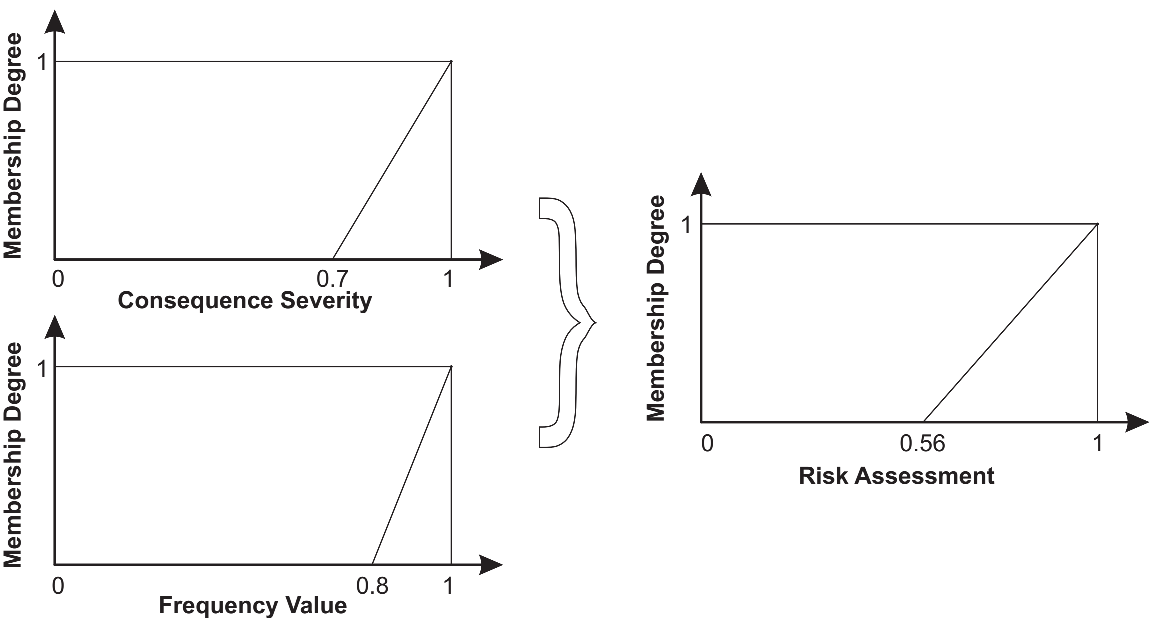

Figure 1. Assessment of risk caused by the influence of objects and parts with a dangerous surface.

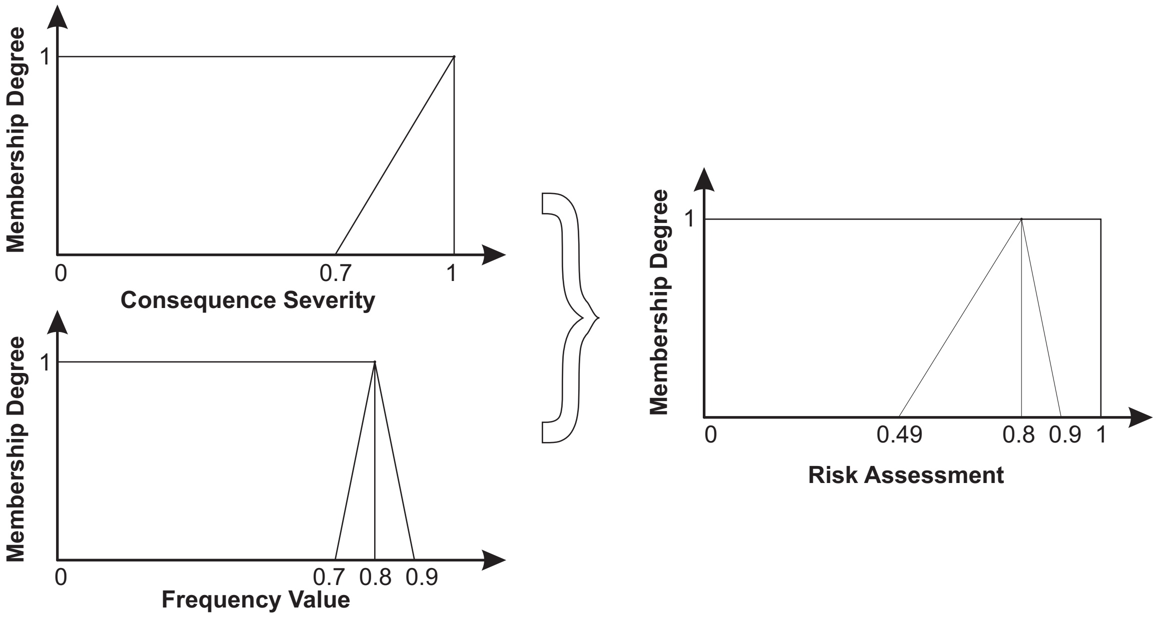

Figure 2. Assessment of risk caused by the influence of lifting and carrying loads.

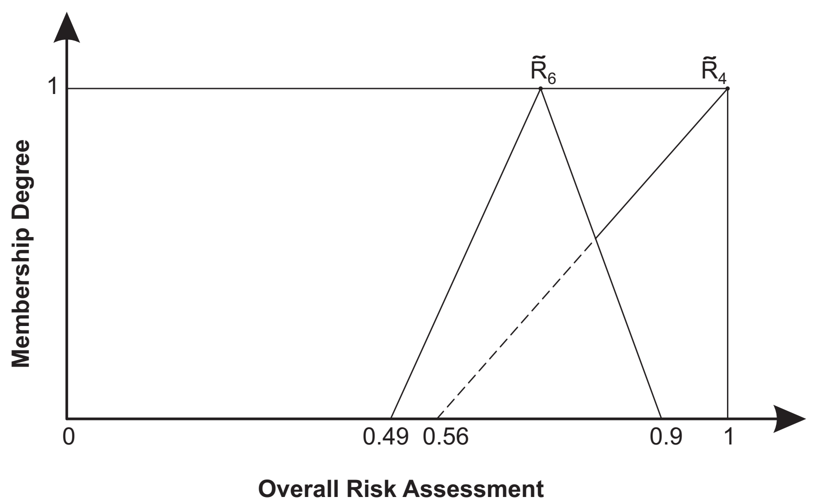

Figure 3. Overall assessment of risk caused by the influence of objects and parts with a dangerous surface and lifting and carrying loads.

Figures 1–2 show occupational risk caused by the influence of objects and parts with a dangerous surface, and caused by the influence of lifting and carrying loads, respectively. Figure 3 shows the overall risk caused by the influence of both hazardous factors. Defuzzified risk value is R = 0.8.

On the basis of the calculated value of the overall risk in the considered fruit processing factories in Central Serbia, it can be concluded that it is very high. The SMT define the plan of developing a procedure on the basis of the obtained ranking. It is clear that the first procedures to develop are for top ranked hazardous factors. Of course, it should be borne in mind that ranking hazardous factors, according to the proposed model, is a continual process, which should be followed by constant improvement in OHS.

5. CONCLUSION

Changes that take place in the business environment cause further changes in a company's organization and management. Risk management is an important, complex problem. A solution to this problem is necessary in all parts of a company, which makes it the most critical factor for successful business activities.

The SMT's experience and knownledge helped identify seven hazardous factors that are the most relevant for risk assessment in the fruit processing industy. The current values of those factors are described with linguistic terms modeled with fuzzy sets. The corresponding membership functions are determined on the basis of the SMT's experience. This paper develops a procedure for determining values of consequences caused by the influence of hazardous factors, depending on their values. This is one of the contributions of the paper. Frequencies are described with linguistic expressions and are modeled with triangular fuzzy numbers. To increase management efficiency, the SMT should classify identified hazardous factors according to their priorities. The developed classification procedure can handle consequences values and their frequencies.

The overall risk is determined in an exact way by applying fuzzy algebra rules. Any solution gained in an exact way is less burdened with the subjective attitudes of the decision makers, thus being more precise, which further influences the precision and effectiveness of OHS management.

The proposed model is flexible: (a) all changes, e.g., in the number of hazardous factors or their consequence severities or frequency values, and the shape of the membership function of fuzzy numbers can be easily incorporated into the model and (b) the fuzzy model can be modified to solve problems in occupational risk in different industries.

The effectiveness of the proposed model is tested with real-life data of the HSE in berry growing and processing [24]. In addition, it is demonstrated how the proposed model can be used to determine the measure of belief that a hazardous factor ranks first. This can further lead to more stable classification of hazardous factors, and consequently, to more efficient and effective risk management.

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APPENDIX

The procedure for determining a measure of belief that linguistic value $\tilde{M}$ is lower than linguistic value $\tilde{N}$, $bel(\tilde{M} < \tilde{N})$ follows Petrović and Petrović [25]. The measure $bel(\tilde{M} < \tilde{N})$ is defined as the probability that a crisp value $m \in$ support $(\tilde{M})$ is lower than a crisp value $n \in$ support $(\tilde{N})$:

$$bel(\tilde{M} < \tilde{N}) = \text{Prob}\ (\text{m} < \text{n}),$$

where support of a fuzzy set is a crisp set with all the elements of the fuzzy set which have nonzero membership degrees.

Let support$(\tilde{M}) = \{m_1, m_2, \ldots, m_M\}$ and support$(\tilde{N}) = \{n_1, n_2, \ldots, n_N\}$. The probability of taking a crisp value m_l such that $m_l \in$ support $(\tilde{M})$ is

$$P_{\tilde{M}}(m_l) = \frac{\mu_{\tilde{M}}(m_l)}{\sum_{j=1}^{M} \mu_{\tilde{M}}(m_j)}.$$

The probability of taking a crisp value which is lower than or equal to m_l is

$$\Phi_{\tilde{M}}(m_l) = \sum_{j=1}^{l} P_{\tilde{M}}(m_j).$$

Consequently, the probability of taking a crisp value that is higher than m_l is $1 - \Phi_{\tilde{M}}(m_l)$.

Under the assumption that random values defined on support$(\tilde{M})$ and support$(\tilde{N})$ are independent, the following holds:

$$bel(\tilde{M} < \tilde{N}) = \sum_{l=1}^{M} \text{Prob}\ [m = m_l \wedge\ n > m_l] = \sum_{l=1}^{M} P_{\tilde{M}}(m_l)\ \ [1 - \Phi_{\tilde{N}}(m_l).$$

In addition, the following relationship holds:

$$bel(\tilde{M} < \tilde{N}) = 1 - bel(\tilde{M} \geq \tilde{N}).$$

Finally, the measure of belief that linguistic value $\tilde{M}$ is lower than linguistic value $\tilde{N}_1$ and linguistic value $\tilde{N}_2$ and linguistic value $\tilde{N}_3$, etc., is

$$bel(\tilde{M}\ < \{\tilde{N}_1 \wedge \tilde{N}_2 \wedge \tilde{N}_3 \wedge\ \ldots)\} = \min\ \{bel(\tilde{M}\ <\ \tilde{N}_1),\ bel(\tilde{M}\ < \tilde{N}_2),\ bel(\tilde{M} < \tilde{N}_3),\ \ldots\}.$$