Designing an Artificial Neural Network Based Model for Online Prediction of Tool Life in Turning

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Received: 29 October 2014, Revised: 12 February 2015, Accepted: 15 February 2015

Abstract: Artificial neural network is one of the most robust and reliable methods for online prediction of nonlinear incidents in machining. Tool flank wear as a tool life criterion is an important task which is needed to be predicted during machining processes to establish an online tool life estimation system. In this study, an artificial neural network model was developed to predict the tool wear and tool life in turning process. Cutting parameters and cutting forces were used as input and tool flank wear rates were regarded as target data for creating the online prediction system. SIMULINK and neural network tool boxes in MATLAB software were used for establishing a reliable online monitoring model. For generalizing the model, full factorial method was used to design the experiments. Predicted results were compared with the test results and a full confirmation of the model was reached.

Keywords: Artificial Neural Networks, Cutting Forces, Prediction, Tool Life

Reference: Salimi, A., Özdemir, A., and Safarian, I., "Designing an Artificial Neural Network Based Model for Online Prediction of Tool Life in Turning", Int J of Advanced Design and Manufacturing Technology, Vol. 8/No. 2, 2015, pp. 65-71.

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1 INTRODUCTION

For establishing an automatic machining system in a manufacturing plant, manufacturers are obliged to develop a reliable and strong monitoring system. Hence, the creation of automation system enhances the significance of tool condition monitoring in machining operations among researchers. In addition to the dead time and the costs resulting from the replacement of a worn tool with a new one, real time monitoring of the tool wear is needed to prevent losses that may occur during tool breakage and machining with a worn tool [1].

Many questions and concerns are involved within the issue of constructing a tool condition monitoring system in machining operations; that is, questions such as sensor selection system, multi sensor detector [2-4], signal processing and feature extraction [1], [5], designing issues in the related experiments [6], [7] and process modeling by using intelligent systems are investigated by related researchers [3], [8]. Although many studies have been conducted in this research domain, researchers have not been able to develop and design a sound method yet and many studies have been dedicated to on-line monitoring of tool conditions, optimization of machining processes, control and prediction.

In general, tool wear monitoring methods can be classified into two categories, namely direct and indirect methods. In direct methods, it is possible to determine tool wear directly. In other words, these methods can really measure the tool wear directly from the inserts. However, despite the development of several direct methods such as visual inspection, computer vision, etc., they are not regarded as promising and favorable methods of monitoring tool conditions; in particular, these methods are not economical and practical [9]. Over the years, indirect methods of estimating tool wear have become increasingly popular. Indirect methods are based on variables which change along with the machining processes.

Many variables can be considered with regard to the machining region, i.e., cutting force, vibration, acoustic emission, sound, temperature, surface quality and etc. All these variables can be affected by the cutting tools and machining conditions [10]. Seven steps should be taken for creating a tool condition monitoring system: 1) an appropriate sensor is selected for measuring the variables (2) received signals are processed (3) the monitoring scope is specified (4) the most effective features are selected (5) features are extracted (6) experiments are designed (7) a decision support system is selected [3], [10].

Effective and efficient monitoring of tool conditions in industry highly depends on robust and reliable sensor signals such as force, power and acoustic emission (AE). They are relatively easy to install in existing or new machines and do not affect machine integrity and stiffness. Recent studies indicate that force signals can be considered as the most useful data in tool condition monitoring [11]. A tool condition monitoring method was developed by cakir et al., [12] using cutting forces in turning. In this research, variation of cutting force during the machining process has been evaluated as a cutting force-wear diagram. The results show that using cutting forces for tool condition monitoring can be reliably used in machining operations. However, the study does not present any online prediction system for tool wear estimation.

Scheffer et al., [13] evaluated tool wear monitoring in their study. They concluded that cutting force is an appropriate variable for tool wear monitoring. In the another research, an ANFİS model was used by Agustin Gajate et al., [14] for tool wear estimation. Fuzzy logic and ANN methods were integrated in this research as an ANFİS method. The results of tool wear estimation model were presented graphically using different cutting parameters. However the study has emphasized to local prediction model rather than a general model and it does not presents a practical online system for tool wear prediction in small machining workshops.

Another fuzzy logic model was developed by Vishal et al. [15] to estimate tool flank wear in turning and the fuzzy logic method has been suggested as a reliable tool for tool wear prediction. As a result of the study, researchers suggested a large number of data size for establishing a reliable model. However, they have not benefited from simulation capabilities which enhance practicality of the prediction model and present an idea in FMS and CİM systems.

The aim of the present study is to develop a reliable tool wear estimation model for improving the deficiencies of the past researches. For this, the cutting force values were applied to predict the tool flank wear in turning operation. Artificial neural network model was applied for constructing the prediction system. Flank wear was used as the tool life criterion which ranged from 0 to 0.3 mm respectively, based on ISO 3685 standard for the new and worn tool. Cutting parameters and cutting forces were regarded as the input and the wear rate was considered as the output in the proposed ANN model. Using of the experimental data a simulation box was created to get the signals directly from the sensor. Then, the wear rate was predicted on-line and immediately. The obtained results confirm reliability of the ANN method for simulating and predicting tool wear.

2 EXPERIMENTS

In this study, tool wear prediction was carried out using cutting parameters and cutting force signals. Johnford TC-35 CNC machine tool was used to perform the experiments. A Sandvik-Coromant insert (TNMG 1604-QM H13) was selected as the cutting tool and a TIZIT Simple (CTANR 2525M16) marked was considered as tool holder. The material used for machining was SAE 4140 with $\emptyset 100 \times 1000$ mm of dimension. Chemical Properties of the workpiece are given in Table1. The cutting parameters used for machining operation were selected based on ISO 3685 Standard (Table2). A Dino Capture microscope was used to measure the flank wear. Cutting forces were measured by using of a Kistler 9272 4-component dynamometer and a Kistler 5070Ax01xx amplifier. The range for tool wear was selected between 0-0.3 for a new and worn tool respectively based on ISO3685 standard. Fig.1 shows the research experimental setup.

Table 1 Chemical properties of the workpiece

Workpiece	SAE 4140 (AISI 4140)						
Chemical compositions (%)	C	Si	Mn	Cr	P	S	Mo
	0.38 -0.43	0.15 -0.30	0.75 -1.00	0.80 -1.10	0.035	0.04	0.15 -0.25

Table 2 Cutting parameters

Cutting speed (m/min)	Feed rate (mm/rev)	Cutting depth (mm)	Tool flank wear intervals (mm)
110	0.17	0.75	Initial (0), 0.1, 0.2, 0.3
135	0.22	1.25	
160	0.27	1.75	

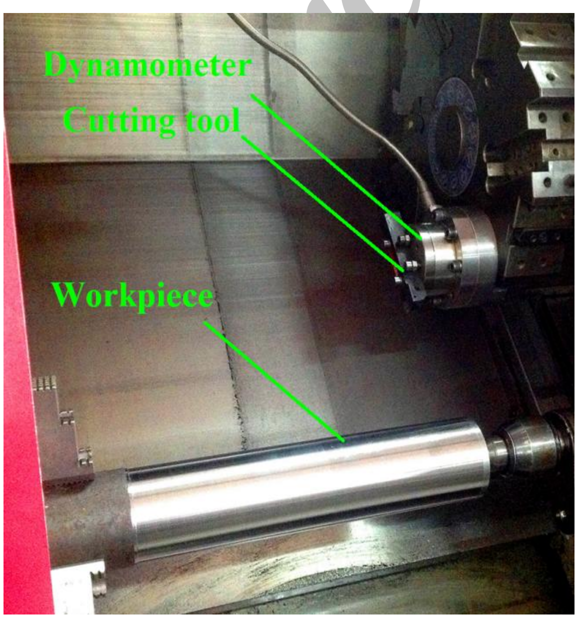

Fig. 1 Experimental setup

3 EXPERIMENTAL PROCEDURE

For establishing a tool wear prediction system, the wear ranges were selected as: 0, 0.1, 0.2, and 0.3 mm for a new, relatively worn, highly worn and worn out tool. Using the cutting parameters and full factorial method, the researchers created an experimental array for conducting the tests. By applying the wear ranges, a total of 108 experiments were carried out to measure the value of cutting forces. Indeed, there are three forces including, F_c (cutting force), F_t (thrust force) and F_r (radial force) in the machining area which result from the metal cutting process. To design a reliable prediction system, all of the three force components were considered in monitoring process. The value of the resultant force is obtained by the following equation:

$$F = \sqrt{F_c^2 + F_t^2 + F_r^2} \quad (1)$$

4 ARTIFICIAL NEURAL NETWORK

Artificial neural networks or parallel distributed processing is an alternative to sequential processing of knowledge as known from symbolic programming [16]. In analogy to the human brain, artificial neural networks consist of single units (neurons) that are interconnected by the so-called synapses. The number of hidden layers or number of neurons in hidden layers is defined based on the experience of the model designer which in turn depends on the data set, accuracy of the model and etc. A small number of hidden layers should be used when the training sample size is moderate or the number of input and output neurons is small. In general, small number of hidden layers and neurons cause inaccurate results where as large number of hidden layers and neurons results in over fitting. Although, there are some methods for determining the number of layers and neurons, they are not useful in many cases [17]. The strengths of the connections between 2 units are called “weights”. The number of hidden layers or number of units in hidden layers is arbitrarily defined. In each hidden layer and output layer, the processing unit sums its input from the previous layer and then applies the activation function to compute its output to the next layer according to the following equations [18].

$$v = \sum_{i=0}^{n} w_{ij} x_i or v = \sum_{i=0}^{n} w_{ij} x_i + b \quad , \quad (2)$$

Where w_{ij} is the weight from node i in the input layer to node j in the hidden layer; x_i is the i^{th} input element; and n is the number of nodes in the input layer. After obtaining the results a nonlinear activation function is used to regulate the output of a node, shown as follows:

$$y = F(v) \tag{3}$$

Where $F(v)$ is the output of the j^{th} node in the hidden layer. Subsequently, output from the hidden layer is used as input to the output node. Finally, the overall response from the network is obtained via the output node in the output layer [19]. The sum of squared errors for the n^{th} iteration is defined as:

$$\sum_{i=1}^{k} E_i = \frac{1}{2}\sum_{i=1}^{k}(h_i - y_i)^2 \tag{4}$$

Where $(h_i - y_i)^2$ represents the squared of error values at the output neuron and shows the difference between desired response (*h*) and computed response (*y*). The weights are updated based on the errors in such a way that the error signal is minimized to the required threshold. There are some algorithms for updating the weights. In this study the back propagation method has been used to change the weights during the training. This method starts renewing the weights from outputs to inputs. These weights are updated automatically based on the algorithm.

Table 3 ANOVA effect tests

Parameters	DF	Sum of squares	F Ratio	Prob> F
Cutting speed, *V, m/min*	1	0.2083646	65.19	<0,0001
Feed rate, *f, mm/rev*	1	0.6325526	197.92	<0,0001
Cutting depth, *d, mm*	1	0.9445369	295.52	<0,0001
Resultant cutting force, *F,N*	1	1.0232160	320.15	<0,0001

5 TOOL WEAR MODELING

Before creating the wear prediction model, the effect of cutting g parameters and cutting force on the tool wear were analyzed by applying the analysis of variance (ANOVA) to the data. As the results of the ANOVA analysis are shown in Table 3, p value for all of the parameters is under 0.05 which confirms that the input variables have a meaningfully affection on the tool flank wear. For creating the ANN model, an activation function is needed to estimate the aggregated value of the nodes. An activation function assigns a value for any node based on the function elements and normalized boundaries. A Hyperbolic tangent was used as the activation function to estimate the values between 1 and -1. The function is defined as:

$$F(v) = \frac{2}{(1+e^{(-2\times v)})} - 1 \tag{5}$$

6 RESULT AND DISCUSSION

A multilayer feed-forward back-propagation network, which was created by generalizing the Levenberg-Marquardt's learning rule to multiple layer networks and nonlinear differential transfer functions, was used to predict flank wear of the tool. In ANN model, the cutting parameters and resultant cutting force were considered as input and the flank wear rates as target data. Three layers and 21 neurons were significantly selected for designing the model.

The network architecture consisted of 4 inputs including: cutting speed (*v*); cutting depth (*d*); feed rate (*f*) and cutting force (*F*), a first layer with 16 neurons, a second layer with 4 neurons and a third layer with 1 neuron (Fig. 2). The number of hidden nodes in a network is critical to network performance, where too few nodes can lead to under fitting. Too many nodes can lead the system toward memorizing the patterns in the data [20].

According to Kolmogorov's theorem, it was understood that twice the number of input nodes plus one is sufficient to compute any arbitrary continuous function [21]. Input vectors and the output vector (targets) were used to train the network until it could approximate a function. Trained back-propagation networks tend to give reasonable answers when presented with inputs that they have never seen.

In the experiments, based on full factorial design, 108 experiments were prepared in three levels of any cutting parameters and four levels of tool flank wear including; initial (0), 0.1, 0.2, and 0.3 mm for training the network. However 85% of the experiments were used to train the ANN and 15% of the experiments were remained for validation of the trained network. Transition of the mean square error of the model during the training process is given in Fig. 3, where the error between the estimated and measured data is dropping during the training process.

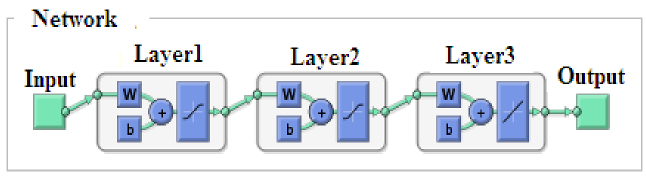

Fig. 2 Designed ANN model

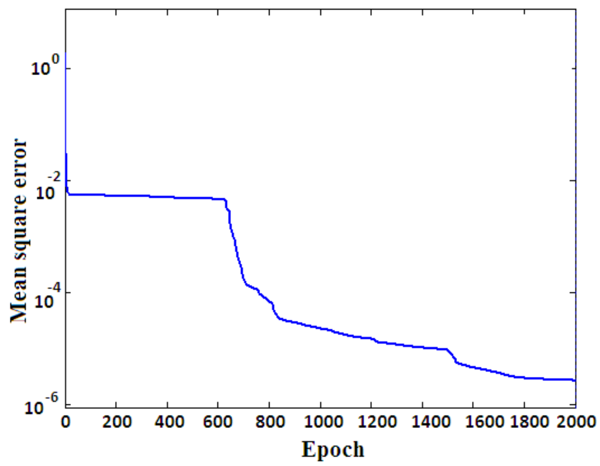

Fig. 3 Training graphic of the ANN model

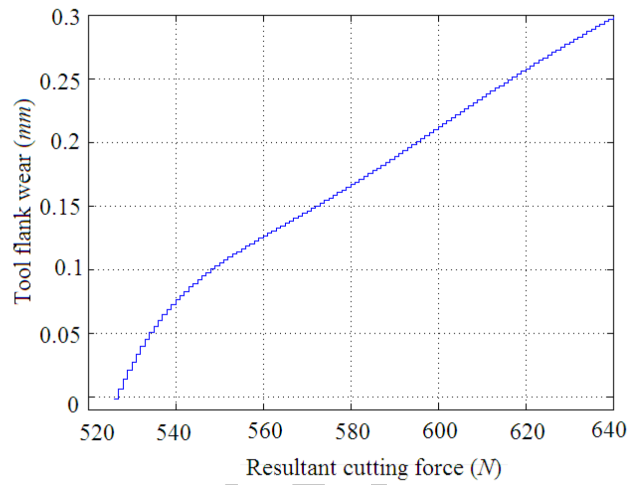

Fig. 5 Simulated tool flank wear graphic during machining for cutting parameters including: V=110 *m/min*, f=0.22*mm/rev* and d=0.75*mm*

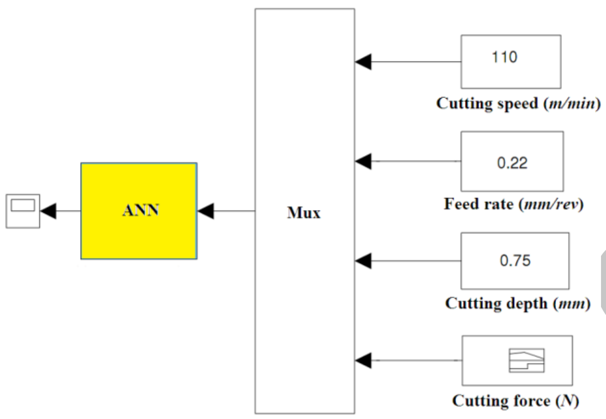

Fig. 4 Simulated block diagram of the ANN online prediction model

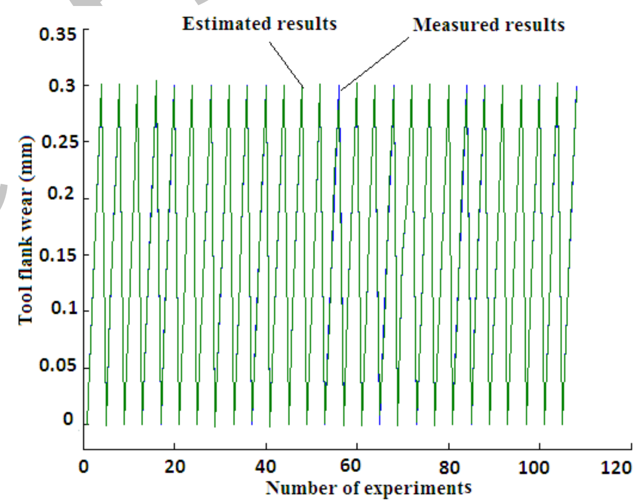

Fig. 6 Simulation of fitting graphics for estimated and measured data

For simulation of the tool wear happening during the machining process a simulated box was created in MATLAB Simulink Tool Box. As shown in Fig. 4, the cutting parameters and the cutting force signals are given in this simulation box and the tool wear rate is estimated online and immediately by changing input values. If a dynamometer, instead of the cutting force box in Fig. 4 is used to take the cutting force, the system can be used as an online monitoring and prediction system to estimate the real data.

In Fig. 5, the graphical result of the simulated model is given as a relationship between the tool flank wear and cutting force. The values of the tool flank wear are changing based on the cutting force changes. As soon as the resultant cutting force (for parameters given in Fig. 5) received from dynamometer is reached to 640 N, the tool flank wear would be estimated as 0.3 mm. The increase in tool wear for all of the cutting parameters continues until the wear rate reaches 0.3 mm, where the tool should be replaced with a new one.

Fitting graphic of the model for all of the used experiments in training is seen in Fig. 6. Based on the ANN simulation model, the predicted and measured results are accurately following each other. Distribution of the errors was simulated and is illustrated in Fig. 7. As seen in this figure, maximum error of the prediction model is about 0.012 mm and almost 98% of prediction errors is less than 0.002 mm. After training the model and designing the prediction system, the model was calibrated using the test results. The parameters of these tests have not been used in training the model. However, comparison results confirm the accuracy and reliability of the prediction model as presented in Table 4. For demonstrating the generality and reliability of the model, regression analysis for the measured and estimated data was carried out. The results were graphically shown in Fig. 8. Based on the regression analysis, the value of R^2 was obtained as 0. 99975 and 0.958 for training and test experiments respectively.

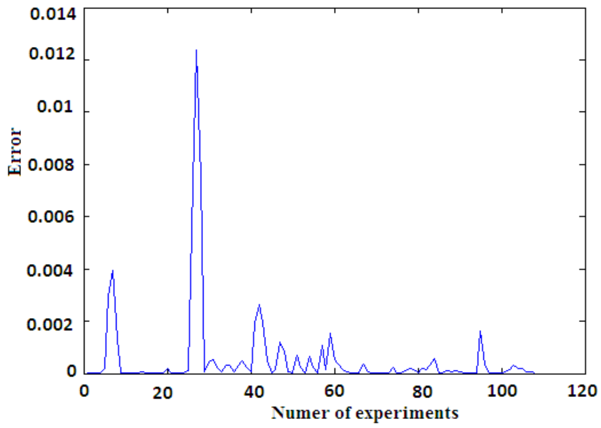

Fig. 7 Distribution of the errors for ANN online prediction model

Table 4 Calibration of the ANN prediction model using test parameters

Testnumber	Cutting speed (m/min)	Feed rate(mm/rev)	Cutting depth (mm)	Cuttingforce (N)	Measured flank wear (mm)	EstimatedFlank wear(mm)
1	110	0.21	1.6	1180	0.1	0.11
2	132	0.22	1.4	1046	0.21	0.195
3	112	0.24	1.4	993	0.11	0.08
4	110	0.2	0.9	731	0.22	0.218
5	125	0.2	1	704	0.16	0.18
6	135	0.23	1	744	0.18	0.22
7	110	0.27	1.2	956	0.12	0.13
8	155	0.27	1.2	968	0.3	0.34
9	160	0.27	1.25	905	0.16	0.17
10	160	0.27	1.1	804	0.09	0.13
11	135	0.17	1.3	816	0.26	0.24
12	110	0.17	1.25	1050	0.49	0.58

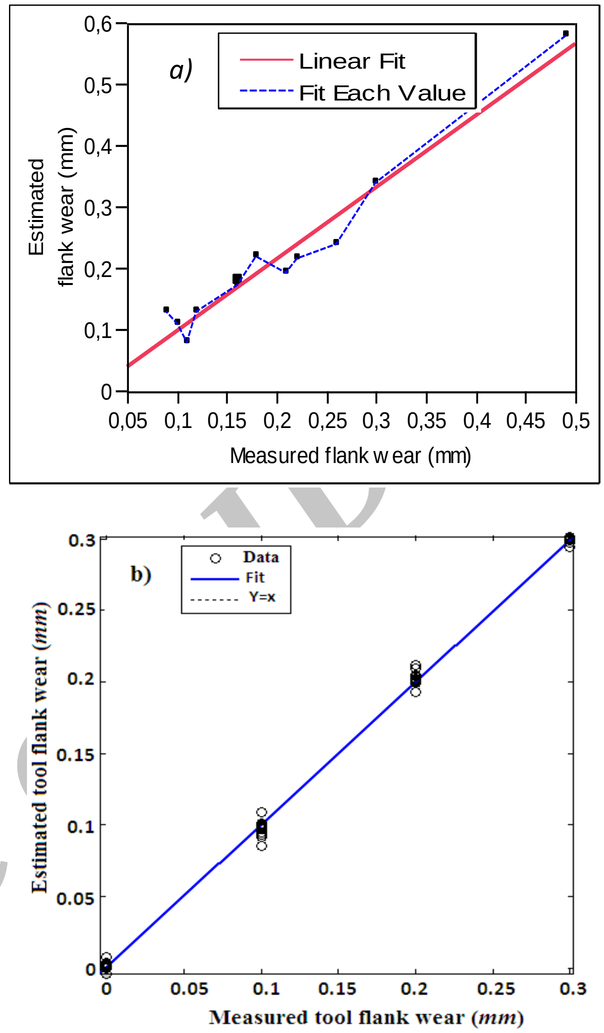

Fig. 8 Comparison of estimated and measured results: a) R^2=0.99975 for training and b) R^2=0.9824 for test experiments in table 4

7 CONCLUSION

In this study, an ANN model was designed for online tool life prediction in turning. As was depicted in Fig. 7, the prediction errors are remained under 0.012 mm. In other words the error estimation capability of the model would not exceed 0.012 mm which is an acceptable error in machining monitoring systems. The comparison of results simulated by ANN model for training data and the measured values shows a R^2 value of 0.99972. This means that the measured and estimated values confirm each other with a high accuracy. The generality of the designed model can be found by putting the unused parameters (in training) in estimation process. To achieve to this aim, 12 tests were conducted and the cutting force and wear rate were measured. Comparing the measured and estimated results using these 12 data showed a R^2 value of 0.9824. This value can prove the reliability of the model in term of generality. The results revealed that ANN is a strong and reliable method for predicting the tool wear rate in machining operations.

Moreover, it was found that online monitoring of the tool wear rate is possible by creating a simulation model of the ANN where the signals are taken from a dynamometer and transferred to the designed box. The model takes the cutting force signals and cutting parameters and estimates the wear rates immediately during the turning operation. Although the most common application of this model rather than the other researches is presenting a practicality in automation and computer integrated manufacturing systems (CIM), however the industrialist can easily apply this method in their work shop based on their individual cutting parameters. Also, application of the designed ANN model in an adaptive control involving machine tools and machining processes can be considered as a result of this research. Applying the ANN for adaptive control in machining processes will be the subject of future research for the researchers of the present study.

8 ACKNOWLEDGMENTS

The authors are very pleased to acknowledge that the work was supported by the Gazi University, Department of Scientific Research Project (Project Number 07/2012-23).

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