

Neural network model in digital prediction of geometric parameters for relative position of the aircraft engine parts

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Abstract. The quality of aircraft and rocket engines depends primarily on the geometric accuracy of assembly units and parts. Mathematical models implemented in the form of computer models are used to predict quality indicators (in particular, assembly parameters). Direct modeling of the conjugation process using numerical conjugation and finite-element models of assemblies requires significant computational resources and is often accompanied by problems convergence of solutions. In order to solve the above problems, it is possible to use neural network models describing the main regularities of the pairing process based on the accumulated results. The work presents a neural network model for predicting assembly parameters of the parts based on the use of actual surfaces of the parts obtained as a result of mathematical modeling. Assembly on conical surfaces is considered. A convolutional neural network was used to predict assembly parameters.

1. Introduction

Complex industrial and knowledge-intensive products are characterized by high requirements to geometrical accuracy of the parts and assembly units. These products include modern aircraft engines which are subject to high requirements for reliability, minimum weight, cost effectiveness and durability. These characteristics are also achieved through improvement of the technology for manufacturing parts and units. While manufacturing and assembling, dimensional accuracy is ensured. The ways to achieve dimensional accuracy are determined at the stage of design and technological reproduction [1,2,3]. The solution of these tasks at each of the stages can be simplified due to availability of mathematical models [4] and means allowing to predict and determine the actual value of geometric parameters [5,6] characterizing achievable accuracy.

The work proposes a model based on the use of neural networks allowing to predict assembly parameters of the parts when conjugating them on flat, cylindrical and conical surfaces with dimensions specific to the gas turbine engine parts.

2. Object of research

The assembly of two conical rings is considered as an object. Figure 1 shows the assembly model for conical items.

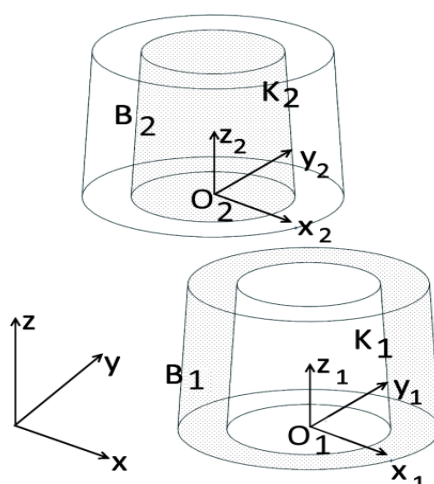


Figure 1. Mechanical system model for assembling two cone rings.

In Figure 1, the cone rings K_1 and K_2 are defined as the local design coordinate systems R_1 and R_2 . Conjugation of the parts occurs on surfaces B_1 and B_2 . Each surface is defined in the local coordinates of the part. One ring is male and deprived of six degrees of freedom, the second one is female and movable [7]. The assembly parameters of two cone rings are the coordinate of axis intersection with the top end face of the movable ring. The coordinates of the point in a plane perpendicular to the axis of the cone are represented by the polar coordinate system and is characterized by a polar radius ρ_c and corresponding polar angle φ_c , varying from 0 up to 360°. The coordinate along the rotation axis describes the displacement δ_o along the corresponding vector of the end surfaces of the outer ring relative to the inner ring. Axle distortions are negligible in this case of assembly.

In order to create a neural network model for predicting assembly parameters, it is necessary to create training sets and to check the quality of network operation on the test data. This requires either accumulating sufficiently large statistics of measured data (from several thousand cases) or augmenting data from fewer statistics. At the same time, it is necessary to calculate the assembly parameters, that will be predicted, accurately. Let's consider in more detail the stages for creating a neural network model for predicting geometric parameters of the relative position of the parts.

3. Neural network model in digital prediction of geometric parameters for relative position of the conical rings

In general, the contact of the surface pairs respectively conjugated occurs on a finite set of points. These tasks are contact ones [8]. Analytical solutions of contact tasks of surfaces, that do not have shape deviation, are known. In general, the finite element method is used to model contact tasks of surfaces with shape deviations. This method allows to take into account the surface geometry features and to solve the tasks for predicting the assembly.

The developed model includes the following stages:

1. Creating valid part models.
2. Creating triangulation grids on the part surfaces.
3. Performing a virtual analysis of a part assembly, saving the results.
4. Training of the neural network, estimation of prediction errors.

3.1. Creating valid part models

The actual part models were created in the following sequence. At the first stage, the finite set of nominal points for the parts conjugated was formed. At the second stage, the actual (model) conjugated point surfaces were calculated based on the coordinates of nominal points, form deflection functions, and location deviation parameters.

In order to describe the form deviation, a harmonic sequence is selected with the help of which it is possible to describe the discrete sequence of deflection data, obtained from the measured geometry, accurately. Harmonic sequence has the following form:

$$\delta_n(x) = \sum_{k=1}^{+\infty} A_k \sin(k \cdot (2 \cdot \pi \cdot x / \tau + \theta_k) + (1 + (-1)^k) \cdot \pi / 2), \quad (1)$$

being A_k is an amplitude set of the harmonic sequence members;

θ_k are phases of the harmonic sequence members;

k is a frequency of the harmonic sequence members;

τ is a function period (curve length);

x is a current curve length from the start point up to the current point (angle).

The parts considered represent rotation bodies. The conjugated panes having geometry deviation are swept ones: they can be obtained by moving an object, such as a section, a broken line, or a curve along a guide curve, over a distance.

The coordinate vector of each point of the section curve guide for a cone face, the axis of which is perpendicular to XOY , can be described using the expression:

$$\vec{p}_u = |(r_c - \delta r_h + \delta r_c + \delta_n(\chi)) \cdot \cos(\chi) \quad (r_c - \delta r_h + \delta r_c + \delta_n(\chi)) \cdot \sin(\chi) \quad h| + \vec{t}, \quad (2)$$

being r_c is a nominal radius of section points;

δr_c is a constant value of the radius deviation from the nominal value;

χ is a polar angle of the point p_u ;

δ_n is a simulated deflection of the form by means of sequence (1) at the point p_c ;

h is a section height.

δr_h is a the height change of the cone radius. Calculated by the formula:

$$\delta r_h = h \cdot \operatorname{tg}(90 - \gamma / 2), \quad (3)$$

being γ is an angle at the cone top.

3.2. Creating triangulation grids on the part surfaces

Accordingly, the curve, that will move along the resulting guide, represent a line. Thus, the points of cone faces may be defined using two equations (2), respectively, at the minimum and maximum heights h . Then sets of three adjacent points (two on one section and one on the other) form facets of the finite-element model.

3.3. Performing a virtual analysis of a part assembly, saving results

In order to solve the contact task with using the developed finite element model, an iterative algorithm was developed, allowing to calculate the conjugation of the parts without taking into account the deformations of the parts in the assembly process described in detail in [9]. Algorithm for finding the conjugated state assumes iterative movement of one conjugated surface relative to another with the application vector of the surface assembly force \vec{D}_1 . The concept of the gap function is introduced $G(\vec{V})$ which specifies achievement of the conjugate state of the surfaces of the parts and depends on the vector of mutual arrangement of surfaces \vec{V} . In order to calculate the function $G(\vec{V})$, the best combination of the conjugated surfaces is performed at each stage. Iteration algorithm (ICP) of the nearest points [10, 11] is used to perform the best alignment procedure. According to this algorithm, at each iteration by methods of nonlinear optimization search, the angles of rotation and displacement are calculated along the coordinate axes. In order to exclude intersections of two surfaces, the system of inequalities presented in work [12] is used, which imposes limitations on the gap function $G(\vec{V})$. In consequence of the algorithm, the rotation matrix and movement vector of the moving part are

calculated determining the transformation of its initial coordinate system into the coordinate system in assembled state:

$$\vec{p}_{as} = \vec{p}_p \cdot \mathbf{R}_{as} + \vec{t}_{as}, \quad (4)$$

being \vec{p}_{as} , \vec{p}_p are vectors of coordinates of points (x, y, z) of the part respectively after the assembly and in the initial state;

\mathbf{R}_{as} , \vec{t}_{as} are the rotation matrix and the point coordinate movement vector that \vec{p}_p specify the movement of the part during the assembly.

The proposed algorithm makes it possible to calculate the conjugations of parts, when their deformations during the assembly process are more than three times as compared with deviations of the geometry. The parameters for assembly of cone rings ρ_c , ϕ_c and δ_o because the axis distortions are negligible small, are contained in the displacement vector \vec{t} from the equation (4).

3.4. Training of the neural network, estimation of prediction errors

The neural network for prediction is a sequence of interconnected layers starting with a convoluted layer and ending with a regression layer (Figure 2).

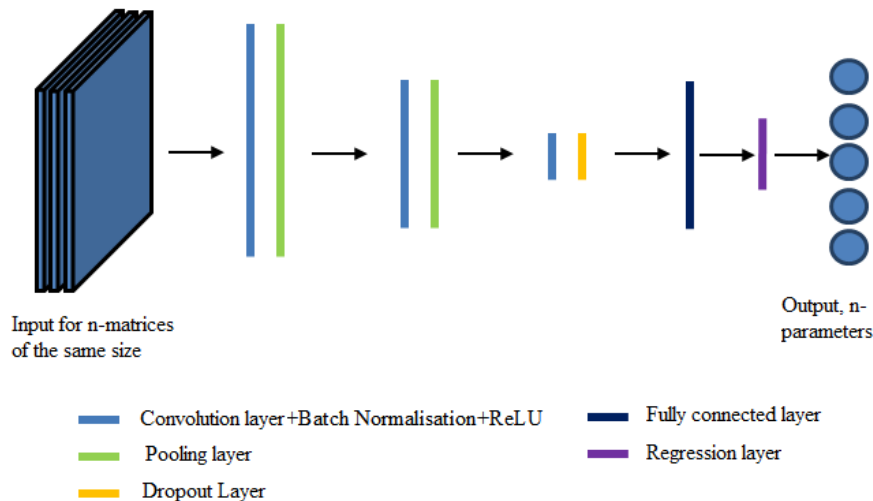


Figure 2. The architecture of a convolutional neural network for predicting parameters.

A set of rectangular matrices of equal size numbers is supplied to the network input. Let us give a brief description to the layers of the network considered.

The convolutional layer is the main block of the convolutional neural network. The convolution layer includes its own filter for each channel, the convolution kernel of which processes the previous layer by fragments (summarizing the results of the matrix product for each fragment).

The scalar result of each convolution falls on the activation function which is a kind of nonlinear function. The activation layer is usually logically combined with the convolution layer (believe that the activation function is embedded in the convolution layer). The piecewise linear *ReLU* function is selected.

Normalization of mini-batches (batch normalization) is described for example in [13], from the Russian sources in [14]. Mini Batch is a small collection of data that is usually selected from the entire training set randomly. Batch normalization solves the problem of gradient mismatches at different network levels, preventing effective training by normalizing the input data in such a way as to get zero mathematical expectation and unit variance. Normalization is performed before entering each layer.

The pulling layer (otherwise subsampling, downsampling) is a nonlinear sealing of the feature map, with a group of pixels (usually 2×2) compacted to one pixel, passing a nonlinear transformation. The averaging function used in this network is most commonly used.

Dropout Layer [15]. Dropout is a method for regulating neural networks. Each neuron (except the most recent one, output layer) is set to a certain probability p which it will be thrown out of the

network with. The training algorithm changes in this way: on each new training example, each neuron with probability p is either used as usual or its output is set strictly to zero. Everything happens then with no changes; zero at the output causes the neuron to drop actually out of the computation graph: and direct calculation, and the reverse spread of the gradient stop at this neuron and do not go further.

A fully connected layer. After several passages of image convolution and compaction using pulling, the system is rebuilt from a specific high-resolution pixel grid to more abstract feature maps, usually the number of channels increases on each next layer and the image size decreases in each channel. After all, there is a large set of channels storing a small number of data (even one parameter) that are interpreted as the most abstract concepts identified from the original image.

These data are combined and transmitted to a normal fully connected neural network which can also consist of several layers. At the same time, fully connected layers already lose the spatial structure of pixels and have a relatively small size (relative to the number of pixels of the original image).

The last layer is a regression layer that uses the *MSE loss function* (mean-square error). Accordingly, the assembly parameters are calculated directly at the network output.

In case of assembly of two planes and cone rings at the input, it is sufficient to supply a single matrix of distances representing the initial gap in the connection. The initial gap is a matrix of distances between points of one surface (a fixed part in a connection) and the adjacent surface of another (a moving part) when the parts are in the nominal position. Or the moving part is shifted to some short distance from the fixed part along one of the axes.

To estimate the prediction results for the parameters of assemblies and to specify the structure of the selected neural network model, it is necessary to estimate prediction errors. Estimation of prediction error parameters shall be made according to two criteria:

- 1 Proportion of the predicted values within the permissible tolerance δ_{add} .
- 2 Mean-square error (*RMSE*) of predicted and actual parameters.

Here is a sequence of calculations for these values:

- 1 Calculate the tolerance between the predicted and the actual parameters:

$$\Delta_n = \Pi_{pr} - \Pi_a. \quad (5)$$

- 2 The number of errors within the permissible area shall be counted $N_{\Delta add}$. The permissible area of errors shall be calculated as a percentage of the maximum value of the predicted parameter — 10%.

- 3 Prediction accuracy shall be calculated as the ratio of quantity $N_{\Delta add}$ to the total sample size:

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

- 4 The mean-square error value shall be calculated by the formula:

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

4. Results of virtual assembly application for prediction of assembly parameters

The points of two cone surfaces are modeled using formulas (1-3). 10,000 sets of points in total were modeled for two types of cones (5,000 of each type). Each set contains 720 points (360 points belonging to two guide curves). Nominally, the guide points lie in planes parallel to *XOY*. Table 1 shows the statistical characteristics (mathematical expectation \bar{X} and standard deviation σ) of the geometric deviations of the two cones.

Table 1. Value of deviation parameters for points of two conjugated cones.

Parameter	The first cone				The second cone			
	A_k , mm	k	θ_k , rad	δr_c , mm	A_k , mm	k	θ_k , rad	δr_c , mm
\bar{X}	0.0041	5.9	1.9783	0.0665	0.0010	5.8	1.9556	0.0001
σ	0.0067	2.3	1.8823	0.0219	0.0009	2.3	1.8308	0.0085

The height of the cones h is 40 mm; the radius at the base r_c is 27,36 mm; the angle at the top is γ 6 degrees.

Statistical characteristics and minimal and maximal values of assembly parameters for cone rings obtained in consequence of simulation using formed sets of measured points of the connected parts are shown in Table 2.

Table 2. Assembly parameters of two cone rings.

Parameters	\bar{X}	σ	Min	Max
ϕ_c , deg	131.0174	75.8793	0.0652	359.9210
ρ_c , mm	0.0104	0.0068	0.0001	0.0453
δ_o , mm	-0.4318	0.7330	-2.3640	0.9730

Figure 3 shows an example of one of the initial gaps in connections of cone surfaces.

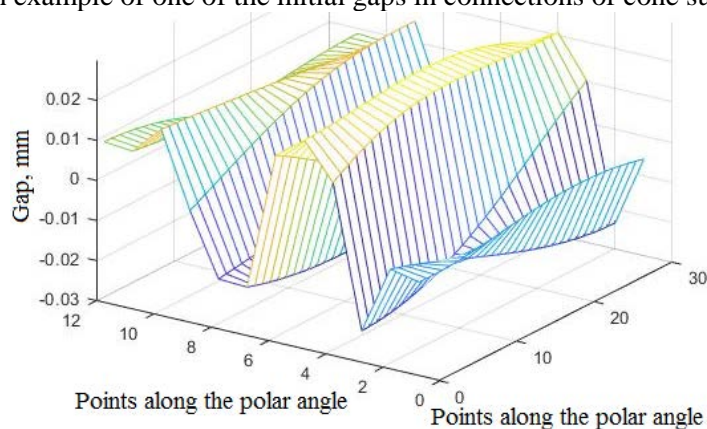


Figure 3. Initial gap in connection of two cones.

The matrix sizes are 12×30 points for the cone rings. Since there are no inclination angles of the rolling ring at the initial stage of assembly, during and at the end of assembly, the gap will be the same in height in zero position. Therefore, a gap in one section (360 points) has been taken and in order to perform several convolution operations, one row is divided into 12 rows for 30 values each. After calculation of all matrices, their values are normalized into the range [0 1].

Selected parameters of a convolutional neural network with a regression layer are: network depth, characterized by the number of convolution subnets N_{CNN} including convolutional layers, layer downsampling layers; the size of the convolution kernel ($N_k \times N_k$); the number of convolution channels M_c ; the probability p in dropout. The window size in pulling does not change — 2×2. After selecting the network architecture, the network training process is optimized according to the following parameters: packet size (batch) of data during training N_b ; number of learning epochs N_{ep} ; number of epochs to reduce learning speed N_{ELS} ; reduction factor of learning speed F_{LS} (varies from 0 to 1); training algorithm (“SGDM” [16, 17] or “RMSProp” [18]).

Table 3 shows the prediction results for the assembly of two planes and two cone rings.

Table 3. Network performance assessment.

Parameters	Cone rings		
	φ_c	ρ_c	δ_o
δ_{add}	0.864	0.866	0.998
<i>RMSE</i>	0.647	0.003	0.056

Table 4 shows the network parameters that achieve the maximum accuracy in predicting assembly parameters.

As it appears from the results given in Table 3, the value δ_{add} of the parameter δ_o is the highest one, the polar coordinates of the center are determined with less smaller accuracy. It should be taken into account that the value ρ_c is almost 19 times smaller indicator $RMSE$ than δ_o , since the values of the center offset in the plane perpendicular to the axis of rotation are significantly lower than its offset along the axis of rotation.

Table 4. Optimal parameters of the networks for predicting assembly of the cone rings.

Parameter	N_{CNN}	N_k	M_c	p	N_b	N_{ep}	N_{ELS}	F_{LS}	Training algorithm
Value	2	4	6	0.4	40	70	30	0.1	“SGDM”

5. Conclusion

The work presents a model for predicting conjugation accuracy of the parts according to the geometry measurement results based on the use of digital models and a convolutional neural network. Connecting of two conical rings is selected as the object for calculations. The data obtained by simulation are used to train a convoluted neural network allowing to predict assembly components based on geometry deviations maps of measured surfaces connection parameters. Evaluation of the accuracy of the results leads to the conclusion about the adequacy of the developed neural network model. The adequacy of the developed model depends on the accuracy of the mathematical description of the actual geometry of the parts, the rigidity of the material and the design and size of the training set. Optimal parameters of the network may depend on the considered object.

6. References

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