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Application of Neural Networks into Prediction of Qualitative Capability of the Preparation Process of Casting Moulds

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Abstract

In the article the problem of assurance of qualitative capability of the preparation process of casting moulds using artificial neural networks is presented. Using STATISTICA Neural Networks a set of the best networks is found. Obtained results of neural modeling were compared with the results of experimental investigations and classical mathematical modeling. The appropriate architecture of the neural network is chosen that predicts the quality capability of the preparation process of casting moulds with the high precision.

Keywords: Automation of casting process; Robotization of casting process; Robot selection

1. Introduction

Modern industrial robots are very universal. They were applied with success in so different areas, such as welding, painting, assembling and casting [1].

In general, the robots working in the foundry are not characterized by high accuracy. An exception, however, is the process of placing of the inserts flooded into a form. In this case, the robot must be sufficiently precise to be able to orient properly and place the insert. An important problem of such robotized casting areas is the problem of ensuring the required level of reliability that can be achieved through the assurance of appropriate values of the qualitative ability index [2, 3]. In the case of the process of placing steel inserts into the casting mould, the study is based on relation of errors generated by the robot (linear and/or angular) to the tolerance range of displacement or torsion of inserts axes [4].

The study of qualitative capability of the process of steel inserts placing inside the casting mould is very complicated and labour-consuming [5, 6]. Classical methods for determining the values of qualitative capability indexes require modeling the total error of the robot as the density function of a random variable subjected to the normal probability distribution. However, these models are appropriate if the robot operates in stable operating environment. Then the values of the model error do not exceed 9%. However, the values of the model error increase when the environmental conditions are not stable. This occurs precisely in the case of foundry processes where not only a burden but mainly robot operating temperature may be altered. The change in a temperature and associated with it both linear and volume expansion affect not only the value of the repeatability positioning error of a robot, but also the density function of the probability distribution. Thus, models assuming conformity of resultant error distribution with a normal distribution are affected by the significant error (sometimes over 10%), which is also reflected in the estimation of qualitative capacity of the casting area as well as the whole process for the preparation of casting moulds [7].

Determination of component of repeatability positioning error associated with thermal expansion is a labour-consuming task because it requires taking into account many parameters. This additionally complicates the mathematical models aimed at determining robot's error and the ability of the qualitative capability of casting area and results in decreasing of their accuracy. An alternative solution to the presented problem may be the use of artificial neural networks, which do not require the modeling of component errors, because they are based mainly on the results of experimental tests. Therefore, this work attempts to develop a numerical model using an artificial neural network to predict the level of mountability of casting area.

2. Neural model

An artificial neural network (ANN) is a powerful data modeling tool that is able to build and analyze complex input/output relationships. The motivation for the development of ANN technology stemmed from the desire to develop a neural system that could perform intelligent tasks similar to those performed by the human brain [8]. The advantage of neural networks lies in their ability to represent non-linear relationships and in their ability to learn these relationships directly from the learning data.

Considering the possibility to include in the modeling process many factors, neural networks offer the opportunity to build a model which is able to forecast the qualitative ability of casting area with high accuracy. However, this requires the collecting learning data and the selection of the input feature vector as well as configuration of the neural network. Data for the ANN analysis were obtained from experimental studies conducted on the robotic assembly stand equipped with Mitsubishi RV-M2 industrial robot. The experimental study consists of measuring the error in the different points of robot's space, at a different ambient temperature (10÷20°C). Based on the results of measurements the value of qualitative ability index of inserts placement process was determined using the following equations:

- for inserts with flat surfaces (Figure 1) [10]:

$$MC_p = \left[\frac{\prod_v^2 \left(USL_i - LSL_i\right)}{\prod_v^2 \left(UPL_i - LPL_i\right)} \right]^{0.5} \tag{1}$$

- for cylindrical inserts (Figure 2) [9]:

$$MC_p = \frac{0.5T_{\Delta l}}{3.44\sigma_{\max(x,y)}} \tag{2}$$

where:

$T_{\Delta l}$ - the tolerance of relative linear displacement of axes of joined parts,

$\sigma_{max(x,y)}$ - the maximal value of standard deviation of relative error of joined parts displacement,

USL_i, LSL_i – upper and lower tolerance range,

USL_i, LSL_i – upper and lower border of modified process space

One of the main tasks necessary to build the optimal model of neural network is the selection of sufficient input variables that essentially influence the output variable value. Too large number of variables may cause noisy data whereas not taking into account even a single variable that essentially influences the output variable may lead to wrong results. Further, adding more input network results in excessive expansion of the network architecture and at the same time the value of training data is increased. In turn, omission of essential variables in input can cause decreasing quality of the network. This indicates that there are no universal criteria to select architecture of ANN [8 11]. The neural network architecture except both input and output layers includes one or more hidden layers [12]. The multilayer networks named multilayer perceptrons (MLP) are mostly utilized.

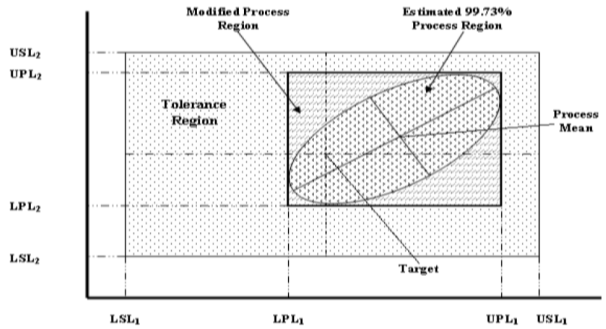

Fig. 2. Rectangular tolerance region versus modified process region [10]

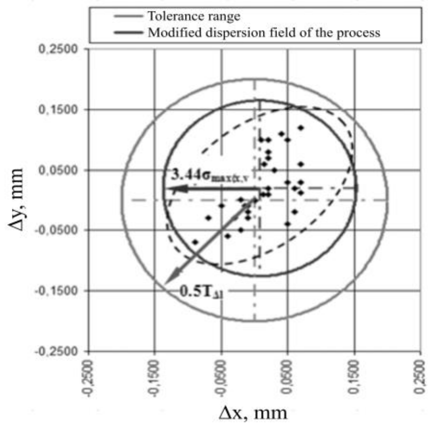

Fig. 2. The methodology of capability index *MCp* determination according to Cheen [9]

To determine weighted sum and threshold activation value of separated neurons it is necessary to prepare the training data set consisting of input signals and the corresponding values of output signals. In this study, the following input sets of variables were assigned as input signals:

- values of joint coordinates of industrial robot determining the place of assembly operation in space of casting area,
- value of tolerance of relative displacement of joined parts axes,
- ambient temperature value.

The expected signal at the output was the value of the probability of a correct realization of the assembly operation.

As the prediction model the ANN with six neurons in the input layer, and one neuron in the output layer is utilized (Figure 3). Using STATISTICA Neural Networks the set of the best network for the placement process of inserts with both cylindrical and flat surfaces was built. Among all experimental sets of input data that correspond with the output signal, 20% were separated and assigned as the test set. Data vectors from a test set did not participate in the training process and served for ANN prognostic evaluation purpose only. From the remaining set of experimental data belonging to training set, 10% was separated and assigned as validation set. Data from this group were used for independent check of training algorithm.

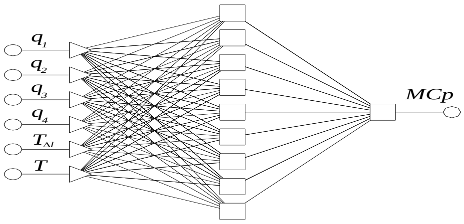

Fig. 3. Architecture of neural network

3. Training the ANN

After determining the number of layers and number of neurons in each layer the weight values and threshold values of all the neurons were determined. This was realized by the training algorithm that minimizes the error of the network working . The ANN training was performed with the back propagation algorithm. As a criterion of the network quality the value of the mean square error *RMS* [8] determined separately for different subsets of data is assumed.

To avoid overlearning process of ANN as a criterion for the stopping of the learning process was assumed (2) the moment when there is no further decrease in the value of the *RMS* error of the validation set (Figure 4). The value of learning coefficient η which is a parameter corresponding to the stability and rate of convergence of the learning algorithm is taken as 0.0001 [10-12]. The value of learning coefficient was the same for all the tested networks

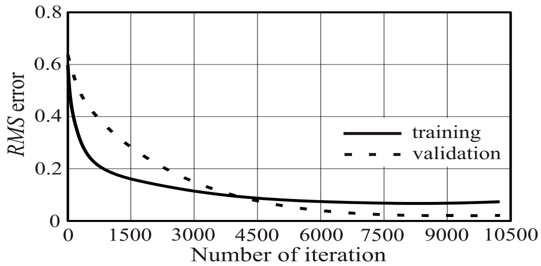

Fig. 4. Value of RMS error during training of network SSN1

4. Results of ANN prediction

To estimate the network model one should pay particular attention to the value of SD Ratio (*SDR*) and the value of R-Pearson correlation coefficient [8]. For a very good ANN model the value of ratio of the standard deviation is less than 0.1. The high value of R-Pearson correlation coefficient and simultaneously the low value of *SDR* for the validation set testify a very good quality of the network. Testing the prediction of neural networks was conducted on the basis of four sets of input data. For these sets, based on the results of measurements, the values of capability index *MCp* were calculated. A comparison of the both results of neural networks, experimental studies and the results obtained based on mathematical modeling [4] are shown in Tables 1 and 2.

Table 1.
Comparison of prediction of *MCp* index between artificial neural networks and results of mathematical model for inserts with cylindrical surfaces

NOE*	Value of input parameters						*MCp* index value		
	q_1, rad	q_2, rad	q_3, rad	q_4, rad	$T_{\Delta l}$, mm	T, °C	Eks.	SSN1	Model
10	0.5236	1.2217	1.3962	1.3962	0.046	16	0.3183	0.3052	0.3283
18	0.5236	0.1745	0.8723	0.8726	0.062	20	0.4740	0.4620	0.5000
24	0.4363	0.5235	0.6981	1.3962	0.104	25	0.9331	0.8997	1.0007
31	0.6981	0.8726	0.8726	1.5707	0.140	27	1.3565	1.3458	1.4220

* - number of observation error

Table 2.
Comparison of prediction of *MCp* index between artificial neural networks and results of mathematical model for inserts with flat surfaces

NOE*	Value of input parameters						*MCp* index value		
	q_1, rad	q_2, rad	q_3, rad	q_4, rad	T_{region}, mm	T, °C	Exp.	SSN1	Model
10	0.5236	1.2217	1.3962	1.3962	0.002116	16	0.3838	0.3901	0.3908
18	0.5236	0.1745	0.8723	0.8726	0.003844	20	0.5749	0.5620	0.6115
24	0.4363	0.5235	0.6981	1.3962	0.01080	25	1.1465	1.1574	1.1953
31	0.6981	0.8726	0.8726	1.5707	0.0196	27	1.6044	1.5769	1.6942

If we assume the RMS error value as the conformity criterion of modeling results with the results of experimental studies, for inserts with both cylindrical (Figure 5) and flat (Figure 6) surfaces, better predicting properties revealed the artificial neural networks.

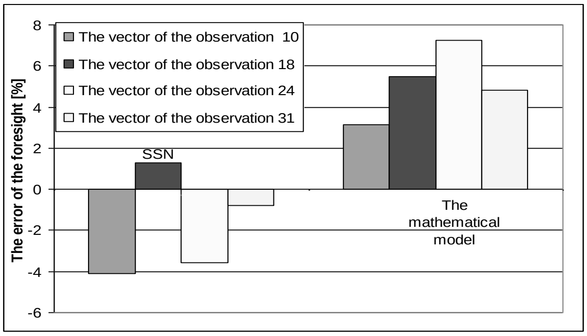

Fig. 5. Comparison of prediction errors values of *MCp* index between artificial neural networks and results of mathematical model for inserts with cylindrical surfaces

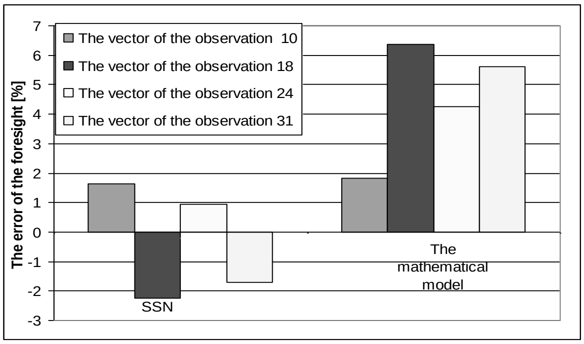

Fig. 6. Comparison of prediction errors value of *MCp* index between artificial neural networks and results of mathematical model for inserts with flat surfaces

For the network predicted *MCp* index value for the process of placing of steel inserts the value of *RMS* errors amounted to 0.039 and 0.0379 for inserts with cylindrical and flat surfaces, respectively. *RMS* error value for the classical mathematical model in both the first and the second case was nearly three times higher and amounted to 0.108 and 0.098. Also, the average error of prediction for the model using neural networks (2.15% and 2.43%) was much smaller than for the classical models (4.51% and 5.17%).

Summary

The results of the study on the use of artificial neural networks to predict the qualitative ability of a process of preparing the casting molds show excellent agreement between experimental data and outcomes of neuron models. As a result of numerical experiments the neural structure which correctly predicts the probability of a part joint in robotic assembly station was selected. The average prediction error for the neural network models (2.15% and 2.43%) was more than half less than in the case of classical mathematical models (4.51% and 5.17%).

Despite the many advantages of neural network it also has limitations. In presented case there is the necessity for a very labor-consuming experimental studies aimed at the determination of qualitative capacity index of the process of inserts placing at many points in the workspace of casting area. These data are necessary for the training the neural network correctly. Thus, considering this aspect, it seems that in industrial environments more often can be used the classic method of mathematical modeling. The results are burdened with admittedly larger error value, but due to the fact that the analysis uses the information about the kinematic structure of assembly robot, requires much less labor consumption when estimating the qualitative ability of the process.

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