DETERMINATION OF THE DRUM MILLS' ENGINE CAPACITY BY USING NEURAL NETWORK WITH SUBORDINATE INPUT PARAMETERS

Ph.D eng. Teodora **HRISTOVA**, UMG "St. Ivan Rilski", Sofia, BULGARIA, teodora@mgu.bg
Ph.D eng. Ivan **MININ**, UMG "St. Ivan Rilski", Sofia, BULGARIA

Abstract: *A successful experiment has been done to train the neural network to determine the drum mills' engine capacity by using the program „QwikNet 2.23". As a result we get a trained neural network with a maximum error of $1.00619.10^{-5}$ which can be used for assessing the capacity of the electric motors of drum mills and can be considered an accurate mathematical model.*

Key Words: neural network, drum mill's engine, subordinate input parameters

1.INTRODUCTION OF THE PROBLEM

During the last years assessing the parameters of electric engines is unthinkable without using computers and programs. When determining the drum mills' engine capacity are used algorithms in which as input parameters count the sizes (measurements), the angular velocity and the drum mills' load with grinding forms. In most cases it turns out that the calculated capacity is usually lower than the requisite amount which leads to installing a much more powerful motor of calculations.

To facilitate the designer's activities, the algorithms for calculating the engines' capacity that operate the drum crushers become automated by using computer calculation programs. The easiest way is to use EXCEL or MatLab . In spite of inputting of correction coefficients the engine's calculated capacity differs again to the one installed in the factory-producer. This is probably because of the fact that many of the input parameters, taking part in the techniques that calculate the mill's engine capacity cannot be set correctly and differ from the real ones. For example when determining the sphere's load of the drum mills it is assumed that all spheres in the drum of the mill have the same diameter. But it came to be known that when proceeding the spheres fatigue and decrease their diameter which leads to increasing the density of the grinding medium, its weight and increasing the capacity spent for raising and transmitting the kinetic energy of the spheres.

To solve this problem it is decided that a neural network should be trained by which the determination of the drum mills' engine capacity is going to be done more precisely.

2.ESSENSE OF NEURAL NETWORKS

The neural network is a mathematical program consisted of interrelated simple computing elements (neurons). The two most essential characteristics of the neural networks are : the ability to "learn" and to "generalize". When "learning" every neuron accepts signals from the others (in the forms of numbers), processes them by a relevant mathematical algorithm and defines its activation which is being transmitted by the outgoing connections to the other neurons. Every connection has weight which multiplicated with the signal defines the significance (power). The connections' weight are analogical to power of the junctional impulses transmitted between the biological neurons. The negative weight value corresponds to a suppressive impulse and the positive – to a stimulating impulse. The neural network has an input and output layer and also several intermediate layers. To achieve accurateness on a higher level the intermediate layers in the neuronal network could be several. After training the neuronal network in a relevant mathematical algorithm a new array is being entered consisting of data that wasn't used for the training and the system generates new gates (Ivanova,2004).

The neural networks can be classified according to different principles. According to the training algorithm they can be with a straightway and contrariwise diffusion, fixed increasement or with a contrariwise diffusion of the mistake. The most used and successful instrument for prognosis is the neural network with a straightway diffusion (Zhang,2004). This type of neural network is being used in 80% of the researches devoted to connectional approach (Remus,2001) and its application in solving predicative problems as its in this case and also the task to determine the capacity of the engine.

With the development of the technologies there are operated neural networks to prognosticate the traffic load, to define the sale or other statistic tasks.

For the training of a neural network to determine the capacity of an engine, operating the sphere's mill, is chosen universal neural network QwikNet2.23 in which array can be used several types of training algorithms.

A data array is being created from the sizes and the load of the working mills and in the gate of the mill are set the parameters of the engine working in real conditions.

The weights of the created neural network are being calculated and as the principle of inputting data is this one : in the neural network the input and output parameters are set. The output parameters are being assigned by an expert assessment or taken from real data. After that the network is being trained until a certain percent of mistake is reached.

The weights that are gotten show the rank of influence between the entrances and the exits.

3. RESULTS FROM THE NEURONAL NETWORK TEACHING

A neuronal network with three layers is being trained – one input, one internal and one output. The entrances are 7. The ones with interrelated input parameters are : the thickness of the facing, mm and the mass of the sphere or the bar load. Independent from each other entrances are 5 : the internal diameter of the drum, mm; volume of the drum, m^3; and speed of the mill, min^{-1}; internal diameter of the drum, mm with relative angular velocity of the drum, % . In the hidden layer there are 5 meetings and one outset – capacity of the engine. Between the entrances exists a connection. Several training algorithms are researched - Rprop, Quickprop, Backprop и Delta-bar-delta.

The least mistake when teaching a neural network is when the Rprop algorithm is used (Hristova and Minin,2012). The correlation mistake is $1.00619.10^{-5}$ and the maximum is $3.76222.10^{-5}$ which is very low value for an engineering problem. On account of it there is no need to train the neuronal network more intermediate layers.

Correspondingly are the weights shown in table 1.

Table 1.

Neurons' weights							
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
0.213256	0.0885575	0.101925	0.0093619	0.548423	0.535239	0.0189155	-0.10442
0.107766	0.196373	0.0599555	0.324386	0.135178	0.481715	0.134074	0.243383
0.322921	0.560508	0.46941	0.199321	0.174821	0.24682	-0.245332	0.247247
0.530203	0.0031545	0.553312	0.495522	0.0918718	0.331125	-0.143651	-0.0762577
0.102346	0.117929	-0.004133	0.165702	0.0117241	0.407647	0.018403	-0.256016

In table 2 there are visualized the parameters of a "taught" neuronal network .

Table 2.

Parameter	**Value**	**Parameter**	**Value**
Epochs	100000	Initial_Weight_Step_Size	0.001
Teaching algorithm	Rprop	Momentum	0
Weight_Increase_Rate	1.2	Input_Noise	0
Weight_Decrease_Rate	0.5	Weight_Decay	0
Min_Weight_Step_Size	1e-006	Final_RMS_error	$1.00619.10^{-5}$
Max_Weight_Step_Size	50	Max error	$- 3.76222.10^{-5}$

*In table 2 Epochs is the number of teaching repetitions.

The results of a teaching mistake are visualized in the next graphics. (Figure 1)

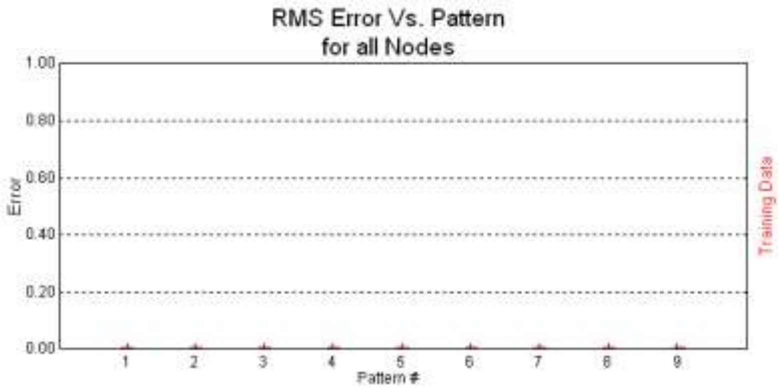

Figure 1

On figure 2 is it shown a taught neuronal network. The colour of the connections defines the mistake and also shows that in the exit it is in the interval 0 -1.

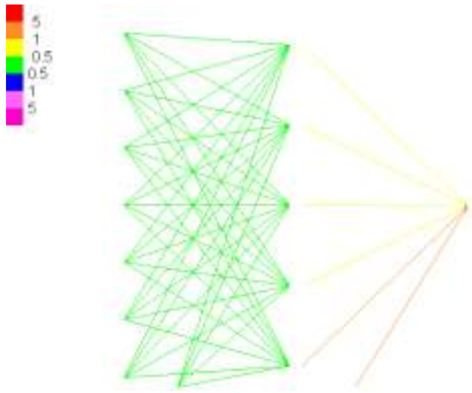

Figure 2.

The colouring of the neural network connections shows that the calculation is accurate which means that their weights are being calculated right. To achieve a better training there are an average number of calculating repetitions because it is acknowledged that some teaching algorithms when increasing the number of repetitions the mistake grows too (Kissiova and Radulov, 2002). The results of the testing report a very low mistake.

When testing the system more accurate prognostic data to determine the capacity of the engine compared to the trained neural network with independent input data (Hristova and Minin,2012).   . The correlation mistake is - Final_RMS_error - $1.00619.10^{-5}$ and the maximum mistake is Final_Max_error - $3.76222.10^{-5}$.

On the next graphics (Figure 3) there is the data of the testing algorithm when there isn't one entrance. Unlike the researches done with independent input data because of the link between the input data, prognosticating of the engine's capacity is done with a lower mistake. It is concluded that when teaching the neuronal network it is necessary to have more input data some of which to have a connection in between. This way, in case it is needed to determine the capacity of the motor and when there is an input parameter missing if the parameter is dependent on the other parameters, the value we get in end is going to be correct. This quality of the neural networks can be used in determing the capacity in rooted already working mills, if it is necessary to repair or change the work load caused of the change in the technology.

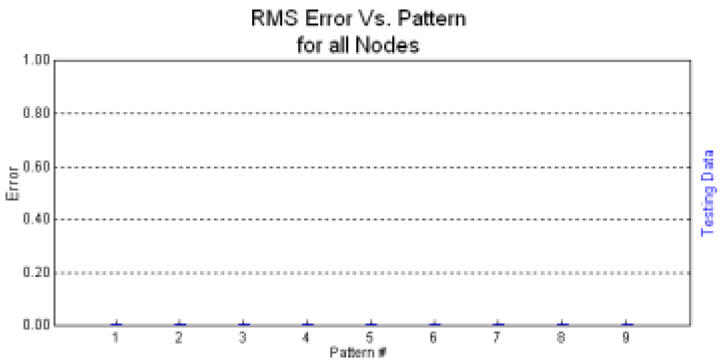

Figure 3

On the next figure (figure4) it is clearly seen that the output data for determing the capacity of the engine have a lower mistake compared to the ones determined with no connection between the entrances on the graphs (Hristova and Minin,2012).

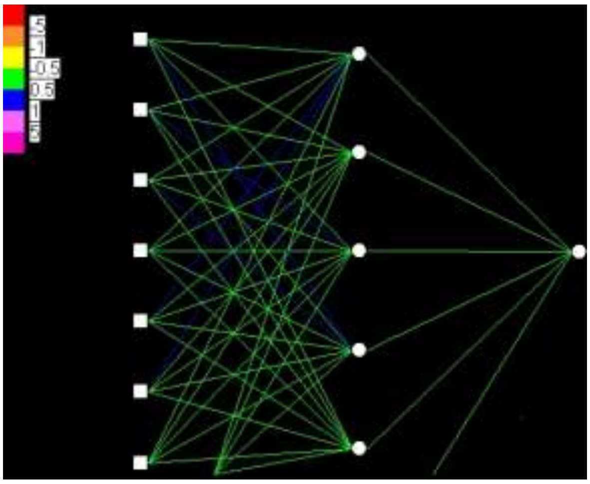

Figure 4.

3.CONCLUSIONS

The trained neural network can be used for determining the capacity of the engines of all kinds of drum mills and can be considered a reliable mathematical model. Defining the capacity of the engine that operates a big industrious equipment is a responsible engineering assignment and it is recommended to use standard algorithm in parallel with neural network. Still the neural network is a reliable indicator for the engine's capacity as the accurateness of the prognosis is higher when using dependent input parameters. It can be used when designing dressing factories related to a determining of the motions installed in the mills' department.

REFERENCES:

Ivanova Mausya http://www.bam.bg/ravda2004/Ivanova_Marusya.htm

1. Hristova Teodora, Minin Ivan "Determination of engine power of drum mills using neural network with independent input parameters", Sofia, Annual of UMG, Volume 55,2012, part "Mechanization, electrification and automation of mining" , in press
2. Kissiova Teodora, G. Radulov, E. Gegov, V. Christov " Logical-probabilistic model for assessing the relationship between environmental pollution according to productivity and climatic conditions in "GORUBSO ROF", Interenational Symposium "Ecology", 2002, pp.393-401
3. Remus, W., O`Connor, M ., "Neural network time-series forecasting" in in Armstrong, J . (Ed.) "Principles of forecasting: a handbook for researchers and practitioners", *Kluwer Academic Publishers* , 2001 , pp.246.
4. Zhang, P ., "Neural networks in business forecasting", *Idea Group Inc.* , 2004, pp.3.