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APPLYING OF ARTIFICIAL NEURAL NETWORK IN MAINTENANCE PLANNING OF METALLURGICAL EQUIPMENT

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Maintenance of metallurgical equipment is very complex and demanding job. Condition Based Maintenance (CBM) is used for complex and significant equipment. The paper shows element selection that will be used in CBM planning as a location on which will be applied neural network. The paper presents few different neural network algorithms that have been used for different prediction problems and review of achieved results. Data structure that has been used in researching problem is part of Information System and its Equipment Maintenance subsystem that was developed for enterprise Aluminij d.d. Mostar.

Key words: *maintenance, neural networks, maintenance information system*

Primjena neuronskih mreža u planiranju održavanja metalurške opreme. Održavanje metalurških postrojenja predstavlja složen i zahtjevan posao. Strategija održavanja po stanju predstavlja strategiju koja se primjenjuje za složeniju i značajniju opremu. U radu se daje jedan od pristupa odabira elementa za koji se provodi istraživanje s ciljem primjene neuronskih mreža u planiranju održavanja po stanju. Istraživano je nekoliko različitih algoritama neuronskih mreža za rješavanje problema predikcije, te se u radu daje pregled ostvarenih rezultata istraživanja. Kao pretpostavka za istraživanje korišteni su podaci iz podsustava održavanja postrojenja Informacijskog sustava razvijenog za potrebe poduzeća Aluminij d.d. Mostar.

Ključne riječi: *održavanje, neuronske mreže, informacijski sustav održavanja*

INTRODUCTION

Maintenance as the function of production system presents complex process. The basic task is to define goals that have to be fulfilled through the maintenance function. According to goals maintenance strategies and organization that depends on integrated Information System will be defined [1]. Result that is achieved through organization of maintenance function is maintenance plan which implements following strategies: corrective, preventive and Condition Based Maintenance (CBM). In progressive organization plan will be achieved through the implementation of many others strategies like: Total Productive Maintenance (TPM), Reliability Centered Maintenance (RCM) etc.

To react before the failure is imperative for maintainer. To collect information from the system, arrange and analyse them has to show conditions of the system. To act according to conditions is strategy well known as Condition Based Maintenance. The most important thing for this strategy is diagnostic control of selected system parameters. Parameters selection is very complex and could be realized through: observing of functions, ways and work conditions of technological system and/or its subsystems; parameters and factors cause-consequence relations that have influence on work capability of technological system; analyze of damages and failures.

Proper definition of preventive and condition based maintenance intervals is baseline for plan definition and implementation of different strategies (TPM, RCM etc.).

DEFINITION OF PROBLEM AND RESEARCHING GOAL

One of the most important decisions in a way of maintenance plan performing is to identify critical resources with the aim to dose activities of certain strategy or combination of strategies for technological systems or its parts. The first suggestion is result of TPM approach that is described in [2, 3], applied and implemented in module Technological data that is part of Equipment Maintenance subsystem [1] through the expression for critical equipment (KO):

$$KO = PO + PP + PZ + QP + S\,I + UC + UO \qquad (1)$$

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where:

PO - maintainability,
PP - productivity growth,
PZ - reliability,
QP - product quality,
SI - safety,
UC - cost,
UO - environment.

Aluminium production process is analyzed. Critical equipment in production process is defined according to expression (1). One of the most important resources (evaluation according to maintainer and people from production process) in aluminium production process is crane for electrolyze which structural form is given (Figure 1.), and also defined and described in Information System [4]. Through the system analysis was ascertain that significant number

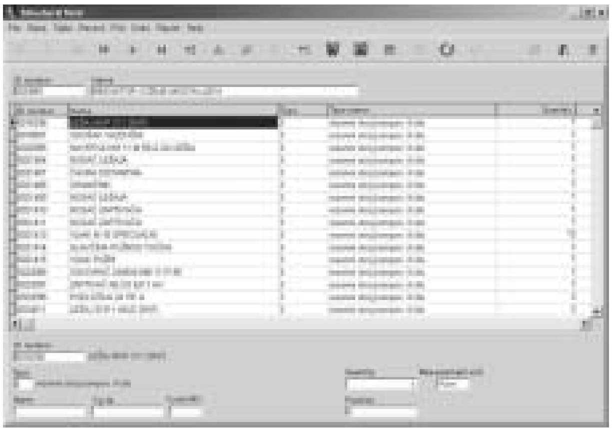

Figure 1. **Structural form from module Technical data**
Slika 1. **Strukturna sastavnica iz modula Tehničkih podataka**

represent rolling bearings. Propriety and condition monitoring of bearings are key elements for crane availability. From the heuristic analysis, observation and element historical data in exploitation it can be concluded that element is under direct or indirect impact of different influences (in further text: variables). These variables have influence on intensity and dynamic of tribological system. Maintenance function has to provide high availability and reliability of maintenance elements equipment and plants so, the logical conclusion according to previous mentioned is that influence on element life cycle is multivariable.

The main goal that wants to be achieved through this article is to research possible applicability of neural network especially in defining work frequency in equipment conditional monitoring. As a research subject, the rolling bearings are chosen because of the following reasons:
- important group of machines elements,
- it changes states in time,
- bearing state depends on different factors,
- depend on process type damages and detriments in work could cause serious consequences.

Different factors decrease the life cycle of rolling bearings [5]. There are four dominant factors: poor lubrication, as a result of preventive maintenance changing of bearing is too often, different types of incompatibility (electro-erosion, non-adequate assembly, starts and suspends etc.) and different types of contamination.

During the exploitation on maintenance elements, different factors can affect (directly or indirectly):
- project-construction attributes,
- attributes that are connected for exploitation,
- conditions and maintenance types,
- environmental condition etc.

According to previous mentioned the researching goal could be defined. The goal is to predict conditional parameters that will allow dynamic planning of following condition monitoring cycles and reserve of bearing appliance. The purpose is to determine proper and opportune activities for equipment maintenance.

Shock Pulse Method is vibration method that is used for measuring of bearing state. This method defines pulses, which are results of permanent impacts, and whose energy is presented through vibrations. So, these mechanical impacts are presented in every rolling bearing. Characteristics of these impacts are amplitude and frequency. The nature of these pulses is stochastic and they have very short life time. The pulse can be defined as impulsive transfer of kinetic energy on system. Mechanical impacts are in close relation with bearing damages.

For bearing damage, identification of two measured values will be used: maximum value of shock pulses and carpet values. According to bearing damage progress both of previous mentioned values would increase and the difference between them, as well. As a function of these changes are measure intervals that depend on:
- stability of measured values,
- momentary bearing condition,
- bearing damage progress.

If the knowledge about problem available in the form of discrete values set of element vector states and output measures from process, the natural choice is selection of neural network for analysis and researching of problem.

The reason why the model is proposed lays in fact that in the literature does not exist similar researches of such kinds of model, which goal is to connect influences of different parameters that act on research object. Some authors have used different approaches [6 - 9], usually model based on Back-Propagation neural network [10 - 12].

For suggested problem, the following model is defined. It has three variables: control intervals of bearing state, maximum value of shock pulses and carpet values. These variables are chosen from the following reasons: to enable efficient dynamical planning of successive control cycle, to define possible reserve in bearing utilization with the main goal to achieve proper maintenance of equipment. As input variables are defined variables that "cover" different influence factors, which react on bearing in exploitation and measured set of values for each of output variables (nine measured values and one that is used for control of calculated output values of neural network). The variables and values are given in Table 1.

Table 1. **Variables and values for suggested model**
Tablica 1. **Varijable s vrijednostima za predloženi model**

No	Variable name	Field Min	Field Max
1	Bearing manufacturer	1	4
2	Axle diameter /mm	10	100
3	Rotation number /(o/min)	100	5000
4	Measured place	1	2
5	Bearing type	1	2
6	Type of loading	1	2
7	Bearing work	1	4
8	Type of assembly	1	10
9	Performing type of assembly	1	4
10	Environment condition - moisture	1	3
11	Environment condition - dust	1	3
12	Environment condition - temperature	1	4
13	Transferred power	1	3
14	Type of lubrications	1	2
15	Type of lubricant	1	2
16	Conditions on measured place	1	2
17 - 25	Measured max. pulse /dB	1	65
26 - 34	Measured carpet value /dB	1	25
35 - 43	Evaluated intervals of further measuring /days	0	45

The next task is to explore and define the structure with the lowest level (threshold) of error. This structure is accepted for researching. Proceedings of research process are done through steps. For each step, new data pattern for specific variable is defined and date learning and testing patterns are specified, as well. Reduced data model has contained 42 input and 3 output variables. Neural network has learned with reduced data model, and after that given results have been analyzed. The research process has 43 steps, which generated 43 neural network structure.

The given error in each step is higher then error for start model. That means that removing of any variable from model will cause higher error. Apropos, the researching is continued with complete set of variable model without reduction. Table 2. shows some of attributes that are used for model reduction. The following step is algorithm and neural network structure definition. Criterion for algorithm selection was availability of programmes solution. Three algorithms for prediction problem were selected: Back-Propagation neural network, Modular neural network and Radial Basis Function neural network. After that for selected neural network architectures progressive optimization techniques have been used.

Table 2. **Some of neural network attributes necessary for model reduction**
Tablica 2. **Neki od atributa neuronske mreže za ispitivanje redukcije modela**

No	Attribute title	Accepted features
1	Number of input neurons	43
2	Number of output neurons	3
3	Number of hidden neurons	12
4	Learning rule	Ext DBD rule
5	Transfer function	Sigmoid
6	Epoha	20
7	Momentum	0,40
8	Learning coefficient	0,50
9	F'Offset	0,1
10	Number of learning iteration	50000
11	Connect P	Enabled
12	MinMax Table	Enabled
13	RMS	0,0328
14	Correlation factor	0,9842

EXPERIMENTAL RESULTS AND DISCUSSION

Results achieved by Back-Propagation Neural Network

Table 3. shows experimental results given by different back-propagation neural network architectures. The best result is achieved through the combination of Sigmoid transfer function and Extended Delta-Bar-Delta learning rule. As a criterion for evaluation, Root Mean Squared Error – RMSE (%) is taken. Experimental work is realized on previously researched and accepted neural network with the best architecture shown in Table 2. Table 2. also presents number of hidden neurons, which are 12. Number of hidden neurons is also confirmed theoretically and calculated according to geometric-pyramid rule [13], for one hidden layer:

$$n_{sn} = \sqrt{n_{un} \cdot m_{in}} \tag{2}$$

where:

n_{un} - number of neurons in input layer,
m_{in} - number of neurons in output layer.

Table 3. **The review of RMSE results that are achieved by Back-Propagation neural network**
Tablica 3. **Pregled rezultata RMS grešaka ostvarenih istraživanjem mreža širenja unazad**

Case			Neural network phases		
No	Transfer function	Learning rule	Learning	Test	Validation
1	Linear	Delta - Bar - Delta	0,0569	0,0833	0,0905
2	Sigmoid	Delta - Bar - Delta	0,0481	0,0432	0,0455
3	Sinus	Delta - Bar - Delta	0,0632	0,0860	0,0923
4	Hyperbolic-tangent	Delta - Bar - Delta	0,0625	0,0848	0,0913
5	Sigmoid	Delta	0,0394	0,0370	0,0392
6	Sinus	Delta	0,7858	0,8493	0,8148
7	Hyperbolic-tangent	Delta	0,0431	0,0883	0,0972
8	Linear	Ext. Delta - Bar - Delta	0,0619	0,0786	0,0905
9	Sigmoid	Ext. Delta - Bar - Delta	0,0328	0,0328	0,0355
10	Sinus	Ext. Delta - Bar - Delta	0,0516	0,0775	0,0867
11	Hyperbolic-tangent	Ext. Delta - Bar - Delta	0,0507	0,0789	0,0921
12	Sigmoid	Normalised cumulative Delta	0,0458	0,0407	0,0422
13	Sinus	Normalised cumulative Delta	0,0475	0,0717	0,0842
14	Hyperbolic-tangent	Normalised cumulative Delta	0,0490	0,0740	0,0847

Calculation according to expression (2) is n_{sn} = 11,36, round on the first main number. That number represents the number of hidden neurons, which is the same as number of neurons earlier given in Table 2.

Through further analysis of results can be concluded that the best results are achieved by Sigmoid transfer function for Back-Propagation neural network. The second place is reserved for Hyperbolic-tangent transfer function. Expectation was that Sigmoid transfer function has better results than Hyperbolic-tangent transfer function. The reason is that Sigmoid transfer function is defined for positive values until Hyperbolic tangent transfer function is defined for positive and negative values.

Applying of Normalized cumulative Delta learning rule gives the best results in a way of results distribution. All others learning rule in combination with transfer function realize wider distribution of results. Combination of Sinus transfer function and Delta learning rule (case 6.) generates RMSE in sum of 78,58 %.

Optimization of selected structure (case 9) gives optimal Back-Propagation neural network architecture through applying certain techniques like: simulated annealing, procedure "Save Best" and avoiding of neurons saturation.

RMSE in learning phase for this case is 2,78 %. Figures 2., 3. and 4. show realized predicted values and real values of neural network.

Results achieved by Modular Neural Network

Table 4. shows results achieved by Modular neural network. Case 11 (defined in Table 4.) is chosen for structure optimization.

After the optimization of selected architecture, RMSE is 2,61% in learning phase.

Table 4. **The review of RMSE results that are achieved by Modular neural network**
Tablica 4. **Pregled rezultata RMS grešaka ostvarenih istraživanjem modularnih neuronskih mreža**

Case			Neural network phases		
No	Transfer function	Learning rule	Learning	Test	Validation
1	Linear	Delta - Bar - Delta	0,0710	0,0799	0,0886
2	Sigmoid	Delta - Bar - Delta	0,0585	0,0647	0,0598
3	Sinus	Delta - Bar - Delta	0,0741	0,0810	0,0890
4	Hyperbolic-tangent	Delta - Bar - Delta	0,0778	0,0813	0,0892
5	DNNA	Delta - Bar - Delta	0,0542	0,0694	0,0659
6	Sigmoid	Delta	0,0329	0,0372	0,0391
7	Sinus	Delta	0,0706	0,0737	0,0811
8	Hyperbolic-tangent	Delta	0,0720	0,0757	0,0824
9	DNNA	Delta	0,0521	0,0632	0,0689
10	Linear	Ext. Delta - Bar - Delta	0,0687	0,0767	0,0818
11	Sigmoid	Ext. Delta - Bar - Delta	0,0303	0,0324	0,0349
12	Sinus	Ext. Delta - Bar - Delta	0,0650	0,0777	0,0822
13	Hyperbolic-tangent	Ext. Delta - Bar - Delta	0,0606	0,0767	0,0823
14	DNNA	Ext. Delta - Bar - Delta	0,0449	0,0504	0,0509
15	Sigmoid	Normalised cumulative Delta	0,0348	0,0400	0,0410
16	Sinus	Normalised cumulative Delta	0,0630	0,0719	0,0813
17	Hyperbolic-tangent	Normalised cumulative Delta	0,0657	0,0722	0,0832
18	DNNA	Normalised cumulative Delta	0,0424	0,0496	0,0479

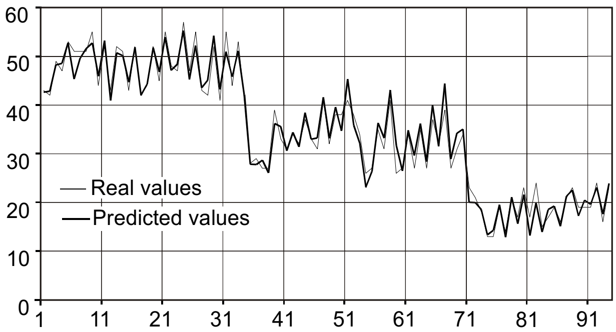

Figure 2. **The real and predicted values of neural network for maximum value of shock pulses**
Slika 2. **Prikaz stvarnih i predviđenih vrijednosti neuronske mreže za maksimalne vrijednosti udarnog impulsa**

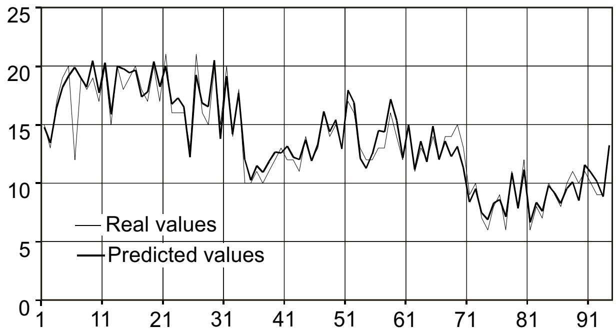

Figure 3. **The real and predicted values of neural network for carpet value**
Slika 3. **Prikaz stvarnih i predviđenih vrijednosti neuronske mreže za tepih vrijednosti**

Realized results confirm theory that results achieved by Modular neural network are better than Back-Propagation neural network results.

Results achieved by Radial Basis Function Neural Network

Table 5. shows RMSE achieved by Radial Neural Network and structure defined in Table 2. The best net architecture is combination of Sigmoid transfer function and Extended Delta-Bar-Delta learning rule that is chosen for optimisation. After the optimisation of selected architecture, RMSE is 3,71% in learning phase.

Table 5. **The review of RMSE results that are achieved by Radial Basis Function neural network**
Tablica 5. **Pregled rezultata RMS grešaka ostvarenih istraživanjem mreža sa radijalnim baznim funkcijama**

Case			Neural network phases		
No	Transfer function	Learning rule	Learning	Test	Validation
1	Linear	Delta - Bar - Delta	0,1520	0,1565	0,1420
2	Sigmoid	Delta - Bar - Delta	0,0739	0,0730	0,0688
3	Sinus	Delta - Bar - Delta	0,1518	0,1541	0,1413
4	Hyperbolic-tangent	Delta - Bar - Delta	0,1499	0,1501	0,1394
5	DNNA	Delta - Bar - Delta	0,0746	0,0662	0,0644
6	Sigmoid	Delta	0,0635	0,0622	0,0578
7	Sinus	Delta	0,1154	0,1295	0,1166
8	Hyperbolic-tangent	Delta	0,1155	0,1275	0,1168
9	DNNA	Delta	0,0635	0,0586	0,0554
10	Linear	Ext. Delta - Bar - Delta	0,1171	0,1355	0,1190
11	Sigmoid	Ext. Delta - Bar - Delta	0,0544	0,0562	0,0510
12	Sinus	Ext. Delta - Bar - Delta	0,1071	0,1192	0,1167
13	Hyperbolic-tangent	Ext. Delta - Bar - Delta	0,0984	0,1069	0,1067
14	DNNA	Ext. Delta - Bar - Delta	0,0621	0,0585	0,0550
15	Sigmoid	Normalised cumulative Delta	0,0651	0,0630	0,0586
16	Sinus	Normalised cumulative Delta	0,1174	0,1326	0,1188
17	Hyperbolic-tangent	Normalised cumulative Delta	0,1088	0,1153	0,1105
18	DNNA	Normalised cumulative Delta	0,0629	0,0587	0,0552

Integration of prediction model based on neural network in Equipment maintenance subsystem

Organization of data from Equipment Maintenance subsystem developed for enterprise Aluminij d.d. Mostar is defined [4] with the goal to apply model of failure prediction based on neural network. Figure 5. presents integration of neural network in Preventive Maintenance subsystem. Preventive Maintenance subsystem is developed as support in realization: preventive maintenance towards work parameters (time, working hours etc.), condition based maintenance and inspections.

To generate dynamic conditional based maintenance plan the following subsystems are used: Common database, Technical data, Material Purchasing and Stocks, Preventive maintenance in interaction with the suggested prediction model based on neural network. Such generated plans contain replacement period (terms) for monitored elements.

Efficient planning and maintenance realization, and in the same time avoiding and decreasing of unplanned delays caused by corrective maintenance will be enabled to maintenance function. Dynamic plan and information about element condition have to provide the rational material man-

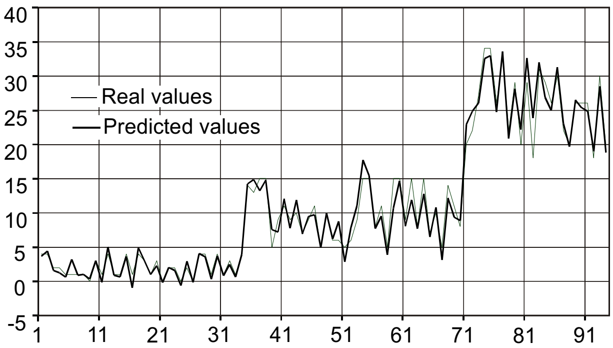

Figure 4. **The real and predicted values of neural network for evolution of conditional monitoring interval**
Slika 4. **Prikaz stvarnih i predviđenih vrijednosti neuronske mreže za procjenu intervala nadzora stanja**

agement. Based on plan the list of spare parts with due dates or implementation terms will be created and delivered to the purchasing function. Thanks to previous mentioned the costs would be taken into consideration, as well.

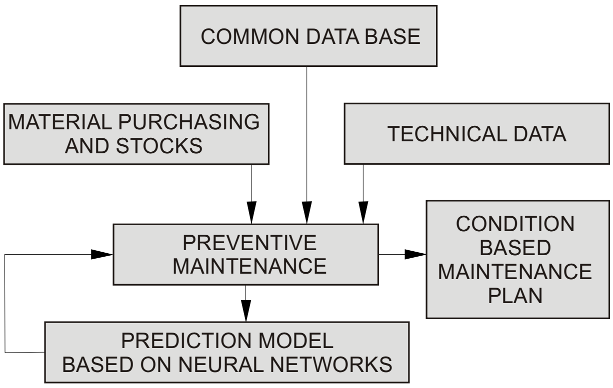

Figure 5. **Integration of neural network model in Preventive Maintenance subsystem**
Slika 5. **Integracija modela neuronskih mreža u podsustav preventivnog održavanja**

CONCLUSION

The paper shows research results that have been done with the main goal to extend possibility of preventive maintenance. Defined prediction model is based on different neural network architectures. Given output results of optimal structures for mentioned architectures had few percent deviations. Through this the verification of applying different neural network architectures for suggested prediction model is done.

Suggested model has to be verified in exploitation and to increase availability of metallurgical equipment because of aluminium process production continuity.

Further researching has to manage:

- Cost analysis of suggested model and possible optimizations according to minimal costs,
- Integration of suggested neural network model with expert system and implementation in Management Information Maintenance.

System with the main goal to improve decision support maintenance system.

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