# On the application of the artificial neural network method to a neural simulator of steam turbine power plant

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ABSTRACT

*In the paper a neural simulator of steam power unit is presented as an example of application of artificial neural networks (ANN) for modeling complex technical objects. A set of one-directional back-propagation networks was applied to simulate distribution of main steam flow parameters in the cycle's crucial points for a broad range of loading. A very good accuracy and short computation time was obtained. The advantages make the simulator useful for on-line diagnostic applications where short response time is very important. The most important features of the simulator, main phases of its elaboration and a certain amount of experience gained from solving the task was presented to make the practical application of the method in question more familiar.*

**Keywords** : neural modeling and simulating, turbine power plants, on-line diagnostics

## INTRODUCTION

Steam power unit or ship power plant is a very complex object. To know its technical state is crucial for carrying out its operation in an optimum way, in which diagnostics is of a great importance.

Today, apart from safety, the taking care of operational process quality to obtain long-term reduction of cost has become a priority. It consists in expanding times between overhauls at simultaneous maintaining the efficiency of devices on a constantly good level. This is on-line diagnostics which makes continuous controlling the technical state of objects under operation possible. As it brings large economical profits the diagnostics becomes more and more important and its dynamical development can be thus explained.

Therefore is needed a device which would be able to accurately determined operational parameters of a given object so fast as to make it possible to compare them with current ones. To achieve that determination time of a correct operational standard should be of the order of milliseconds (resulting from sampling frequency of measuring systems). Heat flow diagnostics of steam power units is based on advanced analytical models. However because of their long computation time they can be used in off-line mode only. It means that periodic control of technical state of an object can be performed on the basis of earlier collected data.

The neural simulator operates as a black box and artificial neurons acts here instead of sophisticated models. Its response process consists in simple mathematical operations. Due to this fact a neural simulator is more primitive than an analytical one but it provides standard operational parameters of a given object very fast and with good accuracy that justifies its application to on-line diagnostics.

## PHASES OF ELABORATION OF THE NEURAL SIMULATOR

### *Choice of a simulated object*

A standard steam power unit of 200 MW output fitted with a modernized TK 200 turbine was selected as the object to be simulated (Fig.1). Such selection has been justified by the wide application of units of the kind in Polish electro-energy system.

### *Training data acquisition*

In the ANN method a fundamental thing is to have an appropriate set of training data as the rules written in neural model structure are generated on their basis. During training the network finds only relations between a given "input" and "output", contrary to an analytical model elaborated on the basis of universal laws of mathematics and physics where experimental data serve only to control if theoretical laws are in compliance with reality.

Hence to apply the ANN method it is necessary to collect in advance a huge amount of experimental data for training the network.

For lack of operational data of a real steam power unit this author made use of DIAGAR software [2] which served as a source of data for elaborating the neural simulator in question. Such situation where an analytical simulator provides training data is very advantageous as it makes it possible to generate an almost arbitrary set of images for training the network.

Fig.2 shows schematic diagram of computations of the object taken into account in DIAGAR software. The main steam jet is marked red and regenerative steam extractions are signed with Roman numerals.

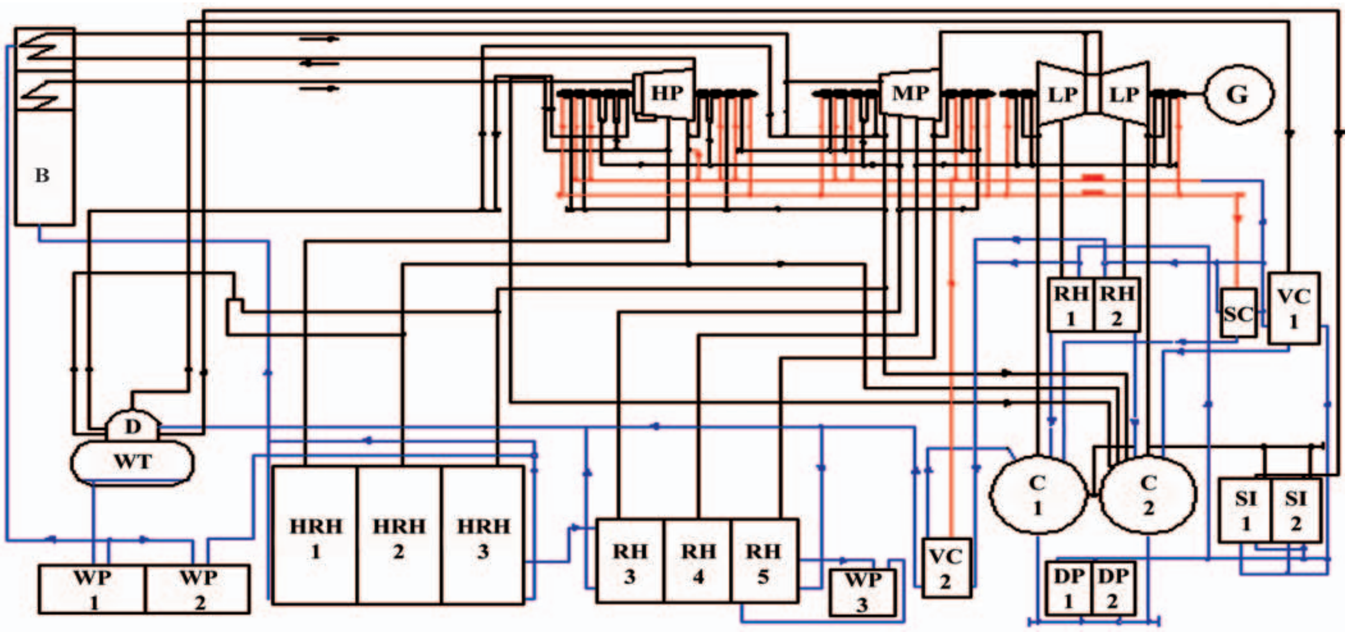


*Fig. 1. Simplified schematic diagram of the steam power plant, where : **B** – Boiler, **C** - Constant pressure condensers, **D** – Degasifier, **DP** - Drip pumps, **G** - Electric generator, **HP** - High Pressure unit of condensing turbine, **HRH** - HP regenerative heaters, **LP** - Low Pressure unit of condensing turbine, **MP** - Medium Pressure unit of condensing turbine, **RH** - LP regenerative heaters, **SC** - Steam cooler, **SI** - Steam injectors, **VC** - Cooler of vapours from stuffing boxes, **WP** - Water supply pump, **WT** - Water supply tank .*

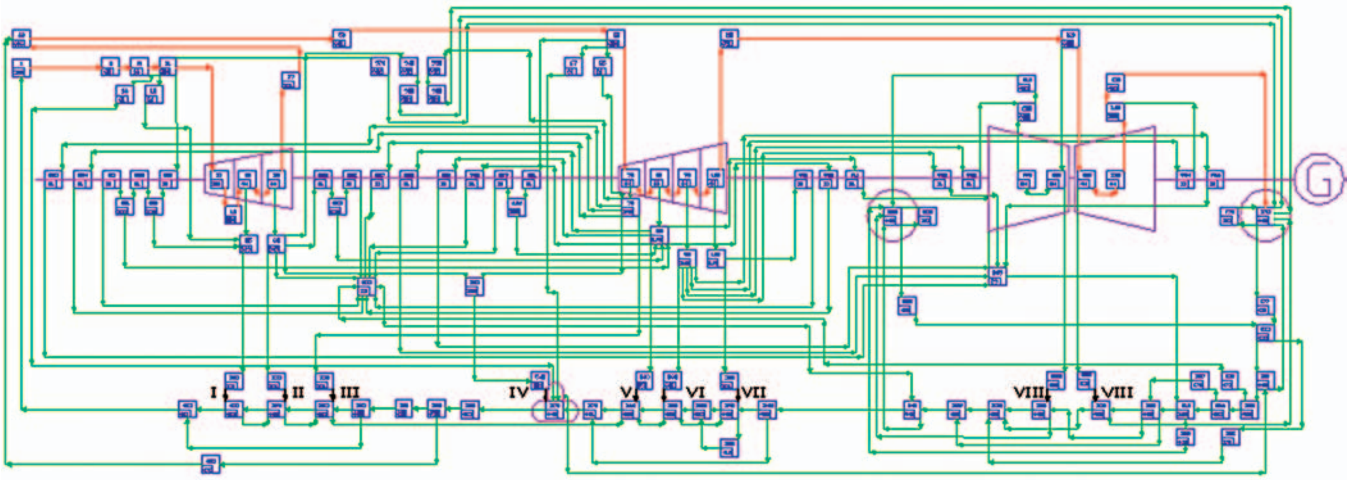


*Fig. 2. Schematic computational diagram for the steam cycle considered in DIAGAR software, where : Main steam jet (flow) Steam extractions (I – VIII) G - Electric generator Particular devices of the steam power unit .*

## *Preparation of the training data set*

The training data set consists of independent and dependent operational parameters of the power unit [1], namely :

***Set of independent parameters*** :

- Turbine set's power output
- Fresh steam pressure
- Fresh steam temperature
- Superheated steam temperature
- Pressure in condenser,

which define loading state of the steam cycle, see Tab.1.

***Set of dependent parameters*** :

- Mass flow rate (m)
- Pressure (p)
- Temperature (t)
- Enthalpy (h).

The heat flow parameters of working medium are determined in 176 points of the cycle. As a result the data set covered a wide range of the power unit's work, and amounted to 6300 combinations defining various loading states.

*Tab. 1. Set of the parameters defining loading states of the power unit [5] (Parameters of rated working state are marked red.) .*

| Set of independent operational parameters of the unit | | | | | |
|---|---|---|---|---|---|
| Power | Fresh steam pressure | Fresh steam temperature | Superheated steam temperature | Pressure in condenser | Number of combinations |
| N [MW] | $p_o$[bar] | $T_1$[°C] | $T_2$[°C] | $p_k$[bar] | 6300 |
| 120 | 110 | 510 | 510 | 0.04 | |
| 140 | 120 | 520 | 520 | 0.05 | |
| 160 | 130 | 530 | 530 | 0.06 | |
| 180 | 140 | 540 | 540 | 0.07 | |
| 200 | 150 | 550 | 550 | 0.08 | |
| | | 560 | 560 | 0.09 | |
| | | | | 0.10 | |

The task consisted in training the network in order to determine a set of diagnostic (dependent) parameters in response to a given set of independent operational parameters of the power unit.

## *Choice of structural arrangement of the network and algorithm of its training*

During the last 20 years neural networks have been developed very dynamically. Their structures have been improved and new algorithms elaborated. However choice of optimum parameters has still remained a time-consuming process as it is realized with the use of trial-and-error method. The structures and algorithms of training the networks of which the neural simulator is consisted, were preliminarily selected on the basis of theoretical knowledge [3,4] and the published comparative analyses [3].

The most important element of the selection process was the testing of effectiveness of particular structures in solving the task in question.

Finally, the structure having two processing layers : a hidden layer of activating sigmoidal functions and an output layer of linear functions, was selected. The series of trial trainings [5] revealed that the most effective training algorithm for the task in question is that of Levenberg-Marquardt (LM). This is one of the fast convergent algorithms which not only converge after a small number of training iterations but also are much superior regarding network's response accuracy than other algorithms. However the advantages are achieved at expense of high requirements for RAM memory of used computer.

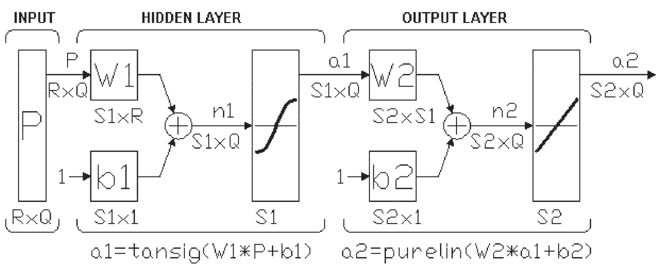


*Fig. 3. Schematic diagram of the network's structure [5], where :*

**a1** - *response matrix of 1st neural layer (hidden one)*
**a2** - *response matrix of 2nd neural layer (network response)*
**b1** - *vector of weight coefficients for 1st neural layer*
**b2** - *vector of weight coefficients for 2nd neural layer*
**n1** - *matrix of neurons in 1st layer*
**n2** - *matrix of neurons in 2nd layer*
**P** - *matrix of network training images*
**Q** - *number of network training vectors (images), Q = 6300*
**R** - *training vector of 5 elements, R=5*
**S1** - *number of neurons in 1st layer for each training vector (assumed value)*
**S2** - *number of neurons in 2nd layer for each training vector (assumed value)*
**W1** - *matrix of weight factors for 1st neural layer*
**W2** - *matrix of weight factors for 2nd neural layer .*

## *Training process of the network*

To train the one-direction network under control the error--back-propagation algorithm is usually applied. The error value determined in one iteration serves as the basis to correct weights and thresholds for the next iteration. This way a continuous improvement of network's response quality is achieved. The training terminates when response accuracy determined by comparing the response with an assumed standard, is satisfactory. However many problems have been met in practice, namely :

**☆ Too small capacity of RAM memory of the applied computer**

To obtain satisfactory accuracy of the simulator a very large set of training data was required. It resulted in very large dimensions of the training matrices (5 x 6300 and 17 x 6300). The next element was a large capacity of memory demanded by the LM algorithm. A remedy for such situation was to limit the number of simulated points of the steam cycle down to those most important and to split the simulator structure into a greater number of modules.

**☆ Difficulties in obtaining a satisfactory accuracy of the network's response**

The to- be- solved problem consisted in simulating distribution of parameters of a real object. Functions of the kind often have a very irregular run, with many discontinuities resulting from the character of physical phenomena occurring in the power unit, which do not represent only regular thermodynamical relationships but also many known and unknown disturbances and small irregularities. If a distribution of a given parameter was correct the network was able to be trained in generating correct responses. However in some load intervals when the irregularities were revealed (e.g. when the set values of the unit's operational parameters were very different from those at rated load) the network's responses appeared loaded by a greater error.

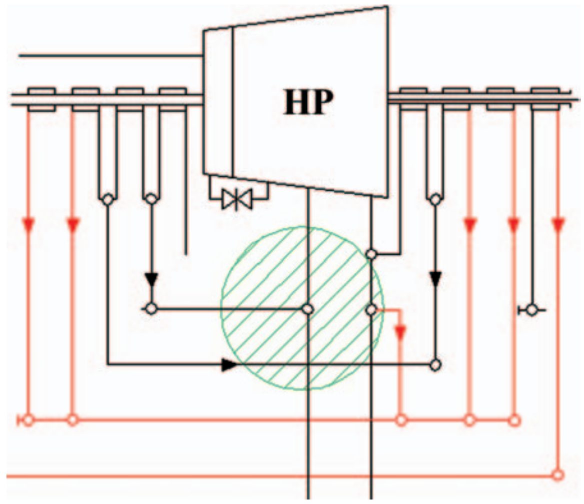


***Fig. 4.*** *Regenerative steam extraction from the first stage of HP turbine (the shaded area) .*

Such situation can be illustrated by the simulation of heat flow relationships at the first steam extraction, see Fig.4. Generally, the steam thermodynamical relationships at this point of the cycle are very complex and sensitive to many factors, that has resulted in much greater difficulties in obtaining a satisfactorily accurate response from the network. Therefore this point of the cycle has been treated in a special way : it was taken out from the remaining extractions and trained separately. The approach made it possible to vacate some capacity in RAM memory. Also, the computation time was shortened thus it was possible to increase number of training iterations. However for some loading states of the unit the network was not capable of reducing the response error, satisfactorily. As a result the obtained accuracy of the network appeared very different, see Fig.5.

**☆ Necessity of application of the networks consisted of many neurons**

Complexity of the problem requires the network to be consisted of many neurons. In the cases when the network was not capable of reducing the error the number of neurons was increased. The operation usually improved abilities of the network however it was connected with some drawbacks, namely :

- increased loading on the processor – computation time was greater
- substantially increased loading on RAM memory
- risk of worsening the network's capability of generalizing.

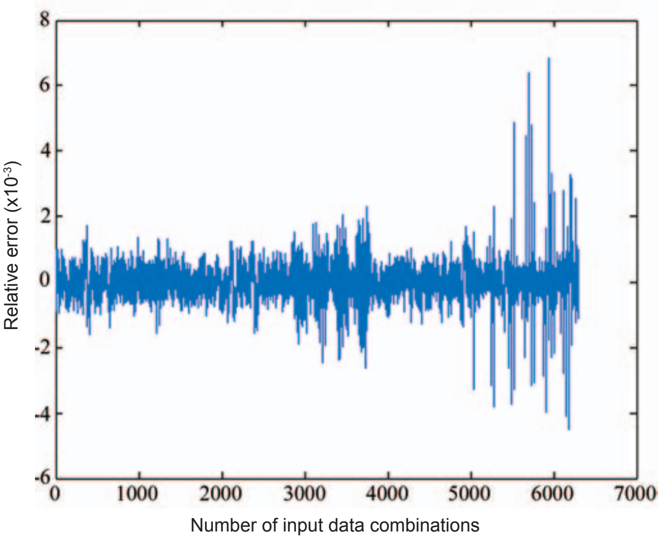


*Fig. 5. Distribution of the relative error of pressure simulation training at the first steam extraction, for the whole set of training data. The mean error : 0.04 %, the maximum error : 0.65% [5] .*

The generalizing capability of the network consists in coping with data sets not included in its training process, which is of fundamental importance for its usefulness to simulate phenomena and dependent on the number of neurons, having its optimum value.

☆ **Necessity of extending the training process**

The second method of reducing the error is the extending of training time, apart from the increasing of number of neurons. This is justified only when the reduction goes on. During training process it often has happened that the network has reduced the error very slowly though the maximum possible number of neurons (with respect to RAM memory capacity) was applied. Then the only way to improve accuracy of the network's response was to increase number of iterations that extended training time.

Summing up one can state that in the case in question the capabilities of the used hardware (a typical personal computer) were of decisive importance; however they did not substantially influence the quality of the elaborated simulator though an additional time outlay was necessary.

## FEATURES OF THE SIMULATOR

The simulator was composed of 12 neural networks. Each of them was separately optimized. Due to the hardware limitations it was necessary to split all the simulated points of the steam cycle into 3 groups (modules), see Fig.2 and 6.

- The main steam jet contains the points 1 through 21 located between the boiler and condenser including the flow part of the turbines.
- The first steam extension is in the point 22 where 3 steam jets are mixed together : the regenerative steam extension from the first stage of the turbine, the steam from the sealing of HP turbine casing and that from the sealing of control valves.
- The remaining extensions (points 23 through 30) are located in the remaining steam extension pipelines leading to relevant regeneration heat exchangers.

Fig.6 illustrates the procedure of information flow during the simulation process. Each of the networks operates separately and provides only one parameter and only within a given group of the cycle's points. In all the 30 points the distribution of 4 parameters, i.e. *p*, *m*, *t*, *h*, can be simulated, or an arbitrary module and a parameter can be selected to obtain the pressure parameters from p1 to p21. The user can also select one of the simulated cycle's points to know a concrete parameter value.

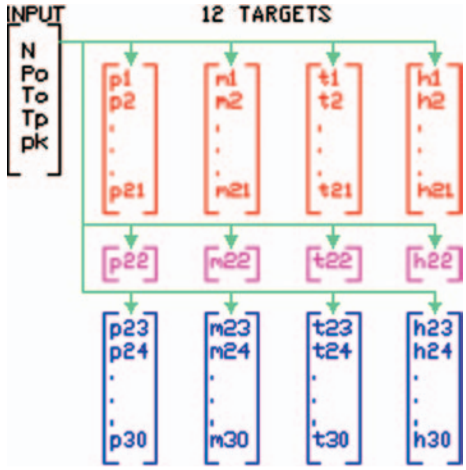


*Fig. 6. Schematic diagram of the simulator's modular structure [6], where :*
**h** - *enthalpy in a given point of cycle [kJ/kg] (resultant)*
**h1 - h21** - *enthalpy put out by 1st module of simulator : main flow*
**h22** - *enthalpy put out by 2nd module of simulator : 1st regenerative steam extraction*
**h23 - h30** - *enthalpy put out by 3rd module of simulator : remaining regenerative steam extractions*
**m** - *mass steam flow rate in a given point of cycle [kg/s] (resultant)*
**m1 - m21** - *mass steam flow rate put out by 1st module of simulator : main flow*
**m22** - *mass steam flow rate put out by 2nd module of simulator : 1st regenerative steam extraction*
**m23 - m30** - *mass steam flow rate put out by 3rd module of simulator : remaining regenerative steam extraction*
**N** - *assumed output of steam power unit [kW]*
**p** - *pressure in a given point of cycle [bar] (resultant)*
**p1 - p21** - *pressure put out by 1st module of simulator : main flow*
**p22** - *pressure put out by 2nd module of simulator : 1st regenerative steam extraction*
**p23 - p30** - *pressure put out by 3rd module of simulator : remaining regenerative steam extractions*
**pk** - *assumed value of pressure within condenser [bar]*
**Po** - *assumed value of fresh steam pressure [bar]*
**t** - *temperature in a given point of cycle [°C] (resultant)*
**t1 - t21** - *temperature put out by 1st module of simulator : main flow*
**t22** - *temperature put out by 2nd module of simulator : 1st regenerative steam extraction*
**t23 - t30** - *temperature put out by 3rd module of simulator : remaining regenerative steam extractions*
**To** - *assumed value of fresh steam temperature [°C]*
**Tp** - *assumed value of superheated steam temperature [°C] .*

## CONTROL OF OPERATIONAL ACCURACY OF THE SIMULATOR

Great attention was paid to continuous control of operation of the neural networks as they represent rather primitive algorithms (not including any interpretation of physical phenomena). Also, much work was done to reliably present the simulator's accuracy, especially as it appeared to be very different, depending on a concrete cycle's point, simulated parameter and assumed state of loading.

Fig.7 presents distribution of values of the relative error of mass flow simulation for the main steam jet and all combinations of training data.

During simulation of the parameters an error value is automatically displayed provided its precise determination is possible at all. If a set of load parameters does not belong to that of training data then an expected value of the error is given.

A more precise verification of operational quality of the simulator was performed by using the DIAGAR analytical simulator since its responses could be taken as a standard for

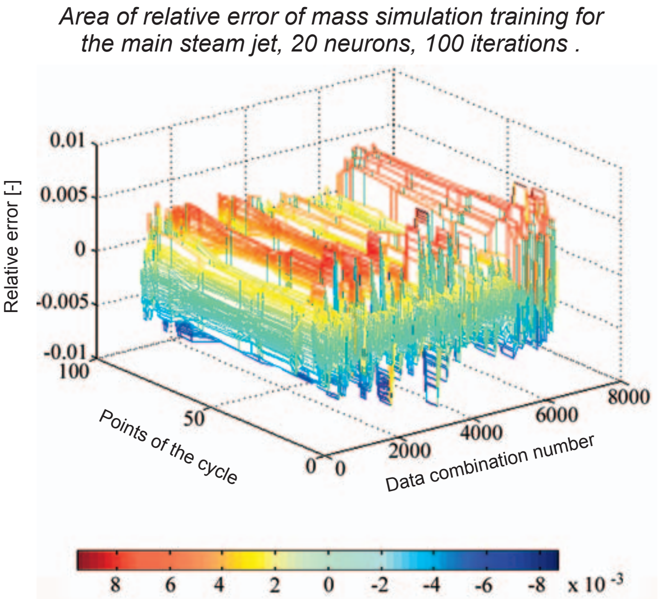


*Fig. 7. Distribution of simulation error of enthalpy parameter for the main steam jet (21 points of the cycle) [5] .*

the neural simulator. This way at the expense of some additional efforts response uncertainty of the network could be reduced to a minimum. Such operation was performed for the first steam extraction and due to its specificity an additional set of testing data was taken from the DIAGAR and on its basis the network's generalization accuracy was determined for this module. In Fig.8 is presented an example of the results of the above described operation for distribution of mass flow rate at the first steam extraction. A testing data set not contained in the training data but belonging to the same loading range, was put into the network.

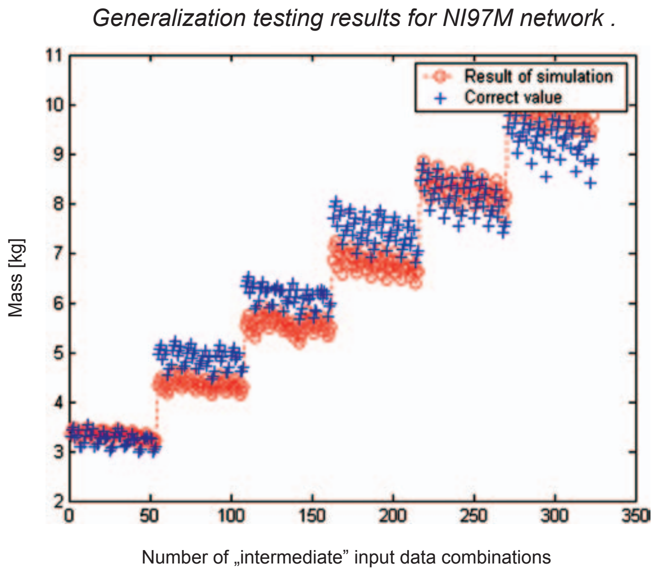


*Fig. 8. Results of testing the network's generalization capability for mass flow rate at the first steam extraction .*

## SUMMARY

- The neural simulator of the steam power unit was elaborated to investigate possibility of its application to an on-line diagnostic system for so complex objects as steam turbine power plants are.
- The presented simulator is a tool of the following features :
  - simple in use
  - fast in operation : determination time of one parameter in 30 points of the cycle amounts to 30 ms
  - sufficiently exact
  - inexpensive : to its manufacturing only a set of operational parameters of a considered object, MATLAB software and a typical personal computer is required.
- On the basis of the performed task were also analyzed some practical aspects of the neural modeling method, constituting its merits and drawbacks related to the considered application. The most important merit is the possibility of omitting the long analytical modeling process, hence lowering the modeling cost; and, the most important drawback is that the neural model does not include any physical interpretation of phenomena.
- Modelling by means of neural networks is realized on the basis of existing operational or statistical data. In the case when character of a phenomenon is complex and multidimensional, and first of all not quite recognized, as well as when availability of the data is high, then such conditions can be taken as very favourable for neural modelling. In some cases the method is the most suitable, and sometimes the only possible. In other cases it can be useful as an aiding element for analytical models.
- The tasks assigned to advanced diagnostic systems applicable to large technical systems make that so different approaches as analytical methods, hidden ones (neural networks) or fuzzy logic, are used for them. Their mutual interaction is often very favourable for accuracy and credibility of an obtained result, i.e. assessed technical state of an object.

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