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Maintenance of belt conveyors using an expert system based on fuzzy logic

D. Mazurkiewicz *

Lublin University of Technology, Nadbystrzycka 36, 20-618 Lublin, Poland

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ABSTRACT

In recent years, conveyor belt transport systems have taken on a new significance due to numerous research studies on innovative design solutions. The application of these new developed solutions leads to considerable reduction in operational costs of transport systems, while ensuring their high reliability and service life at the same time. Nonetheless, there are still areas that pose challenge to both research and development. Typical challenges are analyzed in this paper. The solution to the problems of conveyor transport maintenance can be the implementation of a system for estimation of technical condition of conveyor belt joints. It serves as a second level safety diagnostic system for transport. Besides real-time measurements, the system enables a long-term analysis of historic data for every single joint that makes up the conveyor belt loop, from the moment of its manufacture to the final operation. The effectiveness of a conveyor belt diagnostic system primarily depends on the use of a decision supporting system. With adequate inference rules applied, this system would increase the effectiveness and shorten the time of decision-making as well as verify generated signals. The above tasks can be performed by a suitable expert system that predicts values of the analyzed time series, using the predicted values and inference rules to verify any potential false alarm signals at the same time. The idea and algorithm of such an expert system were presented in this article as well.

1. Introduction

New technological possibilities result in an extremely dynamic industrial development. Due to ever-increasing competition on the market, higher customer demands and pursuit of innovative products, manufacturers are compelled to implement more and more advanced engineering solutions, particularly ones that lead to higher efficiency and reduced operational costs. In effect, machinery and technological devices are becoming more and more complex, which imposes higher demands on their users, including the necessity of applying suitable methods and techniques to ensure durability and reliability of frequently complex and elaborate production systems [1,2].

In recent years, conveyor belt transport systems have taken on a new significance due to numerous research studies on innovative design solutions for conveyor belts [3–10]. The

* Tel.: +48 815384229.
E-mail address: d.mazurkiewicz@pollub.pl

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application of these new developed solutions leads, among others, to considerable reduction in operational costs of transport systems, while ensuring their high reliability and service life at the same time. Nonetheless, there are still areas that pose challenge to both research and development. As demonstrated in the studies [3,4,11], it is absolutely vital from a practical point of view that the service life of conveyor belt joints be made longer owing to the fact that these joints are crucial elements of the entire conveyor transport system. For instance, vulcanized and adhesive-bonded joints of textile-rubber belts are made up of lap joints, their theoretical durability for three separators amounting to only 67% of the belt's rated durability [4]. Moreover, the forces that affect the belt load and durability of both the belt and its joints vary during operation. For this reason, methods applied to this end, e.g. ones for determining non-stationary states, are often inaccurate, which results from lack of precise data and insufficient determination of boundary conditions. On the other hand, it is vital to optimize the belt tension force for various conveyor load conditions, as this should result in higher durability of both the belt and its joints. The application of a solution based on standard control algorithms seems, however, inadequate due to the nature of the problem as well as lack of both sufficient insight into the problem and measurement data.

2. Operation of an intelligent advisory system in considerable uncertainty conditions

The solution to the above problems of conveyor transport maintenance can be the implementation of a system for estimation of technical condition of conveyor belt joints [11] that serves as a second level safety diagnostic system for transport. Besides real-time measurements, the system enables a long-term analysis of historic data for every single joint that makes up the conveyor belt loop, from the moment of its manufacture to the final operation. The monitoring device can also be converted into an autonomously functioning instrument that can independently react to variable operational conditions and thus eliminate states that pose threat to the system's reliability, e.g. it can counteract belt failure by predicting the occurrence of operational parameters and their consequences. However, the vast number of data and information generated by the measuring system (which is the case when the monitoring covers a great deal of joints that are usually located on up to even several conveyors in a complex transport system) leads to a series of complications regarding interpretation of the collected data, which consequently hinders effective decision-making by the monitoring staff. In addition, given the specific nature of operation of conveyor belts (e.g. their exposure to high momentary loads), the measured discrete values of variations in length of an adhesive-bonded joint can generate false alarms that can result in unjustified stoppage of the transport system, unnecessary inspection of the joint or complicated and time-consuming examination of the generated signal by the operator. The system operator is then continuously required to take decisions, analyze a vast data set and observe changes therein, as well as predict the consequences of further changes in functional properties. This means taking decisions in uncertainty conditions [12,13], when we have no information about the probable occurrence of particular states (safe/emergency/alarm) and can only predict values of the analyzed signals that have the form of a discrete time series.

The conveyor transport system is an object that is affected by a number of factors. These factors are either imprecisely determined or difficult, if not impossible, to measure because of their random and incidental nature. This object is hard to describe owing to its dependence on numerous unpredicted variables that are often additionally difficult to be precisely determined. Failure-signaling symptoms can occur either once or many times; they can also have different intensity and nature. Another common problem here is lack of unambiguous information about the analyzed object and the required short time of a potential reaction. When equipping a comprehensive conveyor transport system with efficient and advanced monitoring and diagnostic systems, it is therefore necessary that sophisticated and intelligent tools be used to support the above. More specifically, the intelligent advisory system will be a dynamic system for the supervision of complex processes that are characterized by variable operating conditions and two time scales: micro- and macro-time scales [14], which is essential with regard to the entire life cycle of a single adhesive joint or a belt section that usually undergoes frequent relocations.

3. Inference supporting system based on fuzzy residuum evaluation in the diagnostics of conveyor belts

The effectiveness of a conveyor belt diagnostic system primarily depends on the use of a decision supporting system. With adequate inference rules applied, this system would increase the effectiveness and shorten the time of decision-making as well as verify generated signals. The above tasks can be performed by a suitable expert system that predicts values of the analyzed time series, using the predicted values and inference rules to verify any potential false alarm signals at the same time. The prediction of variations in length of an adhesive-bonded joint involves classification and estimation of time series. Although all standard classification and estimation methods can, under certain conditions, be also employed for prediction, the most effective method for predicting time series involves the use of artificial neural networks [15–20]. A supervision system for adhesive-bonded joints of conveyor belts should therefore also include an intelligent expert system based on the popular knowledge representation and rule-based systems (Fig. 1).

When measuring variations in length of belt joints by a computer-aided measurement system, it can be assumed that the observations are made at discrete and equal intervals of time t. For every joint we have data from the evaluation of its length ΔL in time moments $t-1$, $t-2$, …, $t-n$, which corresponds to the values of $\Delta L_{t-1}, \Delta L_{t-2}, \Delta L_{t-3}, \ldots, \Delta L_{t-n}$. The aim of the analysis is to determine values of elongation of the monitored conveyor belt joint $\overline{\Delta L_t}(w)$, denoting the prediction in a moment $t+w$, i.e. in advance w, with the lowest possible mean deviations $\Delta L_{t+w} - \overline{\Delta L_t}(w)$. When evaluating the potential

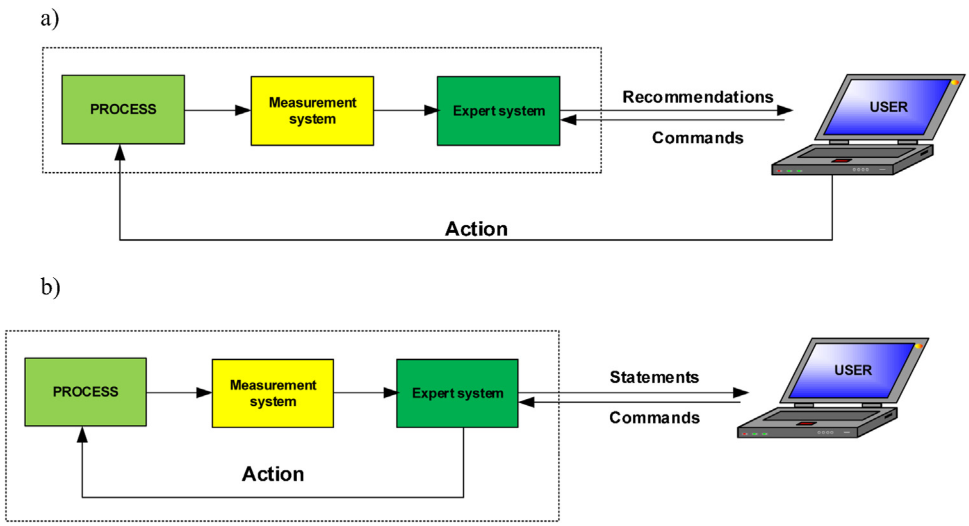

Fig. 1 – Design of an expert control system (a) and a decision support system for conveyor belt transport (b) [11].

occurrence of a false alarm, the deviation between real and predicted values will be used as an element of the inference rule. Having information about the estimated variable at prediction-preceding moments ($t-1, t-2, \ldots, t-n$), the neural network determines the value of the analyzed time series. Taking into account the current prediction error and its past value, it is possible to perform adaptation of network weights, which ensures that the prediction will be even more accurate in the future.

Given the research objectives of the present study, the prediction process based on the use of artificial neural networks to predict elongations of an adhesive-bonded joint was performed using the Matlab software suite along with the application of the standard procedure that involved [21]: preliminary data analysis, selection of training, testing and verifying data, network training, network testing, selection of network architecture with the optimum mesh and using it as an experimental predicator. Prior to designing a time series model, the collected data usually undergo a preliminary analysis that encompasses, among others, examination of data correctness and homogeneity, data transformation (operationalization), reduction of input data set, data decomposition, selection of a method for qualitative data representation and their scaling. With the tested procedures for selecting a neural predicator, the effect of input data quantity on the result of network training had to be investigated in the first place. When it comes to time series obtained from the measurements of variations in length of conveyor belt joints with a vast number of measuring points (prediction-preceding moments starting from $t-200$), the tested network architectures did not produce satisfactory plotting. The best network training results were obtained when the data from the time series $t-20$ to t were used. Among the tested architectures of neural networks, the best results (i.e. suitable capacity of both approximation and generalization) were obtained for a multilayer perceptron (MLP) that had the form: 1-4-4-1 (two hidden layers of neurons, each having four neurons), where the tracking error was 0.06 (Fig. 2).

MLP-based models have generally simple structures and, as a result, they have a short activation time and do not require considerable data storage capacity. Joints in such networks enable communication between neurons in the adjacent layers, while all neurons that make up the network aggregate input data by calculating the total of weighed inputs, i.e. by means of the linear aggregation formula. The input neurons

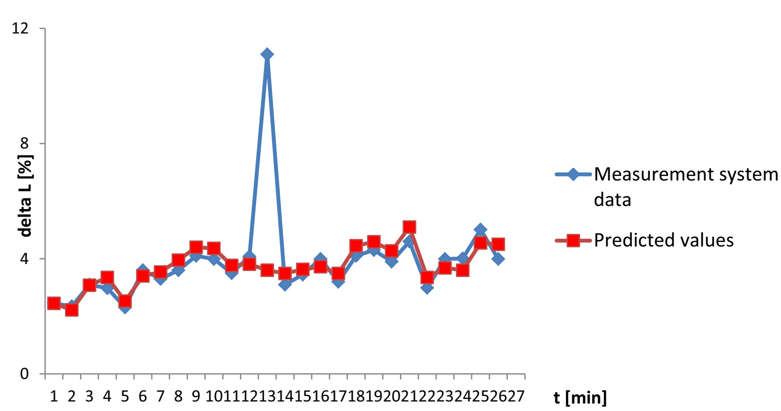

Fig. 2 – Results of predicted lengths of the adhesive-bonded joint of a conveyor belt.

aggregation is described by a linear function, hidden neurons have a non-linear (mostly s-shaped) function, while the function of output neurons is either linear or non-linear [22].

The prediction of lengths of a belt joint or its elongation is vital given the need of using prediction for estimating the deviations between real and predicted values that will then be used as an inference rule for the advisory system. The system will take over from the system operator the decision-making process with regard to information about the joints provided by the measuring system, including decisions that concern elimination of false alarms generated by the diagnostic system, also using the adaptive alarm threshold method to this end (Fig. 3).

Examining deviation results, it can be stated that when the deviation is high the generated alarm signal is false alarm. The problem is to come up with a precise definition of the limit value of a calculated deviation. Due to the resulting ambiguity of interpretation and linguistic descriptions like "high deviation" and "low deviation," we need to find some other solution to the analyzed problem drawing on fuzzy logic rather than inference based on classical algorithms. The combination of fuzzy logic and fuzzy sets leads to effective inference, particularly when dealing with imprecise data, which is the case with of the present object analysis.

Similar to standard systems, expert fuzzy systems comprise a knowledge base (here: with fuzzy rules) and an inference apparatus. The inference procedure is however different, which stems from the fact that data for inference are often figures representing measurement results, while the rules are based on linguistic values [13,23]. The linguistic value is the verbal estimation of a linguistic quantity. The fuzzy set A is a set of pairs in a certain numerical space of the discussion in [24]:

$$A = \{(\mu_A^*(x), x)\} \tag{1}$$

where μ_A is the membership function of the fuzzy set A that assigns each element of $x \in X$ with its degree of membership $\mu_A^*(x)$ in the fuzzy set, when $\mu_A(x) \in [0, 1]$.

The membership function assigns to every element x of a given variable a certain value from the range [0,1], also known as membership degree. This value provides information about the degree to which the element x is part of the fuzzy set A:

$$\mu_A(x) : X \to [0, 1] \tag{2}$$

In many cases, the degree of membership in a fuzzy set is a subjective value that depends on the context. By the same token, the shape of a membership function is more significant than any specific value. Taking advantage of this formula, we can use fuzzy logic to assign to every value an accurate number that indicates agreement between this value and its description in a natural language [25–28]. With data collected by industrial measuring systems, fuzzy numbers allow us to make generalizations about a great deal of information recorded by measuring instruments. Fuzzy numbers are also extremely useful in complex systems where immeasurable or hard-to-define disturbances occur. A similar situation can be observed when the monitoring system cannot measure certain signals in an accurate manner. A vital characteristic of fuzzy logic and fuzzy logic-based models is the fact that – contrary to widely applied artificial neural networks – they do not resemble a "black box", where it is difficult to examine properties of the modeled object based on the neural network analysis. Due to its features, the theory of fuzzy sets enables not only the modeling of complex systems, but also supporting of decision-making processes.

The model of the analyzed object consists of two inputs, x_1, x_2, and one output y. The input x_1 is the momentary relative elongation of a single joint as recorded by the computer measuring system. The input x_2 denotes the deviation of the real relative elongation from its predicted value for a given moment t as indicated by the neural network for the analyzed time series. The proposed advisory system for the diagnostics of conveyor belt joints is a relatively simple system (two inputs, one output) and its task is to take over from the operator once the number of data collected by the monitoring system is too vast to be interpreted in real time.

The design of the fuzzy model requires, among others, the determination of membership functions of input variables, rule base and inference mechanism as well as the definition of membership functions of the output variable. The first stage of fuzzy model design in a fuzzification block involves performing fuzzification in order to define the degree of membership of the entered sharp input in an correct fuzzy set, which requires precise definitions of fuzzy set membership functions for individual inputs. The fuzzy set membership functions of the inputs x_1 and x_2 were defined based on the observations of adhesive-bonded joint behavior at load backed up with the results of verifying experimental tests [3,4].

For every input variable case, three membership functions were applied: left external function, trapezoid asymmetric function and right external function. In this way, we took advantage of the benefits offered by multi-angle functions, including the fact that such functions can be defined using minimum number of information when compared to other membership functions. The momentary value of the measured relative elongation of the joint can be considered low

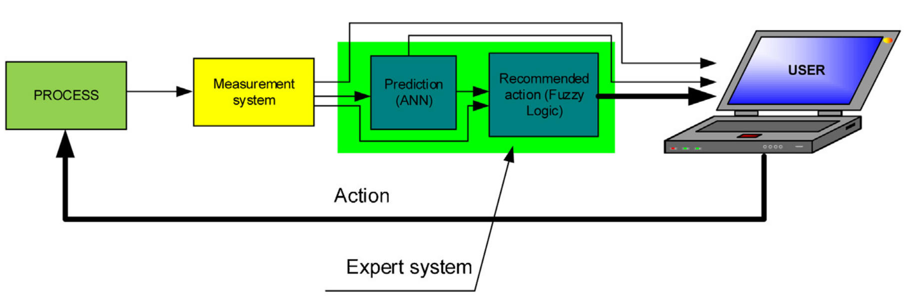

Fig. 3 – Intelligent advisory system for the monitoring of belt joints.

(safe) if it ranges from 0% to 10%, mean (emergency) if it ranges from 8% to 15%, and high (alarm) if it exceeds 12%. In a similar fashion, the deviation between the real momentary elongation and its value predicted by the artificial neural network is considered low (0–15%), mean (10–30%) and high (more than 20%) (Fig. 4).

Another stage of the model design involves taking measurements of the inference block. To do so, it is necessary that a rule base, inference mechanism and membership functions of model output y be defined, which will enable calculating the resulting membership function of the model output. The inference mechanism for performing the tasks of this block (i.e. computation of the resulting membership function $\mu_{wyn}(y)$) consists of the following [24]: elements for calculating the degree of meeting premises and activating conclusions of individual rules R_i as well as an element for describing the resulting form of the output membership function $\mu_{wyn}(y)$ based on the degree of activating conclusions of individual rules.

On analyzing belt joint elongation, the system's response is to indicate that the operator is required to take a decision. The system can, in this case, indicate correct operation of the joint (y_1), recommend condition inspection (y_2), generate a warning signal to indicate the necessity of joint modification (reinforcement) (y_3), or generate an alarm signal to indicate that the belt must be immediately stopped (y_4). For the thereby defined input variables and output variable along with their defined membership functions, it is necessary to create a rule base to obtain the desired accuracy of the fuzzy model (Table 1).

To decrease the size of the model by reducing the number of rules, the membership functions of the input variable x_2 can be alternatively described using only the left and right external membership functions. The deviation between the real momentary elongation and that predicted by the artificial neural network will be considered low if it ranges from zero to 30% and mean if it exceeds 25%. Given this constraint, the model's rule base will consist of only six rules:

R1: IF (x_1 = low) AND (x_2 = low) THEN ($y = y_1$),
R2: IF (x_1 = low) AND (x_2 = high) THEN ($y = y_2$),
R3: IF (x_1 = mean) AND (x_2 = low) THEN ($y = y_3$),
R4: IF (x_1 = mean) AND (x_2 = high) THEN ($y = y_1$),
R5: IF (x_1 = high) AND (x_2 = low) THEN ($y = y_4$),
R6: IF (x_1 = high) AND (x_2 = high) THEN ($y = y_1$).

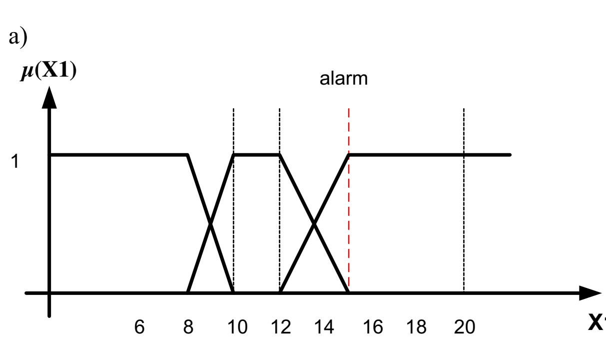

Fig. 4 – Fuzzy set membership functions of inputs x_1.

Table 1 – Rule base of the model.

x_1	x_2		
	Low	Mean	High
Low	y_1	y_1	y_2
Mean	y_3	y_2	y_1
High	y_4	y_3	y_2

Or, taking advantage of the possibility of combining the rules that have the same conclusion into one rule, we reduce the number of rules in the base:

R1: IF (x_1 = low) AND (x_2 = low) OR (x_1 = low) AND (x_2 = mean) OR (x_1 = mean) AND (x_2 = high) THEN ($y = y_1$),
R2: IF (x_1 = low) AND (x_2 = high) OR (x_1 = mean) AND (x_2 = mean) OR (x_1 = high) AND (x_2 = high) THEN ($y = y_2$),
R3: IF (x_1 = mean) AND (x_2 = low) OR (x_1 = high) AND (x_2 = mean) THEN ($y = y_3$),
R4: IF (x_1 = high) AND (x_2 = low) THEN ($y = y_4$).

In the analyzed case, the operation of joining the *AND* sets was performed using the aggregation of premises in rules by the *PROD* operator; the operation of joining the *OR* sets was performed with the *MAX* operator, while the calculation of the degree of activating conclusions of individual rules was performed using the Mamdani implication operator. The resulting output membership function was computed by the *MAX* operator. This inference procedure was selected based on the findings about the effect of operator type on the accuracy of fuzzy modeling reported in [24].

We applied the center-of-gravity method to the defuzzification block; the task of this block is to compute the resulting membership function of the sharp output y^* for the sharp inputs x_1 and x_2. The applied method is universal and considered "democratic" [24] owing to the fact that all activated conclusion-membership functions (active rules) take part in defuzzification. Fig. 5 shows the plot of the input x_1, input x_2 and output y for the developed model. Fig. 6 presents

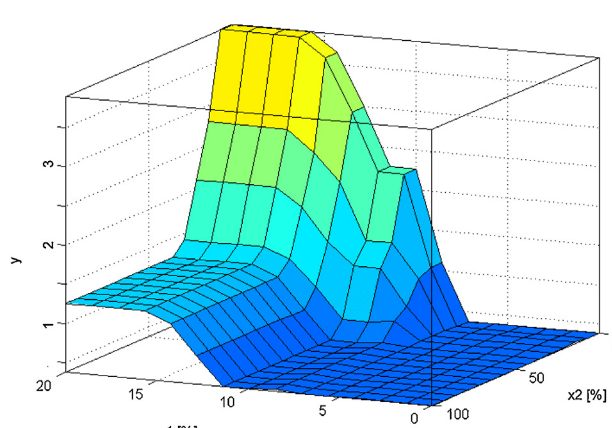

Fig. 5 – Plot of input x_1 (momentary elongation of the joint), input x_2 (deviation estimated when predicting successive time series) and output y (proposed operator response) [29].

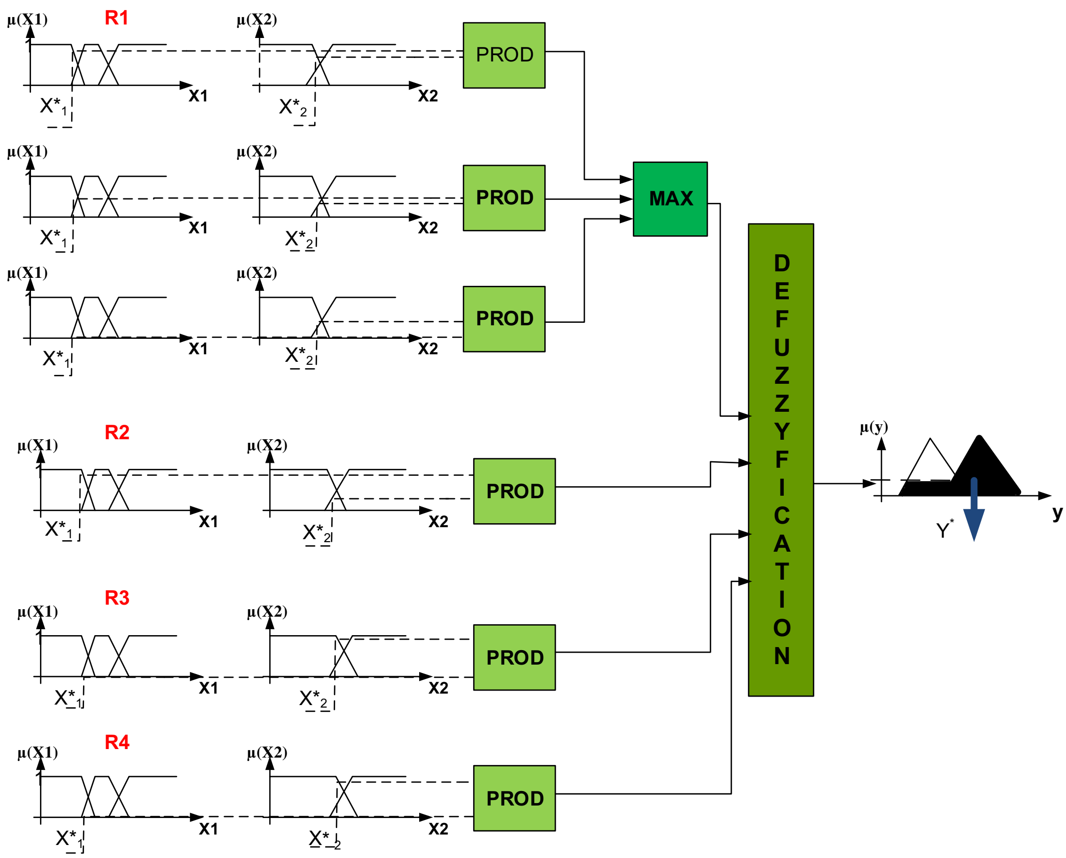

Fig. 6 – Procedure for computing the output y^* for the inputs x_1^* and x_2^* in the developed fuzzy model.

the procedure for computing the output y^* of the developed fuzzy model for sample values of inputs x_1^* and x_2^*.

The expert system [29] in a diagnostic system for adhesive-bonded joints of a conveyor belt operated in any complex transport system and combined with standard dispatcher systems can also be described as an expert system based on fuzzy residue estimation. In this system, the analyzed process is represented by a time series predictive model that processes momentary values of the object-defining parameters, whereas the evaluation of residues showing the difference between the object's behavior (its analyzed parameter) and the behavior defined by the predictive model is conducted by a system based on fuzzy logic.

For operators of oft-complex and sophisticated transport systems, the expert system is an advisory tool that recommends potential actions to be taken, corrects wrong indications of protective systems and eliminates the excess of unprocessed information generated by the monitoring system.

Its task is therefore to support the following: observation of the tested object using the developed computer-aided measurement system, data collecting and processing, as well as inference. The above notwithstanding, it is the machine operator or system dispatcher who makes the final decision with regard to recommendations given by the expert system.

4. Summary

Owing to high economic efficiency of in-house conveyor belt-based transport systems along with their flexibility and relatively simple conveyor design, the number of conveyor transport systems is on the increase. Conveyor belts are mainly operated in aggressive conditions, which means that they are subjected to high loads in transport systems and exposed to constant changes due to their relocation and re-routing. Given that the service life of a belt and the durability of its joints are affected by a number of yet insufficiently investigated factors, effective maintenance and rational belt economy are difficult to ensure. The described design of a computer-aided monitoring system equipped with intelligent expert modules is an important step toward ensuring adequate durability of a conveyor belt's joints. The analyzed design solution based on the state-of-the-art computer-aided systems, including elements of fuzzy logic and artificial neural networks drawing on intelligent methods and techniques, puts into practice the recommendations concerning trends in the development of computer-integrated manufacturing. The intelligent computer-aided monitoring and diagnostic systems equipped with prediction capacity and the control systems based thereon are considered an important field of industrial application for information technology. Given their industrial application, the proposed solutions can effectively and comprehensively combine the problems of computer-aided diagnostics and control using IT knowledge engineering methods.

REFERENCES

[1] A. Jodejko-Pietruczuk, S. Werbińska-Wojciechowska, Analysis of maintenance models' parameters estimation for technical systems with delay time, Eksploatacja i Niezawodnosc – Maintenance and Reliability 16 (2) (2014) 288–294.

[2] K. Antosz, D. Stadnicka, The results of the study concerning the identification of the activities realized in the management of the technical infrastructure in large enterprises, Eksploatacja i Niezawodnosc – Maintenance and Reliability 16 (1) (2014) 112–119.

[3] D. Mazurkiewicz, Problems of numerical simulation of stress and strain in the area of the adhesive-bonded joint of a conveyor belt, Archives of Civil and Mechanical Engineering IX (2) (2009) 75–91.

[4] D. Mazurkiewicz, Analysis of the ageing impact on the strength of the adhesive sealed joints of conveyor belts, Journal of Materials Processing Technology 208 (2008) 477–485.

[5] G. Fedorko, V. Molnar, M. Dovica, T. Toth, M. Kopas, Analysis of pipe conveyor belt damaged by thermal wear, Engineering Failure Analysis 45 (2014) 41–48.

[6] G. Fedorko, V. Molnar, D. Marasova, A. Grincova, et al., Failure analysis of belt conveyor damage caused by the falling material. Part I: Experimental measurements and regression models, Engineering Failure Analysis 36 (2014) 30–38.

[7] R. Zimroz, L. Jurdziak, R. Blazej, Novel approaches for processing of multi-channels NDT signals for damage detection in conveyor belts with steel cords, Key Engineering Materials 569/570 (2013) 978–985.

[8] G. Fedorko, V. Molnár, J. Živčák, M. Dovica, N. Husáková, Failure analysis of textile rubber conveyor belt damage by dynamic wear, Engineering Failure Analysis 28 (2013) 103–114.

[9] A. Grincova, D. Marasova, Experimental research and mathematical modeling as an effective tool of assessing failure of conveyor belts, Eksploatacja i Niezawodnosc – Maintenance and Reliability 16 (2) (2014) 229–235.

[10] H. Komander, M. Hardygóra, M. Bajda, G. Komander, P. Lewandowicz, Assessment methods of conveyor belts impact resistance to the dynamic action of a concentrated load, Eksploatacja i Niezawodnosc – Maintenance and Reliability 16 (4) (2014) 579–584.

[11] D. Mazurkiewicz, Computer-aided maintenance and reliability management systems for conveyor belts, Eksploatacja i Niezawodnosc – Maintenance and Reliability 16 (3) (2014) 377–382.

[12] P. Grzegorzewski, Wspomaganie decyzji w warunkach niepewności. Metody statystyczne dla nieprecyzyjnych danych, Akademicka Oficyna Wydawnicza EXIT, Warszawa, 2006.

[13] A.M. Kwiatkowska, Systemy wspomagania decyzji, Wydawnictwo Naukowe PWN, Warszawa, 2007.

[14] J. Korbicz, J.M. Kościelny, Z. Kowalczuk, W. Cholewa, Diagnostyka procesów. Modele, metody sztucznej inteligencji, zastosowania, WNT, Warszawa, 2002.

[15] S. Ablameyko, L. Goras, M. Gori, V. Piuri, Neural Networks for Instrumentation, Measurement and Related Industrial Applications, NATO Science Series, Series III: Computer and System Sciences, vol. 185, IOS Press, Amsterdam, 2003.

[16] A.J. Curley, H. Hadavinia, A.J. Kinloch, A.C. Taylor, Predicting the service-life of adhesively-bonded joint, International Journal of Fracture 103 (2000) 41–69.

[17] D. Valis, K. Pietrucha-Urbanik, Utilization of diffusion processes and fuzzy logic for vulnerability assessment, Eksploatacja i Niezawodnosc – Maintenance and Reliability 16 (1) (2014) 48–55.

[18] O. Maimon, L. Rokach, The Data Mining and Knowledge Discovery Handbook, Springer-Verlag, New York, 2005.

[19] A.K. Palit, D. Popovic D, Computational Intelligence in Time Series Forecasting. Theory and Engineering Applications, Springer-Verlag, London, 2005.

[20] R.N. Yadav, P.K. Kalra, J. John, Time series prediction with single multiplicative neuron model, Applied Soft Computing 7 (2007) 1157–1163.

[21] A. Quaerteroni, F. Saleri, Scientific Computing with MATLAB, Springer-Verlag, Berlin, 2005.

[22] P. Lula, Wykorzystanie sztucznej inteligencji w prognozowaniu, (2000) www.statsoft.pl/czytelnia/neuron/wstepsieci.html.

[23] D. Rutkowska, Inteligentne systemy obliczeniowe. Algorytmy genetyczne i sieci neuronowe w systemach rozmytych, Akademicka Oficyna Wydawnicza PLJ, Warszawa, 1997.

[24] A. Piegat, Modelowanie i sterowanie rozmyte, Akademicka Oficyna Wydawnicza EXIT, Warszawa, 2003.

[25] J. Harris, Fuzzy Logic Applications in Engineering Science, Springer, Dordrecht, 2006.

[26] K. Leiviska, Industrial Applications of Soft Computing – Paper, Mineral and Metal Processing Industries, Studies in Fuzziness and Soft Computing Nr 71, Springer-Verlag, Berlin, 2002.

[27] S. Li, M.A. Elbestawi, Tool condition monitoring in machining by fuzzy neural networks, Journal of Dynamic Systems, Measurement, and Control 118 (4) (1996) 665–672.

[28] T.J. Ross, Fuzzy Logic with Engineering Applications, Wiley & Sons Ltd., New York, 2005.

[29] D. Mazurkiewicz, A Study of Selected Aspects of Operational Diagnosis of Belt Conveyor, Lublin University of Technology, Lublin, 2011.