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RISK AND HUMAN FACTOR IN CARRIAGE OF DANGEROUS GOODS BY ROAD

Summary. Authors in the article present an original method of risk assessment, taking “human errors” into account in its assumptions, filling an existing methodological gap in this field of study. This article presents a general concept of a method: estimating risk assessment and modeling human factors as the main cause of a road accident. Fuzzy logic techniques have been used to generate the value of the parameter characterizing the human factor. The authors’ “band” model is used in the calculation of the probability of a traffic accident in the transportation of hazardous products. Literary and original research has been conducted in the development of the model. This new approach to risk assessment takes into account in particular the effect of the human factor on the probability of an accident, as well as the diversity of the different segments making up the total route of a dangerous good. This method is useful for estimating the variability of risk, taking into account the human factor both on planned and existing routes depending on the categorization of road sections, the division into classes of dangerous goods, the effect of possible scenarios, and risks on transport safety.

1. INTRODUCTION

Transport is inextricably linked to the economy of each country. The number of shipments of many goods, including dangerous goods, which pose a particular threat to the environment and human life, is increasing every year [1,10]. An extremely important factor in such an approach is the analysis of the planning of transport routes, particular for dangerous goods. Safety should be ensured in every single link of the system: operator-vehicle-environment. Owing to complexity of those systems and means of transport, the issue of safety is multidimensional. This system operates within the imposed legal and organizational framework, which means it is not an isolated system (fig.1).

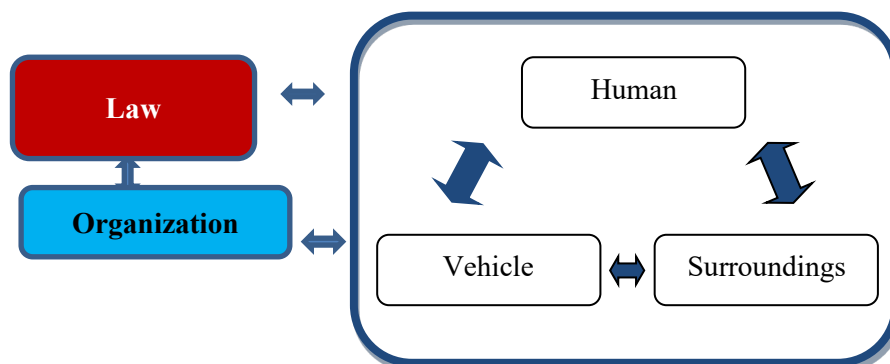


Fig. 1. Interactions in a Transportation System

All the elements can influence human behavior in this system. Selected legal elements as well as the organization affect the elements of the system, which in consequence can lead to danger. Human, vehicle, and the environment can generate hazards, resulting in accidents, environmental disasters, damage to property, or personal injury. Issue of safety is a part of sustainable development, in particular sustainable transport, which nowadays is a key aspect of world's environment and economy [6]. Therefore, the issue of safety and risk in the transport of dangerous goods became a part of the research conducted on Faculty of Transport on the Warsaw University of Technology in Poland, and the key findings are presented in this article. The developed risk assessment method is multi-sectoral. It takes into account the effect of many factors that may lead to an increase in the probability of an accident. In the method, the authors considered the human factor as the main cause of accidents. In addition, they also highlighted the driver fatigue factor, which affects the reduction of efficiency and, consequently, road safety. This method is strictly parameterized, which in turn allows it to be applied to all classes of dangerous goods.

2. THE ESSENCE OF THE RESEARCH PROBLEM

When it comes to transport safety, human is the leading cause of road accidents. Other factors (vehicle and road) are less important. Therefore, in their research, the authors have also considered the human factor and its influence in determining the optimal route for the transport of dangerous goods. The issue of human reliability is addressed by many scientific centers in Poland and in other countries [5, 8, 9]. In the literature, as many as 72 HRA (Human Reliability Analysis) methods have been identified. Those methods can be used to estimate the probability of a human error (error of a human technical operator) occurring throughout the completion of a specific task when influenced by other factors. The most commonly used HRA methods include the following:

- THERP (Technique for Human Error Rate Prediction) – it predicts human error and its effects. This method consists of five steps: 1) identification of those elements that are sensitive to human error; 2) analysis of elements susceptible to human error; 3) estimation of error probability; 4) prediction of the effects of human error; and 5) preparation of corrective actions.
- HEART (Human Error Assessment and Reduction Technique) – it takes into account human tasks and conditions that adversely affect a human. For each task, a specific nominal human unreliability score is determined, whereas for the conditions, specific correction factors are determined. The probability of human error is defined as the product of the coefficients characteristic for given conditions.
- HCR (Human Cognitive Reliability) – it enables estimation of probability of a human error occurring throughout the completion of a specific task as a function of the time constraint and the type of activity, taking into account operator experience, stress level, and ergonomic quality of the control process.
- TESEO (Tecnica Empirica Stima Errori Operatori) – it is an empirical technique for estimating operator errors. A following group of factors is assumed to affect reliability: type of task to be executed, level of training/experience, man-operator preparation characteristics, time stress, threats, environment, and ergonomics.
- The likelihood of a human error is calculated as the product of the correlation coefficients for the reliability factors.
- CREAM (Cognitive Reliability and Error Analysis Method) – it is a cognitive method for testing of reliability and evaluation of human error. The choice is made between the four modes of management: unstructured management (chaotic and random actions); 2) opportunistic management (action based on the current situation, enforced by it); 3) tactical management (action based on existing procedures); and 4) strategic management (long-term planning action).

Notably useful in practical applications is the SPAR-H method developed for the US Nuclear Regulatory Commission. It has been applied in several industrial facilities of low complexity. The SPAR-H method consists of a number of steps: decomposing of the analyzed sequence into subtasks

and assigning certain actions to them, experts assigning scores to each of the 8 adopted performance shaping factors, estimating the probability for each subtask, and calculating the chance of "success" for the particular sequence.

Human reliability methods can help assess the effect of potential human error on the risk of occurrence of a particular emergency scenario. The key human reliability assessment methods are based on empirical evidence from the industry, mainly in the US. These data sets are far from being comprehensive and usually contain sets of random information collected from various facilities. Thus, the methods cannot be applied without caution because they may lead to erroneous results. The publicly available data on the parameters of the carriage of dangerous goods by road is not applicable to the existing reliability methods. Accordingly, estimating the probability of an accident involving human error in the transport of dangerous goods using these methods would be highly difficult, even impracticable. Therefore, the authors have proposed their own approach in this field. Reducing and preventing accidents in transport systems requires a careful analysis of how the human factor works in order to determine how it affects the probability of an accident. The second parameter is the extent of loss, which largely depends on the scenario of the accident and the environment in which it occurs. Reducing the likelihood of an accident and rational planning an optimal route may help reduce the risk levels. A similar approach has been used in risk assessment, e.g. in Switzerland, Canada, and the Czech Republic. The methods developed in these countries have also been used (after some adjustments) in other countries. Unfortunately, these methods have not adequately accounted for the contribution of the human factor, despite its profound effect on transport safety. The human factor is rarely explicitly taken into account, i.e. owing to the large amount of uncertainty and difficulty in quantifying its effect on safety. Transport safety assessment methods evolve toward risk-based approach. This trend is present not only in road transport but also in rail, maritime, or air transport. Humans are the weakest element of the transport process—on the one hand, the most unreliable, and on the other, owing to their complexity, create much difficulties in modeling. One of the ways to overcome these difficulties is fuzzy modeling (based on fuzzy sets theory). This is owing to at least two facts.

First, these models can describe human behavior using a verbal description, formulated by an expert (fuzzy models are called linguistic models.) The description of human behavior is implicit in terms of fuzzy logic. Second, such models naturally take into account the lack of precision in the definition of human behavior and the natural randomness of human perceptual processes. Thus, the authors decided to use linguistic models to solve their problems.

3. MODELLING OF RISK ASSESMENT

Based on the standard formula, to estimate the value of risk, it is the product of the two components: probability that the accident (loss) will occur and the magnitude of the loss. Considering the characteristic of hazardous materials, we can distinguish different types of losses: human, ecological, and consequently, financial. Authors assumed that the probability of an accident is not the same on the whole delivery route of hazardous goods. That is why, the route was divided into segments with defined parameters, and the risk was calculated for each of the sections separately. Then the risks mentioned were summed up into a total risk. The created assessment model allows to choose a delivery route that entails the minimal risk and, consequently, the smallest losses possible. The risk assessment model was developed on the example of liquid fuel transport.

3.1. Key assumptions

The risk assessment model required the following assumptions:

1. selected factors of different nature (human, technical, and environmental) affecting the probability of an accident occurring;
2. take into account the effect of driver error on the probability of an accident by means of a human factors model based on fuzzy-set techniques;

3. construction of a heuristic model, enabling the determination of the intensity λ of an accident resulting from human error;
4. dividing the transport route into segments of different lengths (straight or curved);
5. studies for each road section, defined in relation to the permissible speed of travel, and the surroundings of the road route;
6. determine the parameters for the intensity of accidents caused by the technical condition of vehicles, other road users, driver fatigue, and traffic intensity;
7. determine the value of the λ intensity parameters;
8. define criteria for categorizing losses of a human, environmental, and financial nature;
9. attribute the level of human, environmental, and financial losses to each scenario;
10. for each segment, determine the partial risk and the corresponding measure of loss value;
11. construction of a simulation model to enable the selection of the route of dangerous goods to be taken from the starting point to the end of the journey; and
12. conducting simulation tests and model verification on selected actual routes of dangerous goods transport.

3.2. Modeling probability of an accident

The following relation ties the probability of an accident and its consequences together:

$$R = P_a \cdot L \quad (1)$$

where R – Risk Value; P_a – probability of accident occurring (in transportation of dangerous goods); L – measure of Losses.

Selection of the optimal transportation route for fuels from the starting point, e.g., the refinery to the final destination, i.e. a customer, can be done after the individual segments are characterized and their partial risk is defined. Thus, the formula for determining the risk value for a given segment will be as follows (2):

$$ER_q = Px_q \cdot ES_q \quad (2)$$

where ER_q – partial risk estimated for the q -th segment of the route, Px_q – probability of accident in the q -th segment of the route, ES_q – expected value of loss on the q -th section of the route.

Whereas, the value of the total risk can be calculated as (3).

$$ER_T = \sum_{q=1}^Q ER_q \quad (3)$$

where: ER_T – the estimated total risk for the transportation route, Q – the set of segments constituting the route, ER_q – the fragmentary risk estimated for the q -th segment of the route.

Four specific accident scenarios were assumed, and each of them was assigned a certain probability of occurrence (Tab. 1). Probabilities of occurrence for each specific scenario were determined based on statistical data, interviews with experts and the research of available publications. For a given segment q and each of the scenarios, losses were determined that correspond to five specific categories of threat. A more detailed description is available in the publication [3, 4]. The loss in this case is a discrete random variable. The probabilistic structure of the discrete random variable is described by the mathematical function of probability distribution.

This article focused primarily on estimation of accident probability with particular emphasis on the contribution of the human factor. For modeling of the human factor, fuzzy sets and expert knowledge were applied. Fuzzy logic techniques were used as they allow describing human actions with blurred and fuzzy qualitative terms, using natural language [2, 7]. The usefulness of fuzzy sets in similar situations where mathematical rules cannot be applied is also emphasized in the literature [2, 7].

3.3. Modeling probability of an accident

Assessment of accident probability in transport and the key factors influencing the probability is a complex process.

As mentioned, the number of factors affecting the likelihood is significant, and they are often difficult to quantify. In the modeling process, a band model was proposed.

Table 1

Possible accident scenarios

	Scenario Sci	Probability of occurrence
1.	Vehicle rollover without additional consequences – SC1	P_{SC1}
2.	Vehicle rollover and leak – SC2	P_{SC2}
3.	Vehicle rollover, leak and fire – SC3	P_{SC3}
4.	Vehicle rollover, leak and explosion – SC4	P_{SC4}

$$\sum_{i=1}^4 P_{SCi} = 1$$

Probability of accident, under the assumptions as described in subsection 3.1., was defined for each q-the segment of the route, i.e. the connection between two adjacent vertices. It was assumed that the route is the sum of the analyzed segments. The first step in the band model was to assess the effect of the human, technical, and environmental factor on the probability of an accident in a particular q-th segment of the route. For this purpose, the parameter λ intensity was introduced. The concept of intensity, with reference to technical damage, is applied, i.a. in the reliability theory and is understood as the probability of object damage over a period of time $(t, t + \Delta t)$, where t is high. Unlike the reliability theory, the events analyzed in this article are local in the sense that the time traveled or the road traveled by a vehicle during a simulation is far lower than, respectively, the expected service life of the vehicle or the expected total distance traveled over the entire service life of a vehicle.

The notion of accident occurrence intensity and the probability density of an accident over “short” road segments, relative to the total distance covered by a car during its service life, have the same values and are as such, in this case, identical.

The intensity is defined by the following relation:

$$\lambda_q = \frac{P(x_q)}{x_q} \quad (4)$$

such that: λ_q –the intensity of accident occurrence on the q-th road segment, $P(x_q)$ –the probability of accident occurrence on the q-th road segment, x_q –the q-th road segment [m].

The newly introduced intensity parameter expresses the influence of the human, technological, and environmental factors on the probability of an accident occurrence. The influence of a human driver on the probability of accident occurrence is taken into account by the risk assessment model in two aspects. On the one hand, the characteristics that could determine the driver’s efficiency and, if lowered, could cause mistakes: λ_L . On the other hand, the influence of the driver’s fatigue on his performance are taken into account, adopting the linear relationship λ_Z in the time function at the first approach.

The following limitations have been imposed: λ_L –the intensity of accident occurrence caused by the driver’s mistake, $0 \leq \lambda_L < 1$; λ_Z –the intensity of accident occurrence caused by the driver’s fatigue, $0 \leq \lambda_Z < 1$; λ_T –the intensity of accident occurrence caused by a technological factor, $0 \leq \lambda_T < 1$; λ_{NK} –the intensity of accident occurrence caused by conditions over which the driver has no influence, i.e. caused by other users of the roads, $0 \leq \lambda_{NK} < 1$; and λ_{PK} –the intensity of accident occurrence near fuel storage facilities, $0 \leq \lambda_{PK} < 1$.

In this model, only λ_Z changes over time. Increasing duration of the route along with the increasing total distance covered makes a significant effect on the efficiency of the driver, which decreases as his fatigue increases. In most cases, the values of the intensity for a specific “segment” are assumed to be constant. The values may depend on, for example, the type of road segment (road conditions, which is dependent on e.g. the maximum speed limit) or the traffic congestion level. Parameter λ_{PK} assumes a constant value when the vehicle is in proximity of a fuel storage facility, or a value of 0 if otherwise.

This value was determined based on data collected by the Central Statistical Office, Transport Technical Supervision Service, State Fire Service, and Police Headquarters.

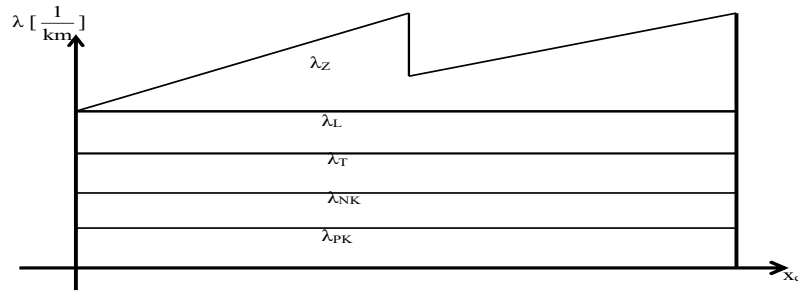


Fig. 2. The band model of risk assessment

The values of the intensity of accident occurrence for specific factors assigned to their own “segment” x_q constituted the base of calculations of the probability of accident occurrence in the transportation of hazardous products for the given x_q “segment”, (5):

$$P_{x_q} = \begin{cases} \int_0^{x_{mn}} (\lambda_L + \lambda_T + \lambda_N + \lambda_{PK} + \lambda_Z(x)) dx \\ 1, \text{ if } \int_0^{x_{mn}} (\lambda_L + \lambda_T + \lambda_N + \lambda_{PK} + \lambda_Z(x)) dx > 1 \end{cases} \quad (5)$$

such that: P_{x_q} – the probability of an accident occurring on the q -th route “segment”; $x_q \Leftrightarrow x_{mn}$ – the length of a segment between the points m and n .

The specification of the methodology on accident intensity assessment in accidents caused by specific factors can be found in other articles [3, 4].

For the purposes of this article, the modeling of the λ_L parameter, or the intensity of an accident as a result of a driver’s mistake, is described in more detail. This factor, in terms of methods of risk assessment in the carriage of dangerous goods, is often overlooked. On the contrary, there are a number of reliability methods discussed in section 2; however, they cannot be applied owing to the lack of adequate data sets of probabilities of driver’s mistake. Therefore, the existing methodological gap in this area was an inspiration for the research on modeling of the effect of human factor on accident probability and, ultimately, its inclusion in the risk assessment model for the road transport of dangerous goods.

3.4. Heuristic Modeling of the Human Factor

A heuristic linguistic model was conceived based on fuzzy structures to determine the intensity of accident occurrence caused by driver’s error λ_L , which constitutes a parameter of the “band” model. The most common fuzzy models are models with Mamdani or Takagi-Sugeno-type inference. The Mamdani model was used in the modeling owing to the fact that Mamdani models [8] provide a qualitative description of the system that is closest to the natural language. The Mamdani inference is useful when dealing with a low number of variables. Otherwise, the following difficulties appear:

- The number of rules grows exponentially with the number of variables in the premise.
- The more rules there are, the more difficult it is to adapt them to the problem.
- If the number of variables in the premise is too large, it will be difficult to understand the relations between the premises and their consequences.

The input parameters of the model are factors that have an influence on the driver’s efficiency. Along with a decrease in efficiency comes a larger number of errors, which in turn increases the intensity of accident occurrence caused by driver’s mistake. These factors were determined through our survey and expert study, which was performed among drivers dealing with transportation of dangerous goods. The selected characteristics were grouped. The characteristics included in the external characteristic subset, that is those that are influenced by organizational and technical conditions, are duration of work, level of training, vibrations, noise, and familiarity with procedures. Vibration and noise are the most common hazards in the driver’s working environment. This fact was confirmed in the survey carried out on the drivers. The survey showed that as many as 95% of the respondents complained about vibration and

about 70% of noise during work. Excessive noise affects human health, reduces mental performance, decreases quality of work, and decreases physiological functions of the body. Vibrations cause changes in the skeletal system, lumbar pain, changes in the lobe, and headaches. Vibroacoustic factors occurring in the work environment significantly increase reaction time, resulting in fatigue and psychomotor changes, and this in turn increases the likelihood of an accident. Therefore, the authors decided to take into account the influence of vibroacoustic factors in the modeling of the probability of the driver's error.

The set of internal characteristics, i.e. of psychological and physiological characteristics, includes stress, age, and the time of the day when the driver is working. Monotony has been put separately, as it has a considerable role when driving through an unchanging environment, e.g. a highway, by inducing the dangerous so-called highway hypnosis phenomenon.

The next step in modeling was the assignment of the appropriate linguistic values to the characteristics, the former being described by fuzzy sets with their assigned membership functions, accordingly as follows: monotony (low, medium, and high); understanding of procedures (good and bad); level of training (low and high); duration of work (normative and over-normative); vibroacoustic conditions (comfortable and onerous); stress, as a submodel forming part of the internal characteristics subset (low, medium, and high); age (young, middle-aged, and elderly); and the time of driving (day and night). The intensity of accident occurrence caused by driver error λ_L was described with fuzzy sets, accordingly as follows: low, lower than average, average, above average, and high.

The most important element in modelling is the selection of the shape of membership functions. As per the literature, there are many methods of selecting membership functions [2, 7]. The simplest shapes of membership functions are triangular, trapezoidal, and Gaussian. At the first attempt, a symmetrically shaped Gaussian curve of a membership function was chosen. In the analyzed case, the selected characteristics are unmeasurable or have various ranges of values, which is why their ranges are standardized in the interval [0,1]. The values of λ_L were also normalized, according to the following relation:

$$\lambda_L = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

such that: λ_L – the intensity of accident occurrence caused by the driver's mistake, x – the current value of a real variable, x_{min} – the minimum value of the real variable; x_{max} – the maximum value of the real variable.

The minimum and maximum values of the real variable were set based on literature analysis, taking into account the data from the Central Statistical Office, the Transport Technical Supervision Service, the State Fire Service, and the Police Headquarters.

The output data block is a fuzzy set describing a linguistic variable - the intensity of an accident as a result of a human error λ_L . The input data underwent an aggregation and defuzzification process, which allowed for the obtaining of a not-fuzzy output value. Table 2 presents the influence of linguistic variables such as the familiarity with procedures, level of training, duration of work, and vibroacoustic conditions (vibrations, noise) on the level of external characteristics.

The aforementioned data were used in the concept of the linguistic model of external characteristics, in which the relations were described in the form of an implication. An example of a fragment of the external characteristic level model would be the following:

“If the familiarity with procedures is bad and the level of training is low and the duration of work is normative and the vibroacoustic conditions are comfortable, then the level of external characteristics is average.

The effects of the remaining linguistic variables on the level of internal characteristics and of monotony as well as the intensity of accident occurrence caused by human error were determined in a similar way.

3.5. The Numerical Implementation of the Linguistic Model

The Mamdani model was implemented numerically in a Matlab_Simulink environment. It contains three linguistic input variables, i.e. monotony, external characteristics, and internal characteristics. The

problem of fuzzification is part of the typical tasks in fuzzy modeling and depends on the determination of membership level of a given input value for each of its appropriate fuzzy sets, covering the entirety of the possible input values. The details of the implementation of fuzzy structures are described in the study by Bęczkowska [3]. A Gaussian membership function has been assigned to each of the characteristics.

Table 2
The Influence of linguistic variables, i.e. understanding of procedures, level of training, duration of work and vibroacoustic conditions (vibrations, noise), on external (selected data)

No.	Familiarity with procedures	Level of Training	Duration of Work	Vibroacoustic Conditions	External Characteristics
1	2	3	4	5	6
1.	bad	low	normative	comfortable	average
2.	bad	low	normative	onerous	below average
3.	bad	low	over-normative	comfortable	low

4. THE RESULTS OF THE SIMULATION STUDY

The numerical implementation of the Mamdani model allowed for the conduction of a series of simulation studies. This section contains the simulation results regarding the intensity of accident occurrence caused by human error for two extreme cases. The first case assumes that the driver is executing steering activity in conditions under the influence of strong “destructors”, i.e. the characteristics in the model were assigned extremely bad levels. This means that the working conditions are characterized by high monotony, onerous vibroacoustic conditions, and excessive work duration. The driver is subjected to high time pressure, to a huge information load, and to high stress levels. Furthermore, as a carrier, the driver is responsible for his/her cargo. In other words, his/her responsibility over his/her cargo is high. It is assumed that the driving is being done during the night, that is, during critical conditions in terms of working hours, characterized by the risk of accident occurrence. Fig. 3 presents a fragment of a visualization of the implication rules for this case.

In the other case, the working conditions were set to “good”, i.e. characterized by a low monotony, comfortable vibroacoustic conditions, within normal work duration, low time pressure, a small information load fed to the driver, and low stress levels. The assumed driving period is during the day.

In this case, the values of every membership function, all corresponding to fuzzy sets describing specific criteria, are equal to 0, whereas the value of λ_L amounts to 0.116 in standardized variables. The results obtained in the simulation studies confirmed the influence of the selected features on λ_L in line with the assumptions of the model.

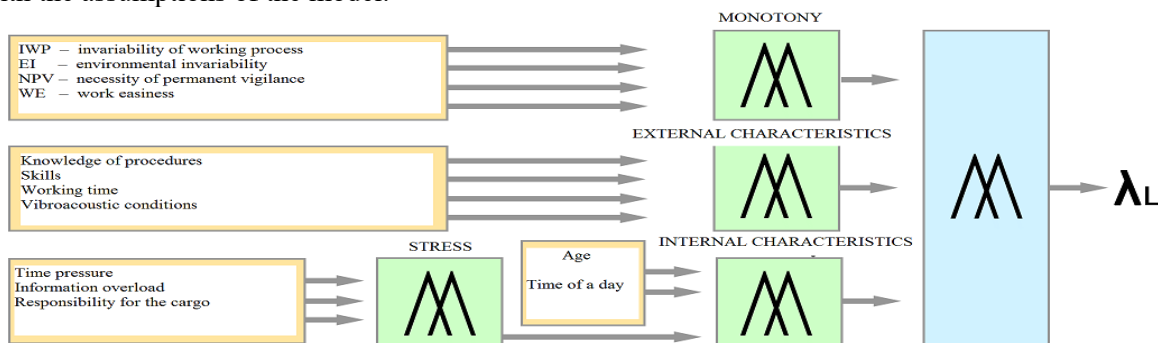


Fig. 3. A Heuristic Mamdani Model of the intensity of accident occurrence caused by driver error

5. DISCUSSION AND CONCLUSIONS

The study presented in the article concerns with the modeling of accident probability, with particular emphasis on the influence of the human factor. The model takes into account the effect of selected features of varying levels on the driver’s performance.

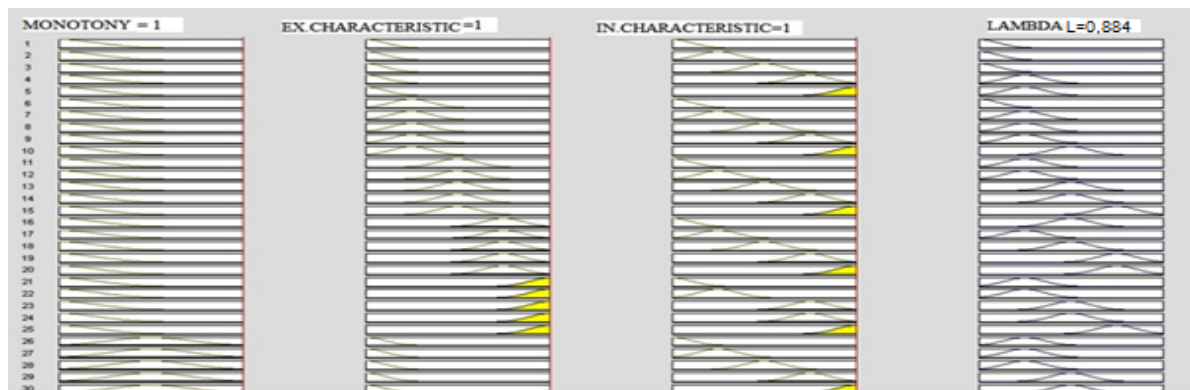


Fig. 4. A fragment of the visualization of the implication rules for the simulation of the λ_L intensity, during critical conditions

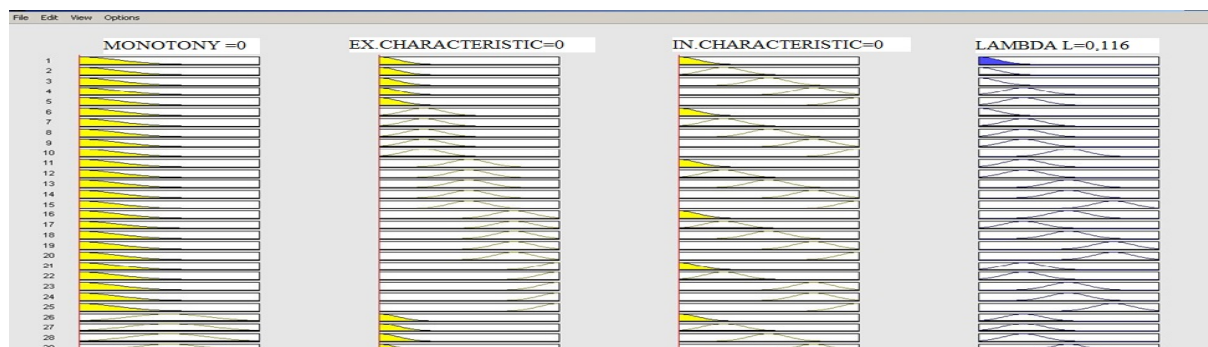


Fig. 5. Fragment of the visualization of the implication rules for the simulation of the λ_L intensity, during good conditions

It was assumed that in consequence to a decrease in efficiency of the driver, errors may arise, leading to an accident. Human errors are a common phenomenon and their number depends on many factors. Even in comfortable conditions, the employees fail to perform correctly one in ten thousand accomplished activities. In the situation of additional impediments, fatigue, time pressure, or reduced risk tolerance, the frequency of erroneous actions increases as much as to one in a thousand. This leads to attempts to learn the causes of accidents and interdependencies in this area. The developed submodel of the human factor based on heuristic methods allowed to formulate qualitative interdependencies, based on expert knowledge. The model also benefitted from a proprietary expert survey on the selection of specific features and input data to the accident intensity model as a result of human error. The resulting values of λ_L are introduced into the risk assessment model and illustrate the effect of the change in the value level / efficiency of the human factor on the probability of an accident occurring in a given route section. The decision to use fuzzy sets theory for λ_L prediction was owing to the fact that it is a convenient tool for describing the uncertainty and inaccuracy of input data inherent in human behavior. The linguistic variables in the model can be modified as more and more data are being collected in a specific area. The difficulties in model validation result from, above all, a lack of reliable data set concerning the number and the causes of transportation accidents involving dangerous goods. Several Polish institutions are collecting such data, and each of them follows their own criteria that differ significantly among each other. Differences also appear in driver's fatigue studies. According to certain sources [5], driver's fatigue is an exponentially varying function. As the model intends to emphasize the relationship between driver's fatigue as a result of the distance traveled and the decrease in his efficiency, which results in an increase in the number of errors, therefore a linear relationship was assumed. To determine the form of this relationship, it would be useful to carry out studies on the influence of fatigue of drivers (carrying dangerous goods) on the number of the resulting errors and apply the results in the "band" model. There is no clear answer to the question whether the stress associated with the transport of dangerous good (often highlighted in the proprietary expert survey)

results in higher levels of fatigue and more errors than in case of other drivers. It should be assumed that in the initial phase of the travel, it is a motivating factor, but over time, it can impair driver's efficiency. The inclusion of noise and vibration in the model is very important, because in combination with other factors such as monotony or stress, they can cause unpredictable effects, which are currently not fully defined. On the contrary, the extension of knowledge about the complex effect of noise and vibration along with other factors at the driver's workplace in the transport of dangerous goods may be an indication to minimize these factors at source. In future research, the described simulation model may be combined with other one, e.g. the model of goods distribution in whole country area (particularly in Poland, but not limited to that country). Such a combination enables other indicators to be input into presented analysis.

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