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ARTIFICIAL INTELLIGENCE-BASED MODELING OF POWER CONSUMPTION IN DRY TURNING OF 42CrMo4 STEEL

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Abstract: *This study presents the development of an artificial intelligence model for predicting power consumption in the dry turning of 42CrMo4 steel. A feedforward neural network (FNN) was designed using experimental data generated through a Central Composite Design approach. The network was trained and validated in MATLAB, achieving high correlation and low prediction errors for both training and test data. Validation with practical experiments demonstrated deviations under 10%, confirming the model's effectiveness for estimating power demand and supporting energy-efficient process optimization in CNC turning operations.*

Key words: *dry turning, feedforward neural network, power consumption, machining parameters, AI modeling, regression, MATLAB, CNC.*

1. INTRODUCTION

In the context of modern manufacturing, metal cutting operations such as turning remain among the most widely used processes for producing precision components [1], [2]. Dry turning, which avoids the use of cutting fluids, has gained popularity due to its environmental and economic benefits, including lower operational costs and improved sustainability [3], [4], [5]. However, dry machining can lead to increased tool wear and higher energy demands if cutting parameters are not carefully optimized [6], [7], [8]. Consequently, accurately predicting and controlling power consumption is essential for achieving both cost efficiency and environmental sustainability in machining operations [9], [10].

Power consumption in turning is a complex function of multiple factors, such as cutting speed (V_c), feed rate (f_n), and depth of cut (a_p) [11]. These parameters interact nonlinearly, making accurate modeling a significant challenge [4], [12]. Conventional analytical models often assume simplified cutting mechanics and fail to capture the true variability of real-world machining processes, especially under dry conditions [4], [13]. Experimental methods, while accurate, are costly and time-consuming when applied at scale [14], [15].

Recent advances in artificial intelligence (AI) and machine learning (ML) have opened new opportunities for overcoming these limitations [16], [17]. Artificial Neural Networks (ANNs) have proven to be especially effective for modeling complex, nonlinear relationships in machining [17], [18], [19]. Unlike conventional regression models, ANNs do not require prior knowledge of the underlying physical relationships and can learn directly from experimental data. Prior research has demonstrated their use in predicting outcomes such as surface roughness [20], tool wear [21], cutting forces [22], and machining-induced vibrations [23].

Despite these promising developments, fewer studies have focused on using ANNs specifically for predicting energy consumption in turning operations, especially for dry cutting of 42CrMo4 steel. For example, Sarıkaya and Güllü [24] used ANN models to predict surface roughness and tool wear under dry turning conditions, but their work did not extend to power consumption. Diniz and Micaroni [5] investigated the effect of cutting parameters on power consumption experimentally but did not develop AI-based predictive models. More recently, Parmar and Dave [25] demonstrated the use of ANNs for energy prediction in milling operations, suggesting the potential for broader application to other machining processes.

Given the significant contribution of machining operations to total manufacturing energy consumption, there is an increasing need for reliable AI-based models that can be integrated into digital twin frameworks and smart manufacturing systems [12], [19], [26]. Such models can support process planning, real-time monitoring, and adaptive control to minimize energy waste and improve sustainability [27], [28], [29], [30].

The present study addresses this gap by developing and validating an ANN-based model to predict power consumption in the dry turning of 42CrMo4 steel, a widely used alloy steel with demanding machinability requirements.

The results presented aim to contribute to ongoing efforts to reduce the carbon footprint of manufacturing operations by enabling more precise control of energy demand through data-driven modeling and smart process optimization.

2. METHODOLOGY

2.1 Experimental Setup

The initial phase of this research involved experimental design. To limit the number of experimental runs while ensuring robust results, a Central Composite Design (CCD) with three factors was selected [7]. The independent variables considered were cutting speed (V_c), feed per revolution (f_n), and depth of cut (a_p). Their respective ranges were as follows:

- Cutting speed (V_c): 50–200 m/min;
- Feed rate (f_n): 0.05–0.2 mm/rev;
- Depth of cut (a_p): 0.5–1.5 mm.

The turning insert used in this experiment was a CCMT09T304-FS model, manufactured by Mitsubishi. It is made of carbide grade MP9025, which offers excellent wear resistance, thermal stability, and toughness. This insert is specifically designed for high-performance turning operations, providing a balance between hardness and durability. Its geometry ensures efficient chip removal and stable cutting performance, making it suitable for dry turning applications where heat and friction are critical factors.

By applying the Central Composite Design (CCD) for the experimental plan, a total of 20 trials were determined. The material selected for machining was 42CrMo4 steel. The experiments were carried out using a LYNX 220 CNC turning center located in the Manufacturing Engineering Department at TU Cluj-Napoca. This turning center is equipped with a main spindle capable of a maximum speed of 7000 revolutions per minute, a two-axis positioning system, and a CNC FANUC controller.

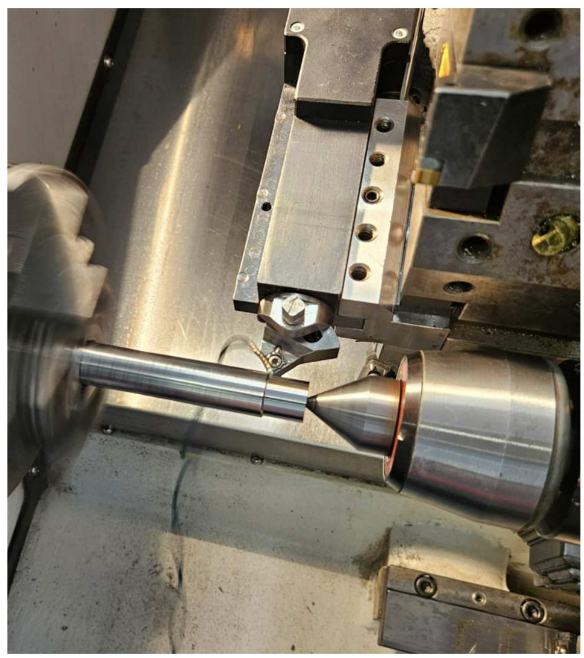

Fig. 1. Experimental setup.

The experimental setup is illustrated in Figure 1. The experimental work was conducted on 42CrMo4 steel bars with a diameter of 20 mm and a length of 200 mm. 42CrMo4, a high-strength alloy steel (EN 10083-3), is known for its toughness, wear resistance, and good hardenability due to chromium and molybdenum content. Its typical chemical composition includes 0.38–0.45% C, 0.60–0.90% Mn, 0.90–1.20% Cr, and 0.15–0.30% Mo.

The turning operations were performed under dry conditions to assess realistic cutting energy requirements without the influence of cutting fluids. The cylindrical workpiece was securely clamped in the chuck and additionally supported by the tailstock to ensure proper alignment and stability during machining.

2.2 Measurement

To measure power consumption during the turning process, an XKM dynamometer was employed. The recorded data were visualized and analyzed using the XKM2000 software. Figure 2 presents the results obtained for a representative experimental trial (Run No. 3) conducted with the following parameters: cutting speed 80.40 m/min, depth of cut 1.30 mm, and feed rate 0.08 mm/rev.

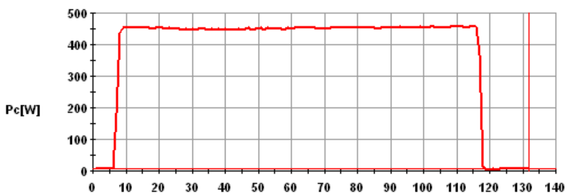

Fig. 2. The graphical representation of power consumption recorded during an experimental trial.

2.3 AI Modeling

A feedforward neural network (FNN) was selected for regression tasks due to its suitability for modeling complex, nonlinear relationships. The network architecture consisted of:

- An input layer with three neurons (one for each cutting parameter).
- One hidden layer with ten neurons and a sigmoid activation function.
- An output layer with one neuron and a linear activation function to predict continuous output.

The modeling process, including network configuration, training, and performance analysis, was executed using the Neural Network Fitting app in MATLAB R2024a, as presented in Figure 3.

The network was trained using the Levenberg–Marquardt backpropagation algorithm. This algorithm was selected for its known high efficiency with small- to medium-sized datasets and its fast convergence properties, particularly for nonlinear regression problems.

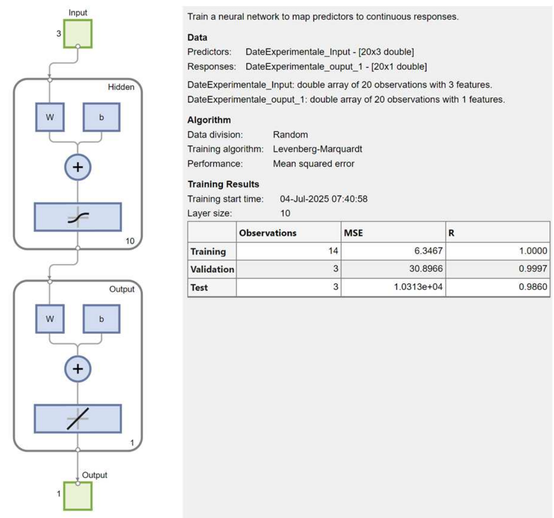

Fig. 3. The Neural Network Fitting app in MATLAB R2024a.

The dataset consisted of 20 observations, which were randomly divided for training, validation, and testing as follows:

- Training Data: 14 observations (70%)
- Validation Data: 3 observations (15%)
- Test Data: 3 observations (15%)

The Mean Squared Error (MSE) was used as the primary performance metric to guide the training process and evaluate the model's accuracy.

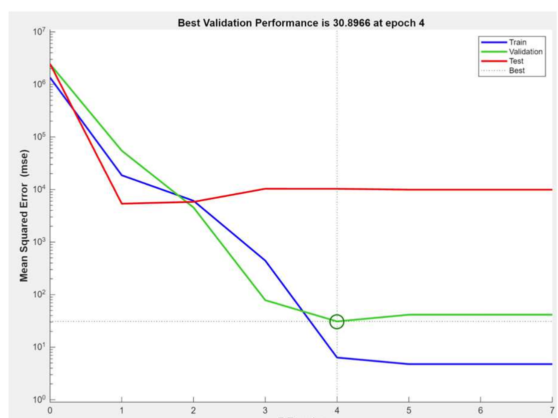

Fig. 4. Performance Plot (Mean Squared Error vs. Epochs).

The performance plot (figure 4.) illustrates the MSE progression during training across epochs:

- The training MSE (blue line) continuously decreased, reaching very low values by the end of training.
- The validation MSE (green line) initially decreased but reached its minimum performance of 30.8966 at epoch 4. After this point, the validation error began to increase slightly, indicating that further training on the given data was leading to overfitting rather than improved generalization.

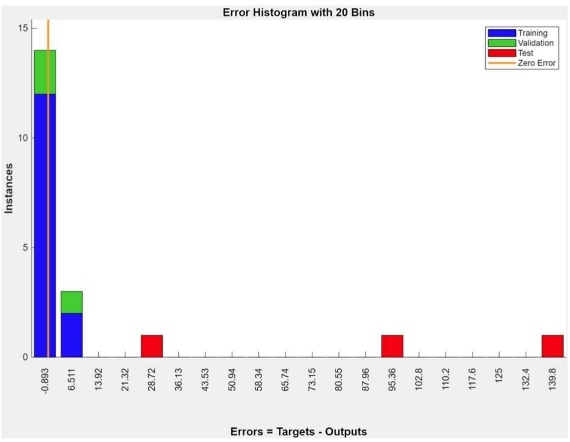

Fig. 5. Error histogram.

- The test MSE (red line) remained consistently high throughout the training process, further supporting the overfitting observation. The significant gap between the training error and the validation/test errors after epoch 4 clearly demonstrates that the model was learning the noise in the training data rather than generalizing well to unseen patterns.

The error histogram, figure 5, (Errors = Targets - Outputs) provides a distribution of prediction errors:

- Training Errors: The majority of training errors are clustered closely around zero, indicating high accuracy on the trained data.
- Validation Errors: A few validation errors are also close to zero.
- Test Errors: Critically, the test errors are distributed across a wider range of values and are not centered around zero. Several instances show errors of significant magnitude (e.g., up to ~140 units). This wider spread and larger error values for the test set strongly reinforce the conclusion of poor generalization and overfitting.

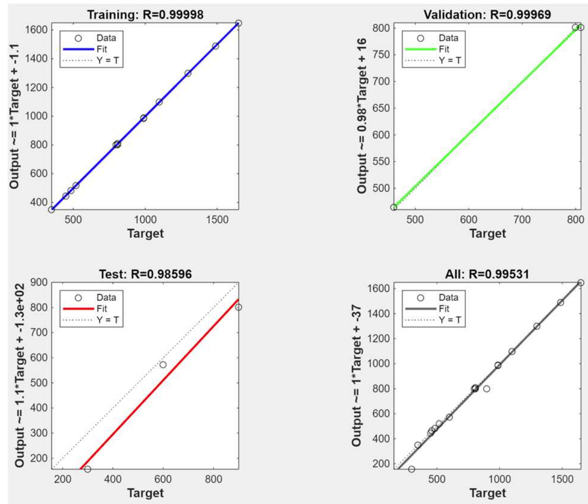

Fig. 6. Regression plots.

The regression plots (figure 6) visualize the relationship between the network's outputs and the true target values for each dataset:

- Training (R=0.99998): The predicted outputs align almost perfectly with the target values, with data points tightly clustered around the ideal Output = Target line. The fit equation (Output = 1 * Target + -1.1) is very close to the ideal.
- Validation (R=0.99969): The fit for the validation set also appears visually strong, with an equation of Output = 0.98 * Target + 16.
- Test (R=0.98596): While the R-value is still high, the test set regression plot shows a noticeable deviation from the ideal Output = Target line. The fit equation (Output = 1.1 * Target + -1.3e+02) indicates a systematic bias, with a significant negative intercept (-130) and a slightly different slope. This confirms the model's diminished ability to accurately predict for unseen test data.

All (R=0.99531): The combined plot shows a good overall correlation, but the underlying overfitting issues are masked by the high training performance.

The high R-values across all sets, despite large MSEs for validation/test, suggest that while the model captures the overall trend of the data, its absolute predictions for unseen data have substantial errors.

The developed ANN model proved to be effective in predicting power consumption based on cutting speed, feed rate, and depth of cut. The low training and validation errors, combined with high correlation coefficients, indicate that the model can accurately describe the complex interactions between cutting parameters and power demand in dry turning operations.

2.4 AI Modeling validation

The use of the Simulink app (figure 7) in MATLAB R2024a further demonstrates the practical integration of the trained ANN model into a simulation environment, making it convenient for real-time predictions and process control applications.

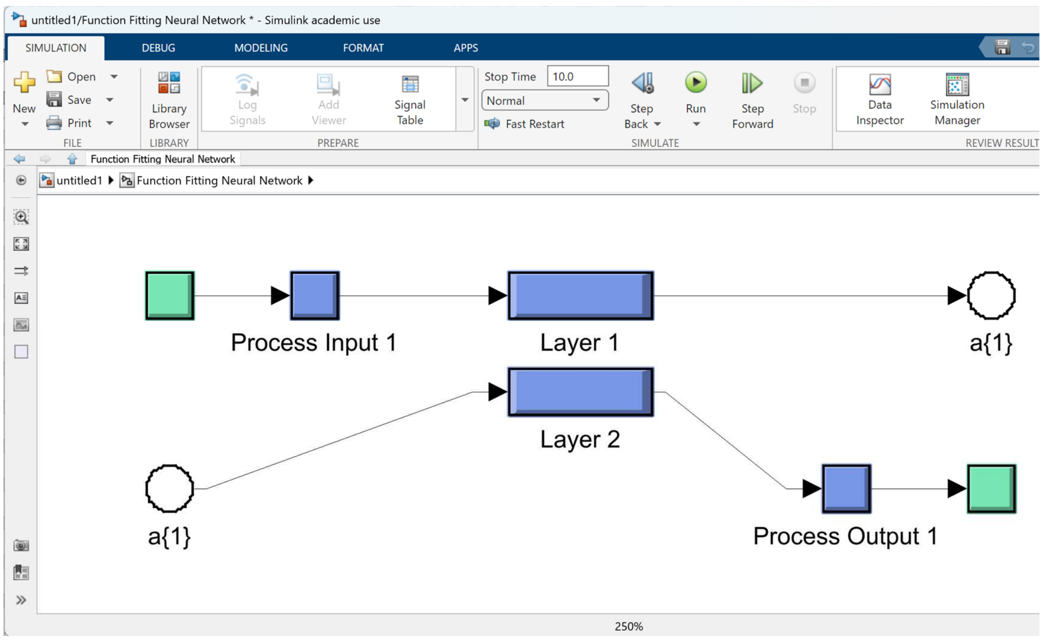

Fig. 7. The Simulink app in MATLAB R2024a.

For all three test cases (table 1), the predicted power consumption values are close to the actual measured values.

Table 1

The validation results.

Run	Parameters	Model	Test	Deviation
1	V_c=150m/min a_p=1 mm, f_n=0.15 mm/rev	1300	1100	100W (9.09%)
2	V_c=100m/min a_p=0.5 mm, f_n=0.15 mm/rev	530	490	40W (8.16%)
3	V_c=200m/min a_p=1.5 mm, f_n=0.2 mm/rev	1650	1606	44W (2.74%)

The differences range from 40 W to 100 W, which is a relatively small deviation considering the magnitude of the power values. The percentage deviations are all below 10%, with the highest at about 9.1% and the lowest at about 2.7%. This indicates very good predictive accuracy for the AI model.

3. CONCLUSIONS

This paper demonstrated the successful application of an artificial intelligence-based model to predict power consumption during the dry turning of 42CrMo4 steel. A feedforward neural network (FNN) was developed, trained, and validated using experimental data collected under controlled conditions. The model accurately captured the nonlinear relationships between cutting speed, feed rate, and depth of cut, achieving high correlation coefficients and low mean squared errors. Experimental validation showed that the predicted power values deviated by less than 10% from the actual measurements. This confirms the model's suitability for practical implementation in process planning and real-time monitoring, contributing to improved energy efficiency in machining operations.

4. ACKNOWLEDGEMENT

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Modelarea consumului de energie în strunjirea uscată a oțelului 42CrMo4 prin intermediul inteligenței artificiale

Rezumat: Acest studiu prezintă dezvoltarea unui model bazat pe inteligență artificială pentru estimarea consumului de energie în strunjirea uscată a oțelului 42CrMo4. A fost concepută o rețea neuronală feedforward (FNN) utilizând date experimentale generate printr-o planificare de tip Central Composite Design. Rețeaua a fost antrenată și validată în MATLAB, obținând o corelație ridicată și erori de predicție reduse atât pentru datele de antrenare, cât și pentru cele de testare. Validarea cu experimente practice a arătat deviații sub 10%, confirmând eficiența modelului pentru estimarea puterii consumate și sprijinirea optimizării proceselor de strunjire CNC în vederea creșterii eficienței energetice.

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