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OPTIMAL CONFIGURATIONS OF THE MACHINE TOOL STRUCTURE BY MEANS OF NEURAL NETWORKS

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ОПТИМІЗАЦІЯ СТРУКТУРИ МЕТАЛОРІЗАЛЬНИХ ВЕРСТАТІВ ЗА ДОПОМОГОЮ НЕЙРОННИХ МЕРЕЖ
Стаття присвячена автоматизації розробки металорізальних верстатів на фазі вибору їхньої оптимальної структури за допомогою нейронних мереж. Для цього мети розроблені алгоритм і програма його реалізації. За допомогою їх визначаються безліч конфігурацій всіх можливих структур верстата на основі відносин між рухами інструмента, заготівлі й вузлів верстата. Потім, конфігурації структури, які відповідають необхідним технічним вимогам, витягають із цієї безлічі. Логічні операції засновані на булевой алгебрі. Через їхню здатність до навчання використання нейронних мереж забезпечує більше гнучкий і швидкий вибір оптимальних структур металорізальних верстатів.

Статья посвящена автоматизации разработки металлорежущих станков на фазе выбора их оптимальной структуры с помощью нейронных сетей. Для этого цели разработаны алгоритм и программа его реализации. С помощью них определяются множество конфигураций всех возможных структур станка на основе отношений между движениями инструмента, заготовки и узлов станка. Затем, конфигурации структуры, которые отвечают необходимым техническим требованиям, извлекают из этого множества. Логические операции основаны на булевой алгебре. Из-за их способности к обучению использование нейронных сетей обеспечивает более гибкий и быстрый выбор оптимальных структур металлорежущих станков.

This paper deals with the automations of the machine tools' development in the phase of selecting of the optimal structure's configuration by means of neural networks. For this purpose, an algorithm and a programme were developed. By using of them a set of all possible machine tool structure's configurations on the basis of the relations between the movements of tool, workpiece and machine tool units by the machining is determined. Then, structure's configurations, which meet the needed technical requirements, are extracted from this set. The usage of neural networks, due to their learning ability, makes the performance of these steps not only faster as the manual performance but more flexible as the similar programmes based on Booleans logic.

INTRODUCTION

The selection of suitable machine tools represents a significant part of production preparation. To guarantee the required accuracy, stiffness, reliability, performance, etc., machine tools need to fulfil a number of requirements, which substantially depend on their structure's configurations. It is therefore necessary to determine the configuration of the machine tool structure in such a way that it meets the technical requirements to the highest degree 0, 0, 0.

The configuration of the machine tool structure is generally selected by highly qualified design engineers, which rely on their experience and intuition. Using intuition and experience, however, does not guarantee that the optimal configuration will be selected. This is mainly because a general algorithm for the selection of machine tool structure's configuration does not exist and because only known solutions are considered, but not all possible configurations 0.

To determine and further analyse different machine tool structure's configuration, various scientific methods have been developed 0, 0, 0, 0, 0, 0, 0. Special attention is given to the method of selecting of the optimal machine tool structure's configuration according to structural characteristics. The algorithm of this method consists of three phases 0, 0, 0, 0:

- determination of the total number of possible configurations;
- structural extraction of subsets, which fulfil the needed requirements;
- final selection of optimal machine tool structure's configuration by comparing their technical and economic characteristics.

Several studies have shown that the method of synthesis of structure's configurations on the basis of the relations between the movements of tool, workpiece and machine tool units is the most suitable method for determining the total number of possible configurations by shape generation 0, 0, 0. The subsets are structurally extracted according to the formulated conditions for machine tool structure's configurations, which determine the necessary spatial location and alignment of the machine tool units 0, 0, 0, 0. In the final selection of the best configuration, methods of the cost-utility analysis are applied, the algorithm of which comprises the compiling of a list of important criteria, the elaboration of a rating scale and the evaluation by convolution of all criteria 0.

The manual performance of all steps mentioned above is very time-consuming and slows down the development of machine tools in general. This is inacceptable for modern market conditions and reduces competitiveness. Therefore, the automation of this process is necessary. Today, the process is implemented with special software for the determination of optimal configurations 0, 0, 0. A particular feature of this software is that it is developed on the basis of the Boolean logic. Such a design causes inflexibility in solving new tasks and optimising existing structure's configurations. To add a new condition into the algorithm for determining of the optimal configuration, for example, the programme code or the database of the entire software needs to be changed. This certainly entails an enormous time and cost effort. This disadvantage can be overcome by using the Fuzzy logic, e.g. of neural networks, which are characterised by high flexibility and their learning ability 0, 0. This learning ability creates a possibility to adapt the programme or the database without the software correction. This considerably reduces the time for solving new tasks and optimising existing configurations.

This paper describes a possible way to the automation of the first and second phase (see above) of the selection of optimal machine tool structure's configurations by means of neural networks.

DETERMINING OF POSSIBLE MACHINE TOOL STRUCTURE'S CONFIGURATIONS

The total number of possible machine tool structure's configurations can be determined according to the method described in 0, 0, 0. This method is based on the relations between the movements of the workpiece, the tool and hence all machine tool units in the shape generation process. To simplify the machine tool design, complex relative movements of the tool and workpiece are combined from the elementary movements of the machine tool units: from three translational movements along the axes x, y, z and three rotary movements around the same axes. Accordingly to that, the relative movements of the tool and workpiece can be expressed as a coordinate code 0, 0, 0:

$$k = k_1 k_2 \ldots k_i, \tag{1}$$

where k_i $(i = 1, \ldots, n)$ is the movement of the i-th machine tool unit relative to the (i - 1)-th unit. 1, 2, 3 describe the codes of the translational movements along the axes x, y, z and 4, 5, 6 – the codes of the rotary movements around the axes x, y, z. n is the number of the mobile machine tool units.

The coordinate code is generated according to the kinematic scheme of the shape generation process. It is to formulate with the following rules 0:

1. The coordinate code should start with the code of the workpiece movement.
2. In the coordinate code, the codes of the rotary movements come first. Then – the codes of the translational movements.
3. Priority is given to the relative movements and then to the guided movements.
4. The codes of the movements are recorded according to increasing of their number.
5. Taking into account these rules, the coordinate code (1) for gear machining with profile milling cutters (see Figure 1), for example, is as follows:

$$k = 61234. \tag{2}$$

In order to receive the code of a complete machine tool structure's configuration from the coordinate code (1), which describes a set of mobile machine tool units, it is necessary to add an immobile basis unit – a machine bed. Symbolically, this is realised by adding the digit "0" to the coordinate code on any position. The thus received coordinate code is called the code of the machine tool structure's configuration. From the coordinate code (2), for example, the following structure's configuration's codes can be derived by adding "0":

$$K_{C_1} = 612340;\ K_{C_2} = 612304;\ K_{C_3} = 612034;\ K_{C_4} = 610234;$$
$$K_{C_5} = 601234;\ K_{C_6} = 062314. \qquad (3)$$

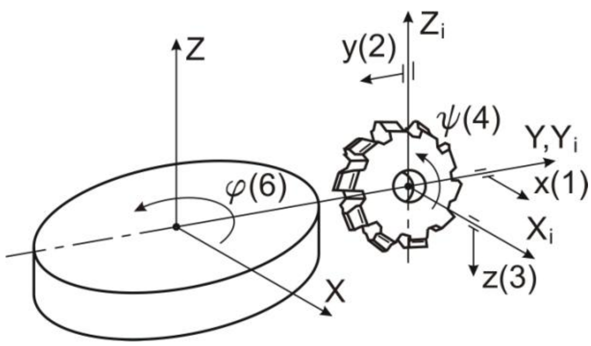

Figure 1 –Kinematic diagram of gear machining with profile milling cutters

Figure 2 shows the two machine tool structure's configurations that correspond to the codes 601234 and 610234.

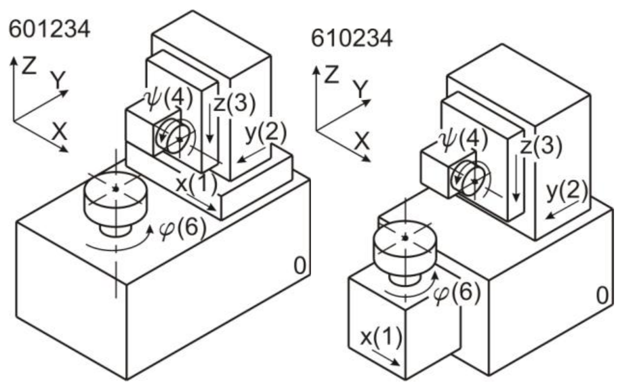

Figure 2 – Examples of gear milling machine structure's configurations

The change of the position of the machine bed and of the corresponding code is not the only possibility to determine alternative machine tool structure's configurations, which have the same shape generation abilities. New configurations can also be obtained by permutations, aggregations or disjunctions of machine tool units or digits in the structure's configuration's code k. Only the following four transformations or a combination of these do not change the shape generation's scheme 0:

- Permutation (rearrangement) of two neighbouring units, which perform translational movements along different axes: 12 = 21, 23 = 32 31 = 13.
- Permutation (rearrangement) of two neighbouring units, the first of which performs the translational movement along the axis and the second of which performs the rotary movement around the same axis (or the unit, which represents a cylindrical pair): 14 = 41 25 = 52, 36 = 63.
- Aggregation (combination) of several units into one, which performs the same movement relative to the same axis: 11 = 1, 22 = 2 33 = 3, 44 = 4, 55 = 5, 66 = 6.
- Disjunction (separation) of one unit into several units, which perform the same movement: 1 = 11; 2 = 22; 3 = 33; 4 = 44; 5 = 55; 6 = 66.

Another option to obtain alternative machine tool structure's configurations is the change of the spatial alignment of its coordinate system. Symbolically, this is realised by the circular permutation of the digits in the code of structure's configuration according to two schemes: 1 → 2 → 3 → 1 and 4 → 5 → 6 → 4.

The total number of configurations with the same shape generation abilities, which can be obtained by using the three methods described above, is determined with the following equation 0:

$$N = (n+1) \cdot N_p \cdot N_f , \tag{4}$$

where n is – the number of mobile machine tool units. N_f – is the number of configurations, which can be obtained by the four permissible transformations. N_p – is the number of configurations, which can be obtained by spatial rotations of the machine tool according to the change of its coordinate system.

The total number of possible structure's configurations of a hobbing machine with coordinate code (2), calculated according to formula (4), equals 198.

The determination of the set of possible structure's configurations of machine tools on the basis of their kinematic schemes of shape generation is automated with a C++ programme, which was developed for this purpose. When the programme is used, the coordinate code of the machine tool or of its kinematic scheme of shape generation should be entered. The result of the calculation is delivered as a text file with a complete list of all possible machine tool designs. Simultaneously, the programme creates an input file for the neural network.

STRUCTURAL EXTRACTION OF A SUBSET OF CONFIGURATIONS

Machine tool structure's configurations that fulfil the required conditions are structurally extracted by means of neural networks. The significant difference and advantage of neural networks, compared to conventional methods, is their *learning ability* 0. Neural networks are trained or instructed by means of examples that are combined into learning sets. The learning sets consist of input and corresponding output data. In the course of learning, the learning sets are analysed and possible dependencies in their structure are determined. Due to these dependencies, rules are created, according to which the further classification can be carried out 0, 0.

The learning set of the neural network is shown in the form of a connectivity matrix T:

$$T = \begin{bmatrix} k_{1,1} & k_{1,2} & \dots & k_{1,j-1} & k_{1,j} \\ k_{2,1} & \ddots & & & k_{2,j} \\ \vdots & & \ddots & & \vdots \\ k_{i-1,1} & & & \ddots & k_{i-1,j} \\ k_{i,1} & k_{i,2} & \dots & k_{i,j-1} & k_{i,j} \\ c_1 & c_2 & \dots & c_{j-1} & c_j \end{bmatrix}, \tag{5}$$

which consists of the i-th number of input vectors (input data of the learning algorithm):

$$\mathbf{p}_i = \begin{bmatrix} k_{i,1} & k_{i,2} & \dots & k_{i,j-1} & k_{i,j} \end{bmatrix}, \tag{6}$$

and of the target vector T_C (output data of the learning algorithm):

$$\mathbf{T}_c = c_1 \quad c_2 \quad \dots \quad c_{i-1} \quad c_i \;. \tag{7}$$

The elements $k_{i,j}$ of the input vectors (6) are generated according to the structural conditions of the extraction of machine tool structure's configurations. These conditions are formulated and determined in the form of structure equations. These structure equations are similar to the structure's configuration's code (3) and have the same number of digits for a defined machine tool. Each of the structure equations, however, does not only correspond to an individual configuration, but to a configurations' set that fulfils a condition of the extraction 0.

The combination of structure equations is explained with the example of a gear milling machine with coordinate code (2). The machine is designed for the machining of medium size workpieces. In this case, the extraction conditions are formulated as follows:

1. The rotation axis of the workpiece should be vertical since structure's configurations with horizontal and tilted rotation axis are suitable for the machining of long parts with small diameter 0. This can be illustrated with the following equation, which describes a configuration's subset with the number

„6“ at the beginning of the code (the machine tool unit rotating around the vertical axis z):

$$\forall_{\square} B \exists_{\square} I \left(\phi_Z = \frac{\pi}{2} \right):\ M_1 \Rightarrow 677777 \vee 767777 \vee 776777\ , \tag{8}$$

where $\square$ is the space of definition of all machine tool structure’s configurations. B is a set of all existing machine tool structure’s configuration and I – a subset of all configurations that need to be determined. ϕ_Z is an inclination angle of the rotation axis of the workpiece to the horizontal level. M_1 describes the subset that fulfils the first extraction condition.

A random digit of the structure’s configuration’s code, i.e. from 0 to 6, can be on the position of number "7". This position is only required to ensure that all elements of the neural network’s learning vector have the same number of characters. This guarantees a correct learning process and further programme functions.

2. Tool and workpiece need to be mobile. The configurations with immobile tool are very complicated and inefficient in the production. The configurations with immobile workpiece are only suitable for machining of very large parts 0. For this condition, the position of the digit “0” or the machine bed’s position is important, which can be on any but the first and last position. Therefore, the second condition can be described with the following logical equation:

$$\forall_{\square} B \exists_{\square} I\ \ F \wedge W \Rightarrow \text{var}\ :\ M_2 \Rightarrow 707777 \vee 770777 \vee 777077 \vee 777707\ , \tag{9}$$

Here F and W are the motion parameters of the tool and workpiece. M_2 is a subset that fulfils the second extraction condition.

3. To increase the stiffness, configurations, in which linear moving unit is attached to rotating unit (moving-out quill) should be avoided 0. Important elements for the neural network’s learning set are the positions of the digits "0", "4" and "6" in the structure’s configuration’s code, which exclude the possible combination of the digits "36" and "41". Accordingly, the logical equation for this condition is as follows:

$$\forall_{\square} B \exists_{\square} I\ \ P = \varnothing\ :\ M_3 \Rightarrow 677774 \vee 067774 \vee 677740\ . \tag{10}$$

Here P represents a motion parameter of the quill. $\varnothing$ describes an empty set. M_3 is a subset that fulfils the third extraction condition.

4. In order to avoid the weight effect of mobile units on the accuracy of the machine tool, horizontal mobile units should be attached to immobile

units 0. Accordingly, there should be a combination of the numbers "102" or "201" in the structure's configuration's code. Then, the logical equation for the fourth condition can be described as follows:

$$\forall B \exists I \; U_M \Leftrightarrow U_S \; : M_4 \Rightarrow 710277 \vee 720177 \vee 771027 \vee 772017 \; . \qquad (11)$$

Here U_m represents a condition parameter of mobile units and U_S – a condition parameter of immobile units. M_4 is a subset that fulfils the fourth extraction condition.

5. The last extraction condition is obtained by the combination of the previously formulated four conditions (8-11):

$$\forall B \exists I : \; M_5 \Rightarrow M_1 \wedge M_2 \wedge M_3 \wedge M_4 \; , \qquad (12)$$

Here M_5 is a subset that fulfils the fifth extraction condition.

If the machine tool structure's configuration fulfils the fifth condition than it is optimal.

Additional conditions can be added to and/or excluded from the formulated extraction conditions. In the first case, the subset of the optimal configurations increases, and in the second case, it decreases. The decision as to which conditions should be added or excluded is taken by the user or engineer at the current state of technology.

Based on the formulated conditions or logical equations (8 – 12), the input vectors (6) are generated. For the first extraction condition (8), for example, the following vectors of the learning set are received:

$$\mathbf{p}_1 = 6 \;\; 7 \;\; 7 \;\; 7 \;\; 7 \;\; 7 \; ; \; \mathbf{p}_2 = 7 \;\; 6 \;\; 7 \;\; 7 \;\; 7 \;\; 7 \; ; \; \mathbf{p}_3 = 7 \;\; 7 \;\; 6 \;\; 7 \;\; 7 \;\; 7 \; . \qquad (13)$$

By assigning the vectors (13) to a class c_i in the target vector $\mathbf{T_C}$ (7), it is ensured that they are bound to a certain extraction condition, i.e. for the first condition c_i = 1, for the second condition c_i = 2 etc. Accordingly, the vectors $\mathbf{p_1}$**,** $\mathbf{p_2}$ and $\mathbf{p_3}$ are assigned to the same class $c_1 = c_2 = c_3 = 1$. Analogue to that, all other input vectors **p** are assigned to the classes in the target vector $\mathbf{T_C}$, according to the logical equations (9-12). Then, the connectivity matrix T (5) is formed.

A radial-basis-function (RBF) network, modelled in Matlab, was used for learning. Such RBF networks can effectively solve the tasks of generalisation and classification of vectors, since they have a large number of neurons, compared to the standard networks with direct transmission of signals and reverse spreading of errors 0. Figure 3 shows a structure scheme of the modelled RBF network for the extraction of the optimal machine tool structure's configuration.

The network consists of two layers: an RBF layer with an activating function $radbas(n)=e^{-n^2}$ and S_1 neurons as well as a linear output layer with an activating function $purelin(n)=n$ and S_2 neurons.

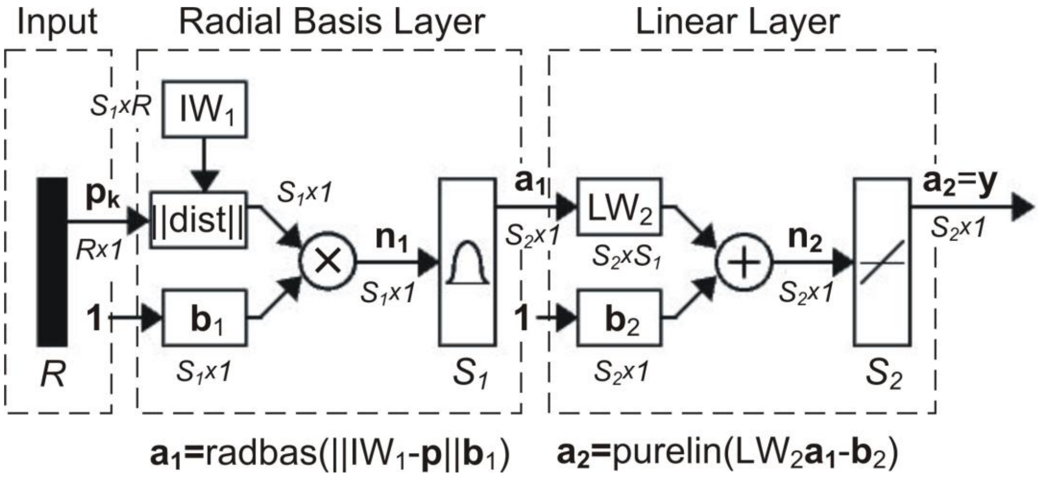

Figure 3 – Structure diagram of the neural network

During the learning with the connectivity matrix *T*, weight matrices are formed for the first IW_1 and second layer LW_2 0, 0. In the first layer, a distance between the new input vector $\mathbf{p_k}$ and the vectors of the learning set is determined. In this process, the data of the vector $\mathbf{p_k}$ is transmitted to the block ||dist||. In this block, the distance between the vector $\mathbf{p_k}$ and the weight matrix IW_1 is determined. The output data of the block ||dist|| is multiplied element by element with a displacement vector $\mathbf{b_1}$. Their product forms the input data of the activating function ***radbas***. If the output of the activating function – vector $\mathbf{a_1}$ – is a number close to „1“, the new vector $\mathbf{p_k}$ is the closest to the vector of the learning set 0. In the second layer, it is determined to which class the vector $\mathbf{p_k}$ should be assigned to. The output vector $\mathbf{a_1}$ is multiplied with the weight matrix LW_2. Their product is summed with the displacement vector $\mathbf{b_2}$. The sum is the input data of the activating function ***purelin***. The output of this function – vector $\mathbf{a_2}$ – takes the value of the class to which the new vector $\mathbf{p_k}$ is assigned by the neural network 0.

The displacement vectors $\mathbf{b_1}$ and $\mathbf{b_2}$ provide a possibility to correct the sensitivity of the neurons in corresponding layers. The user can change the values of the displacement vectors' elements 0. The input vectors $\mathbf{p_k}$ of the neural network include all 198 possible machine tool structure's configurations, which correspond to the coordinate code (2), and are created analogue to the vectors of the learning set (13).

The configurations of the gear milling machine with the coordinate code (2) fulfil the fifth extraction condition (12). Therefore, they are the most suitable for the machining of medium size workpieces. One of these optimal machine tool configurations, which corresponds the code 602134, is shown in Figure 4 on the right side.

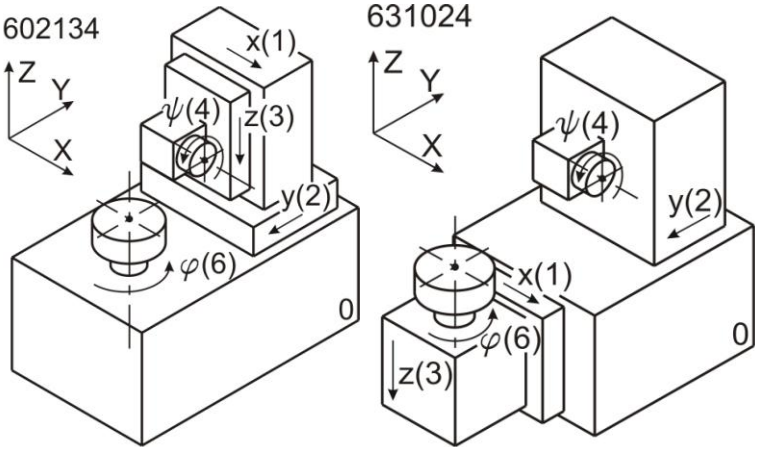

Figure 4 – Examples of the identified optimal configurations of the machine tool structure

To test the operating mode of the developed algorithm and programme more, optimal structure's configurations were extracted for a hobbing machine with the same coordinate code (2), but in the case of machining of large gear wheels. The learning data of the neural network will differ from the previous learning data in three conditions:

1. The second extraction condition is re-formulated as follows: The workpiece can make only one movement or be immobile, because the displacement of the large masses causes an enormous energy consumption and reduce the efficiency 0. Hence, the logical equation is as follows:

$$\forall B \exists I \;\; W = 1 \vee const \;:\; M_2^{'} \Rightarrow 077777 \vee 707777 \;. \tag{14}$$

2. The fourth extraction condition is modified as follows: In order to avoid the weight effect of the units on the accuracy of the machine tool, the horizontal mobile unit, which performs the largest displacements, should be attached to the immobile units 0. Therefore:

$$\forall B \exists I \;\; U_{M\max} \Leftrightarrow U_S \;:\; M_4^{'} \Rightarrow \left. \begin{matrix} 702777 \vee 770277 \vee 777027 \\ \vee 720777 \vee 772077 \vee 777207 \end{matrix} \right\}. \tag{15}$$

3. The fifth condition is formulated analogue to equation (12), but with the logical equations (8), (10), (14), (15):

$$\forall B \exists I : \;\; M_5 \Rightarrow M_1 \wedge M_2^{'} \wedge M_3^{'} \wedge M_4^{'} \;. \tag{16}$$

CONCLUSIONS

The algorithm described above allows an automated development of machine tools in the phase of selecting of the optimal structure's configuration by means of neural networks. The results of the operating tests of the developed neural network correlate with the manual calculations if the structural extraction conditions were correctly formulated. The learning ability of the neural network guarantees high flexibility of the algorithm in solving new tasks and also in optimising of existing machine tool structure's configurations. No direct changes are required in the programme or in its data base if the extraction conditions are changed.

As a further development of the algorithm and programme, the structure equations should be generalised for all types of machine tools. These equations should be entered into a data base of learning sets. This will considerably reduce the calculation time.

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