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SURFACE ROUGHNESS PREDICTION IN CNC TURNING USING ARTIFICIAL NEURAL NETWORK (ANN)

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ABSTRACT

Computer Numerical Control (CNC) turning is one of the most widely applied precision machining technologies in modern manufacturing, where surface quality is a key determinant of product performance and reliability. Surface roughness (Ra) is recognized as one of the most critical parameters for evaluating machining results. However, reliance on operator experience in selecting machining parameters often leads to inefficiencies and inconsistent surface quality, indicating the need for more accurate predictive approaches. This study proposes an Artificial Neural Network (ANN)-based model to predict surface roughness in CNC turning using two distinct experimental configurations. The first experiment (Exp1) employs three identical factor variations, whereas the second experiment (Exp2) incorporates different factorial combinations to introduce broader variability. The developed ANN architecture consists of four dense layers with ReLU and LeakyReLU activation functions, complemented by dropout layers to mitigate overfitting arising from the relatively small dataset. The results show that the ANN model effectively learns the nonlinear relationships between machining parameters and Ra values. Furthermore, the model achieves higher predictive accuracy in Exp2, likely due to its more structured parameter variations. Overall, the findings demonstrate that ANN-based prediction provides a promising and efficient approach for enhancing accuracy in surface quality assessment within CNC turning operations.

***Keywords*—** *CNC turning; surface roughness; Artificial Neural Network (ANN).*

I. INTRODUCTION

The CNC turning process is a precision machining method based on *Computer Numerical Control* (CNC) technology, which is employed to produce cylindrical components by rotating the workpiece at a specific spindle speed while the cutting tool moves linearly to remove excess material from its surface (Zurita, 2017). This process is extensively utilized in the manufacturing industry due to its capability to achieve high levels of dimensional accuracy, surface smoothness, and consistency, even when machining hard-to-cut materials such as stainless steels and nickel-based alloys (Rajesh et al., 2022).Numerous factors affect the quality of machining outcomes in the turning process, among which *surface roughness* is considered one of the most critical parameters, as it significantly influences the functional performance, fatigue strength, and overall quality of the final product (Abubaker et al., 2021).

The surface quality produced by the turning process serves as a fundamental indicator for evaluating machining performance and the integrity of the final product (Hoon & Chen, 2025). Among the most widely adopted parameters for assessing surface quality is surface roughness, which is commonly represented by the Ra value (arithmetical mean roughness). The Ra value is strongly influenced by multiple machining parameters, such as cutting depth, cutting speed, feed rate, and tool condition, as well as other factors that govern the interaction between the cutting tool and the workpiece material (Ate, 2024). Consequently, the identification and optimization of cutting parameters play a crucial role in achieving the desired surface finish, enhancing functional performance, and ensuring that the final product meets the required dimensional and surface specifications (Ruan et al., 2024).

In general, machine operators rely on trial-and-error methods to adjust machining parameters in order to achieve the desired final outcome. However, this approach is inefficient and often requires considerable time to obtain optimal results(Dubey et al., 2022). Over time, efforts to predict surface roughness have increasingly employed empirical models or linear regression methods based on experimental data and analytical formulations. In the study conducted by Mark et al., several regression techniques were evaluated, including Linear Regression, Decision Tree, Random Forest, Epsilon-Support Vector Regression (ε-SVR), and K-Nearest Neighbors Regression (KNN) (Usgaonkar & Gaonkar, 2025). Nevertheless, these approaches still require further development and adjustments to accommodate specific combinations of materials and machining conditions, so that they can be applied flexibly across various machining scenarios. Therefore, a new prediction method is needed to more accurately estimate the Ra value.

With the advancement of artificial intelligence (AI) technologies, new approaches have emerged for predicting the Ra surface roughness value with higher accuracy. One widely adopted technique is the Artificial Neural Network (ANN), a computational model that mimics the functioning of human neural networks in recognizing patterns and capturing complex relationships among variables (Mohd et al., 2010). Several studies have demonstrated the potential of this method, such as the work conducted by Antosz et al., which explored various ANN model configurations and reported that ANN can efficiently and optimally predict Ra values(Antosz et al., 2025). Another study by Abdel et al. compared ANN with fuzzy-based methods, revealing that ANN outperformed the fuzzy approach in terms of prediction accuracy(Sharkawy, 2011). Nevertheless, most of these studies have predominantly focused on

CNC milling, indicating that the application and implementation of ANN in CNC turning for Ra prediction remain relatively limited and warrant further investigation.

Therefore, this study aims to develop a surface roughness prediction model using the Artificial Neural Network (ANN) approach for the CNC turning process. The proposed model is expected to provide more accurate predictions of surface roughness (Ra) compared to traditional empirical methods. In addition, the model is intended to serve as a basis for determining optimal machining parameters, enabling more efficient and consistent operations while ensuring the desired surface quality in manufacturing applications.

II. METHOD

In this study, we employed several key stages to predict the surface roughness (Ra). These stages include the acquisition of CNC turning data, data preprocessing, the development of an Artificial Neural Network (ANN) model for training and testing, followed by a model evaluation phase to assess its predictive performance. The final stage involves generating predictions using the optimized model. The overall workflow of the research process is illustrated in Figure 1, which presents the block diagram of the methodology adopted in this study.

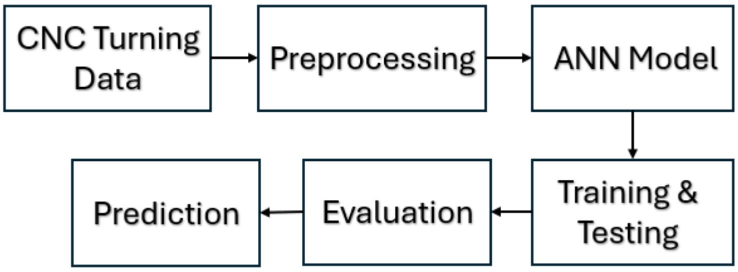

Figure 1. Block diagram

A. CNC Tuning Data

The data used in this study consist of a CNC turning dataset obtained from the Competence Center in Manufacturing (CCM) at the Aeronautics Institute of Technology (ITA), which is publicly available on the Kaggle platform. The dataset comprises two primary experiments, namely Exp1 and Exp2, both conducted using CNC turning operations on AISI H13 steel with the application of cutting fluid (André Dorigueto Canal, 2022).

Experiment 1 (Exp1) was conducted using a new cutting tool and generated 324 samples for each surface roughness parameter. Exp1 consisted of a full factorial experiment with three factors, each varying at three levels (DoE: 3^3), and two replicates, resulting in 54 machining operations. In contrast, Experiment 2 (Exp2) was conducted using tools with three levels of flank wear and generated 288 samples per parameter. Exp2 also employed a full factorial design with three factors at three levels (DoE: 3^3) and two replicates, resulting in 54 machining operations.

The dataset includes several key machining parameters, namely depth of cut (ap), cutting speed (vc), and feed rate (f), as well as response variables such as arithmetic mean surface roughness (Ra), skewness (Rsk), kurtosis (Rku), mean profile width (RSm), and total height (Rt). Additionally, the dataset provides cutting force measurements, including cutting force (Fc), passive force (Fy), feed force (Fz), and resultant force (F), along with information on tool wear condition (TCond). In this study, the primary focus is on predicting the Ra value as an indicator of surface roughness.

B. Preprocessing Data

At this stage, the data are cleaned and prepared prior to being used in the training process of the ANN model. All input features are normalized using the Min–Max Scaler to standardize their value ranges and enhance the stability of the learning process (Sanjay & Jyothi, 2006). The normalization method computes the transformed values based on the following formula:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

where:

- x : Actual value
- x' : Normalized value
- $x_{\min}$: Minimum value of the feature
- $x_{\max}$: Maximum value of the feature

The normalized values fall within the range of [0, 1]. Through normalization, each feature is assigned a comparable scale, thereby preventing any single feature from dominating the learning process. In addition, data quality checks, relevant feature selection, and the partitioning of the dataset into training and testing subsets are performed to ensure an objective evaluation of the model.

C. *ANN Model*

Artificial Neural Network (ANN) is a computational model inspired by the functioning of biological neural networks in processing information. An ANN consists of interconnected artificial neurons that operate in parallel to recognize patterns, learn nonlinear relationships, and generate predictions for output variables based on the given inputs (Mohd et al., 2010).

In this study, an ANN model was developed to predict the surface roughness (Ra) based on the machining parameters contained in the dataset. The model architecture consists of multiple hierarchical layers that enable deeper feature extraction. The first layer is the input layer, which receives all machining parameters that have undergone the preprocessing stage.

Subsequently, the model includes dense layers that function to learn the complex patterns and interactions among the parameters. In this study, the dense layer consists of 52 neurons and is equipped with activation functions. The activation functions employed are ReLU and LeakyReLU, both of which were evaluated using the Exp1 and Exp2 datasets to compare their performance.

The subsequent layer is a dropout layer, which is employed to prevent overfitting, considering that the amount of data in each experiment is relatively limited. The final layer is the output layer, consisting of a single neuron that produces the predicted Ra value. The overall architecture of the model used in this study is illustrated in Figure 2.

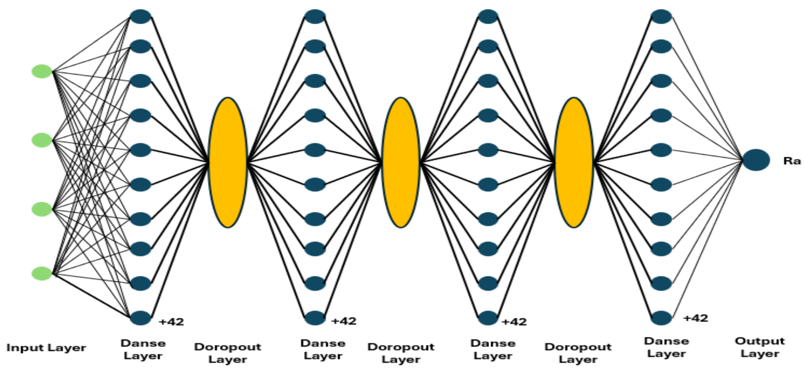

Figure 2. ANN Model Architecture

D. *Evaluation*

This evaluation stage aims to assess the performance of the Artificial Neural Network (ANN) model in accurately and consistently predicting the surface roughness (Ra). The evaluation is conducted by comparing the model's predicted values with the actual Ra values, using several performance metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2 Score) (Borucka & Kozłowski, 2024).

1) Mean Squared Error (MSE)

Mean Squared Error (MSE) is an evaluation metric used to measure the average of the squared differences between the predicted values ($\hat{y}_i$) and the actual values (y_i), which is estimated as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

2) Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is an evaluation metric used to measure the average magnitude of the absolute errors between the model's predicted values and the actual values. The MAE is calculated using the following formula:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\, y_i - \hat{y}_i \,| \tag{3}$$

3) Mean Absolute Persentage (MAPE)

Mean Absolute Percentage Error (MAPE) is an evaluation metric that represents the average absolute error relative to the absolute actual values, and it is calculated as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{max(\epsilon, |\, y_i|)} \,| \tag{4}$$

4) Coefficient of Determination (R^2 Score)

The coefficient of determination (R^2) is an evaluation metric used to indicate the proportion of variability in the dependent variable that can be explained by the model, and it is calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5}$$

III. RESULT AND DISCUSSION

The research process is illustrated in Figure X. In the first stage, the CNC turning dataset consists of two experiments, namely Exp1 and Exp2. Each experiment contains several machining parameters, and in this study, eight parameters were selected as inputs: depth of cut (ap), cutting speed (vc), feed rate (f), cutting force (Fc), passive force (Fy), feed force (Fz), resultant force (F), and tool wear level (TCond). These parameters were used as input variables for predicting the Ra value.

Subsequently, all data were normalized using the Min–Max Scaler method to standardize the range of values before being fed into the model. The dataset was then divided into two partitions: training data and testing data, with proportions of 80% and 20%, respectively. The training data were used to train the model in learning the patterns and characteristics required for prediction, while the testing data were used to evaluate the model's performance after the training and validation processes were completed.

The third stage involves preparing the model to be used in this study. The model employed is an ANN consisting of four dense layers equipped with the ReLU activation function. In addition, the study also incorporates an alternative activation function, LeakyReLU, to compare the resulting model performance.

A dropout layer with a rate of 0.09 is added to each dense layer to mitigate the occurrence of overfitting during the training process. The inclusion of dropout is particularly important given the relatively small size of the dataset, which increases the likelihood of overfitting.

Table 1. Training Configuration

Data	Model	Batch size	Epoch	Optimizer
Exp 1	ANN	16	10000	Adam
Exp 2				

The fourth stage involves the training process, which is carried out using the configuration presented in Table 1. Each experimental dataset is trained using the same configuration, consisting of a batch size of 16 and the Adam optimizer with a total of 10,000 epochs. The training process in this study is implemented using Python 3 and executed on a system equipped with an Intel(R) Core(TM) i5-10500H processor and an NVIDIA GTX 4GB GPU.

In Figure 3 presents the loss curve during the training process for the Exp1 dataset. At the initial epochs, the loss value is relatively high; however, it begins to decrease significantly around the fifth epoch and subsequently stabilizes, with minor fluctuations, reaching a final value of 0.016. This behavior indicates that the model progressively learns the underlying characteristics of the data and successfully captures the relevant patterns. A similar trend is observed in Figure 4, which illustrates the loss curve for the Exp2 dataset. The loss also stabilizes at a final value of 0.012. These results demonstrate that the model employed in this study is capable of learning efficiently and effectively in recognizing the inherent patterns within the dataset.

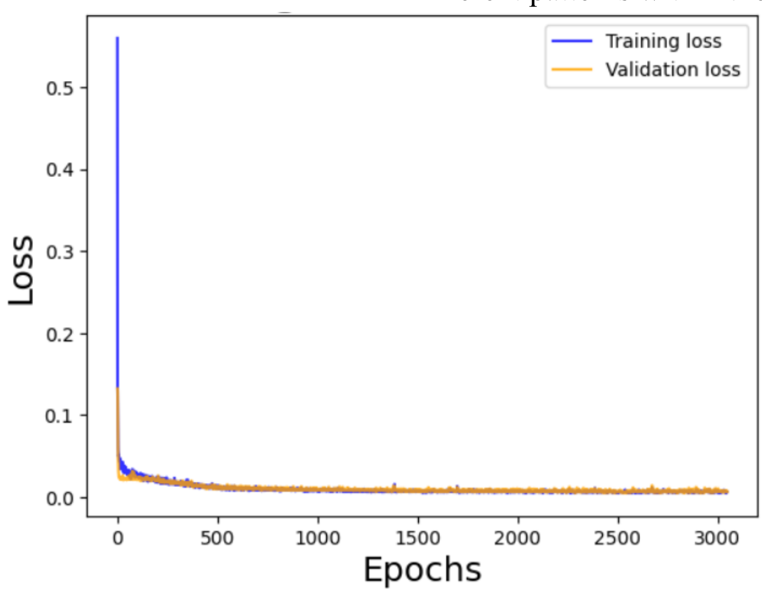

Figure 3. Training and validation loss for Exp1

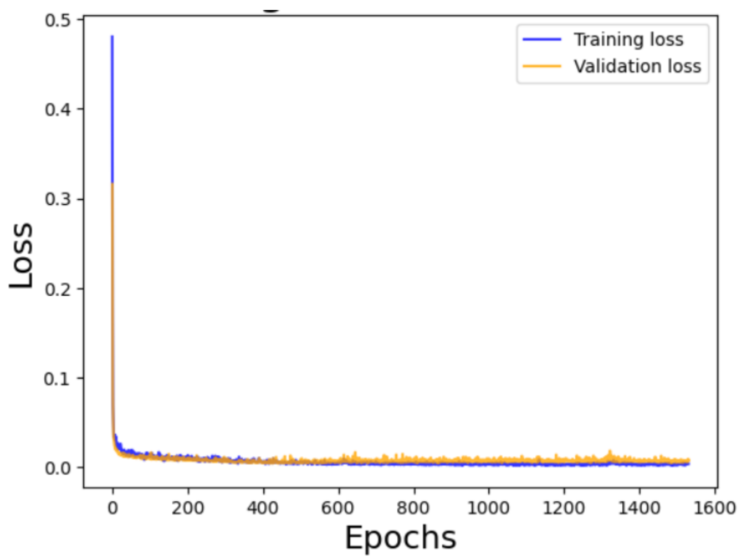

Figure 4. Training and validation loss for Exp2

The next stage involves evaluating the model generated during the training process using both the training and validation datasets. This evaluation phase employs several assessment metrics namely MSE, MAE, MAPE, and R^2 to determine the model's performance for each experimental dataset.

Table 2 presents the evaluation results of the surface roughness (Ra) prediction model for two different experiments, namely Exp1 and Exp2. When compared, the MSE value in Exp2 is lower than that in Exp1, indicating that the model produces smaller squared errors and therefore generates predictions that are closer to the actual values.

Table 2. Comparison of model evaluation in Exp1 and Exp2

Data	MSE	MAE	MAPE	R^2
Exp 1	0,016	0.0884	11.73	0.87
Exp 2	0.003	0.0471	7.88	0.93

The MAE value in Exp2 is also lower, at 0.0471, which is nearly half of the MAE value observed in Exp1. This indicates that the model demonstrates better predictive capability when applied to the Exp2 dataset. Regarding the MAPE metric, values below 10% are generally considered acceptable for predictive performance evaluation. When compared, the MAPE value in Exp2 is lower, at 7.88%, suggesting that the model achieves higher and more stable accuracy on that dataset.

Overall, the MSE, MAE, and MAPE values for Exp2 are significantly lower than those for Exp1. In addition, the R^2 value for Exp2 is higher, indicating that the model in this experiment exhibits superior modeling quality and a stronger ability to capture the relationship between machining parameters and Ra.

This study also compares the use of an alternative activation function, LeakyReLU, and evaluates its performance relative to the ReLU activation function. Table 3 presents the comparative performance results of the surface roughness (Ra) prediction model using these two activation functions across two different experiments, namely Exp1 and Exp2. The evaluation is conducted using the same four primary metrics employed in the previous analysis.

Table 3. Comparison of model evaluation for each activation function

Data	aktivasi	MSE	MAE	MAPE	R2
Exp1	Relu	0,016	0.0884	11.73	0.87
	LeakyRelu	0.014	0.089	12.84	0.88
Exp2	Relu	0.003	0.0471	7.88	0.93
	LeakyRelu	0.004	0.0481	7.78	0.92

In Exp1, the ReLU activation function produced an MSE of 0.016, an MAE of 0.0884, and a MAPE of 11.73%, with an R^2 value of 0.87. These results indicate that the model performs reasonably well overall. The use of the LeakyReLU activation function provided a slight improvement in model performance, as evidenced by a reduction in MSE to 0.014 and an increase in R^2 to 0.88. This suggests that LeakyReLU is slightly more effective in capturing nonlinear patterns in the Exp1 dataset compared to ReLU. Although the MAE and MAPE values are marginally higher, the increase in R^2 indicates improved model stability.

In Exp2, ReLU achieved the best performance, yielding the lowest MSE (0.003), an MAE of 0.0471, a MAPE of 7.88%, and the highest R^2 value (0.93). These results demonstrate that ReLU is highly effective for this dataset, providing high accuracy and low prediction error.

The LeakyReLU activation function exhibited performance that was nearly comparable to ReLU, with an MSE of 0.004 and an R^2 value of 0.92. The MAPE value was also slightly lower (7.78%) compared to ReLU. These findings indicate that LeakyReLU remains competitive and performs only slightly below ReLU in Exp2.

After completing the evaluation stage, the next step involves conducting the prediction process. In this study, five samples were selected from both the Exp1 and Exp2 datasets. These samples were then used to compare the actual surface roughness values (Ra) with the corresponding predictions generated by the model.

Table 4. Prediction results in Exp2

Data	Ra				
Actual	1.133	0.929	0.462	0.969	1.153
prediksi	1.071	0.776	0.409	0.989	1.090

Table 4. presents the comparison between the predicted values and the actual values for the Exp1 dataset. In the first sample, the predicted value is very close to the actual value, indicating that the model is able to capture the underlying patterns effectively. A similar condition is observed in the third, fourth, and fifth samples, where the differences between the actual and predicted values remain relatively small.

In the second sample, the model slightly underestimates the actual value, resulting in a somewhat larger discrepancy compared to the other samples. Nevertheless, overall, the model demonstrates a consistent and stable predictive performance. The prediction trend closely follows the actual values, and the resulting errors remain within an acceptable range. This indicates that the ANN model used in this study possesses good generalization capability in predicting surface roughness (Ra).

Table 5. Prediction results in Exp2

Data	Ra				
Actual	0.813	0.854	0.937	0.486	0.737
Prediksi	0.793	0.870	0.782	0.441	0.709

In Table 5. presents the comparison between the actual surface roughness (Ra) values and the model's predicted values for five samples in the Exp2 dataset. Overall, the model demonstrates good predictive capability, although some discrepancies between the actual and predicted values are observed.

In the first sample, the predicted value is very close to the actual value, indicating strong accuracy. The second sample also shows a positive result, where the predicted value is only slightly higher than the actual value, resulting in a relatively small difference. However, in the third sample, the model yields a predicted value lower than the actual one, indicating a tendency toward underestimation for that data point.

A similar pattern is observed in the fourth sample, where the model again slightly underestimates the actual value, though the difference remains within an acceptable range. In the fifth sample, the predicted value is again close to the actual value with a small discrepancy, showing consistent model performance across most samples.

Overall, although there are several instances of underprediction, the prediction pattern still follows the general trend of the actual values. This indicates that the ANN model used in this study possesses good generalization capability in predicting Ra for the Exp2 dataset and is able to provide stable and reliable results for the majority of the samples.

The comparison between the predicted Ra values in Exp1 and Exp2 demonstrates that the ANN model is capable of producing predictions that closely approximate the actual values in both experiments. However, the prediction accuracy in Exp2 is generally higher than in Exp1. In Exp1, the model exhibits relatively larger deviations, particularly for the second and third samples, which tend to be underpredicted. Nevertheless, the prediction patterns still follow the trend of the actual values, indicating that the model's performance remains acceptable.

In contrast, in Exp2, the model generates more stable and consistent predictions. The differences between the actual and predicted values are generally smaller across nearly all samples, although minor underestimations are still observed in some instances. Overall, these results suggest that the ANN model possesses better generalization capabilities when applied to the Exp2 dataset, resulting in higher prediction accuracy for Ra compared to Exp1. These differences are likely attributable to the characteristics of the Exp2 dataset, which may be more structured or exhibit machining parameter variations that are easier for the model to learn.

IV. CONCLUSION

This study aims to develop a predictive model for surface roughness (Ra) using an Artificial Neural Network (ANN) based on CNC turning datasets from two distinct experiments: Exp1, with three factors varied uniformly, and Exp2, with different factorial variations.

The training results indicate that the model is capable of learning the underlying patterns in the dataset, with the loss stabilizing at final values of 0.016 for Exp1 and 0.012 for Exp2. Evaluation using MSE, MAE, MAPE, and R^2 metrics shows that predictions for Exp2 are more accurate, exhibiting lower error values (MSE = 0.003, MAE = 0.0471, MAPE = 7.88%) and a higher R^2 (0.93) compared to Exp1 (MSE = 0.016, MAE = 0.0884, MAPE = 11.73%, R^2 = 0.87). The study also compares the use of activation functions, revealing that ReLU is more effective for Exp2, whereas LeakyReLU provides slight improvement for Exp1. Prediction analysis on selected samples demonstrates the model's good generalization capability. Although some underpredictions are observed, the predicted Ra values overall follow the trend of the actual measurements with stability.

Overall, the ANN model proves to be effective in predicting surface roughness in CNC turning processes, achieving higher accuracy for the Exp2 dataset. This is likely attributed to the more structured characteristics of Exp2 and the relatively easier-to-learn parameter variations in this dataset.

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