Environment. Technology. Resources. Rezekne, Latvia
Proceedings of the 15th International Scientific and Practical Conference. Volume II, 104-109

Calculation of Human Fatigue in the Environment of Linguistic Variables

Matīss Eriņš
Riga Technical University
Riga, Latvia
Matiss.Erins@rtu.lv

Zigurds Markovičs
Riga Technical University
Riga, Latvia
Zigurds.Markovics@rtu.lv

Abstract. **In order to reduce the number of accidents in such sectors of work, such as, driving vehicles, the operator's work on the radar screen, a system is required capable of determining the degree of fatigue of a particular person at a given moment of time according to the data received from sources of information, preventing arbitrary fall asleep and providing recommendations for further action regarding rest options up to work suspension. The system shall be suitable for a situation where the space of the measured parameters consists predominantly of parameters with no numerical values (gradations). There is only a linguistic description with a scoring scale. For this parameter group, it is proposed to use the theories of the non-strict and linguistic variables for the implementation of decision procedures. It not only brings a portion of the system's operating algorithm calculations into an environment of non-strict mathematics and also allows the decision to return to the normal environment. The work provides a calculation algorithm in a non-strict environment and a description of the resulting computer system.**

Keywords: decision making, human fatigue, linguistic variables, membership functions.

I. INTRODUCTION

In this work, a methodology for determining the level of fatigue and sleepiness is proposed, a set of parameters to be measured or obtained has been created, which has the highest possible informativeness and the lowest possible disturbing impression or inconvenience to the person being tested. The objective parameters to be measured are only eye blink frequency and electroencephalogram (EEG) α, β and θ wave characteristics as it is covered in the previous work of the authors [1]. The emphasis of the previous work was to research the connection of different fatigue indices in relation to mental or physical types of human fatigue. The following article covers decision making in case of mental fatigue. Another research was performed by the authors to distinguish the non-standard relations between mental fatigue and drowsiness to create a fast alert block in case of driver drowsiness condition is detected [2]. However, the fatigue decision making core component is covered in-depth in the current paper.

II. MATERIALS AND METHODS

The fatigue detector input parameters are organized in two groups – objective and subjective measurement parameters. The subjective parameters to be used are organized into 3 groups: the anamnesis questionnaire contains 8 parameters, the survey questionnaire before the start of work includes 3 parameters and during the process intervals, when performing cognitive function tests, another 4 parameters are obtained. Such a combination of input parameters confirms the idea that it is necessary to apply non-strict set theory and linguistic variables [3], [4]. A linguistic variable differs from a numerical one in that its values are not numbers, but words or concepts, for example, the expression of pain is a linguistic variable with the values "weak", "moderate", "strong", "very strong". The situation with the non-strict and linguistic variables can be demonstrated with Fig. 1, where two linguistic variables "stress level" and "night work intensity" obtained from the anamnesis questionnaire are shown.

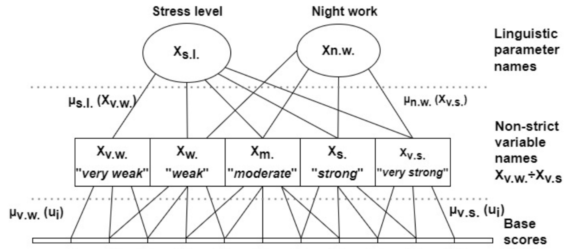

Fig. 1. Linguistic and non-strict variable relations.

Their values are gradations "very weak" (v.w.), "weak" (w.), "moderate" (m.), "strong" (s.), "very strong" (w.s.), which in turn are non-strict variables with values from the base (universal) numerical scale U. At the lowest

Print ISSN 1691-5402
Online ISSN 2256-070X
https://doi.org/10.17770/etr2024vol2.8044

level with compliance function $\mu_{v.w.}(u_i) \div \mu_{v.s.}(u_i)$ it is possible to find the values for the non-strict variables from "very weak" to "very strong" gradation.

At the highest level with compliance functions for linguistic variables Stress level $\mu_{s.l.}(X_{v.w.}) \div \mu_{s.l.}(X_{v.s.})$ and Night work $\mu_{n.w.}(X_{w.}) \div \mu_{n.w.}(X_{v.s.})$ it is possible to find the values for the corresponding linguistic variables $X_{s.l.}$ and $X_{n.w.}$.

The base (universal) numeric scale is selected depending on the nature of the task. For example, the Karolinska KSS scale [5] of the somnolence self-assessment can be 1÷10, while subjective self-assessment scales [6] are usually simplified in the 1÷5 range. Other parameters, such as human age on a scale corresponding to a numeric size of 0÷100. Fig. 2 shows the lowest level matching bell shape membership functions [7] and base scale 0÷100, or percent scale.

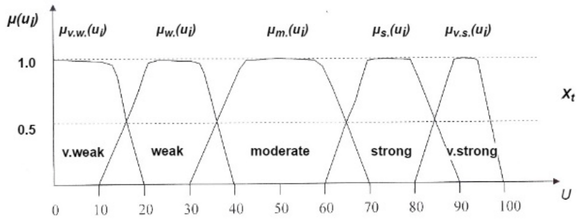

Fig. 2. Non-strict variable membership functions.

If differential diagnostic tasks [8] are addressed where pain levels, s-diagnoses and n-diagnoses are observed instead of $N_{v.w.}$, then the non-strict variable averages can be found at the lowest level (1):

$$N_{v.w.} = \frac{\sum_{u_i \in U} u_i * \mu_{v.w.}(u_i)}{\sum_{u_i \in U} \mu_{v.w.}(u_i)} \quad . \tag{1}$$

Linguistic averages for $L_{s.l.}$ and $L_{n.w.}$ can be found at the highest level (2):

$$L_{s.l.} = \frac{\sum_{X_t \in T} N_t \mu_{s.l.}(X_t)}{\sum_{X_t \in T} \mu_{s.l.}(X_t)};$$

$$L_{n.w.} = \frac{\sum_{X_t \in T} N_t \mu_{n.w.}(X_t)}{\sum_{X_t \in T} \mu_{n.w.}(X_t)}, \tag{2}$$

where T- sets of linguistic values corresponding to $X_{s.l.}$ and $X_{n.w.}$ parameters; X_t – gradation elements of each set.

This results in Ψ - selectivity of the parameter (3):

$$\Psi = L_{s.l.} - L_{n.w.} \tag{3}$$

The fatigue case does not correspond to this calculation example when determining which of the possible diagnoses is correct.

In the case of fatigue, the set of all linguistic parameters promotes and reflects human fatigue levels and can therefore be considered as a vectorial multi-element criterion. It is proposed to use the fuzzy logic and fuzzy control methods. This means that the aggregation methods must be applied to obtain the aggregated evaluation from all non-strict and linguistic variables that serve as the final decision, choosing the following steps depending on the degree of fatigue.

An example calculation is given to this by determining the level of fatigue from two linguistic variables. In this example, the input parameters are $X_{s.l.} = 81$ and $X_{n.w} = 62$.

Stress level (Fig. 3) refers to the term "strong" (s.), which corresponds to "stress at work and at home" with $\mu_{s.} = 0.9$ and to the term "very severe" (v.s.), which corresponds to "stress at work and at home for long periods" with $\mu_{v.s.} = 0.1$.

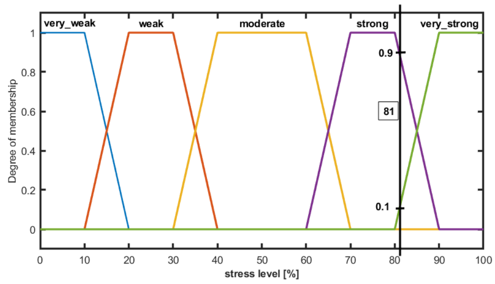

Fig. 3. Membership functions of parameter "stress level".

The expression of night work (Fig. 4) refers to the term "moderate" (m.), which corresponds to "weekly" with $\mu_{m.} = 0.8$ and to the term "strong" (s.), which corresponds to "every 4th night" with $\mu_{s.} = 0.2$.

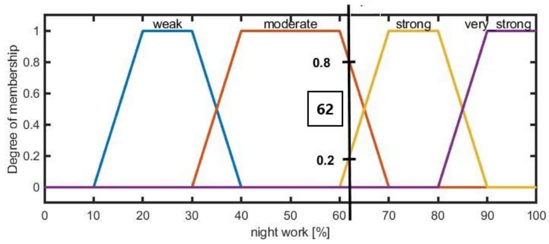

Fig. 4. Membership functions of parameter "night work".

The output parameters are the sleep deprivation level value and the decision taken on further actions of the recommendations. Specific situation is defined, which characterizes focus on 4 linguistic gradations and their combinations. To formulate the decision for each of the situations the experts can formulate the following decision rules in the logical rule base given in table 1.

TABLE 1 PRODUCTION RULE ACTIVATIONS

Rule No.	*IF ($X_{s.l.}$)*	*AND ($X_{n.w.}$)*	*THEN*
R1	$\mu_{s.} = 0.9$	$\mu_{m.} = 0.8$	Lunch break
R2	$\mu_{s.} = 0.9$	$\mu_{s.} = 0.2$	Pause
R3	$\mu_{v.s.} = 0.1$	$\mu_{m.} = 0.8$	Lunch break
R4	$\mu_{v.s.} = 0.1$	$\mu_{s.} = 0.2$	Lunch break

Four sets of conditions are given, relating to the and the logical operator. The minimum rule is used (table 2), and the breakdown is (4):

$$\mu_{A \wedge B} = min\{\mu_{A,}, \mu_{B,}\} \tag{4}$$

TABLE 2 MINIMUM RULE CALCULATION

Rule No.	*Min rule result*	*Decision*
R1	0.8	Lunch break
R2	0.2	Pause
R3	0.1	Lunch break
R4	0.1	Lunch break

Whereas the three rules (R1, R3, R4) give the same decision, but with different linguistic gradations, maximum rule must be applied (5):

$$\mu_{AVB} = max\{\mu_{A,}, \mu_{B,}\}, \qquad (5)$$

where *max (0.8, 0.1, 0,1) = 0.8.*

Linguistic decision is given (Fig. 5):

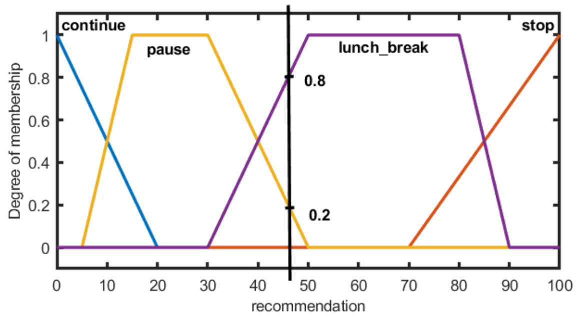

Fig. 5. Linguistic decision parameter about further action.

- decision "Lunch break" with μ = 0.8.
- decision "Pause" with μ = 0.2.

Result obtained in the non-strict environment with linguistic variables. To find a technical conclusion in numerical terms, the strict numerical value needs to be resolved, by using defuzzification method. This can be done using defuzzification techniques, such as, center of sums (COS) [9], center of gravity (COG) [10], mean of maximum (MOM) [11]. In this case, the linguistic mean method (COS) is used (6):

$$L_{COS} = \frac{\sum_{x \in A} x_i \mu(x_i)}{\sum_{X_x \in A} \mu(x_i)}, \qquad (6)$$

where A - points characterising, the linguistic conclusion obtained as 0.2 and 0.8; L – level of fatigue [%], which is calculated as follows (7):

$$L = \frac{0.2*6+0.2*45+0.8*45+0.8*82}{2} = 55{,}9\% \qquad (7)$$

The resulting decision (Fig. 6) is then checked against the value of L=55.9 %, which corresponds to the linguistic output class for "Lunch break".

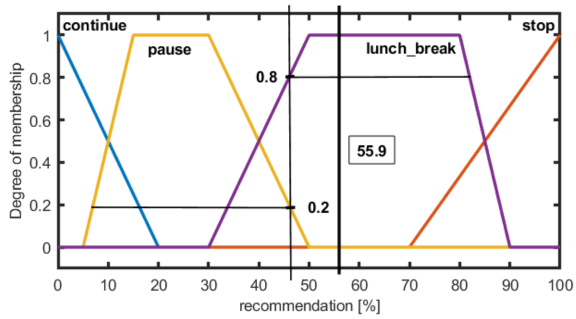

Fig. 6. Deffusification results in real environment.

III. RESULTS AND DISCUSSION

A modular multi-level decision-making system is proposed. The overall structure of the decision-making system divided into 3 levels (DM1 - determination of fatigue components, DM2 - obtaining fatigue assessment, DM3 – recommendations), where each layer of decision making consists of expert-systems (Fig. 7).

The rationale for the three-tier decision-making system is based on a breakdown of fundamental problems addressed by each level of decision-making systems. The parameter input for this expert system shall consist of a subjective objective component. In the course of the work, it has been found that it is not appropriate to apply the exact 10 ball scales as they do not correspond to the experts' assessment capabilities. Also, it is considered, that the quantitative and qualitative input data from objective measurements and subjective surveys will need to apply separate expert logic and configuration of decision-making controller.

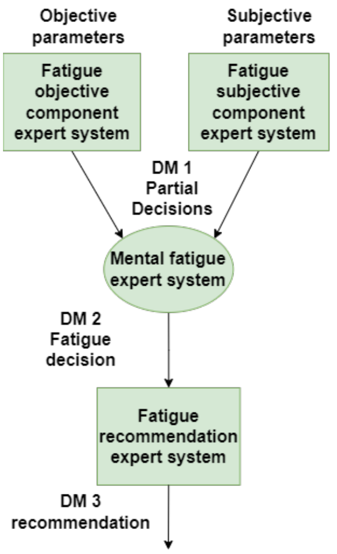

Fig. 7. Linguistic decision parameter about further action.

The first decision making level DM1 uses fuzzification to convert each input parameter to 3 grade scale corresponding to low (L), medium (M) and high (H). It's like a traffic light principle. This decision is also based on the fact that the assessment of fatigue is carried out under the working conditions of the field of use (the driver making the route). Partial values for drowsiness levels from input parameter values on discrete ordinal scale L-M-H are expected to be determined in all input information blocks. Fatigue decision component relies on

13 subjective inputs and 6 objective inputs which require expert validated membership functions in scales. A membership function example for human reaction test result [ms] (Fig. 8) is converted into reaction time linguistic scale with three discrete values [L-M-H].

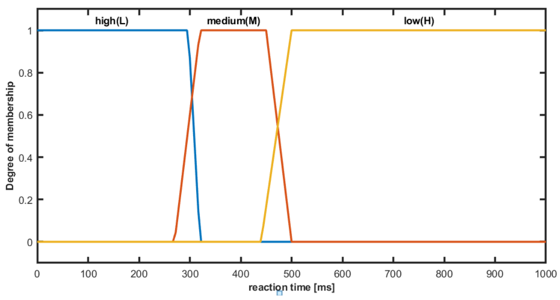

Fig. 8. DM1 membership function for reaction time input.

The subjective input component is divided into two logical groups, S1 and S2. Intermediate score S1, or pre-flight or pre-workout survey, for logically structured human survey data. Intermediate score S2 shall be based on the selected 4 test activities and their results. Intermediate evaluations from these two branches form the subjective component's resulting fatigue partial decision.

The logical structure of the decision algorithm for the objective mental fatigue component (O) consists of 6 objective input parameters, which are divided into three logical groups and can be obtained respectively between the O1 - O3 ratings from physiological sensor data or by using machine learning algorithms to process the incoming signals into discrete decision inputs. Intermediate assessment O1 contains the resulting input values of the first group of algorithms to be obtained using a simple detector of the relative alpha and beta band presence of the electroencephalogram band distribution. The eye blink frequency is obtained using either a video processing technique [12] or an electroencephalogram-defined blinking frequency. The intermediate assessment O2 contains selected electroencephalogram indices J1-involvement in the task and J2 - attention groups of indices based on the common characteristics of these two indices that characterize human attention. The intermediate assessment O3 contains a logical summary of the two electroencephalogram indices J3 – stress and J4 – alertness, which, by the characteristics of these two indices, characterises mental performance [1]. Intermediate evaluations from these three branches form the objective component's resulting fatigue partial decision.

For the synthesis of the set of decision laws from expert knowledge, it is proposed to use a form that is understandable to the person – a table method where the relationship between linguistic gradations of input and output parameters can be realistically implemented. Confirmation of the relationship is the result of an expert vote. The criterion of completeness of the knowledge base is used to verify that the number of cause-effect laws is sufficient to cover all gradation combinations between input parameters and exit decision. If the number of laws is insufficient, there is a problem in deciding because there is no link between any of the gradations in the entrance set and the exit decision. Redundancy is created if the number of laws is excessive above the measure of sufficiency. The number of decision laws for each of the expert systems is given in table 3 and in total 76 expert decision rules are distributed across 4 expert systems (table 3).

TABLE 3 NUMBER OF DECISION RULES FOR EACH EXPERT MODULE

Expert system	***Number of expert rules***
DM1 Objective component	27
DM1 Subjective component	28
DM2- Fatigue decision	9
DM3 – Fatigue recommendations	12

The method of defuzzification is proposed to be used COG (centre-of -gravity) of parameters in the partial decision level DM1 and DM2. However, for conversion of final recommendation in DM3 the system uses COS (centre-of-sums) method. The exit partial decision for each component in DM1 is a linguistic variable with a gradation L-M-H that is respectively "low," "medium," and "high." And forms the input for DM2 (Fig. 9).

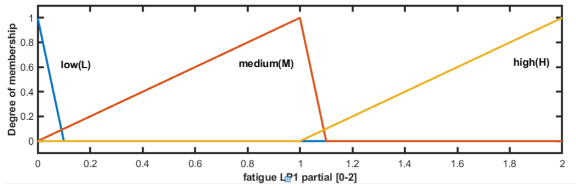

Fig. 9. DM1 partial decision output membership function.

Partial decisions at this level from entrance data, and the mental fatigue decision DM2, are described in this way as the fuzzy variables with three linguistic gradations which use normal distribution statistical Gaussian distribution for the output membership function of the DM2 fatigue level decision (Fig. 10).

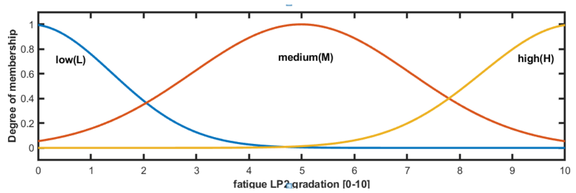

Fig. 10. DM2 fatigue level decision output membership function.

The expert system structure was modelled by using MATLAB Fuzzy Logic Toolbox 2022 and Octave Fuzzy-logic-toolbox. Decision modules are created in the language standard FCL (IEC 61131-7) for the control of fuzzy sets. Modular structure or system tree of decision-making controllers is a function used in this simulation environment to model complex decision systems. Each expert system decision block can be modelled separately by creating the input, output activation functions and the production rules so that a FIS object is formed. Mamdani Type I expert modules are used in the current architecture. The expert modules (FIS objects) then can be linked together, and chained structure called FIS tree, so that the next system input receives the previous output decision. The formed structure shall be uniform according to the characteristics of the modular system. Formally, the tree is responsible for the decision levels of DM1 and DM2, where the input values are semantic non-rigid values processed by algorithms and classifiers. All parameters use semantic gradation 3 linguistic classes when simplified numerically with values in scale [0÷2]. Formally, the complexity of such a tree as a monolith block is characterised by 19 input parameters with 3 gradations with 6852 variations in input data, so it is proposed to split decision making into 4 blocks.

Each decision controller has one parameter output associated with the next module as an input parameter. The subjective module combines 3 decision-making blocks because, as things stand, individual blocks have simplified logic. As the amount of knowledge increases, it would be necessary to transform the structure by splitting logic into 3 blocks and using a separate decision aggregation module. The decision logic of the objective component is divided into 4 modules describing the processing of input decisions in 3 intermediate blocks and the decision aggregation block of the objective component.

Overall, each expert system needs to validate the accuracy of decision-making against at least the synthesised test data of the base decision tree. The unit tests shall, as far as possible, cover the combinations of input parameters and exit decision classes (L-M-H) of each decision system module. The user interface was designed to use all system steps by a human expert and to observe the intermediate results for each expert-system module. To support the six steps of decision making, the following six decision-making expert system modules were created:

- Subjective component,
- Objective parameter monitoring,
- Unordinary situation decision module,
- Fatigue decision,
- Alerts,
- Recommendations.

The expert interface supports three main decision-making process scenarios: pre-flight survey, monitoring scenario during the activity and alert scenario when the system controls alert actuators. In the website expert module is interfaced in a separate column and the decision chain is linked left to right allowing to transparently interact with the system and test the formed decisions in each step. Logical examples of combinations executed during system testing using the directly created client API interface were generated to simulate end-user capabilities and the environments used.

In the MATLAB simulation environment, such decisions may have a different result due to differences in the implementation of the Fuzzy logic engine, so the result was validated at MATLAB first and then compared on the realised system through tests. Because expert logic is made up of knowledge laws, their testing uses the generation of logical combination for the input output pairs. The system must produce a decision at any combination of these input parameters, which were also tested automatically. The baseline criterion for such testing per module 0 deviations from the expected decision. Table 2 summarises the results of the unit tests:

TABLE 2 MINIMUM RULE CALCULATION

Module name	***Unit test count for each module***	***Unit test fault count***
DM1 Objective component	279	0
DM1 Subjective component	200	0
DM 2 – Mental fatigue decision component	9	0
DM3-Recommendations	518	0
Total	1006	0

The purpose of system tests is to check the correct functioning of the entire system in three given scenarios of driver pre-evaluation. To carry out automated testing of these scenarios, it is first necessary to identify the modules involved in each scenario. In this case the pre-evaluation tests used subjective inputs and the monitoring during drive used objective component inputs. Test data, or expert system input parameter values, are formed as combinations of input data from unit test inputs. Validation of system operation is based on the assumption that decisions resulting from the combination should be consistent with those laid down in the rules of expert decisions and appropriate alarm or recommendation should be provided at the system exit. So, the number of faulty tests must be a total of 0. System tests also feed input parameter values that are not defined within the formal boundaries of the parameters. The purpose of the system is to prevent input of such values or to inform you of incorrect parameter assignment. The baseline criterion for such testing per module 0 deviations from the expected decision. The desired condition was reached during testing as a result of 6 iterations over 279 driver pre-evaluation tests and 479 monitoring cases with driver recommendation.

IV. CONCLUSIONS

The following article proposes a transparent multi-level expert-system modular solution for simplified use by domain experts in the domain area of human fatigue evaluation.

The mathematical theories of fuzzy sets and fuzzy logic are still relevant topic nowadays and such decision-making systems are mostly used in areas of expert linguistic descriptions and fuzzy logic, the application area of medicine expertise requires a transparent decision making and models that can be constructed by non-expert in machine learning domain.

For the fatigue evaluation system that is described in this article the possible application areas are medical treatment institutions for patient rehabilitation, construction companies or hazardous substance providers, operator or air traffic controls, sports, educational and military institutions.

The theoretically feasible system should be divided into smaller modules to further exploit the possibilities to reduce the complexities of each module and improve the performance of the decision-making system during the implementation phase. In this case, the timing of the simulation decisions does not differ significantly when comparing the two structures, so the simulation basically uses the possibly simplified structure described in the first case. In the further use of the system, it follows from the perspective of modulation adaptation that it is necessary to implement the finer modules, which can be used independently and linked to each other by creating structures suitable for other applications.

REFERENCES

[1] M. Eriņš and Z. Markovičs, "Unordinary situation assessment of human fatigue and drowsiness in expert decision-making systems," Engineering for Rural Development, pp. 325-331, 2022.

[2] E. Butkevičiūtė, M. Eriņš, and L. Bikulciene, "Mobile Platform for Fatigue Evaluation: HRV Analysis," In: Information and Software Technologies: 25th International Conference (ICIST.2019): Proceedings. Communications in Computer and Information Science. Vol.1078, Lithuania, Vilnius, 10-12 October, 2019. Cham: Springer Nature Switzerland AG, 2019, pp.541-552.

[3] L.A. Zadeh, "Fuzzy Sets," Information Control, vol. 8, pp. 338-353, 1965.

[4] L.A. Zadeh, "The Concept of a Linguistic Variable and Its Application to Approximate Reasoning-1," Information Sciences, vol. 8, pp. 199-249, 1975.

[5] M. Sallinen, M. Harma, R. Akila, A. Holm, R. Luukkonen and H. Mikola, "The effects of sleep debt and monotonous work on sleepiness and performance during a 12-h dayshift," Journal of Sleep Research , vol. 13, pp. 285–94, 2004.

[6] M. Fabbri, A. Beracci, M. Martoni, D. Meneo, L. Tonetti, and V. Natale, "Measuring Subjective Sleep Quality: A Review," International journal of environmental research and public health, vol. 18(3), p. 1082, 2021.

[7] J. Zhao and B. K. Bose, "Evaluation of membership functions for fuzzy logic controlled induction motor drive," 28th Annual Conference of the Industrial Electronics Society. IECON 02, Seville, Spain, pp. 229-234, 2002.

[8] J. Osis, J. Grundspeņķis, and Z. Markovičs, Topological Modeling of Complex Heterogeneous Systems: Theory and Applications. Rīga: RTU, pp. 207-214 , 2012.

[9] E.H. Mamdani and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," International Journal of Man-Machine Studies, vol. 7(1), pp. 1–13, 1975.

[10] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," in IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-15, no. 1, pp. 116-132, Jan.-Feb. 1985.

[11] C. C. Lee, "Fuzzy Logic in Control System: Fuzzy Logic Controller - Part I & II," IEEE Transactions on Systems, Man and Cybernetics, Vol. 20, No. 2, pp. 404-435, 1990.

[12] M. Eriņš and D. Muska, "Methodology for selection and decision making of gradation of sleepiness using algorithms for face video image processing," Engineering for Rural Development, pp.1666-1673. ISSN 1691-3043, 2020.