



# A Dynamic Fuzzy Expert System Based on Maintenance Indicators for Service Type Selection of Machinery

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## KEYWORDS

Expert systems,  
Artificial intelligent,  
Fuzzy logic,  
Preventive repair and  
maintenance,  
Conveyors belt,  
Maintenance indicators.

## ABSTRACT

*Due to the multiplicity of standards and complex rules, maintenance, repair, and servicing of machinery could be done only by the fully qualified and proficient experts. Since the knowledge of such experts is not accessible all times, using expert systems can help to improve the maintenance process. To address this need and the uncertainty of the maintenance process indicators, this research proposed a Fuzzy Expert Systems (FES) for decision-making on the type of service. Since not all indicators identified in the literature are important adequately, firstly, indicators that are more influential in the service type selection are chosen using inferential statistical analysis. Then, these selected indicators designed the fuzzy rules of the knowledge based. Finally, Inference engine has been designed based on Mamdani model to detect the service type of equipment. This research selected Shemsh Sazan Zanjan Company as a case study to implement the proposed expert system. According to our experiments, the proposed system increases the reliability by suggesting effective ideas that lead to decreasing production line breakdowns. The main contribution of this paper is providing a new approach to designing maintenance dynamic FES based on Maintenance Indicators for service-type selection that can decrease production line breakdowns.*

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## 1. Introduction

Machinery and equipment are becoming 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]. A proper maintenance policy for equipment and machinery increases equipment reliability and makes a competitive advantage for companies with high automation [2].

Maintenance can be considered a set of activities restoring an item to a state in which it can perform its designated functions [2]. In other words, maintenance activities are some tasks that are planned and carried out timely to prevent sudden breakdowns of machinery, equipment, and installation in order to increase their reliability and availability. Repairs include a set of activities conducted on a system that is broken or disabled to return it to standby or operation mode.

Maintenance strategies can broadly be classified into Corrective Maintenance (CM) and Preventive Maintenance (PM) strategies [3,4]. Preventive maintenance is better due to regular periodic inspections of machinery and equipment.

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ISO 14224 has been developed with the aim of carrying out the preventive maintenance. Application scope includes all the manufacturing and laboratory machinery and equipment. The main objective of the ISO14224 is to conduct maintenance activities with planning, prevention, and prediction to ensure the safety of equipment and machinery at the time of application. The continuity of ISO14224 implementation can reduce machine downtime [2].

Usually, in industrial plants, gathered information is not used in the process of maintenance properly. Collected data about a specific issue can contain useful, relevant knowledge. This knowledge will be more accurate and comprehensive if the history of gathered data be older, larger, and more massive. To use this information, this paper presents an approach to the design and development of a knowledge-based system in general and its application in the field of maintenance management in particular. With adequate inference rules applied, this system would increase the effectiveness and shorten the time of decision-making. The above tasks can be performed by a suitable expert system based on Maintenance Indicators for service-type selection

A prototype knowledge-based system for the maintenance activities in Shemsh Sazan Zanzan Company has been worked out as a case study and is described in the paper. This is based on the experts' knowledge stored in a knowledge base. The knowledge representation scheme is rule based, and the inference strategy mechanism is backward chaining.

### **1-1. Motivation**

Reducing costs, increasing the quality of product, continuous improvement with considering high competitiveness, lack of natural resources, energy crisis, etc. are considered as the main objectives of production systems, and considering the maintenance as a strategic task to achieve the above objectives is vital and inevitable.

Using the experience and information of experts is a major assistance to people in order to make accurate decisions. The permanent presence of technical and operating teams in the workshop is not possible due to the high cost of work force and lack of regular accessibility. Therefore, we design and implement a system that could use individuals' knowledge in the least cost. Therefore, the fuzzy expert system was designed to use the experienced consultants and experts' knowledge in the field of preventive maintenance.

### **1-2. Contribution**

The contribution of this paper is as follows:

- 1- Providing a new approach to designing a maintenance dynamic fuzzy expert system for service type selection that can decrease production line breakdowns.
- 2- Introducing the appropriate Maintenance Indicators based on expert's opinions and experiment results.
- 3- Meeting the ISO 14224 through preventive maintenance and repairs programs by decreasing the machinery breakdowns.
- 4- Improving the service-type selection accuracy using fuzzy logic.

The rest of this paper is organized as follows: In Section 2, the previous related research papers on different strategies for preventive maintenance, especially expert system strategy are discussed. Section 3 introduces the overall system framework and describes the proposed expert system step by step. Experiment section applies the proposed approach to a real world to evaluate and analyze the performance of method. Finally, Conclusion section provides the concluding remarks.

## **2. Literature Review**

In this section, we review the related research works about different strategies of preventive maintenance; especially, expert system strategy are discussed.

Expert systems have been used for many areas such as systems evaluation [5], project selection [6], manufacturing [7], and maintenance. Chen et al. [8] presented a research for repair and maintenance of building installation with the increasing reliability approach. They discussed the importance of timely maintenance decisions in construction industry and building installation, and spoke of the advantages of expert systems that are based on reliability in the management of building installations repair and maintenance systems. Note that in this study the increasing reliability module has been used to verify the correctness of the data. Shin and Jun [9] addressed several aspects of Condition Based Maintenance (CBM) approach: definition, related international standards, procedure, and techniques with the introduction of some relevant case studies that they have carried out. Lokko et al. [10] investigated information integration from the perspective of maintenance and repair in the oil and gas industry. In this study, it is referred to the use of expert systems to improve forecasting

capabilities of dynamic repair and maintenance that leads to the increase of the reliability of the hardware equipment in oil and gas industry as well as timely planning for repairs and maintenance of equipment and timely allocation of resources to them. Anand et al. [11] presented a neural fuzzy expert system to optimize performance of steam boiler. In this study, a neural network is used to enhance reinforcement learning. Various parameters, such as substance concentration, chemical composition, the intensity of particles mutation that does not include constant measures, are taken into account. Then, it monitors parameters directly and results of learning using fuzzy logic until the education system is over. Dejan et al. [12] presented a model to assess the risk of equipment failure in a mine based on fuzzy logic. For this purpose, mining machinery and equipment should be assessed and analyzed all the times in order not to expose damage and eliminate stoppages of extractions. Assessing damages' risk might provide a proper indication of the failure of maintenance and repairs services. In this study on the assessment model of risk, suffering fracture has been used based on the theory of fuzzy sets and fuzzy logic.

Prioritizing tasks in a maintenance system with a fuzzy approach is a method that was carried out by Kumar et al. [13]. This paper aims to prioritize preventive maintenance measures by the risk assessment using repair data rather than maintenance records. Khanlari [14] proposed a model of fuzzy logic for preventive maintenance process, which is used to interpret language variables for setting priorities.

Suliman and Jawad [15] developed a mathematical model to optimize the adequate time of the preventive maintenance in a single-product system with high volume of production. Analysis was conducted to determine the effect of various parameters on the system including inspection combined with preventive maintenance and repair, the introduction of non-negligible time in preventive maintenance and repair system.

Park et al. [16] introduced a new model to deploy preventive maintenance system in a stressful environment. In this design, a model of failure rates and two models of preventive maintenance cost were used to optimize the structure of maintenance that minimizes the rate of cost. The effect of preventive maintenance has been introduced as a factor in decreasing tension and stress on the system in the model of failure rate

and two types of failure structure model in the model of categorical cost. There is a direct relationship between emergency fault detection, periodic failure detection, and an optimal management planning for preventive maintenance and lifetime of system.

Wn [17] examined how preventative maintenance systems can be implemented as outsourcing. In this research, reward functions and preventive repairs maintenance policies were used. Zhong and Jin [18] proposed a new policy of preventive maintenance to systems that are in standby mode based on the theory of Markova. Results were simulated and tested with numerical examples. Wang et al. [19] proposed preventive maintenance with the dihedral inspection policy based on three-stage process failure. Perez-Canto and Rubio [20] proposed a model for planning preventive maintenance that can be used in power plants and wind energy plants. Solving the problem has been based on reliability. Doostparast [21] presented a method based on reliability to optimize preventive maintenance scheduling in integrated systems for a system with equipment in failure stage. In this model, the goal is a system with a given level of confidence with maximum efficiency.

Considerable studies have been conducted on management systems of maintenance. Repair and maintenance areas and identifying appropriate strategies and available facilities to prevent repair interruptions are of high importance for managers. There has been some research on estimating failure rates of maintenance methods [22,23]. In addition, some studies have been conducted based on theoretical and practical methods of artificial intelligence to support decision-making in repair and maintenance systems and management of various facilities [24,25].

Rastegari and Mobin [26] provided and examined TOPSIS, k-means clustering technique, and one decision making model borrowed from the literature, which can be linked to CMMS and add value to the collected data. This research has been conducted within a global project in a large manufacturing site in Sweden to provide a new maintenance management system for the company. The results indicate that the most appropriate maintenance decision for each of the selected machines/parts is according to factors, such as frequency of breakdowns, downtime, and cost of repairing.

Li et al. [27] constructed the task assignment framework consisting of three parts: building

expert database, selecting experts for tasks, and implementing the tasks, in which selecting experts for tasks based on expert knowledge is the key part of the model.

Chou [28] suggested a plan in transportation field that was indeed an expert system based on web, in which, according to recordings of previous projects recordings, the cost of construction as well as repair and maintenance related costs are estimated, resulting in the allocation of funds to the project implementation.

Maintenance and repair of the bridge deck was the content of a study conducted by Trighat and Miyamoto [29]. In this study, the fuzzy expert system was designed to support decision-making task by creating membership functions and fuzzy rules.

Ebersbach & Peng [30] proposed an expert system to monitor vibration analysis on central system and one-way frequency in algorithm of vibration data analysis to detect flaws precisely.

Cebiestrojen [31] conducted a study based on extant technical knowledge, effective indicators in system, and previous failure experiences to detect faults in auxiliary equipment in the process of troubleshooting marine systems machinery.

Lu and Sy [32] carried out the design of a fuzzy system using linguistic variables and possible estimates of parameters and created a uniform fuzzy model for troubleshooting.

However, according to the best of our knowledge, there are no studies that use a fuzzy expert system for service type selection. In addition, in this research, we introduce the

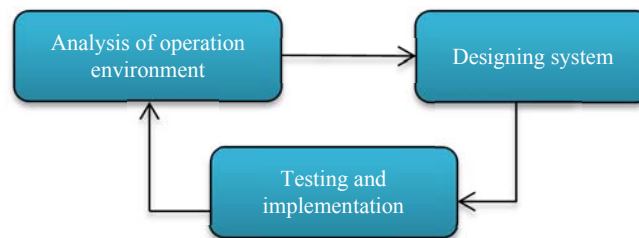
appropriate maintenance indicators based on expert's opinions and experiment results and also meet the ISO 14224 through preventive maintenance and repairs programs by decreasing the machinery breakdowns.

### 3. Proposed Approach

In this section, the proposed approach to the design and implementation of the expert system is described gradually.

#### 3-1. Designing of expert system

One of the most prevalent designing methods used by manufacturers of expert systems is Prototyping [33]. This means that the operating environment analysis is done; the system is designed, and then it is tested in practical environment. This process can preserve the dynamics of an expert system as shown in Figure 1. In each stage, if necessary, the required parameters and the dependency rules will be defined, modified, added, or eliminated. As Figure 1 shows, by restarting a static expert system periodically, it is possible to cope with dynamic environments. This quasi-static approach to dynamics is suitable if the environment is changing slowly enough. The resulting dynamic expert system never stops, occasionally interrogating the user if it suspects that some of the previously entered data are obsolete. In this sense, the computer system behaves as a "live creature".



**Fig. 1. A diagram of expert system prototype**

#### 3-2. Operating environment

This research uses the expertise's knowledge of Shemsh Sazan Zanzan Company that produces zinc ingot. The annual production capacity is 5,000 tons of zinc ingots and Plates with %99.98 purity. After crushing the ore into small pebbles, they are converted into powder used for the electrolysis process of zinc production. Transformation system of material is the conveyor belt. Among the company's machinery, the conveyor belt of active crushers in the

crushing and material handling section was selected as a sample. The necessary raw data for the study was collected in collaboration with the experts in the field of maintenance and repairs. This company was selected as a case study, because the conveyor belt transport systems are important vehicles in many factories and numerous researches have been conducted to study them. In addition, due to technical complications and high volume of emergency

repairs at the zinc plants, it is necessary to establish the proposed system for these factories.

### 3-3. Objectives of the system

The purpose of the proposed expert system is to eliminate duplicate repairs in the process of preventive maintenance. Hence, the designed system should give us an accurate and correct decision about the necessary services during the process of preventive maintenance of crusher's conveyor belt, and it should be determined what kinds of decisions must be considered based on condition of the conveyor belt. In this study, four outputs are considered:

- 1- The need to inspection,
- 2- The need to repair,
- 3- The need to replace a gadget,
- 4- None of them.

Therefore, the aim of designing the proposed system is to determine the appropriate decision on the type of service based on the accumulated knowledge in the proposed knowledge-based expert system during the process of preventive maintenance. The proposed expert system will suggest one of four alternatives for service of the conveyor belt.

### 3-4. Formation of experts' team

The proposed system requires some experts who can verify their knowledge in the expert system. The expert's team consists of four specialists invited for this study. Each of the selected experts has one or more of the following features:

- Management or specialization of maintenance and repairs units.
- Experience in teaching with sufficient knowledge of mechanical equipment.
- Expertise that has knowledge about of the related field of machinery.

### 3-5. Extraction of raw data

At this stage, the data should be extracted after sufficient and accurate understanding of our operating environment and equipment. Therefore, by studying catalogs, resources, articles, and reviews about the related equipment, the main requirements of operating environment and equipment were identified and, then, based on these requirements and the main objective research, the affecting factors in the quality of work were extracted. As mention above, conveyor belt was selected, and it must detect the type of preventive maintenance service during the performance of the preventive maintenance process by the expert system. Therefore, the influential factors and attributes in the optimal performance of the machine were extracted.

### 3-6. Formation of delphi panel

Delphi panel has been used to accumulate the expert's opinion. The Delphi method has been used due to its fast achievement of convergence, lack of geographical restrictions for participants, and the ability to cover a large range of experts. The consensus and prediction process was implemented by Delphi method as follows:

1. Choose one person to monitor the implementation of the Delphi process
2. Establish one or more panels to participate in activities (The members of the panel are professionals and experts in the field of research)
3. Set a questionnaire of the effective parameters in the quality of conveyor belt to get comments from experts in the Delphi panel
4. Evaluate the questionnaire (removing inferential ambiguities, etc.)
5. Send the first questionnaire to the panel members containing effective parameters in the quality of conveyor belt
6. Analyze the received responses in the first round
7. Prepare the second-round questionnaire (with the required revisions)
8. Send the second-round questionnaires to the members of Delphi panel
9. Analyze the second-round responses (stages 7 and 9 must be repeated to achieve stability in responses)
10. Calculate Kendall coefficient to determine a measure of consensus.

$$w = \frac{NCP - NDP}{\frac{1}{2}(N^2 - N)}$$

*NCP*: Number of concordant pairs

*NDP*: Number of discordant pairs

*N*: Number of observation

As it can be seen in the calculation of Kendall's coefficient, the coefficient value represents the closeness in the experts' idea.

### 3-7. Selection of the effective parameters

Among the various parameters that were extracted from preliminary studies, effective parameters were selected and approved by experts through Delphi method. If a particular parameter that was proposed by experts was not in the list, it would be added in this stage. Table 1 shows the characteristics and effects of them on the type of service. These parameters are: rolling average life, interval between failures, injecting grease and rolling average life.

The proposed system includes an inference engine with the inputs, outputs, and separate membership functions. In order to support decision making in type of service selection of conveyor belt in the active crushing and transportation section, the inference engine was

used. The inference engine performs the main job and meets the main goal of the study.

While the indicators are quantitative, classic methods of measurement can be used, but when there is uncertainty and ambiguity in the indicators, they cannot be easily measured. In this situation, the fuzzy logic can be used.

**Tab. 1. Effect of characteristics on output production**

	average life	Rolling grease	Injecting failure	Interval between	Rolling average life
The need to inspection	**	**	**	**	**
The need to repair	**	**	**	**	**
The need to gadget replacement	**	**	**	**	**
None of them					**

### 3-8. System architecture

In order to apply fuzzy logic to a particular system, first, it is needed to make a "Fuzzy model," a collection that determines the system and the way to manage it. Creating such a model includes analysis of the problem and the establishment of appropriate legislation to define it. This process is called Fuzzification. After testing Fuzzy model, a programmer determines the effectiveness of the fuzzy rules and implements model's adaptation.

This research uses Matlab coding software. Using this software knowledge-based system, fuzzy inference engine and user interface system are provided.

### 3-9. Knowledge-based system

Since fuzzy inference system is used for reasoning in this study, knowledge-based system includes fuzzy rules, fuzzy sets, and their membership functions. As noted, to understand the structure of knowledge-based decision-

making system better, the fuzzy rules are presented in a table.

A simple method to generate fuzzy rules is classifying the range of the input characteristics values using fuzzy membership functions (For example, a triangular membership function and allocation of a verbal variable to each category). Having a divided space per pattern, a way to generate fuzzy rules is to take into account all the possible combinations of antecedents. In this section, the number of output rules is determined by regarding the number of possible scenarios for each parameter and the number of parameters. These rules are provided and saved in the system based on expert' opinion. In these rules, different diagnostic parameters have been combined so that the weight of all rules is equal. Specifying the number of possible rules for the system that cover all conditions is done in this section. These rules are determined based on input and input modes.

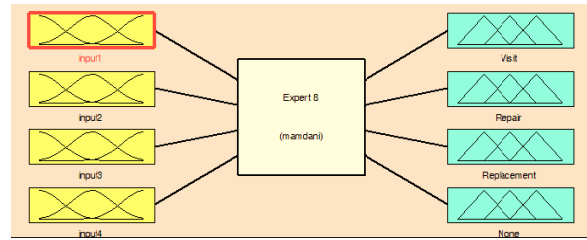


Fig. 2. The structure of fuzzy system

Figure 2 demonstrates four outputs that are the recommendations of the expert system for service type based on the inputs. Therefore, each rule can be presented as follows:

If input1 is  $x_1$ , input2 is  $x_2$ , input3 is  $x_3$ , input4 is  $x_4$ , then out1 is  $y_1$ , output2 is  $y_2$ , output3 is  $y_3$ , and output4 is  $y_4$  (1).

Tab. 2. Input of Fuzzy expert system

St	Input1	Input2	Input3	Input4
	Rolling average life (years)	Interval between failure	Injecting grease Interval (week)	Sound vibration (Db)
	[1 6]	[1 10]	[1 6]	[1 10]
Number of modes	3	4	3	3
low	[1 2]	[1 2]	[1 2]	[1 2]
medium	[2 5]	[2 4]	[2 4]	[2 5]
many	[5 6]	[4 6]	[4 6]	[5 10]
Very many		[6 10]		

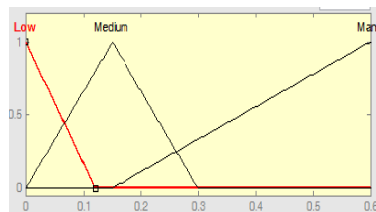


Fig. 3. Average lifetime, conveyor belt

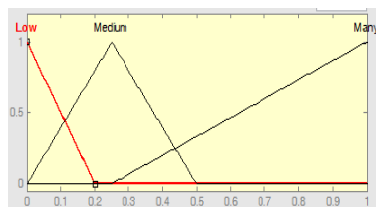


Fig. 4. Conveyor belt failure average parameters

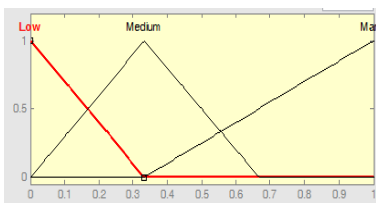


Fig. 5. Average parameter of injecting grease of conveyor belt

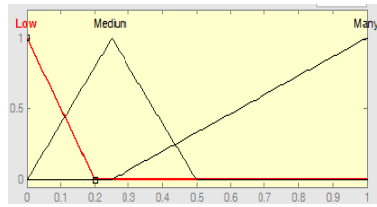


Fig. 6. Parameters of sound vibration of conveyor belts

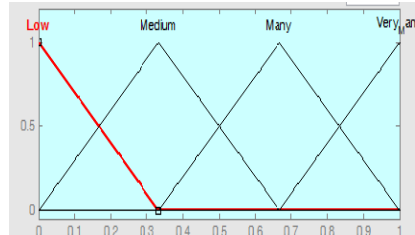


Fig. 7. First output membership function

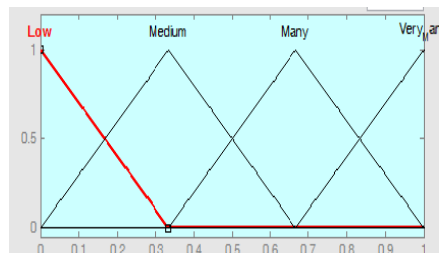


Fig. 8. The second output membership function

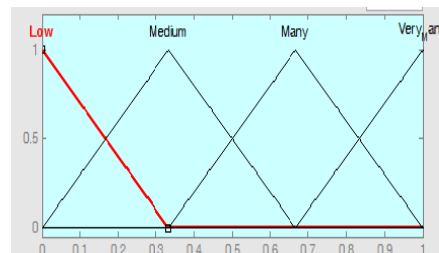


Fig. 9. The third output membership function

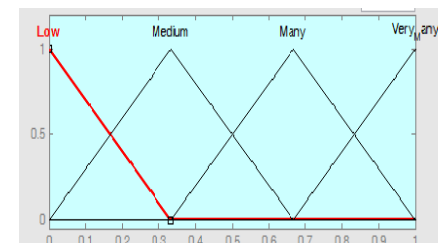


Fig. 10. The fourth output membership

Table 2 indicates Input of Fuzzy expert system. Figures 3 to 6 demonstrate the corresponding diagrams of input parameters. Figures 7 to 10 also demonstrate the corresponding diagrams of outputs parameters.

**3-10. Fuzzy inference engine**

Inference engine has been designed based on Mamdani method to detect the service type of equipment. This method is widely recommended

as an expert method for mastering fuzzy logic. The output from Mamdani Fuzzy Inference System (FIS) can be easily transformed to a linguistic form as the inference result before defuzzification [34]. Mamdani-type FIS is widely used in particular for decision support application and is well suited for human input; therefore, this research uses Mamdani method.



**Fuzzification of inputs:** In this stage, the input that is entered through the user interface is fuzzified using membership functions. During this phase, each input can be mapped onto a value between zero and one.

**Applying fuzzy operators:** At this stage, the fuzzy operators are applied in the given part of the rules. For 'AND' and 'OR', operators 'MIN' and MAX are used and the value of each rule is specified.

**Applying indication method:** At this stage, with regarding the results of each rule in the previous stage and the value of each rule, the effect of rules on output is recognized. For this, the MIN function is used.

**Output aggregation:** At this stage, Fuzzy rules are combined based on the number of outputs and a fuzzy set is established for each output. Since the system has a fuzzy output, a fuzzy set is created. This is completed by MAX function.

**Non-Fuzzification:** During the non-Fuzzification, the fuzzy set of each output becomes a number. In the detection system of equipment service type, there is an output with two modes: possible and impossible. Non-Fuzzification is performed by the center of mass. The overall model of the proposed FES is shown in Figure 2. In this model, the membership functions of four input parameters along with related categories as well as the output

membership function with its category are specified in a way that adjustments of each parameter are shown separately in Table 2. As it can be seen in the model, the Mamdani inference method will be used. All the numerical ranges for all the input-output parameters have become fuzzy numbers. It should be mentioned that, due to the low number of input features, all of the rules have been written regarding the consultants and experts' opinions.

The number of rules that should be inserted into the expert system is calculated as follows:

N: number of indicators

M: number of indicators' category

$N * M =$  number of rules

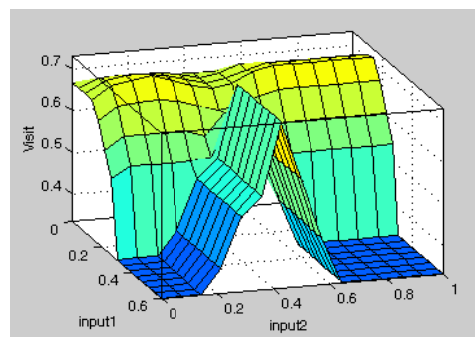
Therefore,  $N=4$ ,  $M= 13$ , and  $N * M= 4 * 13$ . Each rule can be also presented as follows:

If (A=low & B=many & ...), then (out1=low & out2=varymany ...)

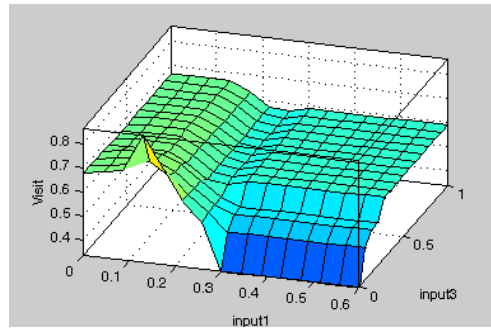
Notice that the weight value of each rule can be taken into account regarding the experts' opinion of real extraction environment at the time of simulation. Some of rules are presented in Table 3. At the end of this section, it reaches the final stage of expert system establishment to support decision making on detection of service type during preventive maintenance of active crushing conveyor belt in the crushing and transferring substance sector.

**Tab. 3. Some rules of FES supporting the decision making**

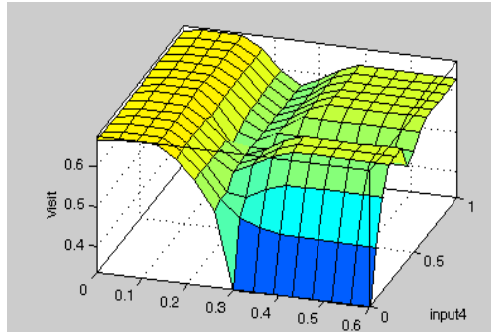
If	Input1	Input2	Input3	Input4	Visit	Repair	Replacement	None	
if	low	low	low	low	then	Many	Very Many	many	Low
if	low	medium	low	low	then	Many	Very Many	Medium	Low
if	low	many	low	low	then	Many	Very Many	Medium	Low
if	low	very many	low	low	then	Many	Medium	Low	Very Many
if	medium	low	low	low	then	Very Many	Many	Medium	Low
if	medium	medium	low	low	then	Very Many	many	Medium	Low
if	medium	many	low	low	then	Very Many	Many	Medium	Low



**Fig. 11. Gaussian diagram of effect of the first and second parameters on each other**



**Fig. 12. Gaussian diagram of effect of the first and third parameters on each other**



**Fig. 13. Gaussian diagram of effect of the fourth and third parameters on each other**

To illustrate the effect of parameters on each other, the Gaussian diagram related to the effect of both parameters on each other can be seen in Figures 11-13. For example, Figure 12 shows that when input 3 or injecting grease interval decreases, the need for visiting or inspecting the conveyor belt also decreases. On the other hand, when input 1 or rolling average life decreases, the need for visiting or inspecting conveyor belt increases. In addition, this figure can show the effect of these two input parameters simultaneously. Figures 11 and 13 also present similar effects for the first and second parameters and the fourth and third parameters, respectively.

### 3-11. User interface

Receiving inputs from the user, transmitting them to the inference engine, and then receiving and displaying system response for the user are the main tasks of this section. Inputs include the information related to the targeted parameters. For example, the input of our system may be as follows: [0.2;0.3;0.1;0.1]; it indicates that the rolling average life is 0.2 year, interval between failure is 0.3 year, injecting grease interval is 0.1 week, and sound vibration is 0.1 Db. Then, data are delivered to inference engine of the detection system of equipment service type to apply the inference mechanism. System's response is received, and it is recognized that the need to what kind of service is higher in this situation. If

required, software can be used to link the user with expert system.

## 4. Evaluation

In order to evaluate the proposed expert system, we implement some experiments on the real and simulated environment.

### 4-1. Evaluation by experts' opinion

After implementing the proposed fuzzy expert system as a decision support system, it is required to evaluate its performance based on the outputs results. In this section, we compare the output of the expert system with experts' opinions. In order to increase the accuracy of the assessment, a team of experts was formed consisting of the experts in the system design and the activists of the conveyor belt maintenance. Eighteen records were randomly selected, as shown in Table 4. The first four columns of Table 4 indicate the inputs that were mapped onto a value between zero and one. The second four columns indicate the outputs. Based on the outputs' results, system suggests visit (inspection), repair, replacement or none. Then, the simulation result is compared with the experts' idea.

**Tab. 4. Comparing experts` opinion with the result of the proposed FES**

Input1	Input2	Input3	Input4	Output1 (visit)	Output2 (repair)	Output3 (replacement)	Output4 (none)	Simulation Results	Expert`s Idea	Evaluation
0.83	0.16	0.11	0.39	0.33	0.74	0.67	0.13	repair	replace	0
0.16	0.14	0.35	0.85	0.68	0.5	0.29	0.13	visit	repair	0
0.14	0.39	0.34	0.86	0.66	0.73	0.33	0.13	repair	repair	1
0.18	0.47	0.31	0.87	0.67	0.78	0.33	0.13	repair	repair	1
0.12	0.85	0.32	0.88	0.7	0.7	0.33	0.13	repair	repair	1
0.49	0.13	0.39	0.89	0.36	0.66	0.66	0.13	repair	repair	1
0.47	0.25	0.38	0.9	0.49	0.6	0.5	0.14	repair	visit	0
0.29	0.48	0.36	0.91	0.63	0.76	0.37	0.13	repair	repair	1
0.32	0.44	0.26	0.65	0.56	0.66	0.46	0.13	repair	repair	1
0.47	0.45	0.26	0.69	0.61	0.66	0.43	0.12	repair	repair	1
0.25	0.49	0.31	0.87	0.58	0.71	0.43	0.13	repair	repair	1
0.24	0.86	0.25	0.92	0.81	0.67	0.33	0.11	visit	visit	1
0.32	0.78	0.32	0.55	0.33	0.86	0.66	0.13	visit	visit	1
0.45	0.89	0.29	0.89	0.33	0.88	0.66	0.11	visit	visit	1
0.49	0.98	0.38	0.56	0.33	0.86	0.66	0.13	visit	visit	1
0.74	0.14	0.26	0.93	0.33	0.68	0.74	0.11	replace	replace	1
0.79	0.36	0.24	0.94	0.64	0.67	0.41	0.11	repair	repair	1
0.78	0.56	0.24	0.95	0.7	0.48	0.52	0.14	visit	visit	1

The evaluations were implemented in a simulated system by Matlab software, and the occurrence probability of each output was specified. After comparing experts` opinions for decision making while performing preventive maintenance process with what the proposed expert system has suggested, the accuracy of results was confirmed to 83%. This indicates that our proposed approach can act as a team of experts.

**4-2. Evaluation by real data**

In order to evaluate the proposed FES in decision making during the performing of the preventive maintenance process of conveyor belt, a sample was selected randomly from real environment. Then, it was examined whether the suggestion of FES on the diagnosis of service type of conveyor belt with what has occurred in real environment that has not resulted in failure is the same or not. Notice that, in this study, it was explored that after conducting operation (implementation of the selected service type) in the real environment for the mentioned technical complication, the possibility of breakdown in the conveyor belt was minimized. Therefore, if the proposed FES could predict the proper

service type, it could be stated that the system has been designed properly and has generated the response accurately. In the following, the collected database of operational environment will be tested.

Tab. 5. Evaluation of FES using the real data

	Input1	Input2	Input3	Input4	Output1	Output2	Output3	Output4	?
1	0.26	0.83	0.21	0.13	0.83	0.66	0.43	0.12	FALSE
2	0.65	0.12	0.26	0.17	0.33	0.72	0.69	0.12	FALSE
3	0.59	0.25	0.35	0.19	0.47	0.72	0.53	0.13	TRUE
4	0.51	0.54	0.24	0.15	0.52	0.68	0.5	0.14	FALSE
5	0.66	0.91	0.36	0.16	0.33	0.86	0.66	0.13	TRUE
6	0.67	0.87	0.36	0.11	0.33	0.87	0.66	0.13	TRUE
7	0.87	0.95	0.29	0.18	0.33	0.88	0.66	0.11	TRUE
8	0.14	0.17	0.59	0.14	0.66	0.87	0.33	0.12	TRUE

**Features of database:** The information of database was related to the repairs reports during 17 months (2013-2014) for conveyor belt of active crusher in crushing and substance transferring section of operational environment. In the mentioned period, all occurred technical complications in this unit were recorded. In fact, the extracted data were collected from records of emergency and preventive operations of the conveyor belt. Based on the targeted parameters of the study, a database was prepared and given to the designed expert system to accomplish the necessary evaluations. It should be mentioned that two experts of the system verified the accuracy of collected data.

The test results of 75 records of the database showed 84% success for the designed system, confirming the accuracy of performance and verifying the proposed approach. Some of results are shown in Table 5. The final column indicates that the system can diagnose a true or false service type. TPM emphasizes proactive and preventative maintenance to maximize the operational efficiency of equipment. Therefore,

improvement in the selection of an appropriate service type can blur the distinction between the roles of production and maintenance by placing a strong emphasis on empowering operators to help maintain their equipment.

After the establishment of fuzzy expert decision support system in preventive maintenance (PM) to make the best decision in choosing the service type of preventative maintenance for the conveyor belt of crusher in the crushing section, significant changes arose in the number of the possible technical complications. Table 6 indicates the status of repairs within one month in the environment.

As can be seen in Table 6, before the implementation of FES decision support, 9240 minutes of service operations were performed per month for the conveyor belt of crusher in the crushing section. However, after design, implementation and establishment of the proposed FES, the time decreased to 6930 minutes. Therefore, the time maintenance of this type of equipment in the operating environment decreased about %25.

Tab. 6. Comparing preventive maintenances before and after of applying FES

Total time for the eleven conveyor belts (minutes)	After applying the proposed FES support decision			Before applying the proposed FES support decision				
	Total	Time (min)	Number of Service	Total time for the eleven conveyor belts (minutes)	Total	Time (min)	Number of Service	Service
1650	150	30	5	1320	120	30	4	Inspection
3960	360	120	3	5280	480	120	4	Repairs
1320	120	120	1	2640	240	120	2	Replacing pieces
6930	630	270	9	9240	840	270	10	Total

**Tab. 7. A comparison of service-type recommendation accuracy of various methods**

	Input1	Input2	Input3	Input4	Output1	Output2	Output3	Output4	Proposed Fuzzy Expert System	Proposed Expert System	khanlari et al. [14]
1	0.43	0.83	0.56	0.46	0.66	0.86	0.33	0.13	TRUE	TRUE	TRUE
2	0.48	0.63	0.42	0.37	0.66	0.86	0.33	0.13	TRUE	TRUE	TRUE
3	0.71	0.14	0.48	0.21	0.33	0.75	0.68	0.12	FALSE	FALSE	FALSE
4	0.54	0.21	0.49	0.22	0.37	0.81	0.63	0.13	TRUE	FALSE	FALSE
5	0.76	0.23	0.54	0.24	0.37	0.81	0.63	0.13	TRUE	TRUE	TRUE
6	0.85	0.26	0.52	0.42	0.37	0.81	0.63	0.13	TRUE	TRUE	TRUE
7	0.64	0.38	0.56	0.48	0.37	0.81	0.63	0.13	TRUE	TRUE	TRUE
8	0.82	0.31	0.48	0.37	0.37	0.81	0.63	0.13	TRUE	TRUE	FALSE
9	0.59	0.41	0.44	0.23	0.82	0.66	0.34	0.13	TRUE	TRUE	TRUE
10	0.69	0.53	0.59	0.24	0.82	0.66	0.34	0.13	TRUE	TRUE	TRUE
11	0.76	0.49	0.43	0.42	0.82	0.66	0.34	0.13	TRUE	TRUE	TRUE
12	0.85	0.41	0.42	0.48	0.82	0.66	0.34	0.13	TRUE	TRUE	TRUE
13	0.54	0.69	0.45	0.24	0.33	0.86	0.66	0.13	TRUE	TRUE	TRUE
15	0.64	0.93	0.48	0.24	0.33	0.86	0.66	0.13	TRUE	TRUE	TRUE
15	0.82	0.73	0.46	0.42	0.33	0.86	0.66	0.13	TRUE	TRUE	TRUE
....	....	....	....	....	....	....	....	....	....	....	....
Result									84%	78%	63%

**4-4. Comparative study with the existing work**

We have conducted a set of experiments to examine the effectiveness of our proposed expert system in terms of recommendation accuracy for the service type selection. Therefore, to compare our approach with those of the expert system, since there is no standard dataset for maintenance expert systems, we used the data of our case and also simulated a dataset as a numerical example base on expert’s opinion. Table 7 presents the experimental results obtained by the proposed expert system with script data, the proposed expert system with fuzzy data, and the proposed expert system by Khanlari et al. [14]. It must be noted that Khanlari et al. [14] used expert system for prioritizing equipment for preventive maintenance (PM) activities. Therefore, they used Sensitivity of Operation (SO), Mean Time between Failures (MTBF), Mean Time to Repair (MTTR), Availability of Required Parts (ARPa), Availability of Repair Personnel (ARPe), and Work Load (WL) as inputs of expert system. However, since we want to select the optimal service type of unique equipment, we must eliminate the inputs that are not related with service type selection of one equipment (SO,

ARPa, ARPe, and WL). In addition, using the new input indicators that have been used in this research (MTBF, MTTR), we extract new rules by expert opinions.

Since the data set will influence the service-type recommendation accuracy results, comparing different algorithms is difficult. Therefore, since there are no standard datasets for maintenance expert systems, we generate a numerical simulate data using our expert systems.

The results of the proposed method obtained from the same data set outperform those of Khanlari et al. [14] that used MTBF, MTTR as inputs of rules. In addition, it can be seen that the proposed indicators with fuzzy numbers have better prediction accuracy without fuzzy numbers.

**5. Conclusions**

This research designs a fuzzy expert system to support the decision on selecting the best type of services when performing preventive maintenance on the conveyor belt of active crusher in the crushing and substance transferring. After designing, implementing, and deploying the system in Ingot Company as an

operational environment, the effect of deployment of the proposed plan on preventive maintenance process was implemented and evaluated. Having evaluated the actual data in operating environment differently using experts' opinion, 85% success in implementation was achieved. This important issue can verify the performance of the proposed expert system since it has led to the decrease of downtimes in machinery and implemented ISO 14224 objectives that minimize the downtimes of machinery through applying preventive maintenance program. Since there has not been designed any expert system in the zinc industry to detect possible troubleshooting types, it will be an effective approach in this industry. Moreover, it can prevent possible stops and decrease operational costs.

Weighting effective parameters in fuzzy expert systems and also weighting rules with regard to the identification of the most effective factors in the operating environment can provide more an accurate expert system.

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