The Influence of Cutting Parameters on the Surface Hardness in Turning of 6061 Aluminum Alloy

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ABSTRACT

The primary design property necessary to ensure the longevity and durability of manufactured materials is the material hardness. The primary objective of this study was to investigate the effect of cutting parameters, namely feed rate, cutting speed, and depth of cut, on the surface hardness generated during the turning process of aluminum alloy 6061. The turning experiments were conducted using a Taguchi L27 orthogonal array arranged for three-level cutting parameters. The Analysis of Variance (ANOVA) was employed to determine the relative importance of each parameter on surface hardness. Additionally, an Artificial Nural Network (ANN) predictive model using the back-propagation learning algorithm was created to predict surface hardness levels at each level of the cutting parameters. The results revealed that increasing the values of all the turning parameters resulted in an increase in hardness, and it was concluded that the feed rate was the most critical factor (53.41%) in achieving high surface hardness, followed by the depth of cut (27.89%), whereas cutting speed had a lower impact (18.7%). This study also suggests a simple equation for estimating the surface hardness from the cutting parameters. The ANN model could accurately estimate the surface hardness with a coefficient of correlation (R) higher than 0.98 between the predicted and experimental values. The predicted values of hardness by ANN were more precise (R^2 =0.973839) than those predicted by ANOVA (R^2=0.893).

Keywords-AA6061; micro-hardness; correlation coefficient; ANN; ANOVA; feed rate; cutting speed; depth of cut

I. INTRODUCTION

Turning is an essential machining process in which a single point cutting tool removes small chips of material from a rotating cylindrical workpiece surface. The surface layers become deformed and hardened after the process, which allows them to withstand plastic deformation. This is important for designers when testing corrosion resistance and initiating fatigue cracks in parts throughout their use. Consequently, caution should be taken when choosing cutting parameters such as feed rate, cutting speed, depth of cut, cutting tools, and type of machine tools, whether with manual or Computer Numerical

Control (CNC) [1]. Round bars made of aluminum alloy 6061 are highly adaptable and are used in a variety of applications because of their strength, ease of machining, and heat treatability. This material is quite good at withstanding and tolerating high temperatures without breaking down [2]. Few studies have investigated the hardness of machined Al alloys. Most previous research has concentrated on surface roughness and optimizing the appropriate cutting settings [3-5]. Several optimization methods have been employed to enhance the production process by optimizing input parameters for machining through the Taguchi optimization method. This method requires fewer trials for optimization, thereby lowering the cost associated with testing and manufacturing [6-9].

Several studies on the parameters affecting the surface hardness of different materials after turning have been performed using different optimization algorithms based on Response Surface Methodology (RSM) and proper design of experiments [10]. For example, the authors in [11] used the Box-Behnken design to optimize the cutting process parameters to improve the quality of machined components made from 6082-T6 aluminum alloy. The parameters considered were cutting speed, feed rate, and depth of cut. The authors in [12] demonstrated that during dry turning and minimum quantity cooling of turning magnesium alloys (AZ91D), the cutting process parameters had a significant impact on the force needed for cutting, surface quality, tool flank wear, and cutting temperature. They found that the feed rate and cutting speed were the most important factors. Optimization of the parameters was performed following the Taguchi method and Taguchi-based Grey Relational Analysis (GRA). The authors in [13] employed the Taguchi L9 orthogonal array experimental design, adjusting the feed rate, depth of cut, and nose radius to study their impact on the surface roughness, rate of material removal, cutting duration, and cutting force. Similarly, the Taguchi method was used to determine the optimal turning parameters for achieving the maximum hardness of aluminum 6061 [14]. The influence of the cutting parameters along with the cooling method, blank size, and work material on the dimensional accuracy, circularity, diameter error, and surface roughness (Ra) of turned aluminum 6061, mild steel 1030, and alloy steel 4340 workpieces were investigated using the Taguchi method and statistical analysis [15]. The optimal turning parameters for turning aluminum 6063 with carbon nitride inserts were estimated through statistical methods. Experiments based on the Taguchi method L27 orthogonal array were evaluated using the "lower the better" approach [16].

Artificial Neural Network (ANN) models have also been used to optimize turning parameters. Al-Ani [10] compared an ANN model and the RSM for predicting surface roughness after turning aluminum 6061. The ANN exhibited better predictive performance. However, both the ANN and RSM found that the cutting speed and feed rate were the major factors affecting the surface finish. Other sophisticated approaches for predicting and optimizing the surface finish of machined Al alloys include the finite element model [17] and genetic algorithms [18].

According to the previous literature review, there is a considerable body of knowledge regarding the machinability of aluminum alloys. However, it should be noted that extensive studies on the surface hardness of 6061 alloys using different cutting tools have not yet been conducted. Consequently, this study aims to develop a mathematical model for predicting the surface hardness (HV) of aluminum 6061. To this end, turning tests were performed, and the hardness of the turning surface was estimated. The mathematical model was then formulated using an ANN, and an Analysis of Variance (ANOVA) was employed to determine the contribution of the cutting parameters to HV. Additionally, the mathematical model was validated by examining the influence of the turning cutting parameters (feed rate, cutting speed, and cutting depth) on the surface hardness of aluminum alloy 6061. The aim was to assess the impact of these parameters in the surface hardness using ANN and ANOVA analyses [19].

This research is pioneering in that it establishes a dependable and precise model for predicting the surface hardness and optimizing the turning parameters of Al 6061 alloy. The results of this study are expected to have a substantial positive impact on the aerospace industry and CNC machining.

II. METHODOLOGY

A. *Turning Process*

Cylindrical bars (diameter, D = 50 mm; length, L = 300 mm) of aluminum alloy 6061 were machined to obtain specimens 30 mm in length by turning in a medium CNC turning machine using an uncoated carbide cutting tool. A new insert edge was utilized for each experiment to guarantee the same cutting conditions.

The design of experiments was performed using three controllable factors of three levels and one response variable. The three factors were Cutting Speed (Cs), Feed Rate (Fr), and Depth of Cut (Dc). The values for each factor and level were selected based on our experience with aluminum alloy 6061 and are shown in Table I. For a full factorial design, 27 runs were needed. Therefore, turning experiments were conducted for 27 sets of cutting parameters, which were reported according to the orthogonal array of L27. After turning, the micro-hardness, HV, of the 27 turned parts was estimated. In turning operations, usually greater micro-hardness values are ideal for surface integrity.

TABLE I. SELECTED PROCESS PARAMETERS AND LEVELS FOR EXPERIMENTAL TRIALS

Level	Cs (rpm)	Fr (mm/rev)	Dc (mm)
1	150	0.07	0.2
2	230	0.13	0.4
3	355	0.3	0.6

The tool architecture parameters and geometry were selected from the tool database in the Mastercam X5 program, as shown in Figure 1. For each set of factors (Cs, Fr, and Dc), the Vickers micro-hardness profile was measured by creating five random indentations and rejecting the outliers. An HM-200 tester was used for the micro-Vickers hardness measurements and to determine the average hardness value from the three measurements.

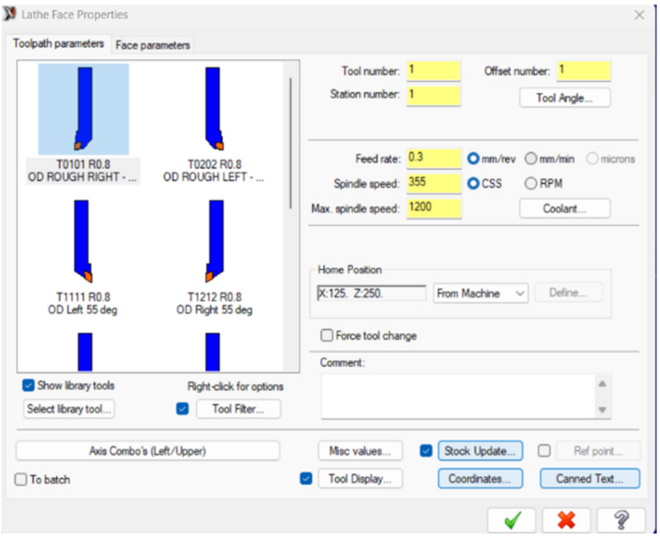

Fig. 1. A turning tool was selected using Mastercam X5.

B. Analysis of HV Results Utilizing Taguchi Method

The results were analyzed using the Minitab-17 software. For the analysis, the dependent variable was HV, whereas the independent variables were Cs, Fr, and Dc. Furthermore, Pareto-ANOVA analysis was performed to determine the impact of each factor according to the following criteria [13]:

When P>0.10, the factor has insignificant impact. When 0.05<P<0.10, the factor is moderately significant. When P<0.05, the factor has significant impact.

The Taguchi Signal-to-Noise (S/N) ratio was used to optimize the process parameters by measuring how the response factor varied with respect to a target value under various noise conditions. The experimental data were converted to the corresponding S/N ratios using the following equation [19]:

$$S/N(n) = -10log_{10}\frac{1}{n}\sum_{i=1}^{n} 1/y_i^2 \qquad (1)$$

S/N is the signal-to-noise ratio in decibels, y_i is the result of the ith experiment, and n is the overall number of observations for each response, y_i. The S/N ratio analysis was performed according to the "bigger is better" option, that is, the higher the S/N ratio value, the higher the quality characteristics. Consequently, the optimum set of process parameters was selected based on the higher S/N value. A response was then generated to estimate the order of the parameters that affect the hardness [20].

C. Artificial Neural Network Model

The ANN is capable of finding complex relationships among various factors influencing a desired outcome [21]. Although the Back Propagation Algorithm (BPA) is commonly used as a neural network training method, its convergence tends to be slow. In contrast, Levenberg Marquardt (LM) offers a faster alternative, leading to the utilization of BPA with LM for network training. The input layer of the network comprises three neurons representing Cs, Fr, and Dc. The output layer contained one neuron for the response factor. The appropriate number of neurons inside the hidden layer was determined through trial and error. The optimal configuration, resulting in the minimum mean squared error for surface roughness prediction, was found to include 20 neurons in the hidden layer.

MATLAB provides a Neural Network Toolbox for simulating neural networks, which facilitates the construction of a neural network model for training and testing data to categorize, identify hidden models, group, and make predictions. The most accurate artificial neural network architecture designed in the MATLAB toolbox is illustrated in Figure 2.

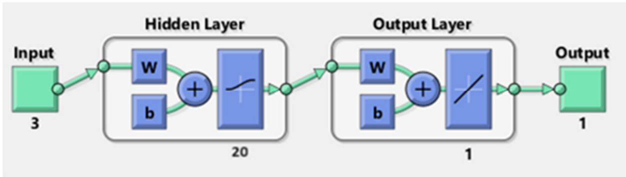

Fig. 2. The neural network architecture.

An experiment was conducted using the NN Toolbox provided by MATLAB with the cutting parameters set of data as previously described. The dataset, comprised of 27 models, was randomly divided into two groups, with 70% used for training and the remaining 30% for testing. Using the training data, a neural network model was generated and the impact of various activation functions on the network layers was evaluated with respect to hardness values and MSE in the results. Nineteen models were trained to analyze ANN surface irregularities, and the weights after training were fixed for evaluation. We confirmed the network's adherence to the experimental results and calculated its compliance using the mean absolute percentage error and correlation coefficient (R^2) as key metrics.

III. RESULTS AND DISCUSSION

A. Experimental Results Analysis

The results of the 27 experiment runs are listed in Table II, showing the average surface hardness HV and S/N ratio. The influence of each cutting parameter on HV is shown in Figure 3. It can be observed from Figure 3a that micro-hardness increased with increasing feed rate. This can be explained by the fact that as the feed rate increases, the cutting force also increases because the tool propagation exerts a higher resistance. As shown in Figure 3b, the microhardness increased as the cutting speed increased. This can be rationalized as an increase in the cutting force when the cutting speed increases. Figure 3c shows that an increase in the cut depth causes the hardness to increase. This phenomenon indicates that an improvement in the cut of depth value results in an improvement in cutting forces, which leads to a more work-hardened surface layer.

TABLE II. EXPERIMENTAL TESTS WITH A MEASURED SURFACE HARDNESS AND S/N

No	Cs (rpm)	Fr (mm/rev)	Dc (mm)	HV	S/N (dB)
1	355	0.3	0.6	138.1	42.8039
2	355	0.3	0.4	125.7	41.9867
3	355	0.3	0.2	120	41.5836
4	355	0.13	0.6	128.85	42.2017
5	355	0.13	0.4	118.33	41.4619
6	355	0.13	0.2	104.66	40.3956
7	355	0.07	0.6	110	40.8279
8	355	0.07	0.4	101	40.0864
9	355	0.07	0.2	90.8	39.1617
10	230	0.3	0.6	130	42.2789
11	230	0.3	0.4	120.1	41.5909
12	230	0.3	0.2	110	40.8279
13	230	0.13	0.6	125	41.9382
14	230	0.13	0.4	105.6	40.4733
15	230	0.13	0.2	87.95	38.8847
16	230	0.07	0.6	100.5	40.0433
17	230	0.07	0.4	90	39.0849
18	230	0.07	0.2	75.73	37.5854
19	150	0.3	0.6	120.4	41.6125
20	150	0.3	0.4	115	41.2140
21	150	0.3	0.2	110	40.8279
22	150	0.13	0.6	102.7	40.2314
23	150	0.13	0.4	99.7	39.9739
24	150	0.13	0.2	93.6	39.4255
25	150	0.07	0.6	93.8	39.4441
26	150	0.07	0.4	81.3	38.2018
27	150	0.07	0.2	64.22	36.1534

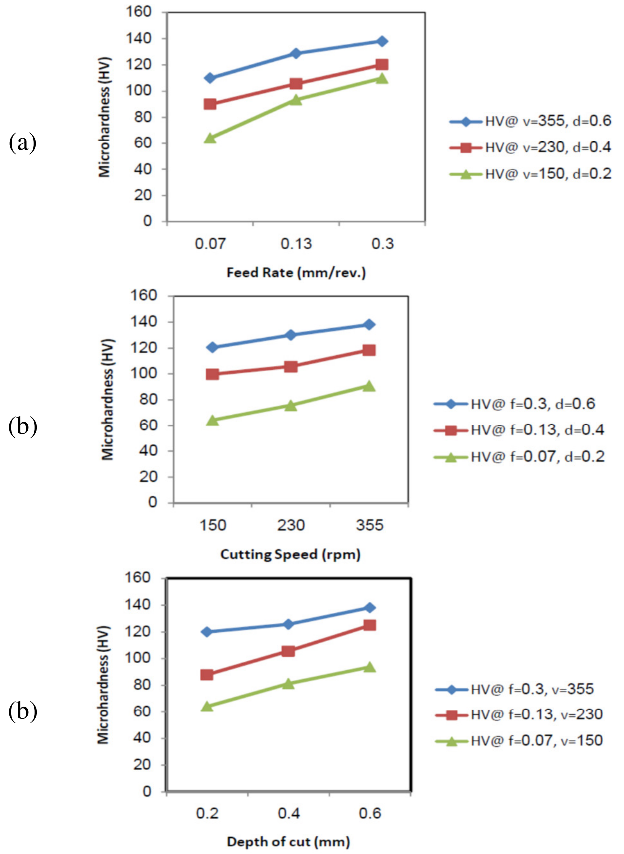

Fig. 3. Effect of feed rate, cutting speed, and depth of cut on hardness.

B. Analysis of the Parameters Results in Micro-Hardness

To enhance the outcome of the reaction on the aluminum alloy 6061, the S/N was employed as an indicator of the output quality to identify the optimal level of each parameter. Typically, a higher S/N ratio signifies a higher quality output, as depicted in Table II.

Table III displays the response table of the S/N for the three-level factors. The optimal parameters for maximum surface hardness corresponded to the highest S/N. Figure 4 shows the optimal parameters according to the highest S/N ratio for HV, which are Cs=355 rpm, Fr=0.30 mm/rev, and Dc=0.6 mm.

TABLE III. RESPONSE TABLE OF S/N RATIOS FOR THE THREE LEVEL FACTORS

Level	Cs	Fr	Dc
1	39.68	38.95	39.43
2	40.3	40.55	40.45
3	41.17	41.64	41.26
Delta	1.49	2.68	1.84
Rank	3	1	2

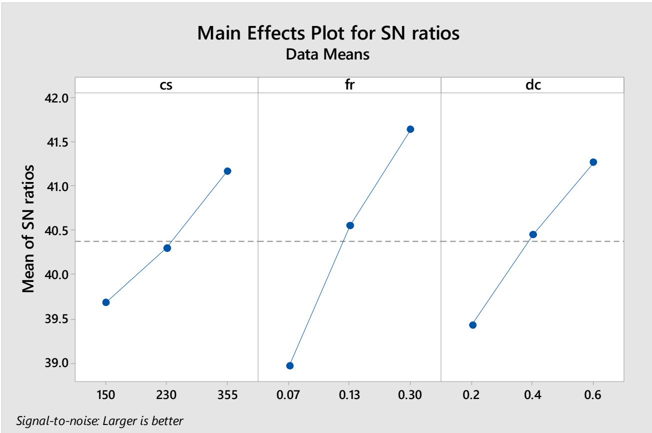

Fig. 4. Main effects of turning parameters on HV.

An ANOVA statistical analysis of the experimental data was performed for the HV values, and the results are shown in Table IV. The obtained results demonstrated a considerable impact ($P<0.05$) for all the factors on the HV values. Additionally, the F-value signifies the percentage of influence of each parameter. The higher the F value, the greater is the impact on the machining performance characteristics. According to Table IV, the feed rate had the highest contribution to HV (53.41%), followed by the depth of cut (27.89%), and the cutting speed, which was less significant (18.7%).

TABLE IV. ANOVA FOR SURFACE MICRO-HARDNESS.

Factor	Degree of Freedom	Sum of Squares	Mean Squares	F-value	P- value	Contribution (%)
Cs	1	1378.8	1378.79	35.91	0	18.7
Fr	1	3937.6	3937.61	102.54	0	53.41
Dc	1	2056.3	2056.33	53.55	0	27.89
Error	23	883.2	38.4			
Total	26	8255.9				

Using significant regression coefficients, the micro-hardness HV can be estimated according to the following equation:

$$HV= 43.25 + 0.0847\ Cs + 124.0\ Fr + 53.44\ Dc \quad (2)$$

$R^2 = 0.893$, $R^2_{adj}= 0.89$

The R_2 and R^2_{adj} values of about 90% indicate that the model is acceptable and adequate. The plots in Figure 5 display that the residuals form a straight line, which implies that the errors are consistent and demonstrate the reliability of the model [13].

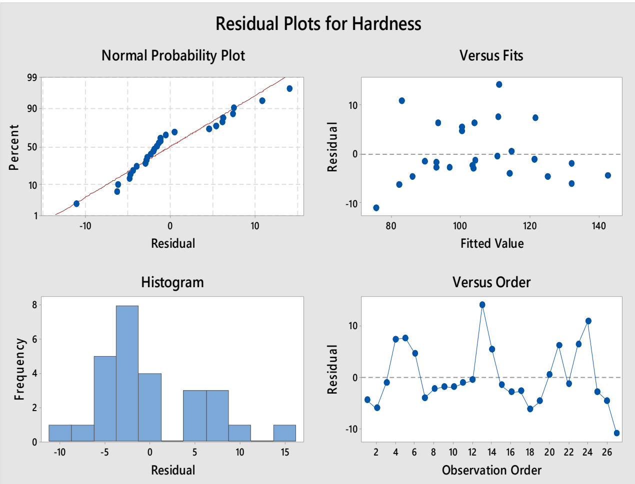

Fig. 5. Residual plots for the mathematical expression of hardness.

C. Simulation Result of ANN

The neural network model receives input data to target the output parameter of surface hardness for three individual variables: cutting speed, feed rate, and depth of cut. The model is layered, distributing the input data until it produces an output. The output is then compared to the goal, which is actual surface hardness in this case. The error is measured, and the network is propagated backward until the minimum error value is reached. Figure 6 shows that the resultant tracks have a strong training orientation, confirmation, and experimentation with R-values of 0.99444, 0.99995, and 0.996151, respectively. These values result in an overall R-value of 0.98683, with a reported MSE of 0.00328. In this case, the network output is favorable, and the model can be utilized for new inputs. The regression (R) plot displays the significance of the difference between the target (measured hardness value) and the ANN output (predicted hardness value), with an R-value of 0.9665 indicating that the output of the ANN closely resembles the intended result.

To predict the output responses, the trained ANN was simulated using data from the input process variables. The predicted outputs were in the same range as the normalized range of the output data group used to train the neural network. It is evident from Figure 7 that the predicted values of hardness by ANN are more accurate (R^2= 0.973839) than those predicted by ANOVA (R^2 =0.893) when compared with the experimental values of hardness [22].

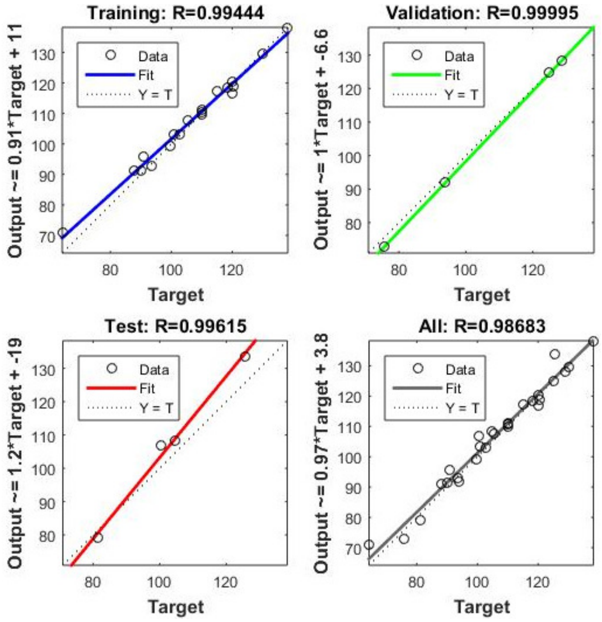

Fig. 6. Correlation coefficient of the trained ANN model.

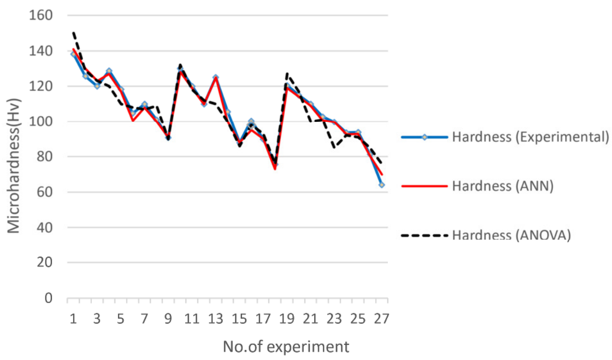

Fig. 7. Comparison of surface hardness values from experiments and predictions.

IV. CONCLUSIONS

The manufacturing process plays a crucial role in determining the surface hardness of the finished product. Therefore, understanding the relationship between the machining process and the surface hardness is essential. In this study, the hardening of aluminum alloy 6061 during turning was examined, and reasonable conclusions were drawn based on the context investigated.

The optimal cutting parameters for turning were determined using the Taguchi signal-to-noise (S/N) ratio. The minimum hardness was found to be achieved at cutting speed of 150 rpm, feed rate of 0.13 mm/rev, and depth of cut of 0.6 mm. In contrast, the maximum hardness was obtained at a cutting speed of 355 rpm, feed rate of 0.13 mm/rev, and depth of cut of 0.6 mm. Generally, the surface micro-hardness increases when all the cutting parameters increase. The verification tests concluded that the results achieved were precise, up to 89.3%. An Analysis of Variance (ANOVA) revealed that the feed rate had the most significant impact (53.41%) on surface hardness, followed by the depth of cut (27.89%), and the cutting speed had the least impact (18.7%). The results suggest that the three parameters used in the turning process have a significant effect on the surface hardness [23]. Moreover, an Artificial Neural Network (ANN) was used to predict surface micro-hardness, and the ANN model was found to be more accurate than Taguchi's method. The predicted values of hardness estimated by the ANN were more accurate (R^2 =0.973839) than those predicted by ANOVA (R^2= 0.893) and when compared with the experimental values of hardness [24].

The novelty of this study lies in the evaluation of sustainability indicators and machining characteristics to enhance machining efficiency, reduce tool wear, and improve surface hardness. This study is expected to boost manufacturing productivity, increase production efficiency, reduce production costs, and enhance competitiveness in the aluminum 6061 alloy manufacturing industry. The primary novelty lies in avoiding the traditional manual experimental selection of process parameters and employing optimization methods to determine efficient cutting process parameters. In future research, it would be beneficial to investigate the influence of additional turning cutting parameters, such as coolant, cutting material, and tool geometry, on the surface hardness of the aluminum alloy AA-6061.

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