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Definition of Fuzzy Conditions in the Model of Dynamic Collective Decision-Making in Emergency Evacuation Tasks in Fuzzy Conditions

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***Abstract*: Quantitative assessment in collective behavior and decision-making in fuzzy conditions is crucial for ensuring the health and safety of the population, ensuring effective response to various emergencies. The task of modeling and predicting behavior in fuzzy conditions, as is known, has increased complexity due to many factors from which an NP-complete multi-criteria task is formed. There is a difficulty in determining the quantitative assessment of the influence of fuzzy factors using a mathematical model. The paper proposes a stochastic model of human decision-making to describe the empirical behavior of subjects in an experiment simulating an emergency scenario. The developed fuzzy model combines fuzzy logic into a conventional model of social behavior. Unlike existing models and applications, this approach uses fuzzy sets and membership functions to describe the evacuation process in an emergency. The purpose of this work is to define fuzzy rules and analyze existing solutions. The scientific novelty lies in the formation of a set of factors that form fuzzy rules for making dynamic decisions. The problem statement in this paper is as follows: to form a set of factors affecting the behavior of pedestrians, which are modeled as fuzzy input data. The practical value of the work lies in the creation of a new set of fuzzy rules that allow them to be used in the evacuation algorithm [2] for the effective solution of the task. The fundamental difference from the known approaches is in the application of a new set of fuzzy rules, which contains factors: perception, intention, attitude. To implement the proposed model, the process of social behavior during evacuation, independent variables are determined. These variables include measurements related to social factors, in other words, the behavior of individual subjects and individual small groups, which are of fundamental importance at the early stage of evacuation. The results of modeling the proposed models of decision-making in fuzzy conditions are carried out, quantifying the degree of optimality of human decisions, and determining the conditions under which optimal or quasi-optimal decisions are made. Modeling has shown acceptable results of the proposed approach in solving the problem of evacuation in emergency situations in fuzzy conditions.**

Keywords: Evacuation, human factor, risk management, decision-making, fuzzy conditions, multi-criteria decision-making, intuitionistic fuzzy set, group decision-making**.**

I. Introduction

Special attention is paid to several issues in the field of evacuation. The task under consideration includes understanding how the population reacts to evacuation signals, how individual groups of people react to an obvious risk and how such groups of people make decisions about protective actions because of various emergency situations (emergencies). The available literature is quite informative in this area [1-3]. In this study, the task of forming a model for making dynamic collective decisions in emergency evacuation tasks in fuzzy conditions is considered, highlighting important aspects of evacuation decision-making, discussing studies on prevention, risk perception and studies specifically devoted to evacuation [3-5].

In recent years, research has been conducted on emergency evacuation, and many scientists have adopted various methods to study the problem, which in general can be attributed to mathematical analysis and computer modeling [3]. The method of mathematical analysis is based on a mathematical model, and the actual evacuation parameters are transformed into a solvable mathematical model, which can be divided into macroscopic models and microscopic models [4]. Microscopic models, such as the k-line automaton model, the multi-lattice model, and the probability model, consider the evacuees' individual characteristics and interactions during the evacuation process. However, the choice of the escape route during the evacuation of the area can be easily solved due to the large size of the building. Macroscopic models ignore the behavior of people during evacuation and are based on models of network flows that can solve the problem of emergency evacuation routes [5].

Tjandra [6] proposed a single-source evacuation model, which refers to the type of macroscopic models, to solve the routing problem. However, the capacity limit and the priority of the path are also important for the choice of escape routes, Chen [7] believes that escape routes can be calculated using a fast flow control algorithm to obtain several optimal escape routes. Yang [8] established a mathematical model based on the minimum evacuation time, giving priority to the saturated shortest path. In addition, it was reported about some models for optimizing escape routes in case of smoke during a fire. Coe [9] proposed a model of the shortest path based on the determination of the equivalent length at the concentration of fire smoke and the density of congestion of people. Optimal escape routes can be calculated based on the above-mentioned evacuation models, to some extent considering the uncertainty and dynamics of evacuation. However, different evacuation modes are usually re-quired to create different backgrounds.
In this paper, we mainly consider the characteristics of the

density of personnel and the spread of smoke from a fire and determine the optimal escape routes in a building with several exits by minimizing the total evacuation time. In addition, this paper investigates the method of drawing up an optimal evacuation plan, while the actual inequality of routes is not established, and the significance of an important arc in the evacuation routes is determined.

II. Evacuation planning

In this study, two main aspects are considered: predicting the behavior of a group in an emergency, making decisions more effectively than using simple random decisions; factors influencing the choice of a decision chain.

The article is aimed at solving the problem of evacuation in emergency situations in fuzzy conditions using machine learning interpretation tools. This approach will increase the effectiveness of forecasting the evacuation options of the group and will reveal the factors affecting the effectiveness of forecasting.

To simplify the description of the algorithm and the behavior model of the group, the members of the group under consideration will be considered as agents with individual characteristics.

Within the framework of the considered decision-making modeling model, aspects have been adopted that will be disclosed in more detail later.

Agents have two behavioral strategies: normal and reaction stage. Agents are in the normal stage when they perform their pre-emergency actions. Agents in the reaction stage are those who reacted to an emergency either by investigation or evacuation. This assumption is based on the model proposed in [4], which showed that evacuation behavior can be classified according to various behavioral states.

The normal stage is characterized by certain actions, such as:

- Proactive evacuation, agents move from an unprotected area to a safe place outside of that area before a disaster occurs.
- Shelter: Agents move to shelters inside a potentially unprotected area.
- Local shelter: agents move to higher levels (for example, upper floors) of multi-stored buildings, for example in case of flooding.

In the case of the reaction stage, the following actions occur:

- Rescue: moving victims with the help of rescue services to get out of the danger zone.
- Escape: salvation by the escape of the victim himself, to escape from danger after its onset.

Pre-evacuation planning and preparation are necessary to ensure effective and successful mass evacuation of the endangered population. With the approach of a natural disaster, an expert, or a group of experts (depending on the complexity of the task) needs to decide about evacuation. After the decision to evacuate is made, evacuation plans should be drawn up.

The agents involved in the evacuation behave rationally, and their transitions from the normal to the reaction stage are controlled by a binary decision-making process, such behavior can be described using mathematical models based on graph theory. Agents make decisions based on available information and signals during an emergency, following several steps: perception, interpretation, and decision-making [5, 6]. Thus, based on the interpreted information and hints, passengers can decide whether to move from the normal to the reaction stage.

The decision-making process is influenced by both environmental factors (external) and individual characteristics of agents (internal). Decision-making by agents depends on perceived information, such influence is called external factors. However, the characteristics of agents (for example, previous experience, physical and mental state, and alertness) can play a key role, since these internal factors can influence how an individual agent perceives, interprets, and makes decisions [6].

This study uses models based on the binary structure of the decision-making process, which is an approach to modeling that allows us to investigate how several internal and external factors influence the decisions of both individual agents and groups.

III. Definition of fuzzy conditions and analysis of existing solutions

The need for an accurate analysis of evacuation decisions is due to the high cost, objective difficulties, and unpopularity of evacuation among the population. How-ever, decision makers face difficulties in comprehensively assessing the circumstances of decision-making, considering many factors and uncertainties. Studies of com-plex methods and models of evacuation decision-making for assessing situations involving a large amount of information at the beginning of an approaching natural disaster have not yet been investigated. In this case, fuzzy logic serves as a suitable tool for modeling the uncertainty inherent in evacuation tasks [10-17].

Fuzzy logic is a logical–mathematical approach that allows you to present approximate, rather than exact, reasoning of people. It provides a simple way of reasoning with vague, ambiguous, and inaccurate input data or knowledge that fits the context of risk and crisis management [1-5].

Fuzzy logic provides an effective way to assess the levels of risk and vulnerability in cases where experts do not have enough reliable data to apply statistical or analytical approaches [17].

The fuzzy integrated assessment model consists of two main parts: the first part is the process of analytical hierarchy; the second part is the fuzzy integrated assessment. Among them, a fuzzy integrated assessment was carried out based on the analytical hierarchy process, they complement each other, improve the reliability and reliability of the assessment together, the technical route is shown in Figure 1. The training effect - The fuzzy integrated assessment method is to combine the analytical hierarchy process and the fuzzy integrated assessment method to assess the training status, namely, to make sure that the goals and weight of each index through hierarchy analysis, using the fuzzy integrated assessment method.

The process of analytical hierarchy contains factors of cause and effect, to de-compose the problem for solution into different levels, make up a recursive hierarchy of classes. Then the factors of each level are compared in accordance with the established standards, the matrix of judgments is established. Using a special mathematical method to calculate the maximum eigenvalue and the corresponding orthogonal characteristic vector, the matrix of judgments, we can get the weight of each value of the factor at each level, then we conduct a compliance check. After the consistency check is passed, the weight of the hierarchy combination corresponding to the given task is calculated. On this basis, an assessment, sorting and a complex set of problems are carried out.

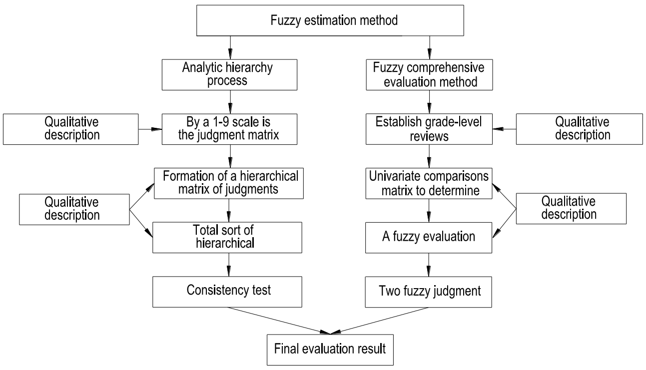

Figure 1. Integrated assessment model

Before applying the process of analytical hierarchy, first, we need to establish an appropriate system of evaluation indices, namely, to perform a hierarchical analysis of the evaluation object, to establish a clear system of evaluation indices, such as target level A, criterion level B, specific indicators C, a set of factors of the evaluation object and a set of subfactors, they are presented in Figure 2 as follows.

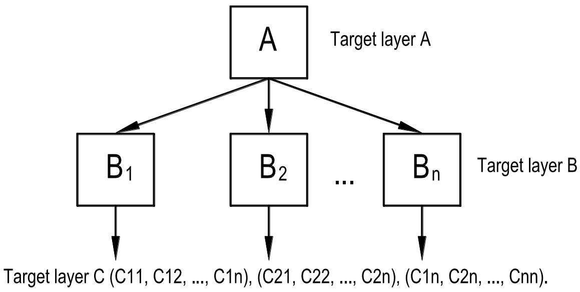

Figure 2. Structure of hierarchical indicators

The process of analytical hierarchy solves the problem of a process reflecting the main individual parameters of each agent: decomposition — suspension — complexity. This makes the process of judging and solving a complex problem systematic and quantitative. Using the analytical hierarchy process to determine the weight of the evaluation elements.

Vulnerability assessment for natural disasters such as earthquakes, floods, etc., can be considered as a poorly structured problem for which there is no unique, optimal solution. However, the assessment of natural disasters based on fuzzy logic con-tributes to improving the effectiveness of risk management and can help interested parties to make more informed and relevant decisions.

Fuzzy logic has also been successfully applied in modeling disaster forecasts and operational management in real time [1]. The fuzzy logic approach works well when the physical phenomena under consideration are synthesized by both a limited number of variables and logical operators "IF-THEN" [1-6].

Fuzzy logic is expressed in linguistic rules, which are used as "IF the input variable is a fuzzy set, THEN the output variable is a fuzzy set." Fuzzy inference systems process it as follows:

• Fuzzification: at this stage, clear input data is transformed into fuzzy data, the degree of belonging of clear input data to pre-defined fuzzy sets.

• Conclusion: you can combine input data using logical fuzzy rules, which allows you to determine the degree of reliability of the data.

• Defuzzification: Defuzzification is required when it is necessary to get a clear number as an output from a fuzzy system.

Despite the advantages of the fuzzy logic apparatus in solving evacuation problems, its use is limited for decision-making in the case of mass evacuation. The decision on mass evacuation, taken in difficult conditions, is characterized by the presence of many aspects, usually depends on uncertainty. This uncertainty is mainly due to the insufficient and/or inaccurate nature of the initial data, as well as the subjective preferences of the decision-maker. Expert knowledge also plays a very important role in the evacuation decision-making process. Expert systems using the "IF-THEN" rules were developed to support decisions on shelter and evacuation in the event of a nuclear threat [2].

Due to the relatively low frequency of mass evacuation cases, there are few statis-tical data on which one could learn.

Statistical and numerical methods need long-term experiments to be well calibrated. Deterministic methods and approaches to optimization can give acceptable results for some problems of finite dimension, but without considering uncertainties.

Since decision-making must consider human subjectivity, fuzzy logic dealing with subjective uncertainty turns out to be more effective than using only objective prob-ability or heuristic approaches.

When studying the applications of fuzzy logic in disaster management, the use of fuzzy set theory makes it possible to include non-quantifiable, incomplete, and unattainable information, as well as partially ignored facts in the decision-making model.

The approaches of fuzzy set theory to disaster management are few. In [3-8], a hybrid approach of fuzzy clustering and optimization to the joint distribution of logistics in emergency situations is considered. In [4-6] et al. applied the theory of fuzzy sets for decision-making in a geographical information system to the placement of shelters in the event of natural disasters.

In [5-7], a new technique was developed to eliminate various uncertainties when making decisions about water resources, which provided a tangible improvement in the quality of flood management. Using fuzzy integrated risk assessment supported by decision-making for insurance pricing considering fuzziness and uncertainty.

In [7-9], a method for classifying buildings in terms of their vulnerability to a possible earthquake is proposed. The most important factors affecting the impact of an earthquake on buildings and their relationship to the five hazard categories are determined by fuzzy numbers. The relations are presented using the method of classification of hazard centers. In [10], an adaptive fuzzy inference network system was used to build a predictive reservoir management model. In [8-11], a methodology was used to collect the opinions of a multitude of stakeholders related to the problems of making decisions on flood management, using the theory of fuzzy sets and fuzzy logic. Using a fuzzy expected value, three different possible forms of contribution from individual stakeholders are analyzed to obtain a cumulative contribution.

To describe the degrees of truth, a fuzzy variable must contain several fuzzy sets. One set has one validity function, the arguments of the function must correspond to certain values, and the resulting solution must be within a given range [0;1], this parameter reflects the degree of truth of the solution. The fuzzy inference system uses fuzzy theory as the main computational tool for implementing complex nonlinear mapping. Based on the reviewed papers [3-11], it is possible to identify common parameters for describing the membership function: similarity, preference. The convergence is reflected in the fuzzy analysis of cluster groups and their systems. Preference characterizes one of the tools in the decision-making process. The uncertainty parameter shows the degree of reliability of solutions obtained at the desired stage by expert systems or machine learning methods. The parameters similarity, preference and uncertainty do not exclude each other, and can be combined into a multi-criteria fuzzy decision-making system. The main properties and uncertainty of the behavior of individual agents of the group are described in [8-15]. The rules for the formation of a fuzzy decision-making system are discussed in detail in [10-16], the parameters of the developed fuzzy rules are formulated using real data.

Analysis of sources shows that articles using fuzzy set theory in disaster management focus on estimating the scale of disasters such as fires, earthquakes, and floods.

Thus, there is a limited amount of research based on fuzzy set theory on disaster management, especially on disaster response.

The analysis of fuzzy rules shows that this topic is relevant and is described in a limited list of sources of modern literature. The main sources describing fuzzy rules in the field of behavior during evacuation are considered. The formulated fuzzy rules are used to obtain linguistic fuzzy rules that can fully describe the uncertainty of the behavior of agents using machine learning methods.

IV. Dynamic decision-making model

The proposed dynamic decision-making model uses fuzzy logic to control the evacuation of agents. Fuzzy sets and rules are defined for the behavior of each agent, which is influenced by the external environment and individual characteristics. Environmental factors and individual characteristics of agents are analyzed within the framework of determining the main aspects affecting the decision-making process of agents, as shown in Figure 3.

The decision-making process has a multilevel hierarchical structure. For example, decisions can be made based on the influence of the environment, psychological foundations, and physiological parameters.

As shown in Figure 4, this article uses fuzzy logic to simulate the evacuation process. Factors affecting pedestrian behavior are modeled as fuzzy inputs, and traffic decisions are modeled as fuzzy outputs.

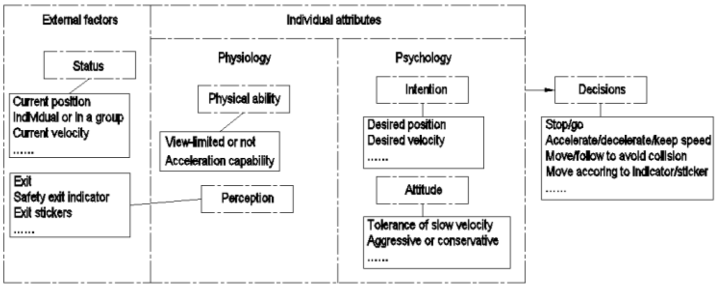

Figure. 3. Decision-making process

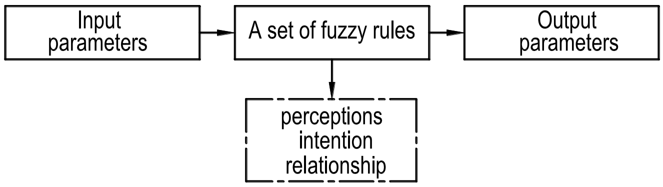

Figure 4. Dynamic decision-making model

Perception includes the location of the exit, the visibility of the safe exit sign/exit sticker, nearby pedestrians, and obstacles (walls, tables, and chairs). The intent contains the desired speed and position. The relation contains whether he/she is. aggressive or conservative, does he feel panic or peace.

The "perception" factor includes the location of the exit, the visibility of the safe exit sign/exit sticker, neighboring agents, and various obstacles.

The "intention" factor contains the value of the speed of movement and the coordination of the position of the agent.

The "attitude" factor contains individual qualities of character and stress resistance of each agent. Different combinations allow agents to make different decisions, for example, whether he should go or stop, to which position he should move and whether he should move in accordance with the safe exit sign/exit stickers.

Machine learning algorithms try to "classify" or unify agent selection models based on observed data. An integral part of machine learning is an objective function that displays input output data and criteria for evaluating the efficiency of the algorithm.

$$y = f(x|\varphi) \tag{1}$$

where φ is a vector of agent parameters for a machine earning model.

Machine learning classifiers can be divided into two main categories, i.e., hard classification and soft classification. The rigid classification seeks to sort through all possible solutions, while the soft classification predicts conditional probabilities for different classes and outputs the resulting solution with a probability fraction. With the help of soft classification, it is possible to estimate the probability of choosing each option on an individual level, which gives much more information than the methods of a complete search. In other words, it is necessary to evaluate:

$$f(x|\varphi) = P(\arg maxg(x|\varphi)), \tag{2}$$

if $g_k(x|\varphi) = P(k)$, where $k \in \{0, 1\}$.

As shown in Figure 5, this article uses fuzzy logic and machine learning methods to model the process of cognition.

The factors influencing the behavior of individual agents are modeled as fuzzy input data. For example, the current speed of the agent, the position of the agent, the relative route of the main group. All these factors can influence the formation of the individual status of each agent in the next iteration.

Interpreted or explicable machine learning is becoming increasingly important in the broad field of machine learning [14-16]. Machine learning methods can be roughly divided into two main categories, including model-dependent and model-independent. Model-independent methods are usually more flexible, which makes it possible to use a wide range of performance evaluation criteria for various machine learning models.

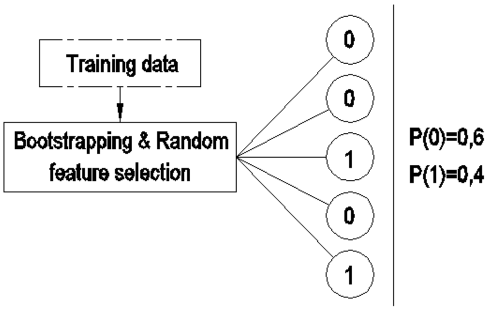

Figure 5. Dynamic decision-making model with soft prediction mechanism

By means of the considered objective function with a partial dependence of the criteria for evaluating the effectiveness of the solution, it is possible to graphically display the dependence between the input data and the predicted probabilities [13, 16].

To properly initialize partial dependency graphs, let's assume that we need to define a dependency $x_s, S \subseteq \{1, \dots, p\}$, on the results of soft forecasting (probability of choice). It is worth noting that it is necessary to consider the probability of choice g_k, where $k \in \{0, 1\}$. Partial dependence between x_s and g_k defined by the formula (3)

$$g_{ks}(x_s) = \frac{1}{N}\sum_{i=1}^{n} g_k(x_s, x_{c(i)}), \tag{3}$$

where $x_{c(i)}, (i = 1, \dots, N)$, this variable determines the average marginal effect on the predicted probability of choosing each agent.

In many previous studies, this approach was used to quickly identify nonlinear relationships between output data and response data for machine learning models, for example, in the framework of solving a problem (black box) [13, 14].

V. Mathematical model

The model is aimed at the safe evacuation of all evacuation personnel in the shortest possible time, which considers the restrictions on smoke from the fire and the capacity of the tracks. The definitions of the evacuation model to solve the problem are as follows [10-16]:

$$minT = min \sum t_{tj}, \tag{4}$$

where T – total evacuation time, t_{tj} – travel time of each agent.

$$\int_{t_j}^{t_t} h_{tj}(t)\,dt = l_{tj}, \tag{5}$$

where h_{tj} – the speed of movement of each agent, l_{tj} – path length.

$$h_{tj}(t) = h_0 \cdot a_{tj} \cdot e^{-\beta_{tj}t}, \tag{6}$$

A recursive equation for the evacuation time, for which the evacuees are taken for the time t_{tj} with the speed $h_{tj}(t)$ along the arc l_{tj}.

$$\sum_{t=0}^{T}\sum_{i\in S} x_{tj} = \sum_{t=0}^{T}\sum_{i\in S} x_{tj}(t) = x, \tag{7}$$

where x_{tj} – total number of evacuees. Checking that the evacuation was carried out during the total evacuation time, and the evaluation network flow is provided.

$$T_{ki} = T_p + \frac{x_{ki}}{PC_i}, \tag{8}$$

where PC_i – maximum capacity in an evacuation route. Here (8) it is determined that the evacuation time on the way consists of the time of passage of a given path and the exit time.

VI. Algorithm for making dynamic decisions

Based on the method of network optimization and graph theory, according to the objective function and the constraint function in the mathematical model, a heuristic evacuation algorithm with one source and several outputs is considered, taking into account a given vector of criteria for evaluating the effectiveness of evacuation in an emergency situation.

During the execution of this algorithm, the shortest path to the exit was chosen as a priority, and the bandwidth of the path is fully used.

Since there are several exits in the evacuation network, if you calculate and compare the passage time of all exits, the complexity of the algorithm will increase. Thus, the concept of an endpoint is introduced to simplify complexity, for example, D0 is considered as the end point of the algorithm [11], as shown in Figure 6.

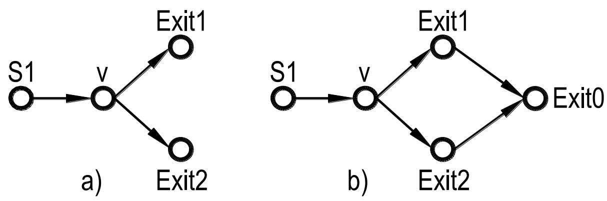

Figure 6. The scheme of the initial evacuation network (a) and the transformed scheme of the evacuation network (b)

The bandwidth of each output is converted into a path whose bandwidth is the same and the path length is zero, and each direction of the path once again combines a new virtual output node, called the endpoint of the algorithm. In Figure 6 (a), S1 is the source, Exit1 and Exit2 are the outputs, and v is defined as the middle node. The numbers in parentheses denote, respectively, the length and maximum throughput of each arc, as well as the maximum throughput of Exit1 and Exit2 per unit of time is 8 and 9. In Figure 6 (b) after the introduction the endpoint, Exit1 and Exit2 are connected to Exit0, which turn into a new evacuation network.

The main idea of the algorithm: taking into account the influence of external factors on the evacuation rate, the optimal path from the source to the end point is calculated using the proposed algorithm. The path, throughput and maximum throughput of the path are recorded, while the throughput of the evacuation network is updated. The optimal paths between the source and the endpoint are calculated by the evacuation network update cycle until all paths are calculated.

The use of a super endpoint is based on the fact that there is no bandwidth of the middle nodes, and congestion occurs only between the output node and each direction of movement of agents.

The selection and calibration of the objective function is based on the simulation results. In this article, three criteria are used from which the target fiction is formed: triangular, standard deviation and Gaussian function [15]:

$$triangmf(x) = \begin{cases} 0, 1 \\ \dfrac{x-a}{b-a} \\ \dfrac{c-x}{c-b} \end{cases} \tag{9}$$

$$sigmf(x) = \frac{1}{1+e^{x}}, \tag{10}$$

$$gausmf(x) = e^{-((x-c)^2/2)}, \tag{11}$$

where a, b, c parameters that reflect the angle of increase of the graph of the objective function.

The process of preliminary formation of the objective function improves the quality of the solutions obtained, it is necessary to form a vector of criteria for the objective function considering each fuzzy factor, as shown in Figure 7.

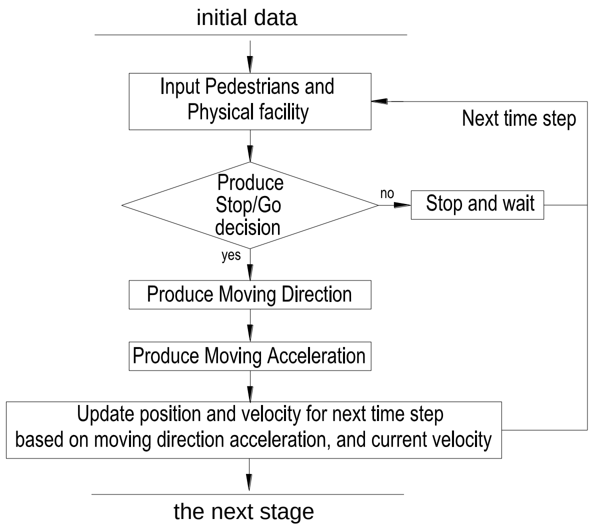

Figure 7. Decision-making algorithm

Step 1. The fuzzy component is divided into several linguistic groups. The time allocated for rest can also be divided into several linguistic groups.

Step 2. The time allocated for rest can be determined by modeling [11-16].

Step 3. In accordance with the formed pre-selection function and a set of fuzzy rules, a rest mechanism with a periodicity system is initialized. After each stage of rest, the target function is calibrated in accordance with the current indicators obtained.

An example of the formation of an objective function based on a fuzzy rest criterion is considered, for the remaining criteria, target functions are also formed and a certain algorithm for data processing and calibration of the main objective function is performed. For the program implementation, the authors of the article selected an individual flow model of the movement of people from the building [5]. The flowchart (Figure 8) shows the sequence of calculating the evacuation time. The essence of this mathematical model is to consider the value of the local flow density to determine the speed of a person. The calculation is carried out for each person separately at each time until all people leave the building.

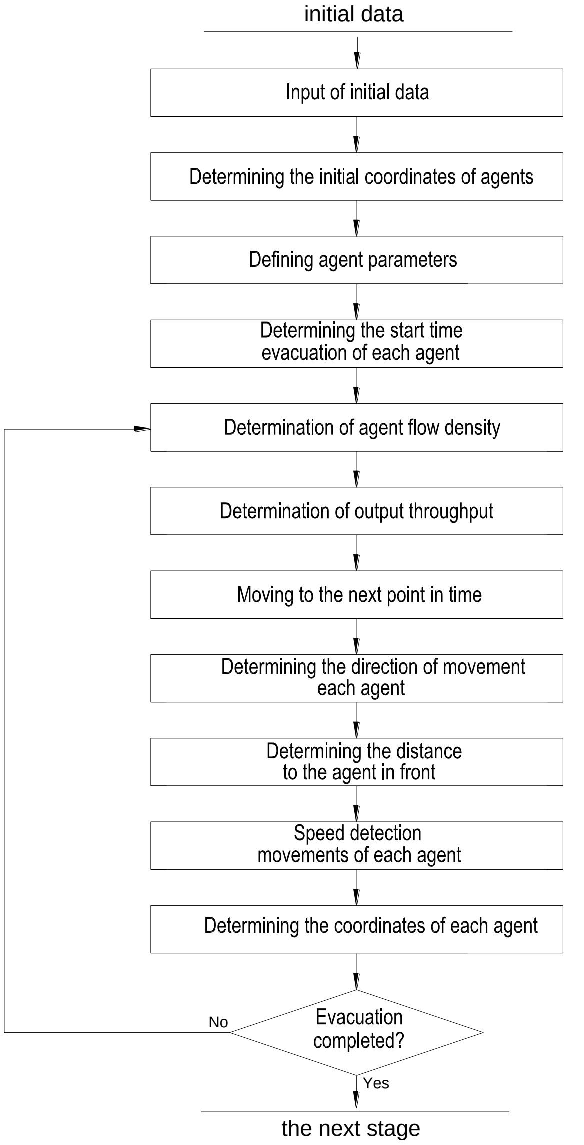

Figure 8. Block diagram for determining the time of evacuation of agents

Note that because of the dynamic decision-making algorithm, an optimal solution was obtained, since the CF value decreased, in other words, it was possible to satisfy the vector of the target function criteria considering each fuzzy factor, which indicates the effectiveness of the proposed dynamic decision-making algorithm, as shown in Figure 9.

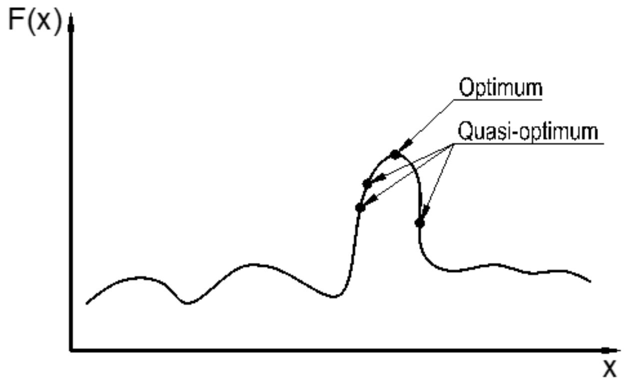

Figure 9. Dynamic decision-making

The time complexity of the developed algorithm for making dynamic decisions is within: O(α*n^2) - O(β*n^3).

VII. Experimental part of the study

As an example, the work models a cinema room. The simulation room is shown in Figure 10. The room contains two exits, one in front, the other in the back. The personal characteristics of each agent were considered individually for each decision made. The relevant event of each agent is his decision to respond to an emergency and a change in the state of at least one of the other visible participants or belonging to his/her personal group (i.e., the group with which the participant is watching the film).

The shaded squares represent agents who are in contact with the agent in question (making the decision). The remaining squares represent agents belonging to the personal group of the decision-making agent.

To validate and verify the implemented computational model presented in Figure 10, the following experiments were carried out: Checking the implementation of the dependence of the velocity on the density of the flow. The time calculated in the program is compared with the time calculated according to the formulas of the methodology [5] for different densities of the human flow. The driving time according to the method is determined by the formula t = l/v, where l – corridor length, v – скорость потока [20-25].

The following example confirms the feasibility and effectiveness of the algorithm. In the evacuation network, assume that we initially have 400 evacuees at the source nodes, and the maximum throughput of the output nodes Exit_1 and Exit_2 per unit of time 10 and 8. The initial velocity at the source nodes is 15, and the path length S=15, coefficient l_{ti}, parameters in the evacuation network in table 1, where c_{ti} – maximum capacity in a unit time.

Table 1. Part of the parameters during evacuation.

v_{ti}	l_{ti}	α_{ti}	β_{ti}	c_{ti}
1,4	20	0,56	0,02	2
1,5	30	0,6	0,02	5
2,5	50	0,85	0,04	3
2,3	10	0,56	0,03	4
3,5	60	0,8	0,02	5
4,7	10	0,6	0,01	5
5,6	20	0,75	0,02	9
6,8	10	0,8	0,02	4

Sets of escape routes *P*, evacuation time *TP* and evacuation flow *F* are calculated after entering parameters into the model, an example of input is given in Table 2.

Table 2. Possible escape route.

№	P	T_p	f
1	$S-2-5-6-Exit1$	15,7	3
2	$S-1-4-7-Exit2$	17,6	2
3	$S-1-5-6-Exit1$	27,4	2
4	$S-3-5-6-Exit1$	29,1	1
5	$S-3-5-8-7-Exit1$	39,8	2
6	$S-3-5-8-Exit1$	40,6	1

Task condition: a corridor with a width of 2 m and a length of 50 m, filled with people with different densities, the projection area of a person is 0.12 m^2. The results are presented in the Table 3.

Table 3. Travel time depending on density.

Flow density, $м^2/м^2$	Number of agents	Methodology, c	Implemented model, c	Deviation, %
0,04	40	29,94	30,00	–0,2
0,16	160	45,16	44,00	2,6
0,32	320	65,37	67,60	–3,4
0,4	400	76,38	75,74	0,83

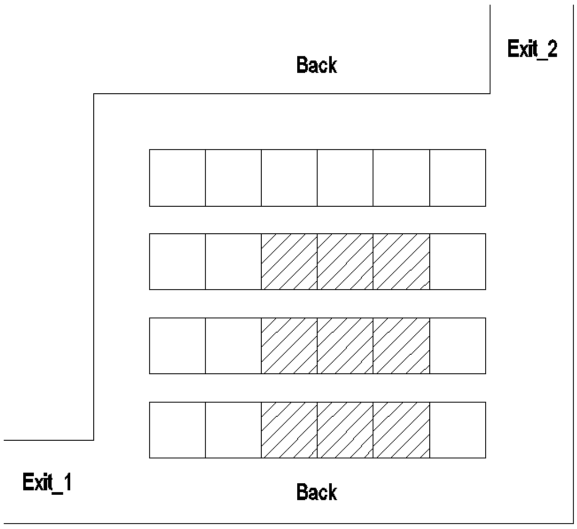

Figure 10. Simulated room

Based on the analysis of the experiment, it can be concluded that there is an identical dependence of the speed of movement on the density of the flow both in the implemented model and in the state methodology. At the same time, based on Table 1, the travel time exceeds the time of the technique with a spare 0,86%.

For numerical verification, the implemented model was compared with another model of the methodology, namely the simplified analytical model of the human flow movement. Task condition: a narrowing corridor is the first section with a width of 4 m and a length of 20 m, the second section with a width of 2 m and a length of 20 m, filled with people with different densities, the projection area of a person is 0,125 m^2.

The results are presented in the Table 4.

Table 4. Evacuation time of various models.

Flow density, $м^2/м^2$	Number of agents	Simplified model, c	Implemented model, c	Deviation, %
0,075	55	31	30,5	4
0,16	140	53	54,5	-1,2
0,3	250	95	92,5	2,2
0,4	350	140	136	1,5

From the data given in Table 1, 2 and Figure 11, it can be concluded that for simple calculations, the simplified analytical model and the implemented individual flow model produce a time close in value with a slight deviation equal to ≈ 1,7%.

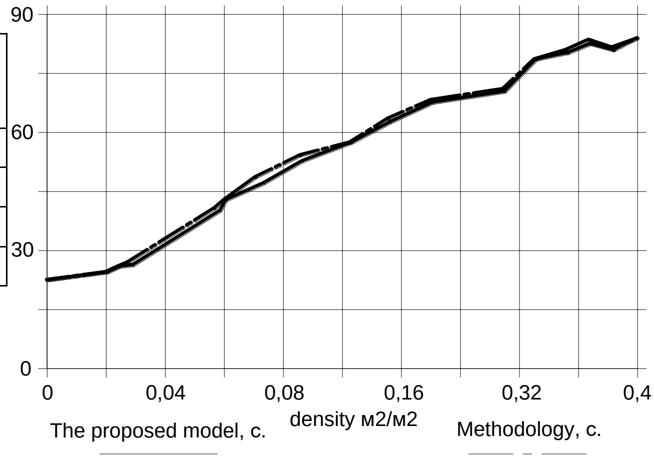

Figure 11. Modeling the objective function

In this paper, the objective function F_1 is used as an indicator of the performance of the dynamic decision-making model in fuzzy conditions

$$F_1 = 2\frac{P \cdot R}{P + R}, \tag{12}$$

where P - this is the ratio of solutions with an indicator of the objective function satisfying the efficiency criterion to the total number of positive solutions, and R - solutions with an indicator of the objective function satisfying the efficiency criterion for all solutions obtained, including sampling errors F_1 - it is a weighted average of the ratio of variables P and R. According to the simulation results, the most effective model for agents = 400. The graphs show different personal parameters of the agents when modeling the model. It is worth noting that the parameter P (accuracy) is a more important indicator than R in the case of evacuation, since there is many false positives or erroneous calls, this causes low accuracy, which can increase the level of false positive decisions.

A model with a high accuracy parameter seems to be more optimal, while the value of the objective function seems to be the best metric, considering a given vector of criteria.

In the Figure 12, 13, 14 the results of modeling the objective function, criteria are shown P, R.

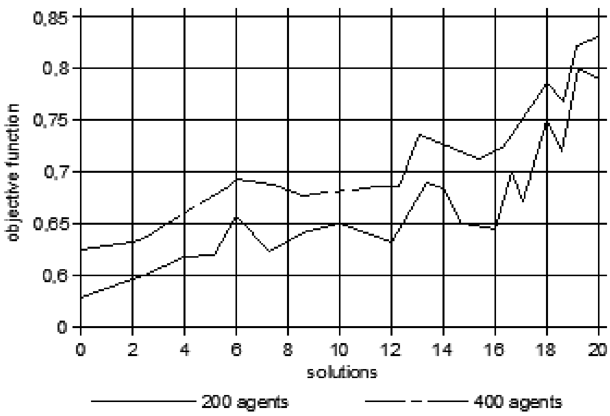

Figure 12. Modeling the objective function

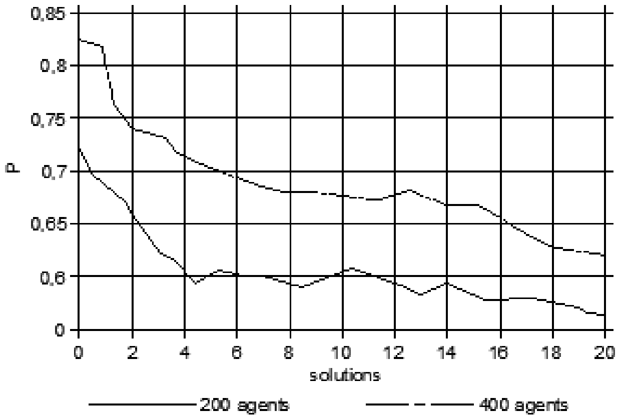

Figure 13. Criterion modeling P

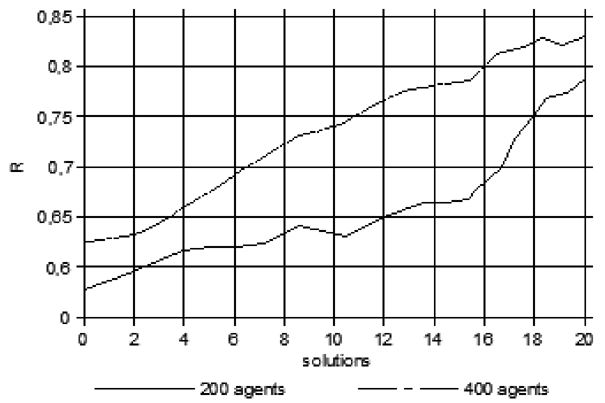

Figure 14. Criterion modeling R

In this work, an optimal model is obtained, mainly based on an estimate of the value of the objective function. This model has one of the best solutions within the given criteria.

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Conclusion

As part of this work, we modeled and interpreted decision-making before evacuation using machine learning interpretation tools in fuzzy conditions. The conducted tests have shown that the proposed algorithm for making dynamic decisions in fuzzy conditions can improve the result by using fuzzy rules for modeling the movements and behavior of the team when making dynamic decisions. The analysis of fuzzy rules shows that this topic is relevant and is described in a limited list of sources of modern literature. The main sources describing fuzzy rules in the field of behavior during evacuation are considered.

The formulated fuzzy rules are used to obtain linguistic fuzzy rules that can fully describe the uncertainty of the behavior of agents. The paper considers the current rules of evacuation planning in fuzzy conditions. Pre-evacuation planning and preparation are necessary to ensure effective and successful mass evacuation of the population at risk. In this regard, there are three main stages of preparation for evacuation. The research literature on forecasting various hazards, models and methods of risk assessment, evacuation time, planning evacuation routes, criteria for making evacuation decisions is considered. The study showed that there is a limited amount of research based on the theory of fuzzy sets on disaster management, especially on responding to natural disasters. Also, the model of dynamic decision-making is considered. In comparison with the traditional model of social behavior, the fuzzy model of social behavior proposed in this article may partially solve the problem of choosing the right route in emergency situations

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