simply "be translated into a programming language." At this stage, the program is a console application in which you want to set a matrix of weights (the program asks for a specific value, the user enters it), and then a starting and final points are requested and the shortest way is calculated. In the future, we plan to issue a more intuitive and simple interface, add a graphical representation of the network, add some modifications of the algorithm.

The program will be useful for pupils and students in order to understand Dijkstra's algorithm while dealing with the problem of finding the shortest way. The program is also useful for teachers to test the solutions pupils and students find quicker. Developing this project, you can get quite an interesting, useful product, besides being unique and versatile.

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APPLICATION OF FUZZY LOGIC IN MODEL OF OCCUPATIONAL RISK ASSESSMENT

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The paper discusses the use of fuzzy logic in the problem of occupational risk assessment.

Soft computing includes fuzzy logic, neural networks, probabilistic reasoning, and genetic algorithms. Today, techniques or a combination of techniques from all these areas are used to design an intelligence system. Neural networks provide algorithms for learning, classification, and optimization, whereas fuzzy logic deals with issues such as forming impressions and reasoning on a semantic or linguistic level.

Fuzzy logic was initiated in 1965 [1] by Lotfi A. Zadeh, professor for computer science at the University of California in Berkeley. Basically, fuzzy logic is a multivalued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking in the programming of computers [2].

In 1993 Kosko (Kosko) proved a theorem on fuzzy approximation (FAT – Fuzzy Approximation Theorem) [3], which states that any mathematical system can be approximated by a system of fuzzy logic. Therefore, using natural language rules "If – then" followed by their formalization by means of the theory of fuzzy sets can be any arbitrary accurately reflect the relationship "Input Output" without the use of complex apparatus of differential and integral calculus, traditionally used in the management and identification.

Fuzzy logic has emerged as a profitable tool for the controlling and steering of systems and complex industrial processes, as well as for household and entertainment electronics, as well as for other expert systems and applications like occupational risk assessment.

In the real world, vagueness and ambiguity exist because of the limitations of our language and other factors, such as context and perception. Closely related to this ambiguity is the question of lexical imprecision in natural language; when expressing knowledge, individuals would rather use words than numbers.

Occupational risk assessment deals with uncertain situations, that is, situations in which we do not have complete and accurate knowledge about the system state, such as estimate severity consequences of occupational accidents.

Additionally, legal records, statistical data and site documentation produced by companies are generally insufficient for determining risks. On-site inspections generally use linguistic expressions rather than metrics to assess the safety risks. These facts increase the imprecision and inaccuracies of the occupational risk assessment process, and this imprecision is the reason why we use a fuzzy approach.

For systems in which imprecise and inaccurate information is available, fuzzy concepts and techniques provide suitable ways to collect observed input data and represent it in a uniform and scalable way. Fuzzy sets seem to be quite relevant in three classes of applications: classification and data analysis, reasoning under uncertainty, and decision-making problems.

In our work, we use the lattermost application of decision making because it will allow the combination of all risk factors using aggregation operators to define a general level of risk assessment.

A fuzzy inference system (FIS) essentially defines a nonlinear mapping of the input data vector into a scalar output, using fuzzy rules. The mapping process involves input/output membership functions, FL operators, fuzzy if – then rules, aggregation of output sets, and defuzzification.

The FIS contains four components: the fuzzifier, inference engine, rule base, and defuzzifier. The rule base contains linguistic rules that are provided by experts. It is also possible to extract rules from numeric data. Once the rules have been established, the FIS can be viewed as a system that maps an input vector to an output vector. The fuzzifier maps input numbers into corresponding fuzzy memberships. This is required in order to activate rules that are in terms of linguistic variables. The fuzzifier takes input values and determines the degree to which they belong to each of the fuzzy sets via membership functions. The inference engine defines mapping from input fuzzy sets into output fuzzy sets. It determines the degree to which the antecedent is satisfied for each rule. If the antecedent of a given rule has more than one clause, fuzzy operators are applied to obtain one number that represents the result of the antecedent for that rule. It is possible that one or more rules may fire at the same time. Outputs for all rules are then aggregated. During aggregation, fuzzy sets that represent the output of each rule are combined into a single fuzzy set. The defuzzifier maps output fuzzy sets into a crisp number. Several methods for defuzzification are used in practice, including the centroid, maximum, mean of maxima, height, and modified height defuzzifier. The most popular defuzzification method is the centroid, which calculates and returns the center of gravity of the aggregated fuzzy set. FISs employ rules. However, unlike rules in conventional expert systems, a fuzzy rule localizes a region of space along the function surface instead of isolating a point on the surface. Also, in an FIS, multiple regions are combined in the output space to produce a composite region. A general schematic of an FIS is shown in Figure.

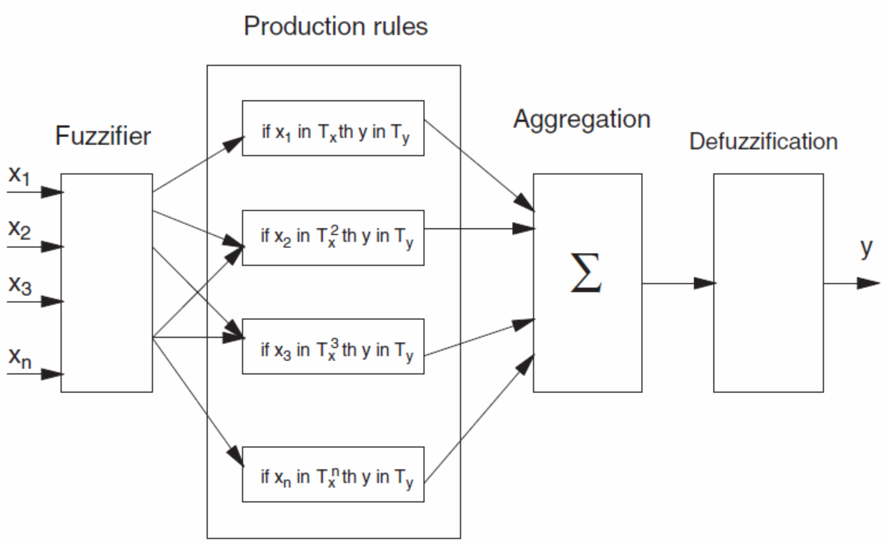

Fig. Schematic diagram of a fuzzy inference system

The fuzzy model includes three fuzzy inference systems FS_1, FS_2 and FS_3 [4].

Input variables of the first fuzzy inference system: the probability (frequency) of hazard (P_i), which considers prescription of accident (K_i), severity of the consequences of hazards influence (S_i) and the duration of hazards exposure (D_i). An output variable of the first fuzzy inference system is a level of occupational risk ($R_{ОПФi}$), which caused by unsafe hazard. The level of occupational risk is used as a basis for making a decision about the necessity of risk management actions.

Two variables are accepted in second fuzzy inference system: class working conditions – ($КУТ_i$) and relative risk (OP_j) for a certain class of diseases. The result of the fuzzy inference system is the second linguistic variable – "professional risk of effect of occupational hazard" ($R_{ВПФi}$).

The first variable of third fuzzy inference system – is hazard index ($ИВ_k$) for definite profession or to the structural subdivision. The second variable FS_3 is number of temporary disability for all illness per 100 employees ($ЗВУТ_k$). An output variable of third fuzzy inference system is "an occupational risk of complex effect of hazards" ($R_{ВПФk}$).

According to the results, employees of following subdivisions are exposed to high level risk of complex influence work environment: tankage facilities, base equipment and repair department. It is necessary to develop preventive control solutions to reduce risk.

The main advantage of using fuzzy logic in our modeling compared with other mathematical modeling techniques is the easy representation and manipulation of empirical knowledge about ill-defined concepts.

Application of the proposed fuzzy model of occupational risk assessment for health workers at oil refinery would prejudge adequate administrative decisions on elimination or limitation impact factors of production in the face of uncertainty as a result improve the quality of functioning of occupational safety management systems.

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ON THE PROPERTY OF PARTIAL UNIFORM GLOBAL ATTAINABILITY OF LINEAR CONTROL SYSTEMS

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In this paper we consider the problem of global Lyapunov reducibility of linear differential systems and shows the main results available to solve this problem. With entered our concept of partial uniform global attainability, we obtain a solution of this problem for three-dimensional systems with discontinuous and rapidly varying coefficients.

Consider a linear non-stationary control system

$$\dot{x} = A(t)x + B(t)u, \quad x \in \mathbb{R}^n, \quad u \in \mathbb{R}^m, \quad t \geqslant 0, \tag{1}$$

with locally integrable and integrally bounded matrix coefficients A and $B.$ Closing the system (1) with the control defined in the form of a linear feedback

$$u = U(t)x, \tag{2}$$

where U is a measurable and bounded $(m \times n)$ – matrix, we obtain a closed system

$$\dot{x} = (A(t) + B(t)U(t))x, \quad x \in \mathbb{R}^n, \quad t \geqslant 0, \tag{3}$$

coefficients are also locally integrable and integrally bounded. Along with (3) we also consider an arbitrary system

$$\dot{z} = C(t)z, \quad z \in \mathbb{R}^n, \quad t \geqslant 0, \tag{4}$$

with measurable integrally bounded matrix coefficients C.

The problem of global Lyapunov reducibility of linear system (3) is to construct for a system (1) a measurable and bounded control (2) that the linear system (3), closed this control will be asymptotically equivalent [1, c. 56 - 57] to system (4). This means [1, c. 57 - 58] that there will be a linear transformation relating system (3) and (4)

$$x = L(t)z,$$

matrix which satisfies

$$\sup_{t \geqslant 0}(\| L(t) \| + \| \dot{L}(t) \| + \| L^{-1}(t) \|) < \infty.$$

There $\| \cdot \|$ – is spectral (operator) norm of matrices [2, c. 355], i.e. matrix norm induced by the Euclidean norm.

The problem of global Lyapunov reducibility was formulated [3] by representatives of the Izhevsk school of mathematics Tonkov E.L. and Zaitsev V.A. in the early 90th years of the 20th century. Professor Tonkov E.L. proposed to seek a solution to this problem assuming uniform complete controllability of system (1).

Definition 1 [3, 4]. The system (1) is *uniformly completely controllable* if there are numbers $\sigma > 0,$ $\gamma > 0,$ that for any $t_0 \geqslant 0$ and $x_0 \in \mathbb{R}^n$ in interval $[t_0, t_0 + \sigma]$ there is a measurable and bounded control u at all $t \in [t_0, t_0 + \sigma]$ satisfying the inequality $\| u(t) \| \leqslant \gamma \| x_0 \|$ and transforming the vector of the initial condition $x(t_0) = x_0$ of the system (1) to zero on this interval.