Creation of neural network models to solve the problems of forecasting the product geometrical accuracy

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Abstract—The article considers the problems of creating a tool for operational forecasting of quality indicators (assembly parameters) for knowledge-intensive products. The basis of forecasting is the creation and use of actual geometrical models of parts containing data on their geometrical deviations, and numerical models of part mating. Actual geometrical models are created based on the data on coordinate measurements of parts. The developed models have been validated using the example of an assembly unit composed of three parts of an aircraft engine turbine rotor. To reduce computing resources, the use of a radial-basis neural network to calculate assembly parameters has been considered. Training and test samples have been modelled, the network operating parameters have been optimized, and the obtained results have been generalized.

Keywords—numerical model, actual geometry, assembly parameter, neural network

I. Introduction

The most critical quality indicator for engineering products is the geometrical accuracy of machines, which has a significant impact on the performance. The geometrical accuracy of products can be increased and their production cost can be decreased by developing and implementing digital technologies into product design and production processes. The new generation high-tech industry is based on data use. A promising approach to improve design processes and manufacture high-tech products provides for the development of digital counterparts of objects being digital analogues of actual objects [1]. In respect to assembly of engines and power plants, a digital counterpart represents related actual models of parts.

Mathematical models [2] implemented in the form of computer models are used to forecast quality indicators (in particular, assembly parameters). The assembly model choice depends on the stiffness requirements. Some models are based on the solid state hypothesis, for example, the T-Map model [3]. Other models, such as the Skin form model and the Deviation Area Model (DD), canal so simulate a flexible part or assembly [4]. These models can be either point-based or feature-based. Compared to the features that simultaneously characterize position and direction information, the position of a point in space is described by its location rather than orientation, with variations that vary depending on the choice of different points [5].

Direct modelling of mating using numerical models of mating and finite element models of the assemblies requires significant computing resources [6] and often has decision coincidence problems. Artificial neural networks can be used to improve the forecasting efficiency for the assembly parameters.

The article considers the option developed to solve the problem of the product geometrical accuracy based on the data on specific part measurements, neural network models, and digital counterparts of the assemblies. The goal of the article is to study the estimate of the assembly parameter calculation error with the help of the neural network model based on a lot of data obtained using a digital counterpart of the assembly.

II. Subject of the Research

The assembly of three turbine parts is considered as the subject: shaft, retainer, and disc. Fig. 1 shows a sketch of the assembly unit under consideration.

The bases *A* and *B* in Fig. 1 form a rotation axis (basic axis). The requirements for face runout P_{tr} of the disc*3* surface, and radial runout P_{rr} of the disc surface *П* have been set in relation to the basic axis. Let's consider models and algorithms that allow virtual forecasting of runouts.

III. Digital Counterpart of the Rotor Assembly

The digital counterpart of the assembly includes the following: digital models of parts including the actual geometry containing production deviations; calculation of mating states of parts [7, 8]; calculation of assembly geometrical parameters.

A. *Creation of part models with actual geometry*

Information about the actual geometry represented as data on the part surface measurements is required for the modelling. The assembly model accuracy mostly depends on the accuracy of the actual geometry measurements on coordinate inspection machines [9, 10] or scanning devices. Part surfaces were measured on a coordinate measuring machine (CMM) of DEA GlobalPerformance.

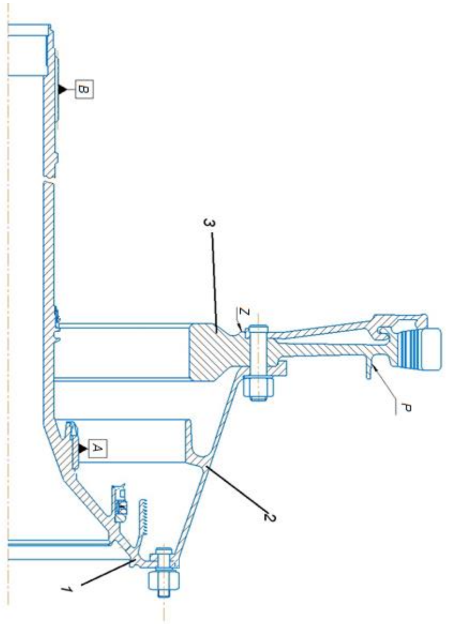

Fig. 1. Assembly unit and controlled surfaces, 1 – shaft, 2 – retainer, 3 – disc.

The number of points measured on the planes and cylindrical surfaces was 200 points. Part ends were measured in cross-sections. In case of cylindrical surfaces, cross-sections represent intersection lines of the surface and planes which are perpendicular to the rotation axes. For face surfaces, cross-sections represent intersection lines of the surface and cylindrical surfaces which axis and centre coincide with the normal plane vector. The coordinates of the measured points were saved as *.txt files for further analysis in the MATLAB system.

After downloading the point coordinates on the surfaces, they are processed and brought to a specific structure for further creation of actual surfaces. Processing of the point coordinates lies in smoothing outliers and calculating point coordinates which are not enough to build the data structure. The coordinates were smoothed with the moving average method. Calculation of the point coordinates lies in creating cross-sections of the part surfaces by approximating or interpolating the measured sets of surface point coordinates using spline functions in the form of profiles or surfaces [12].

The general view shows the complex part surfaces in a portion way, like a patchwork quilt. Complex curves and surfaces in CAD systems and metrology software of measuring equipment are described using spline equations. A 3rd degree normalized cubic spline, namely the Hermite curve, was used for mathematical representation of spatial curves [13]. The surfaces created on the basis of the bicubic portions were used to describe the part surfaces with geometrical deviations of the forms (Coons portions [13]).

So digital models of the parts represent a set of the interconnected part surfaces involved in the assembly and control.

B. *Virtual calculation of the part assembly, result saving*

To solve the contact task using the surface models, an iterative algorithm has been developed; it allows calculating the parts mating without taking into account deformation of the parts in the process of assembly detailed in [7]. The algorithm for determining the mated state assumes iterative movement of one mating surface in relation to the other one, with the stress application vector of the surface assembly. $\vec{D}_1$ To ensure the best adjustment, the iterative algorithm of nearest points (ICP) is used [14, 15]. According to this algorithm, the rotation and movement angles along the coordinate axes are calculated at each iteration with the non-linear optimization search methods. The system of inequalities presented in the work [16] limiting the gap function is used to exclude the intersection of two surfaces $G(\vec{V})$. The use of the algorithm results in calculating a rotation matrix and moving part movement vector that determines the conversion of its initial coordinate system into the coordinate system in the assembled state.

C. *Calculating the assembly geometrical parameters*

The radial runout between the control surface *P* and bases *A* and *B* (Fig. 1) is calculated in the following order:

- The main axis of the coordinate system coincides with the normal vector of the $\vec{a}_c$ rotation axis set using the bases *A* and *B*.
- The distances from the measured points *P* to the rotation axis are calculated.
- The value of the radial runout δ_{r_r} is calculated as the difference between maximum d_{max} and minimum d_{min} from the measured points of the surface *P* to the rotation axis.

The face runout of surface *3* is calculated as the difference of maximum and minimum distances from the measured points of face *3* to the plane perpendicular to the rotation axis.

The coincidence of the modelling results with actual parameters obtained during the assembly was estimated by calculating absolute deviations:

$$\delta_a = P_{meas} - P_m \,, \tag{1}$$

and relative deviations:

$$\delta_{rel} = \delta_a / T \cdot 100\% \,, \tag{2}$$

where P_m – is the parameter calculated as a result of modelling;

P_{meas} is the measured parameter.

IV. NEURAL NETWORK MODEL OF GEOMETRIC ACCURACY FORECASTING

To obtain an adequate forecast using the neural network, the following is required: determine the composition of the network input parameters; create a sufficiently large quantity of training samples; select an appropriate architecture of the neural network. The sufficient volume of the training sample, as a rule, exceeds the available statistics on measurements. In addition, the parts obtained in a certain batch may not cover all the potential cases, and the next batch will have combinations of deviations absent in the previous one, which will have an effect on the forecast quality. This caused the selection of artificial modelling of the training set of actual models based on the data of the available production statistics.

A. *Creating a set of actual part models*

The measured points were modelled using production statistics on geometrical deviations of cylindrical and flat parts of the assembly parts to create training and test data sets. The cylindrical and flat ends of the parts are considered. The point coordinate can be set by formula:

$$\vec{p}_m = (\vec{p}_n + \vec{n} \cdot \delta_f) \cdot \mathbf{R} + \vec{t}\,, \quad (3)$$

where $\vec{p}_m$ $\vec{p}_n$ is the vector of (x, y, z) point coordinates of the measured (modelled) and nominal (CAD) surfaces, respectively;

$\vec{n}$ is the normal vector in point $\vec{p}_n$;

δ_f is the form deviation value in point $\vec{p}_n$;

$\mathbf{R}$, $\vec{t}$ is the turn matrix and the vector of coordinate transposition for point $\vec{p}_n$ characterizing the arrangement deviation.

The Fourier's series were used for the form deviation δ_f [8].

B. *Training the neural network, assessing the forecasting errors*

A widely used architecture was selected as the neural network for forecasting tasks, namely fully connected radial basic networks [17]. The architecture of the generalized regressive neural network (GRNN) has two layers – hidden radial basic layer and output linear layer. A radial basic neuron converts the distance from this input vector into the "center" corresponding to it by a certain non-linear law (generally, the Gaussian function). The influence parameters that have an effect on displacements P_{sp} in neurons and are an adjusted neuron parameter is the changed parameter of the network. The number of neurons in the radial basic layer is equal to the number of elements in the training set. Figure 2 shows the network architecture when the training sample number is 9,500.

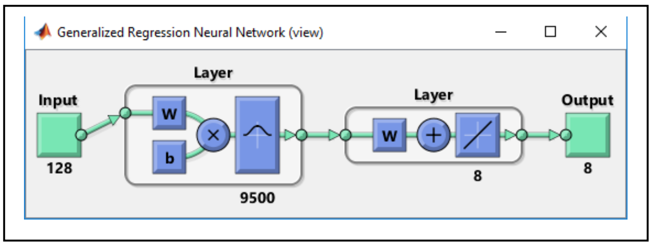

Fig. 2. GRNN architecture for parameter forecasting.

The data that has a direct correlation dependence on the assembly parameters shall be entered into the network. The following derived parameters were used as these inputs: parameters of the harmonic series describing the form deviation for all the surfaces; radius deviations in case of cylindrical ends; parameters of surface parallel alignment; displacement of cylindrical end centres. A total of 128 parameters were used for the assembly of three parts under consideration. The input data was adjusted within the range [0; 1].

Forecasting errors should be estimated to assess the results of the assembly parameter forecast and update the structure of the selected neural network model. The parameter forecasting errors are estimated by two criteria:

- Share of predicted values within the allowable accuracy δ_{add}.
- Root-mean-square error (*RMSE*) of predicted and actual parameters.

Let's specify the order of these values calculation:

- Calculate the error between the predicted and actual parameters:

$$\Delta_n = P_{pr} - P_a\,. \quad (5)$$

- The number of errors is counted within the allowable area $N_{\Delta add}$. The allowable area of errors is calculated as a percent of the maximum value of the predicted parameter, namely 10 %.
- The forecast accuracy is calculated as the quantity $N_{\Delta add}$ to total sample volume ratio:

$$\delta_{add} = N_{\Delta add} / N_{com}\,. \quad (6)$$

- The root-mean-square error value is calculated by formula:

$$RSME = \sqrt{\Delta^2 / N_{com}}\,. \quad (7)$$

V. Work Results

The required data on the assembly part deviations were obtained as a result of the part measurement. The rotor was assembled. The assembly was installed in a special tool and the measurement was made on the CMM. This stage of assembly is performed for four shaft positions. The shaft is rotated at an angle of 90° for each new position. The points of the surfaces *Z* and *P* are measured (Fig. 1) in relation to the shaft bases. The radial and face runouts are calculated. The measured data of certain parts were processed and the assembly parameters were calculated virtually in the MATLAB system. The results of the assembly parameters measured in the experiments and resulted from the virtual modelling are given in Table 1.

TABLE I. Comparison of the assembly parameters obtained in the process of modelling and measurement

Parameter	Angle, °	P_{meas}	P_m	δ_a, mm	$\delta_{omн}$, %
P_{rr}	0	0.133	0.13	0.003	2.31
	90	0.139	0.14	-0.001	-0.71
	180	0.150	0.15	0.000	0.00
	270	0.111	0.13	-0.019	-14.62
P_{tr}	0	0.078	0.10	-0.022	-22.00
	90	0.107	0.09	0.017	18.89
	180	0.109	0.10	0.009	9.00
	270	0.090	0.09	0.000	0.00

Based on the results in Table 1 it may be concluded that the modelling results are mostly sufficiently close to the experimental data when the developed digital counterpart is used. The differences are explained by the following: measurement errors and creation of the part surface models; necessity of part stiffness consideration; assumptions made in the process of the assembly model development. Elimination of the above reasons to reduce the number of deviations is the task of further development of the digital model.

Various cases of the assembly under consideration were modelled to make a forecast using neural networks. A total of

10,000 cases were modelled. Their calculation lasted 72 hours of machine time, in the computer with AMD Ryzen 7 2700 Eight-Core processor, clock rate of 3.2 GHz, and RAM 32 Gb. 128 parameters of geometrical deviations of the surfaces and resultant runouts are saved for each case. The allowable error field is calculated as a percent of the maximum value of the predicted parameter and is accepted as equal to 10 %. As to the parameter P_{rr} , the error tolerance (on the basis of 10 % of the maximum parameter value for the assembly) is ± 0.047 mm; as to the parameter P_{tr} , the tolerance is ± 0.049 mm. The value of the parameter P_{sp} was selected so that the total value of the parameter $RSME$ is minimum and the value of the parameter δ_{add} is maximum. The parameter P_{sp} was selected within a range of 0.001–3. The test sample was not changed and amounted to 500 cases. Different volumes of training samples were N_v were considered: 500, 1,000, 2,500, 5,000, and 9,500 cases.

128 parameters of the measured surfaces, which assembly parameters are given in Table 1 for four positions, were entered after selecting the parameter P_{sp} and network training. Table 2 contains the results of the network operation related to forecasting parameters of radial and face runouts for the measured assembly.

TABLE II. RESULTS OF THE NEURAL NETWORK MODELLING

P_{sp}	1	1	0.5	0.5	1
N_v	500	1000	2500	5000	9500
Angle, °	P_{rr} , mm				
0	0.117	0.115	0.122	0.116	0.116
90	0.113	0.114	0.119	0.111	0.111
180	0.117	0.121	0.125	0.111	0.119
270	0.125	0.123	0.123	0.119	0.121
Angle, °	P_{tr} , mm				
0	0.111	0.110	0.106	0.109	0.115
90	0.109	0.112	0.109	0.112	0.115
180	0.114	0.115	0.108	0.106	0.113
270	0.115	0.112	0.107	0.108	0.113

The values of relative deviations δ_{rel} of the data in Table 2 are considered in Table 3. The measurement results in Table 1 are taken as the basis. Besides, Table 3 includes the arithmetical means of the parameter deviations (overall average M , M_{rr} average for P_{rr} , and M_{tr} average for P_{tr}).

Generalizing the results in Tables 2 and 3 it may be noted that the highest accuracy is achieved when the volume of the training sample amounts to 2,500 cases. Based on the average and limit values δ_{rel} in Table 3, the number of radial runout forecast errors is less than the number of face runout forecast errors. At the same time the absolute values of the limit errors in forecasting with the help of direct modelling and neural network are close (results in Tables 1 and 3): for P_{rr} – (-14.62 %) and (-16.67 %), respectively, in case of direct forecast and forecast with the help of the neural network; for P_{tr} – 21.11 % and (-22 %).

TABLE III. VALUES δ_{rel} FOR THE FORECAST

N_v	500	1000	2500	5000	9500
Angle, °	δ_{rel} for P_{rr} , %				
0	-10.00	-11.54	-6.15	-10.77	-10.77
90	-19.29	-18.57	-15.00	-20.71	-20.71
180	-22.00	-19.33	-16.67	-26.00	-20.67
270	-3.85	-5.38	-5.38	-8.46	-6.92
Angle, °	δ_{rel} for P_{tr} , %				
0	11.00	10.00	6.00	9.00	15.00
90	21.11	24.44	21.11	24.44	27.78
180	14.00	15.00	8.00	6.00	13.00
270	27.78	24.44	18.89	20.00	25.56
M	16.13	16.09	12.15	15.67	17.55
M_{rr}	13.78	13.71	10.80	16.49	14.77
M_{tr}	18.47	18.47	13.50	14.86	20.33

None of the deviations has exceeded the tolerance by 10 % of the maximum parameter value. The results show that the selected neural network architecture allows achieving the same accuracy, when the training sample value is 2,500 cases and the parameter is P_{sp} =0.5, as the developed digital model based on the direct modelling of the part surfaces and assembly process.

VI. CONCLUSION

The article contains the research results that allow forecasting the resultant assembly geometrical parameters on the basis of the measured data. The problem of creating the digital counterpart of the rotor assembly that allows reproducing the part assembly process on the actual surfaces has been solved. The tasks of modelling the actual surfaces using small statistics and modelling the measurement data itself have been solved. The relative deviations of forecasting the assembly of three parts of the turbine rotor do not exceed 22 % and allow speaking about the adequacy of the proposed decision. A total of 128 affecting parameters of geometrical deviations have been selected. The radial basic neural network appropriate for forecasting the assembly parameters, which accuracy is comparable to the direct modelling performed using the digital counterpart of assembly, has been created and trained. The use of the trained neural network to forecast the assembly parameters of the assembly under consideration allows significantly reducing the labor intensity of calculations and using the developed decision immediately after the part measurement and measured data processing. In addition to the solved tasks, there is a number of other tasks (labor intensity of measurements, consideration of the part stiffness during assembly modelling) which will be the focus of further researches.

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