Scientific Journal of Silesian University of Technology. Series Transport
Zeszyty Naukowe Politechniki Śląskiej. Seria Transport

Volume 107 **2020**

p-ISSN: 0209-3324

e-ISSN: 2450-1549

DOI: https://doi.org/10.20858/sjsutst.2020.107.7

Journal homepage: http://sjsutst.polsl.pl

Article citation information:
Manafov, E. The use of a fuzzy expert system to increase the reliability of diagnostics of axle boxes of rolling stocks. *Scientific Journal of Silesian University of Technology. Series Transport*. 2020, **107**, 95-106. ISSN: 0209-3324.
DOI: https://doi.org/10.20858/sjsutst.2020.107.7.

Elshan MANAFOV[1]

THE USE OF A FUZZY EXPERT SYSTEM TO INCREASE THE RELIABILITY OF DIAGNOSTICS OF AXLE BOXES OF ROLLING STOCKS

Summary. This paper is devoted to the development of an effective system for monitoring the technical condition of the axle boxes of rolling stock. To this end, the possibility of solving problems of fault diagnostics based on the theory of fuzzy sets is considered. This allows one note such difficult-to-formalise factors as experience and intuition of a highly qualified expert specialist. It showed that an expert system-based monitoring approach allows evaluation of the technical condition of the axle boxes, characterised by internal and external operating uncertainty. It also proposed the use of parameters such as vibration and noise for comprehensive monitoring of the technical condition of axle box units together with temperature. Furthermore, the combination of these diagnostic parameters and expert system's possibility to receive all necessary information about the condition of the most critical components of the axle boxes in real-time and analyse the changes in their operational parameters was explored. The stages of modelling an expert system in the Fuzzy Logic Toolbox package of the MATLAB computing environment are presented.
Keywords: rolling stock, axle box, control, fault, fuzzy sets, technical condition, temperature, vibration, noise

---

[1] Faculty of Transportation and Logistics, Azerbaijan Technical University, H.Javid ave 25, Baku AZ1073, Azerbaijan. Email: elshan_manafov@mail.ru

1. INTRODUCTION

The main condition for ensuring the safety of train movement in railway transport is the reliable and fail-safe operation of the rolling stock. To ensure the required reliability of the rolling stock, it is necessary to constantly control the technical condition of its running gear. In modern conditions, obtaining reliable information about its technical condition is impossible without technical diagnostic systems. Various diagnostic systems are currently used to assess the technical condition of the running gear of rolling stock in motion (based on the principle of their use: stationary, airborne, portable, incorporated directly into the controlled object, etc.). The main goal of technical diagnostics is to determine the type and location of defects [1, 3, 8, 10-12, 16].

Parameters, which bear information on the technical condition of rolling stock units, are sources of input information of the diagnostic system. These parameters directly or indirectly reflect the technical condition of the object being diagnosed.

One of the essential units of the rolling stock running gear is the axle units of wheelsets, which mainly consist of roller bearings. This time automatic temperature monitoring systems are used to monitor the technical condition of the bearings of the axle boxes. Such systems can be both stationary and with built-in sensors in the axle boxes [4].

2. PROBLEM STATEMENT

Existing diagnostic systems with built-in sensors make it possible to monitor the parameters of the technical condition of the box units and gain information about deviations from nominal readings. This allows measures to be taken in a timely manner and prevent the development of emergencies. The system provides the possibility of obtaining information about the temperature of the axle box unit by means of sensors built into the box housing. The monitoring system provides processing of the received information, its preservation and signals about dangerous heating of bearings. The system used only monitors the temperature of the node and notifies it of its value. The use of a single diagnostic parameter does not always allow the analysis of the development of bearing damage. To better analyse the state of the bearing assembly, it is necessary to supplement the temperature monitoring system with vibration and acoustic control, using improved hardware and computing. The use of such analysis permits not only the monitoring of the current state of the axle box assembly but also the performance of an analysis of the wear dynamics of the bearings [2, 9].

Moreover, when information is received in traffic about deviations from nominal readings of monitored parameters (temperature, vibration, noise, etc.), the driver of the high-speed passenger train informs the dispatcher who then informs the corresponding division. Further processes depend on the output of the tug specialist (stop the train in place, can be followed to the nearest station at a reduced speed, can be followed to the destination, etc.). To simplify these operations, a fuzzy expert system to diagnose the axle boxes of the rolling stock is proposed.

In this direction, a system approach to solving problems of diagnostics of rolling stock box faults, based on the concept of fuzzy sets with consideration of factors as difficult to formalise as the experience and intuition of a highly skilled expert.

In a fuzzy expert system for the diagnosis of axle boxes of rolling stock, the apparatus of the theory of odd sets is used, which makes it possible to obtain operational conclusions on the technical diagnosis of faults by abandoning the traditional requirements for the accuracy of the description of its functioning [5, 6].

3. POSSIBILITY OF USING FUZZY SET THEORY IN FAULT DIAGNOSTICS

Studies have shown that to solve the problems of diagnosing faults of axle boxes and other units of rolling stock, fuzzy sets can be used, as they consider such difficult-to-formalise factors as the experience and intuition of a highly qualified expert specialist. The apparatus of the theory of fuzzy sets for the diagnosis of axle boxes of rolling stock (ARS) in a fuzzy expert system (FES) allows one to get operational conclusions about the technical diagnosis of faults by abandoning the traditional requirements for the accuracy of its functional description [5-7,13].

One of the possible architecture versions of a fuzzy diagnostic expert system for ARS is denoted in Fig. 1.

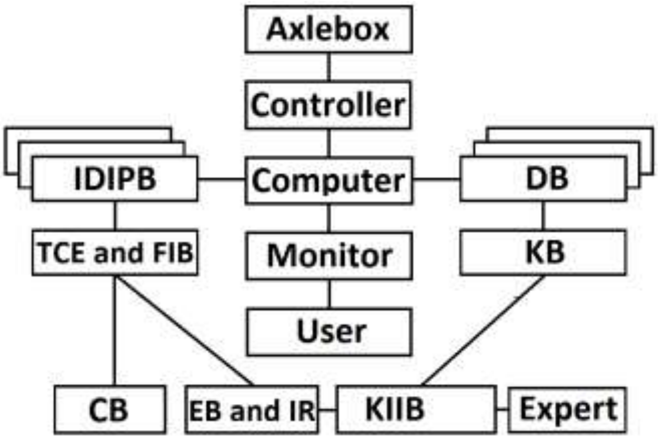

Fig. 1. The architecture of the fuzzy diagnostic expert system of ARS: User - driver of the train; IDIPB - initial data input and processing block; DB - database; KB - knowledge base; KIIB - knowledge input and interpretation block; CB - calculation block; TCE and FIB - technical condition evaluation and fuzzy inference block; EB and IR - explainer block and issuing recommendations

To enter knowledge into the knowledge base (KB) of a diagnostic FES, a knowledge representation language that takes into account the specific features of ARS is used. When developing the knowledge base, the following was taken into perspective:

- ARS is described by a set of faults and fault symptoms (FS);
- FS of elements essential for ARS (noise level, bearing temperature, vibration level, etc.);
- FS can take values reflecting the fixed state of the ARS, for example, object NOISE_LEVEL – value of 50 dB, object BEARING_TEMPERATURE – value of 60° C;

- values can also be specified in the form of linguistic terms: LOW, NORM, LIMIT, OVER_LIMIT, PERMISSIBLE, etc.;
- values of linguistic variables can be computational, for example, DFAA=((CVF – PVF)/PVF)100, where DFAA – deviations of the forces acting on the axle box, CVF – current value of the forces acting on the axle box, PVF – the permissible value of the forces acting on the axle box;
- values of linguistic variables can also be productive:

IF NOISE_LEVEL=LOW
AND BEARING_TEMPERATURE=LOW
AND VIBRATION_ LEVEL =LOW
THEN AXLEBOX_OPERATION=NORM.

With more inputs, it becomes more difficult for the expert to describe relationships of cause and effect by fuzzy rules, as no more than 7 ± 2 concept-signs can be simultaneously stored in the human memory. Therefore, the number of input variables in one knowledge base should not exceed this number. Past studies show that good knowledge bases are obtained when the number of inputs is less than five. As shown above in this expert system, the input variables are temperature, vibration, and noise. Values of parameters for the range of linguistic variable are calculated based on permissible deviations of parameters from average values in accordance with technical operation rules. In the development of the knowledge base of the expert system, the results of indication were used, which were converted into 3-5 ranges of parameter values according to linguistic variables (Tab. 1) [7, 13].

Tab. 1

Composition of technical condition parameters

Parameter name	Parameter value				
	verylow	low	average	high	veryhigh
Temperature level of ARS [ºS]	0-20	10-40	30-60	50-90	80-120
Vibration level of ARS [mm/sec^2]	0-3	2-5	4-7	6-9	8-12
Noise level of ARS [dB]	-	10-30	40-70	80-140	-

The formal knowledge model in the system is represented as follows. Assume $X=\{x_1,x_2,\ldots,x_n\}$ is the set of ARS faults. Description of FS as objects is performed using OB constructions (ω,n,d,l), where ω is the short name of FS; n is the full name of FS; d is the normal variation range of FS values; l is the unit of measurement of FS, with corresponding membership functions – $\mu(X)$.

The membership function has the form of a trapezoid and is determined by the parameters $(\alpha_l,\alpha l,\alpha_r,\alpha r)$, α_l is the left deviation; αl is the left peak; αr is the right peak; α_r is the right deviation. If we need to define our own linguistic values, then this can be done using LING ("short name of the object", "linguistic value", $(\alpha_l,\alpha l,\alpha r,\alpha_r,)$) [13].

The database contains objects (linguistic variables) X_i (Tab. 2) with the values (A_{ij},cf_{ij}), where A_{ij} is the value of linguistic variables; $cf_{ij}\,\epsilon[0;100]$ is the validity factor of the value A_{ij}:

OB (NL, "NOISE_LEVEL", 10, 84, "DB");
OB (BT, "BEARING_TEMPERATURE", 42, 56, "DEG.C");
OB (VL, "VIBRATION_LEVEL", 0,37; 0,51, "mm/sec^2");
…………………………………………
OB (AL, "AXLEBOX_LOAD", 100, 140, "%");
OB (ET, "ENVIRONMENT_TEMPERATURE", -30, 40, "DEG.C");
OB (ALO, " AMOUNT_OF_LUBRICATING_OIL", 40, 150, "%").

Tab. 2

Fragment of primary knowledge (database)

№	Temperature level of ARS	Vibration level of ARS	Noise level of ARS
1	verylow	verylow	low
2	verylow	verylow	average
…	....	....	....
31	average	verylow	low
32	average	verylow	average
...	....	....	....
74	veryhigh	veryhigh	average
75	veryhigh	veryhigh	high

$\mu(X)$ is analytically written as follows:

$$\mu(u)=\begin{cases}1-\dfrac{al-x}{\alpha_l}, & if \quad a_1-\alpha_l\le x\le a_1;\\ 1, \quad if \quad a_1\le x\le a_2; & \\ 1-\dfrac{x-ar}{\alpha_r}, & if \quad a_2\le x\le a_2+\alpha_r;\\ 0, \quad in\ other\ cases. & \end{cases} \tag{1}$$

Graphically, the accessory functions for temperature, vibration and noise are represented as a trapezoid. Two components interact in the fuzzy inference process: the Knowledge Base and the Database. The knowledge base contains production rules that have left- and right-hand parts, for example:

IF $X_1=A_{l1}$ *AND* $X_2=A_{l2}$ *AND…AND* $X_n=A_{ln}$ *THEN* $Y_1= B_{l1}$ *OR* $Y_2 =B_{l2}$ *OR…OR* $Y_n =B_{ln}$
IF $X_1=A_{n1}$ *AND* $X_2=A_{n2}$ *AND…AND* $X_n=A_{nn}$ *THEN* $Y_1= B_{n1}$ *OR* $Y_2 =B_{n2}$ *OR…OR* $Y_n =B_{nn}$

An analysis of the applicability of the rules involves the assessment of the degree of truth of the premise based on current values (A_{ij},cf_{ij}) of output objects X_i taken from the database and the values recorded in the rule (to what degree the first are equal or unequal to the second). If the rules are applicable, then the actions from the right-hand side are performed, leading in most cases to the input of the “object-value” pairs into the database, and the process is repeated until all applicable rules are fulfilled [5-7,13].

To calculate the degree of truth of production rules during the inference, the fuzzy similarity operation $a_1 \Theta a_2$ is used, where a_1 and a_2 are linguistic values; Θ is the "close to" operation, that is, for the selected format of the membership function, we have:

$$a_1 \Theta a_1 = \begin{cases} Poss(a_1/a_2) = \max\min\left(\mu_{a1}(x), \mu_{a2}(x)\right) \in [0;1]; \\ 1 - \dfrac{al_1 - ar_2}{\alpha_1 + \alpha_2}, \; if \quad 0 < al_1 - ar_2 < \alpha_1 + \alpha_2; \\ 1, \; if \quad \max\left(al_1, al_2\right) \le \min\left(ar_1, ar_2\right); \\ 1 - \dfrac{al_2 - ar_1}{\alpha_2 + \beta_1}, \; if \quad 0 < al_2 - ar_1 < \alpha_2 + \alpha_1; \\ 0, \; in\, other\, cases. \end{cases} \tag{2}$$

A set of heuristics used by highly qualified specialists serves as the algorithm for solving the problem. Heuristics formulated by experts are entered into the system knowledge base. Give for clarity, a fragment of fault diagnostics ARS:

NOISE_LEVEL (dB) = 11
TEMPERATURE_LEVEL (ºC) = 74
VIBRATION_LEVEL (mm/sec^2) = 7
………………………………………………………………………………………
NOISE_LEVEL (dB) = "LOW"
TEMPERATURE_LEVEL (ºS) = "HIGH"
VIBRATION_LEVEL (mm/sec^2) = "AVERAGE"
………………………………………………………………………………………
ENVIRONMENTAL TEMPERATURE MORE THAN NORMAL (ET) – RELIABILITY 40 %
OR AMOUNT OF LUBRICATING OIL IS MORE THAN NORMAL (ALO) - RELIABILITY 30 %
OR AMOUNT OF LUBRICATING OIL IS LESS THAN NORMAL (ALO) - RELIABILITY 20 %
OR DEVIATIONS OF THE FORCES ACTING ON THE AXLE BOX ARE MORE THAN NORMAL (DFAA) - RELIABILITY 10 %
………………………………………………………………………………………
IF ET = "MORE THAN NORMAL"
DISPLAY ("RECOMMENDATION: FOLLOW TO DESTINATION STATION WITH SET SPEED")
SO_THAT, "UNDER THE INFLUENCE OF AMBIENT TEMPERATURE THE AXLEBOXES LOCATED ON THE SIDE OF THE SUN ARE HEATED TO THE LIMIT LEVEL"
IF ET = NORMAL THEN INQUIRY LOMN
………………………………………………………………………………………
IF ALO = "MORE THAN NORMAL" AND "FIRST TRIP AFTER INSTALLATION OF THE AXLE BOX"
DISPLAY ("RECOMMENDATION: FOLLOW TO DESTINATION STATION WITH SET SPEED")

SO_THAT “LARGE AMOUNT OF LUBRICANT MAKES IT DIFFICULT TO ROTATE ROLLERS AND CAUSES HEATING. FRICTION MAY STOP AS EXCESS LUBRICANT IS EXTRUDED”

İF “IT IS NOT THE FIRST TRIP AFTER INSTALLATION OF THE AXLE BOX” INQUIRY ALO = “LESS THAN NORMAL” OR DFAA= MORE THAN NORMAL

…………………………………………………………………………………………

İF ALO = “LESS THAN NORMAL” OR DFAA= MORE THAN NORMAL

DISPLAY ("RECOMMENDATION: FOLLOW TO THE NEAREST STATION WITH TECHNICAL INSPECTION POINT WITH SET SPEED"

SO_THAT “INSUFFICIENT LUBRICATION OF BEARINGS CAUSES HEATING AND MAY END WITH MALFUNCTION OF AXLE BOX OR IN CASE OF INCORRECT ASSEMBLY OF BOGIE, SKEW OF ROLLING STOCK FRAME LOADS ON AXLEBOXES INCREASE”.

4. SIMULATION OF THE FUZZY EXPERT SYSTEM FOR APS DIAGNOSTICS IN MATLAB APPLICATION PACKAGE

Special fuzzy modelling tools in MATLAB enables the performance of complex research on the development and application of fuzzy models. With the MATLAB software, it is possible to implement theoretical concepts of fuzzy sets and fuzzy inference procedure. Hence, a structural diagram of the model of fuzzy expert system in the package Fuzzy Logic Toolbox for diagnostics of ARS was composed (Fig. 2) [14, 15].

Temperature, vibration and noise levels are input parameters in the model. The outputs are the distance (zero distance, distance to the nearest station, distance to the nearest station with a technical inspection point, distance to the destination station) and speed (zero speed, reduced speed, set speed) of the train. From the output parameters, it is possible to form a recommendation to experts: to stop the train in place, to follow to the nearest station at a reduced speed, to follow to the nearest station with a technical inspection point at a set or reduced speed, to follow to the destination station at a set speed.

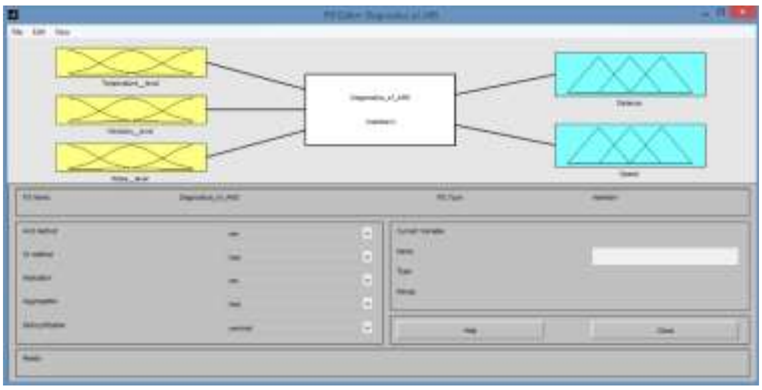

Fig. 2. Structural diagram of diagnostics of the ARS in the window of the editor MATLAB 7

In the process of phasification based on known values of input parameters, fuzzy sets are formed, where values of membership functions of fuzzy sets are determined based on normal initial data. Values of input parameters are brought into their fuzzy linguistic variables (Tab. 1) and subsequent selection of the law of membership function change is chosen for them.

For each input parameter, a trapezoidal law of change of membership function is specified: y = trapmf (x, [a, b, c, d]), where argument a is the minimum permissible value of the parameter with zero probability of norm, the segment between arguments [b, c] shows the belonging of the parameter to the norm with probability 1. Accordingly, the argument d is the maximum allowed value of the parameter with zero probability of the norm. The selection of the trapezoidal form of the belonging function is because the belonging of the parameter to the norm with probability 1 is determined not by one value of the variable, but by a range of permissible values. An example of the membership function of input parameters is shown in Fig. 3 – a graph of the parameter “temperature level”.

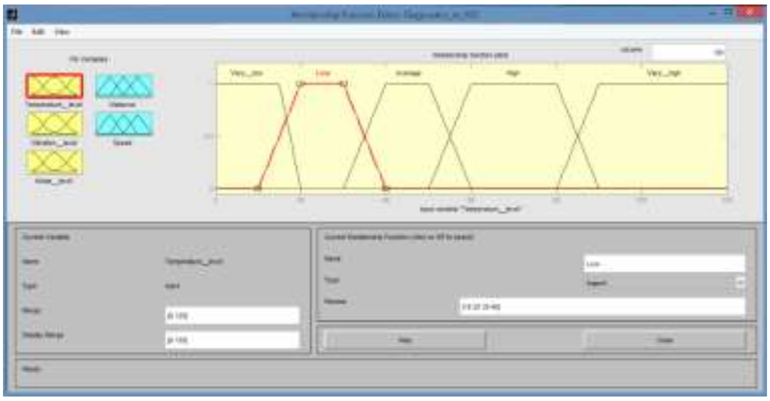

Fig. 3. Membership functions of parameter “temperature level”

Each parameter has its own change range. After completion of the phasification step, specific values of the membership functions for each of the linguistic terms are determined for the input variables. These terms are used in the conditions of the base of rules of a system of fuzzy conclusion: if parameter N is (very low/low/average/high/very high).

Causal relationships between parameter values and solution output are formalised in the form of a set of fuzzy logical rules. The format of the base if-then output rule is called fuzzy implication. The condition of the rule may be the statement "temperature level is high" where "high". The conclusion for this condition may be to "follow to the nearest station at a reduced rate." This implication can be written down in a look: "temperature high" → "to follow to the nearest station with the reduced speed".

Fuzzy knowledge base with information on the "parameter value - decision making" dependency can contain linguistic rules (Fig. 4): If (temperature level is low) and (vibration level is low) and (noise level is high) then (distance is high) (speed is low).

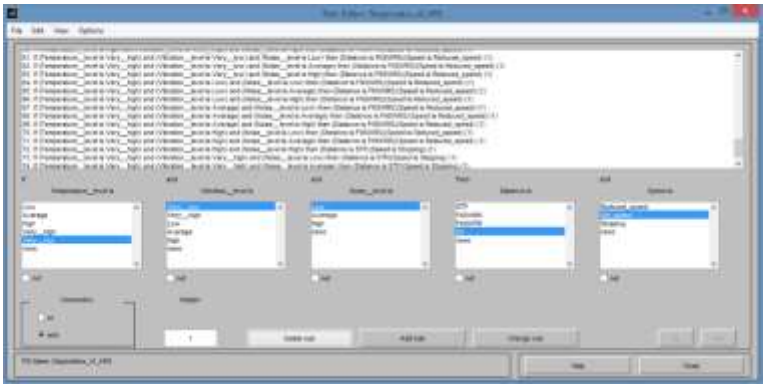

Fig. 4. Window of the editor of rules

At the stage of defuzzification, the problem of reverse phasification is solved: conversion of linguistic variables of input parameters into the value of output parameters (Fig. 5).

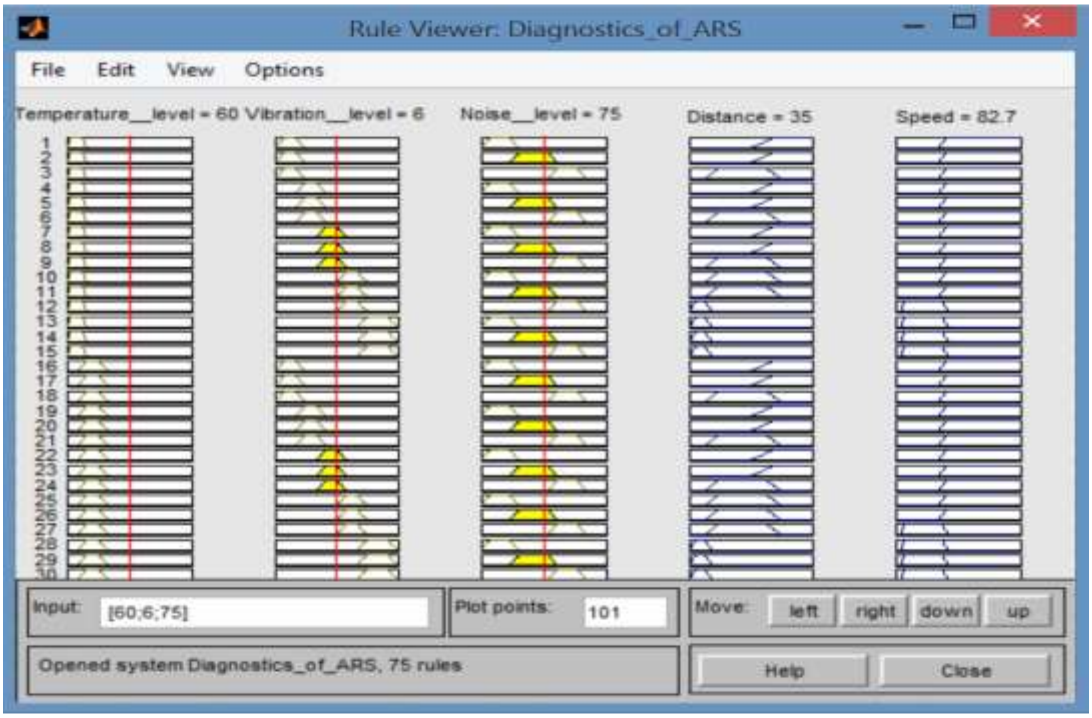

Fig. 5. Visualisation of fuzzy decision

It is also possible to obtain “2 input-output” surface from the results of the fuzzy logical output. With the help of it, the distance or velocity values of two input variables can be seen (Fig. 6).

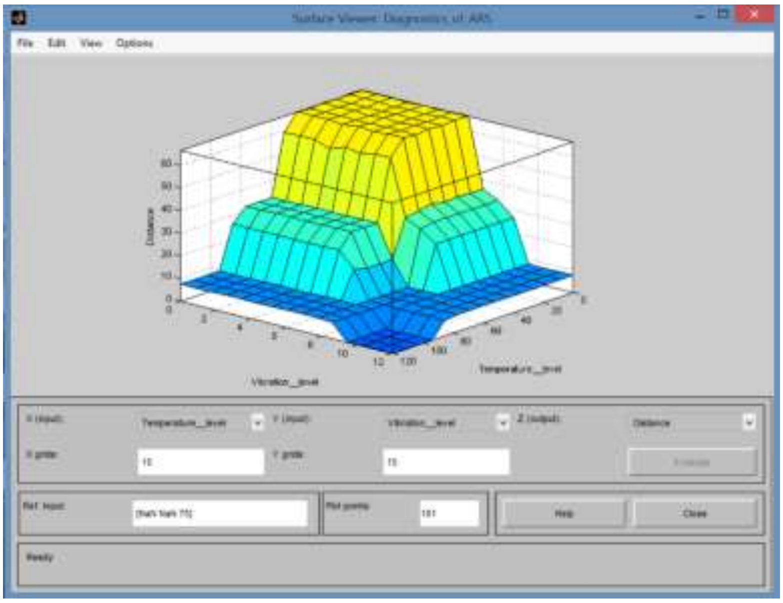

Fig. 6. Synthesised "2 inputs-output" surface

5. CONCLUSIONS

Thus, for a deeper analysis of the ARS state, a temperature monitoring system needs to be supplemented with vibration and acoustic monitoring. Application of such complex analysis makes monitoring of the current state of ARS and conduct of the analysis of bearing wear dynamics possible. To assess the technical condition of ARS, which is characterised by internal and external operational uncertainty, an expert control system was developed. The combination of these diagnostic parameters and the developed expert system made it possible to receive all necessary information about the condition of the most critical components of the axle boxes in real-time, analysing the changes in their operational parameters. This facilitates prediction of time to maintenance and repair, thereby preventing emergencies during operation.

To conduct research on the creation of an expert system, a simulation of ARS diagnostics system was materialised in the Fuzzy Logic Toolbox package. The developed model of the expert system in MATLAB based on fuzzy logic and input parameters allows us to adequately reflect at an early stage, the growing probability of a malfunction when the input parameters change in real-time.

References

1. Dižo J., M. Blatnický, S. Steišūnas. 2017. "Assessment of negative effects of a coach running with the wheel-flat on a track by means of simulation computations". *Diagnostyka* 18(3): 31-37.

2. Entezami Mani, Clive Roberts, Paul Weston, Edward Stewart, Arash Amini, Mayorkinos Papaelias. 2020. "Perspectives on railway axle bearing condition monitoring". *Proceedings of the Institution of Mechanical Engineers, Part F*: *Journal of Rail and Rapid Transit* 234(1): 17-31. ISSN: 0954-4097. DOI: https://doi.org/10.1177/0954409719831822.
3. Frischer R., J. David, P. Švec, O. Krejcar. 2015. "Usage of analytical diagnostics when evaluating functional surface material defects". *Metalurgija* 54(4): 667-670. ISSN: 0543-5846.
4. Gerdun Viktor, Tomaz Sedmak, Viktor Sinkovec, Igor Kovse, Bojan Cene. 2007. "Failures of bearings and axles in railway freight wagons". *Engineering Failure Analysis* 14(5): 884-894. ISSN: 1350-6307. DOİ: https://doi.org/10.1016/j.engfailanal.2006.11.044.
5. Gudwin Ricardo, Edgar Simeon, Alberto Alvares. 2010. "An expert system for fault diagnostics in condition based maintenance". *ABCM Symposium Series in Mechatronics* 4: 304-313. ISBN: 978-85-85769-47-5.
6. He Qing, Xiaotong Zhao, Dongmei Du. 2013. "A novel expert system of fault diagnosis based on vibration for rotating machinery". *Journal of Measurements in Engineering* 1(4): 219-227. ISSN: 2335-2124.
7. Jackson Peter. 1998. *Introduction to expert systems*. England, Harlow: Addison - Wesley. ISBN: 0-201-87686-8.
8. Kosicka E., E. Kozłowski, D. Mazurkiewicz. 2015. „The use of stationary tests for analysis of monitored residual processes". *Eksploatacja i Niezawodnosc – Maintenance and Reliability* 17(4): 604-609. DOI: http://dx.doi.org/10.17531/ein.2015.4.17.
9. Lunys Olegas, Stasys Dailydka, Gintautas Bureika. 2015. „Investigation on features and tendencies of axle-box heating". *Transport Problems* 10(1):105-114. ISSN 1896-0596. DOI: 10.21307/tp-2015-011.
10. Mazurkiewicz D. 2014. „Computer-aided maintenance and reliability management systems for conveyor belts". *Eksploatacja i Niezawodnosc – Maintenance and Reliability* 16(3): 377-382.
11. Mazurkiewicz D. 2010. „Tests of extendability and strength of adhesive-sealed joints in the context of developing a computer system for monitoring the condition of belt joints during conveyor operation". *Eksploatacja i Niezawodnosc – Maintenance and Reliability* 3: 34-39.
12. Michalski R., S. Wierzbicki. 2008. „An analysis of degradation of vehicles in operation". *Eksploatacja i Niezawodnosc – Maintenance and Reliability* 1: 30-32.
13. Piegat Andrzej. 2001. *Fuzzy Modeling and Control.* Heidelberg: Springer Science & Business Media. ISBN: 10 3790824860. ISBN: 13 9783790824865.
14. Sivanandam S.N., Sumathi S., Deepa S.N. 2007. *Introduction to Fuzzy Logic using MATLAB.* Heidelberg: Springer-Verlag. ISBN-10: 3540357807. ISBN-13: 978-3540357803.
15. Штовба С.Д. 2007. *Проектирование нечетких систем средствами MATLAB.* Москва: Горячая линия-Телеком. [In Russian: Shtovba S.D. 2007. *Designing fuzzy systems with MATLAB.* Moscow: Hotline-Telecom. ISBN 5-93517-359-X].
16. Štroffek E., P. Peterka, J. Krešák, S. Kropuch. 2006."Diagnostics of pipelines system". *Metalurgija* 45(2): 137-139. ISSN: 0543-5846.

Received 10.02.2020; accepted in revised form 20.05.2020

Scientific Journal of Silesian University of Technology. Series Transport is licensed under
a Creative Commons Attribution 4.0 International License