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NEURAL NETWORKS IN MODELLING MAINTENANCE UNIT LOAD STATUS

ABSTRACT

This paper deals with a way of applying a neural network for describing service station load in a maintenance unit. Data acquired by measuring the workload of single stations in a maintenance unit were used in the process of training the neural network in order to create a model of the observed system. The model developed in this way enables us to make more accurate predictions over critical overload. Modelling was realised by developing and using m-functions of the Matlab software.

KEY WORDS

Artificial Intelligence, expert systems, neural networks, maintenance, logistic analysis

1. INTRODUCTION

Technological development inevitably changes the quality and the quantity of knowledge application in everyday life. Certain individuals, experts, who are not numerous, possess specialised knowledge, but the most appropriate ways of conveying this knowledge have still not been identified. Application of new artificial intelligence products in the form of expert systems that assist in decision-making makes managing system processes easier.

A developed identification model of the repair system and predicting repair unit jams is one of the possible applications of expert systems in repair unit management with the purpose of timely and adequate decision-making.

Fast development and overall computer usage has evolved from initial data processing and database management into a synthesis of knowledge base creating and developing expert system algorithms for simple everyday problem-solving. However, knowledge is still comprehensive, difficult to determine and constantly changeable. Therefore it is very difficult to find a universal model of knowledge manipulation. Instead, specialised expert systems that contain certain knowledge or expert shells initially without knowledge are developed. This approach to problem solving has resulted in application of new management as well as knowledge and data organisation processes.

Artificial intelligence is understood as capability of mechanical systems (computer) to display behaviours, which are with humans referred to as intelligent; such as learning ability, recognition, inferring, decision-making and planning.

Components of a knowledge-based system are data acquisition module, knowledge base, inference procedure and user interface.

A system based on knowledge expanded by a specialised knowledge base is called an expert system *(Figure 1)*.

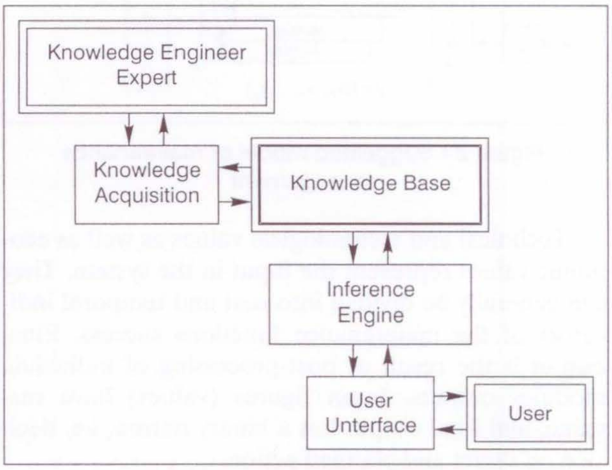

Figure 1 - An expert system

Expert systems are often used in activity planning in production systems. In that case databases of conventional plans of production processes are used as initial knowledge bases for expert systems.

While managing a system it is necessary to create a system model based on actually measurable data (identification).

When using neural networks it is possible to include system properties (non-linearity, time delays, or temporally changeable parameters), into the model without using the traditional analytical models that often provide unsatisfactory or unacceptable solutions. Identification procedure of activities in an overhaul unit contains the following stages:

1. Collecting the input and output values;
2. Shaping choice and setup of model structure of the neural network;
3. Choosing the quality criteria for the model;
4. Parameter estimate – implementation of the experiment;
5. Check *(validation)* – testing and choosing the best model.

2. OVERHAUL UNIT MANAGEMENT MODEL

The suggested model of a dynamic system of maintenance management comprises several various interrelated and interdependent modules consisting of neural networks. Modules are used for modelling the relationship between input and output values.

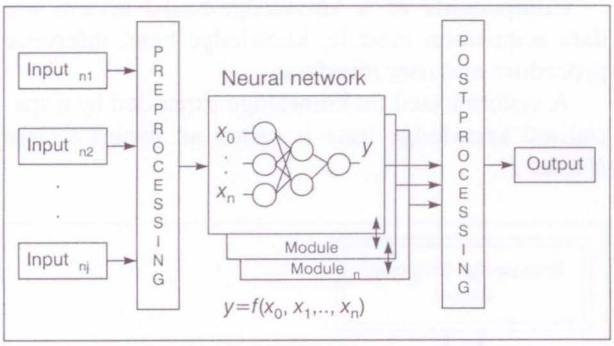

Figure 2 - Suggested model of maintenance management

Technical and technological values as well as economic values represent the input in the system. They can generally be divided into cost and temporal indicators of the maintenance functions success. Final output is the result of post-processing of individual modules outputs. Input figures (values) have real value, and final output has a binary nature, i.e. decision on direct and planned action.

3. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks have been developed based on the present knowledge of human brain function. They are an important contribution in creating technical systems of artificial intelligence. Unlike the conventional calculation models where programmed operations on a smaller number of processing units are done mechanically and do not show intelligent behaviour, models of artificial neural networks are based on a large number of connected processing units (neurones) and learning mechanisms (changes in strength of neurone connection) which are similar to brain function. Systems of artificial neural networks display basic informational properties of conventional computer systems (input, processing, storing, transmission) with additional properties of intelligent behaviour.

The ability to autonomously generalised characteristics of input-output pairs based on multiple occurrences of examples at the input and the output of the network makes it possible to apply neural networks in systems based on knowledge. Memorising pair properties of input-output examples and upgrading the network's capabilities takes place in the network's learning stage. In the working stage the network alone finds the appropriate equivalent for the given sample based on previously learned dependencies, which is exactly what is expected to happen in this process.

Besides basic generalisation capability, other properties of neural networks are:

- ***Parallel distribution of information processing***
  Process units of an artificial neural network simultaneously accept and process several input samples.
- ***Learning and adaptive ability***
  Ability to learn and to adapt make neural networks capable of processing less precise and damaged data on erratic and indefinite phenomena.
- ***Universal approximation of common properties of input-output pair samples***
  Neural networks approximate arbitrary continuous non-linear function up to a desired precision.
- ***Multiple modularity of the network***
  According to their structure, neural networks are multiple modular systems, which makes them applicable for modelling, identification and managing of multiple modular processes.
- ***Framework implementation***
  Framework versions of neural network models have been developed for real time functioning.

3.1. Biological neural model

The biological neurone structure model consists of four major parts, *Figure 3.* Cell body with the nucleus, intake filaments - dendrites, long exit filament – axon and terminal arborizations *(axons)*.

Through dendrites the cell body receives data in the form of electrical signals from neighbouring neurones. Axon is the exit relay through which the transformed input data are transferred towards other neurones. The terminal arborizations are placed at the end of the neurone. They take part in the process

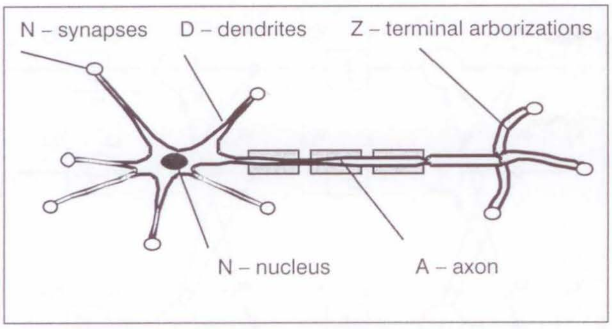

Figure 3 - The model of a biological neurone.

of transformation of electrical signals into chemical substances that relay data to other neurones through synapses (gaps between cells).

3.2. Artificial neural model

Figure 4 shows a simple computer model of a biological neurone - McCulloch-Pitts neurone, 1943. The adder and activation function are equivalent to the cell body, dendrites are equivalent to the entrance into the adder axon is the exit. Activation function takes over the role of a biological neurone's sensitivity threshold. Synaptic links of a biological neurone with its environment is equivalent to weight factors, through which the neurone link is established with its environment and with the neighbouring neurones. At the exit of the neurone an amount signal will appear which is equivalent to the value of the activation function for its argument, which is equal to the sum of products of input figures and corresponding weight factors.

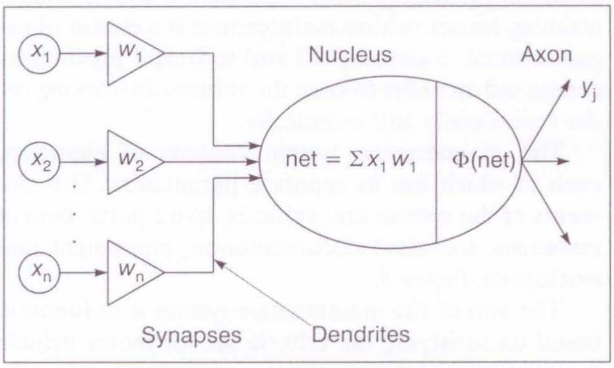

Figure 4 - Artificial neural model

3.3. Activation functions

The most common activation functions used for transfer of weight inputs *(net)* are step function, linear function, sigmoid functions, sinus function and the Gaussian function, *Figure 5*.

Threshold function is a simple non-linear function, applicable for discrete neural model realisation. Activation functions which are adjusted to analogue models are the so-called squashing functions. Invariably growing functions with saturation which project sum value into output transfer of neurone are mostly used activation functions. Activation functions can be linear and non-linear. The choice depends on the group of given studying values and the group of given values for neural network testing. The majority of activation functions norm output values in the range of 0 to 1 or –1 to 1.

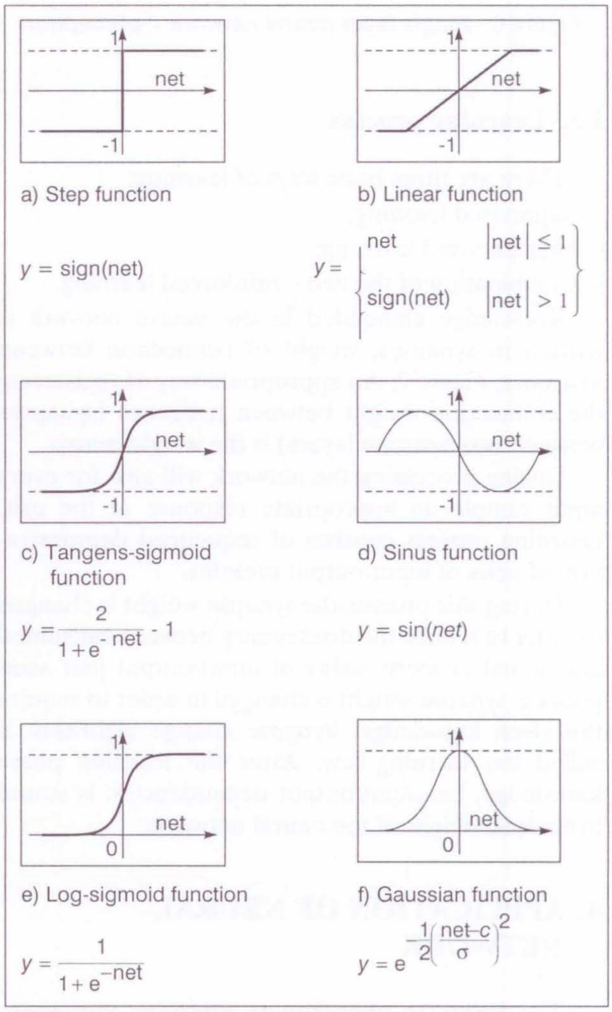

Figure 5 - Typical activation functions

3.4. Perceptron

Perceptron is a simple model of a single layer neural network with learning capability, known as F. Rosenblatt's Perceptron. Learning is conducted through algorithm of changing the weight factors of link between neurones by reverse transmission of error of the calculated and the desired output sample *(backpropagation algorithm)*.

Depending on the number of neurone layers we divide networks into single layer networks and multi-layer networks.

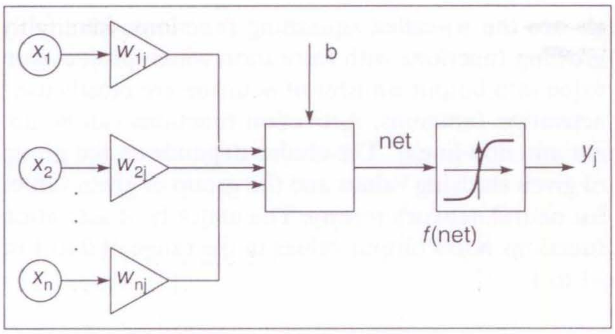

Figure 6 - Single layer neural network - perceptron

3.5. Learning process

There are three basic ways of learning:
- Supervised learning;
- Unsupervised learning;
- Combination of the two – reinforced learning.

Knowledge embedded in the neural network is written in synapses, weight of connection between neurones, *Figure 7*. An appropriate way of registering the connection weight between neurones (synapses between two neurone layers) is the weight matrix.

During processing the network will give for every input sample an appropriate response at the exit. Learning process consists of sequenced demonstration of pairs of input/output samples.

During this process the synapse weight is changed in order to reduce the discrepancy between calculated and actual property value of input/output pair samples, i.e. synapse weight is changed in order to acquire the given knowledge. Synapse change algorithm is called the learning law. After the learning phase knowledge, i.e. input/output dependencies, is stored in synapse weight of the neural network.

4. APPLICATION OF NEURAL NETWORK

The ability to approximate arbitrary continuous functions is one of the most important characteristics of artificial neural networks.

The property of uniform approximation of continuous function $f{:}D_f \subset R^n \rightarrow R^m$ by function f^* to D_f, with given precision has been proved [4].

The optimal number of neurones and layers has still not been determined, but practice has shown that networks with two hidden layers provide adequate precision of approximation. It has also been proved that it is possible to apply approximation by using networks with activation functions of radial base [1].

The above mentioned property can be useful in producing a model for identification of load state. It is also possible to apply it in making and integrating adequate modules for production of an expert system based on modular approach to neural network application.

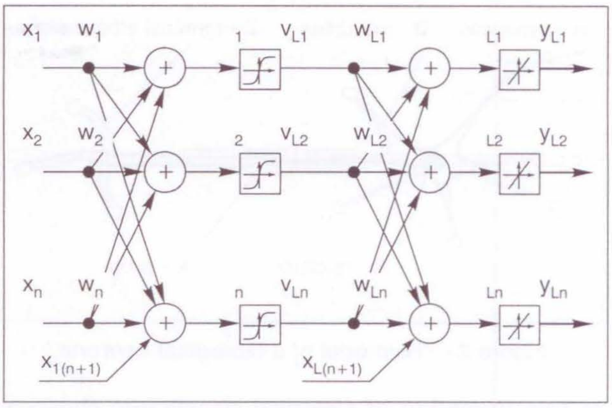

Figure 7 - Multi-layered neural network

Appropriate maintenance of such an expert system is a new requirement.

4.1. Description of load state of a maintenance unit

Maintenance is a complex and dynamic organisational and technical process. A quality description of such a process requires a large number of parameters to be considered, and at the same time crucial elements and factors to be extracted.

The increasing number and diversity of motor vehicles that participate in the process of technological maintenance need taking into account more application elements and requirements that need to be fulfilled during management organisation and personnel training. Motor vehicle maintenance is a cluster of organisational, technological and technical procedures conducted on order to keep the vehicles in working order functionally and technically.

The maintenance system consists of elements, each of which has its separate parameters. The elements of the system are: vehicles, spare parts, human resources, technical documentation, equipment and workspace, *Figure 8*.

The aim of the maintenance system is to function based on satisfying the criteria set for motor vehicle maintenance.

Prescribed equipment is used for both levels of maintenance (preventive and corrective) and depends

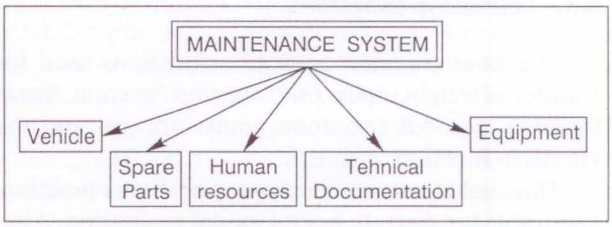

Figure 8 - Maintenance system elements

on technology of prescribed maintenance for a specific kind of motor vehicle. Increasing diversity, complexity and number of motor vehicles implies increasing diversity of servicing equipment which improves the condition of vehicles, but extends time needed for maintenance, as well as maintenance costs. Consequently, considerations on rational usage of resources are justified.

Motor vehicles maintenance unit is a complex mass service system that includes users. The amount of service time is the determining factor. Service time has random character and is represented by a random variable with its own distribution of probability. The randomness of maintenance process requires using methods from the field of probability theory and theory of random events *(contingency)*. Current research on optimising maintenance units has been based on simulations. A computer experiment with an abstract model is considered to be a simulation.

Since a simulation is an experiment, it processes only certain independent variables and parameters used in the experiment [10]. Simulation does not indicate functional interdependencies between input and output, but possible influence of a single parameter change on the change of output. Simulation is not used for optimising a process, but the most favourable alternative can be singled out after a certain number of iterations.

4.2. Estimation module of a maintenance unit load status

Neural networks compensate for the mentioned flaws. The problem of modelling dynamic processes comes down to approximation of a non-linear function.

Figure *9a* represents a chart of load state (n), a specific station in the maintenance unit observed in a specific time. At a certain moment the unit reached the state of overload due to its limited capacity, i.e. number of vehicles waiting was above the given value of optimal capability of the unit's elements, e.g. 0.5. Load *Kz, Figure 9b*, is for a specific time defined as ratio of vehicles waiting and total number of entries in the service unit (n). Load is expressed through values in the range from 0 to 1. The operator has so far been determining future states of overload *Kz* and it was based entirely on his experience. He has to make the decision about the moment when a client will be transferred to another station or other organisational measures will be taken in order to prevent the extra waiting costs from endangering regular procedures. The obtained load data *T* will be used for understanding the relation of vehicles waiting or being worked on.

They are at the same time the desired characteristics of the model. When the load state value exceeds a given limit, it represents the level of impossibility to service vehicles.

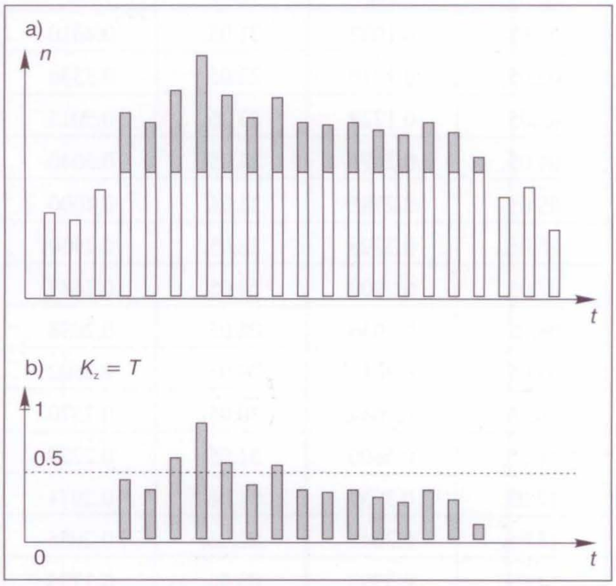

Figure 9 - Maintenance unit load status

The first step in modelling the maintenance unit load status by a neural network is teaching the network through presenting input (time-*t*) and output (load status coefficient-*Kz) pair values. A two-layer neural network with one input neurone, with ten neurones in the hidden layer and one output neurone was used. Tangens-sigmoid function was used in hidden and linear activation function was used in the output layer.*

Network was trained under supervision by using backpropagation algorithm. The used algorithms were implemented as *m-functions of the Matlab software package. Modelling was conducted on a personal computer.*

4.3. Neural network parameters

The following coefficient values of maintenance unit overload were collected during the one-month observation period. They are used as goal values for the neural network, *Chart 1*.

Before the learning process begun maximum number of epochs to train, sum-squared error goal and initial learning rate were set as network parameter values.

Backpropagation learning rule was applied in the model, where the quality of the learned is proportional to the difference between actually achieved activation and the desired activation. Neural network should ideally achieve the lowest error level possible and approach the optimal solution, i.e. the global minimum and avoid being trapped in the local minimum.

Chart 1 - Overload coefficient

Date	Kz	Date	Kz
01.05.	0.1002	21.05.	0.4810
02.05.	0.1770	22.05.	0.5336
03.05.	0.1729	23.05.	0.5013
04.05.	0.2771	24.05.	0.5040
05.05.	0.2785	25.05.	0.4000
06.05.	0.2799	26.05.	0.2930
07.05.	0,2909	28.05.	0.2647
08.05.	0.3036	28.05.	0.2098
09.05.	0.3013	29.05.	0.2602
10.05.	0.3044	30.05.	0.2370
11.05.	0.3600	31.05.	0.2229
12.05.	0.3930	01.06.	0.2071
13.05.	0.3647	02.06.	0.2085
14.05.	0.3798	03.06.	0.1799
15.05.	0.4307	04.06.	0.1909
16.05.	0.4346	05.06.	0.1307
17.05.	0.4354	06.06.	0.1369
18.05.	0.4181	07.06.	0.1804
19.05.	0.4331	08.06.	0.1311
20.05.	0.4418	09.06.	0.1131
		10.06.	0.1189

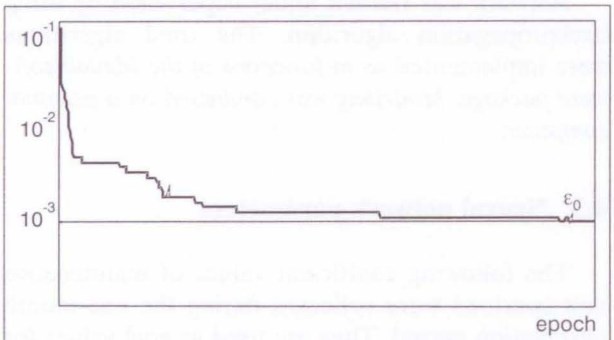

Figure 10 - Values of sum squared error during neural network learning process

It is evident in *Figures 10*, as well as in *Chart 2* (decrease of sum-squared error) that visible learning advancement was achieved when using the steepest descent algorithm applied in the error backpropagation algorithm.

With desired sum-squared error of 10^{-3} achieved, a satisfactory model of station load status of a maintenance unit is accomplished, Figure *11*.

After teaching the network about dependence of workload at service stations, it is possible to apply the

Chart 2 - Changes of error value

Epoch no./Max. No. of epochs	Learning rate	Sum-squared error
0/10000	0.01	516.434
100/10000	0.0146999	5.08718
300/10000	0.00637019	0.667988
600/10000	0.00637019	0.171013
900/10000	0.00688262	0.0662167
1200/10000	0.00642372	0.0311926
1500/10000	0.00469757	0.0172309
1702/10000	0.01282454	0.0099757

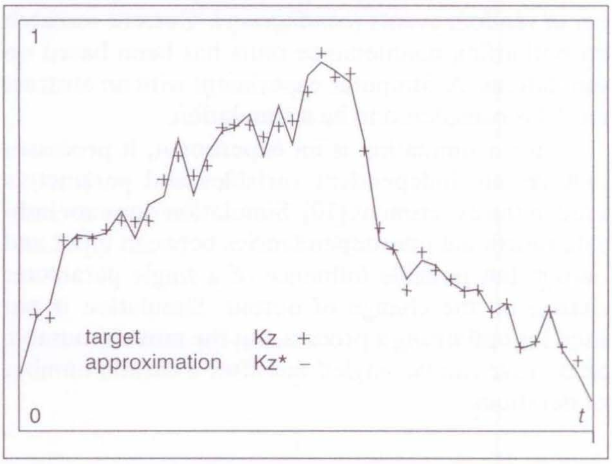

Figure 11 - Approximation of station load status in a maintenance unit

knowledge on a new time line –t*, i.e. to calculate the load status value. The network taught in such a way has a certain generalisation capability. This property is shown in the ability to establish connection between values at its entry, and which were not part of the values presented to it during its learning time, and the output values.

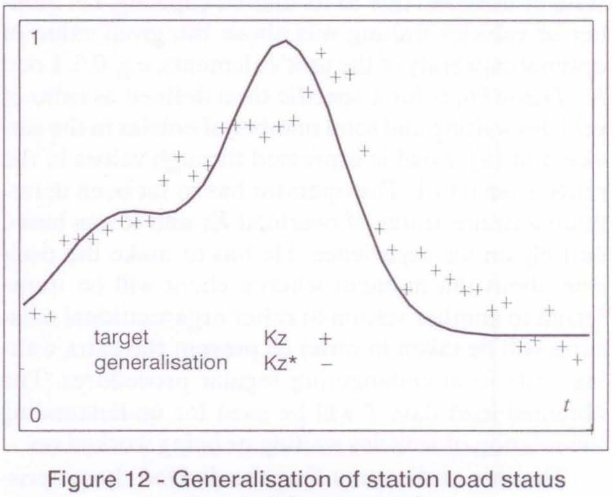

Figure 12 - Generalisation of station load status in a maintenance unit

Updating the model with new data requires new learning, which means generalisation, *Figure 12,* of the new knowledge.

During the experiment with different number of hidden tansig neurones, sum-squared error goal and learning rate, it may be concluded that changes of these factors reflect on the complexity of the problem.

In addition, it is necessary to conduct a long-term observation of the system as to notice daily, weekly or monthly load stoups, as well as any seasonal changes.

5. CONCLUSION

The above presented solution can be used as assistance in managing and supervising the load status process of service stations in a maintenance unit.

A developed neural network showed a satisfactory level of approximation of the given functional dependence for the known load states in a monthly period. Recording load status of service stations over a longer period of time will make the model more suitable. Repeated teaching with reduced error value did not bring a satisfactory result (time of teaching was substantially increased). For reducing the network training time and keeping the same error value, it is necessary to choose an adequate number of neurones in the hidden layer. Therefore, experiments are underway which should show a correlation between the number of hidden layers and the number of neurones with the repair unit whose behaviour is modelled.

A module developed in this way can be built in a user model of an expert system for managing a maintenance unit.

Additional development of expert systems will result in construction of a prediction module based on adaptive algorithm for teaching linear or RBF neural network. Input values of the prediction module are acquired in the phase of neural network exploitation. Consequently, a more accurate prediction about the system overload can be made. In addition, there is also a possibility of making qualified decisions in the maintenance unit management process.

Such knowledge enables us to make timely decisions in the process of work management. The suggested modules and those developed in the future, when mutually connected, will possibly create a highly efficient expert system with the purpose of maintenance unit management.

SAŽETAK

MODELIRANJE STANJA OPTEREĆENOSTI SERVISNE STANICE NEURONSKOM MREŽOM

U radu je prikazana primjena neuronske mreže u opisu opterećenja mjesta posluživanja servisne stanice. Podaci dobiveni mjerenjem opterećenosti mjesta posluživanja servisne stanice korišteni su u procesu učenja neuronske mreže s ciljem izrade modela promatranog sustava. Razvijeni model pruža mogućnost predikcije stanja kritičnih opterećenja. Modeliranje je izvedeno pomoću m-funkcija programskog sustava Matlab.

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