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ANN-based power consumption modelling for feed drive systems in CNC machining using systematic data acquisition

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Abstract

The growing focus on sustainable manufacturing has increased the need to reduce the energy consumption of machine tools. For energy-aware optimisation of CNC machining processes, accurate modelling of feed drive power demand is essential. This paper introduces a systematic data-collection procedure and a predictive modelling framework based on artificial neural networks (ANNs) for estimating feed-drive current consumption without additional sensors, relying solely on internal CNC control signals.

Experimental results demonstrated that instantaneous axis velocity and acceleration are necessary and sufficient input parameters for the precise prediction of feed drive current consumption. To efficiently generate a wide range of velocity–acceleration combinations, a specially designed motion cycle was developed, enabling dataset acquisition in approximately one minute per axis. The analysis demonstrated that a simple fully connected feed-forward neural network with three hidden layers of 64 neurons each effectively captures the nonlinear relationships between motion parameters and current consumption. The proposed ANN model significantly outperformed traditional second- and third-order regression models, achieving a high coefficient of determination without overfitting.

Case studies conducted on a three-axis machining centre confirmed rapid adaptability and strong generalisation capability, with relative prediction errors below 5% for complex trajectories. The proposed framework provides a solid basis for energy-aware tool path optimisation, digital twin applications, and process monitoring. The approach can be extended to spindle power modelling and integrated with cutting force models to enable comprehensive energy optimisation of CNC machining processes.

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1. Introduction

A major challenge in our century is achieving sustainability, which also necessitates significant changes in the manufacturing sector [1]. Green manufacturing technologies are gaining more and more ground, striving to minimise environmental impact [2]. Despite these initiatives, the manufacturing sector still consumes a huge amount of electrical energy [3]. Rising energy prices [4] and stricter

regulatory requirements such as the EU Energy Efficiency Directive [5] have further emphasised the need for component-level energy analysis in manufacturing systems. CNC machine tools account for a significant portion of energy consumption [6], and several studies have shown that motion-related subsystems have a substantial impact on overall energy consumption, particularly feed drives [7], as they are constantly engaged in machining operations [8] [9]. Most research studies on the power consumption of machine tools

primarily focus on the energy demand resulting from the cutting process and are based on modelling of cutting force [10]. However, these approaches often overlook the significant energy consumption resulting from axis movements. Some approaches use analytical models of kinematic and frictional relationships [7], but accurately describing component behaviour remains challenging.

Data-driven solutions are often an effective way to describe the behaviour of complex physical systems. Studies integrating digital twin technology and data-driven control systems indicated that motion-related energy usage can be monitored and predicted with high accuracy [11] [12]. These findings also emphasised the strong correlation between energy consumption and feed drive behaviour [13]. However, data-driven models are frequently trained on application-specific data, which diminishes their generality and weakens their connection to the underlying physical behaviour of the machine.

Recently, hybrid and physics-informed modelling approaches have also been explored as a response to the limitations observed in purely data-driven methods used in manufacturing [14]. Although promising, these approaches require consideration of multiple external factors, which complicates industrial implementation.

This paper presents a data-driven method for modelling the energy consumption of feed drive systems without additional sensors, relying solely on internal CNC signals for seamless industrial integration. The proposed systematic data-collection procedure enables rapid adaptation and recalibration across various machine architectures and changing operating conditions, such as the presence of heavy fixtures or workpieces. The short acquisition cycle aligns with the limited buffer capacity of high-resolution CNC monitoring systems, enabling practical deployment. Validation of the feed-forward ANN model confirmed high predictive accuracy and practical applicability.

The rest of the paper is structured as follows. Section 2 discusses the modelling approaches for the feed drive's power consumption. Section 3 describes the experimental validation of the developed method. Finally, Section 4 concludes the paper with a summary of the main findings and recommendations for future work.

2. Modelling of power consumption

2.1. Experimental environment

The experiments for model creation and testing were conducted using a FANUC Robodrill 3-axis machine centre (model: α -D14 MiB8). The Servo Viewer function of the FANUC control was utilised for data acquisition, allowing for the measurement of instantaneous current consumption, along with axis positions and speeds, at a high frequency. During the experiments, sampling interval of 5 ms was utilised.

2.2. Calculation of energy and power consumption

The energy consumption of CNC machine tools originates from multiple sources. As outlined in the introduction, some

components are time-dependent, while others depend on the intensity of use. The FANUC control system accounts for components such as pump and valve elements for cooling, lubrication, flood and mist coolant, chip conveyor, and lighting, which have a predetermined constant power based on operating time. The power consumption of feed drives and the main spindle can be estimated based on current consumption, which varies with the applied load. Although feed drives are not the largest contributors to the overall energy consumption of machine tools, this paper focuses, due to space limitations, exclusively on the development of a measurement and modelling procedure for feed drive energy consumption.

To monitor the current consumption of feed drives, several parameters can be measured using the FANUC Servo Viewer function: IR (R-phase current), IS (S-phase current), ID (reactive current), IQ (active current), and I EFF (actual current). Among these parameters, IQ, which represents the torque-forming current, is particularly useful.

The energy consumption of feed drives can be calculated from the mechanical power as follows:

$$E = \frac{\int P_{mech}(t) dt}{\eta} [Ws] \quad (1)$$

where $P_{mech}(t)$ [W] is the mechanical power, η [–] is the efficiency. The mechanical power is given by:

$$P_{mech}(t) = M(t) \cdot \omega(t) [W] \quad (2)$$

where $M(t)$ [Nm] is the motor torque, $\omega(t)$ [rad/s] is the angular velocity. The angular velocity can be derived from the ball screw pitch and the slide speed, while the motor torque is calculated as follows:

$$M(t) = K_t \cdot I_q(t) [Nm] \quad (3)$$

where K_t [Nm/A] is the torque factor, which is constant in the case of permanent magnet synchronous motors (PMSM) used in feed drive systems [15], and $I_q(t)$ [A] is the torque forming current, which is the only variable to be measured in the calculations detailed above. Due to static torque, stationary axes ($\omega = 0$) can consume energy even when there is no mechanical performance ($P_{mech} = 0$), as indicated by Eq. 2. This case, the energy consumption can be estimated based on electrical loss power, primarily involving stator copper losses that are proportional to the square of the motor current: $P_{Cu}(t) \approx 3R_s (I_d^2(t) + I_q^2(t))$.

2.3. Systematic data acquisition

As mentioned earlier, this paper presents a data-driven approach to modelling power consumption. A crucial aspect of data-driven methods is the generation of an appropriate training dataset. To accomplish this, a systematic data acquisition method was developed that can generate the required training data pairs rapidly, covering the entire parameter range within a few minutes.

Based on the scientific literature and the experiments conducted, it was determined that the instantaneous velocity

and acceleration of the slide are required to predict the power consumption of feed drives accurately. Consequently, the objective of the data collection was to generate as many combinations of these two parameters as possible within a short time. To achieve this, two data acquisition strategies were developed: one for feed movements and another for rapid movements.

In uniform circular motion, velocity and acceleration are described by functions that are phase-shifted by $\pi/2$ relative to one another (see Fig. 1a and b). When the parameter combinations corresponding to one complete period are plotted on a velocity–acceleration map, an elliptical shape is formed (see Fig. 1c). By repeating this process at various velocities, a series of concentric ellipses is generated, collectively covering the entire parameter range.

During the experiments, circular arcs with a radius of 5 mm were programmed using a feed rate ranging from 250 to 6000 mm/min in increments of 250 mm/min. This approach yielded 24 equally spaced steps within the velocity range below 100 mm/s (as shown in Fig. 1c). Although the feed drives of the FANUC Robodrill can reach an acceleration of 3000 mm/s², the "Normal Machining" servo settings limited this to 2000 mm/s², which fully utilised during this series of experiments. Notably, the measurement process for a single axis took less than 60 seconds.

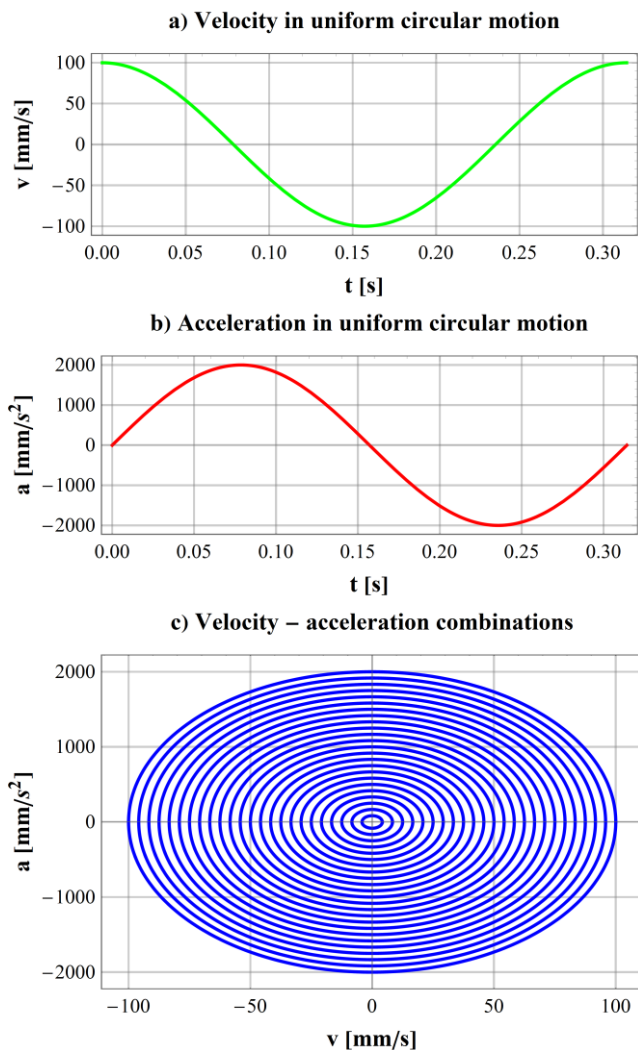


Figure 1 Data acquisition strategy for feed movements

The previous method effectively generates the data pairs needed for feed movements. However, rapid movements can occur at higher velocities and accelerations, necessitating a separate data collection process. For this purpose, rapid traverse transitions were performed, in which the velocity follows an S-shaped profile and the acceleration exhibits a trapezoidal profile. On the FANUC Robodrill machine tool, the maximum rapid traverse speed was 54000 mm/min (which is 900 mm/s), and the maximum acceleration was 10000 mm/s² (see Fig. 2a and b). When these movements are plotted on a velocity–acceleration map, the result is a slightly angular figure-of-eight loop. By adjusting the feed potentiometer to different settings, concentric curves can be generated that thoroughly cover a wide range of velocity–acceleration combinations. The measurement process for a single axis took less than 15 seconds.

It should be noted that the feed potentiometer on the machine tool's control panel typically affects only the velocity, not the acceleration. Therefore, to override the rapid traverse movements, the M47 C[%] command was used to adjust in 10% increments between 0% and 100% (see Fig. 2c). If this function is not available on a given machine tool, an alternative approach is to perform diagonal movements across multiple axes, allowing the projected motion component along a single axis to be set to the desired value.

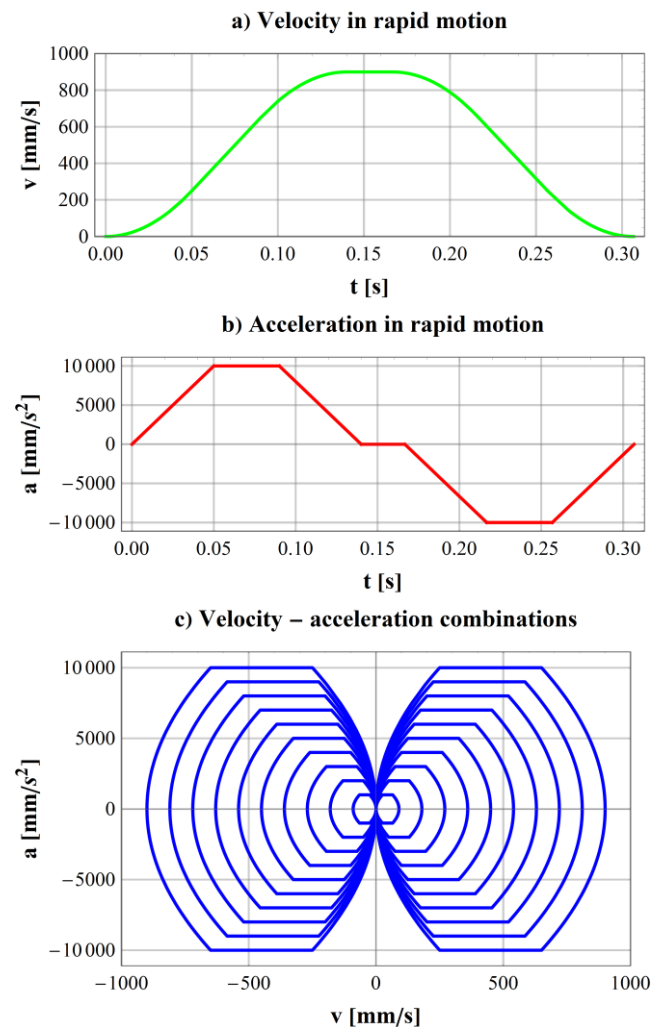


Figure 2 Data acquisition strategy for rapid movements

Resulting from the two experimental procedure described above, the dataset generated for modelling the current consumption of the X-axis' feed drive is presented in Fig. 3. The current consumption of each axis must be modelled separately, as differences in moved mass lead to distinct characteristics. In the following, the X-axis, which moves the table, and the Z-axis, which moves the spindle, will be discussed in detail. The behaviour of the Y-axis is similar to that of the X-axis, since it also moves the table.

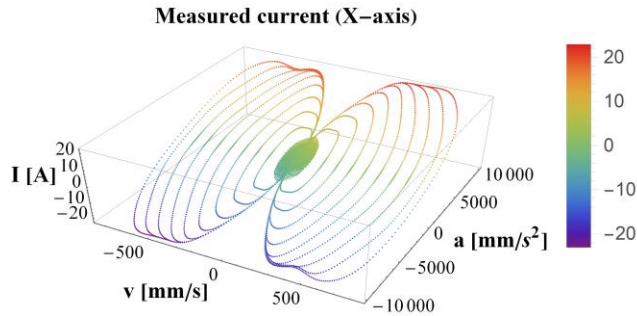


Figure 3 Dataset collected for a single feed drive axis

2.4. Model fitting by traditional regression methods

The predictive function $f(v, a)$, describing the current consumption as a function of velocity and acceleration, was first modelled using traditional linear regression methods. The first-order version was quickly dismissed due to its poor performance, therefore, second- and third-order versions were examined, which can be expressed in the following form:

$$f(v, a) = \sum_{0 \leq i+j \leq p} \beta_{i,j} \cdot v^i \cdot a^j \quad (4)$$

where p denotes the order of regression (in this case, two and three, respectively), and $\beta_{i,j}$ are the regression coefficients.

The regression coefficients, six in the second-order case and ten in the third-order case, were determined using Wolfram Mathematica 14.2 and the least-squares method. The analysis of variance indicated that, in both models, only the p-values associated with the $v \cdot a$ and a^2 remained above the significance threshold of $\alpha = 0.05$. Consequently, all remaining regression terms can be considered statistically significant. The adequacy of the model fitting will be examined in Section 2.6.

2.5. Model fitting by ANN-based regression

The high sampling rate employed during the measurements enables the generation of thousands of training data points within a short time, making this approach well suited for neural-network-based predictive modelling. For this purpose, a fully-connected feed-forward neural network was implemented in Wolfram Mathematica 14.2 environment.

The approximately 20,000 data pairs generated per feed drive were divided into three subsets: 70% for training, 15% for validation during training, and 15% for post-training testing. Several network architectures were examined, and the

results indicated that a three-layer network with 64 neurons per each delivered high performance. The training was conducted for 1,000 epochs using a learning rate of 0.001 with the Adam optimiser. An example of the utilised data points, and the corresponding fitted predictive model is illustrated in Fig. 4.

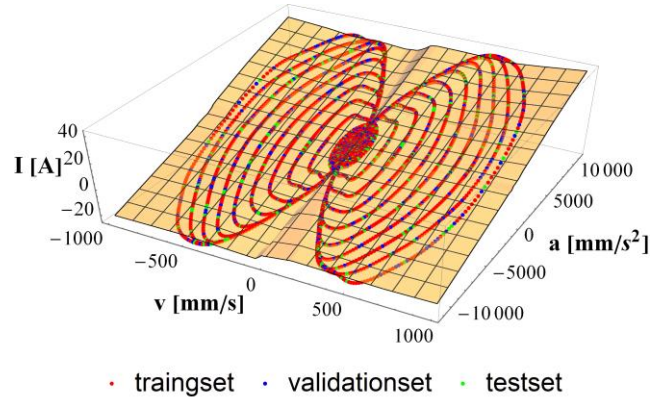


Figure 4 ANN-based predictive model for current consumption (Z-axis)

2.6. Evaluating the regression models

The accuracy and reliability of the fitted models were evaluated using parity plots and coefficients of determination (R^2).

Fig. 5 shows the results obtained for the current consumption model of the X-axis feed drive. Although the R^2 parameter was high for the linear models (0.9779 and 0.9831 for the second and third-order models, respectively), the ANN model yielded an even better result (0.9993). Notably, the same R^2 value of 0.9993 was obtained for the data not used during training, indicating that overfitting did not occur. In addition, a comparison of the parity plots demonstrates that the ANN-based model provides significantly more accurate predictions of the measured values.

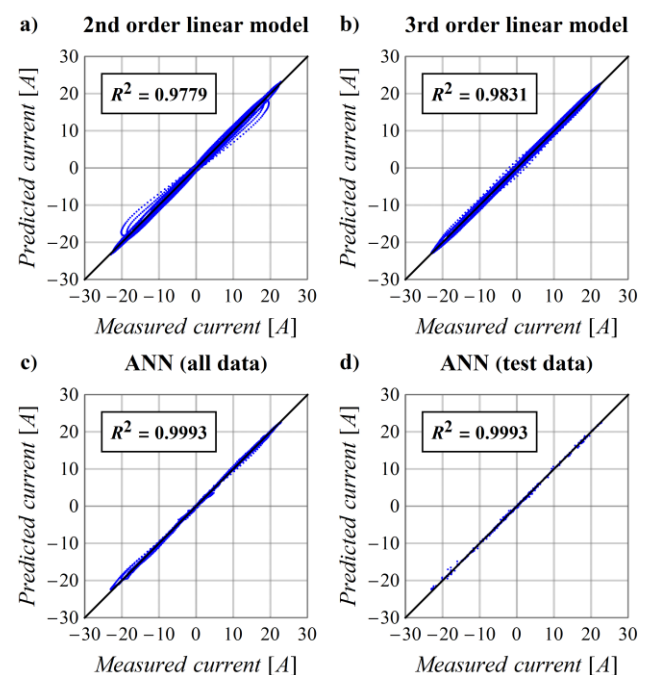


Figure 5 Comparison of fitted predictive models (X-axis)

Fig. 6 illustrates a comparison of the models developed for the Z-axis. Since the Z-axis is responsible for moving the spindle, it drives a significantly larger mass, which results in higher current values drawn by the feed drive. Although the measured signal was slightly noisier, all predictive models still exhibited high R^2 values. The rankings among the models remained consistent: the second-order linear model achieved an R^2 value of 0.9747, the third-order linear model reached 0.9800, and the ANN-based model excelled with a value of 0.9990. The R^2 value calculated exclusively from the separated test dataset was 0.9988, indicating that overfitting could be ruled out in this case as well. Furthermore, comparison of the parity plots shows that the superior accuracy of the ANN-based model is even more evident for the Z-axis.

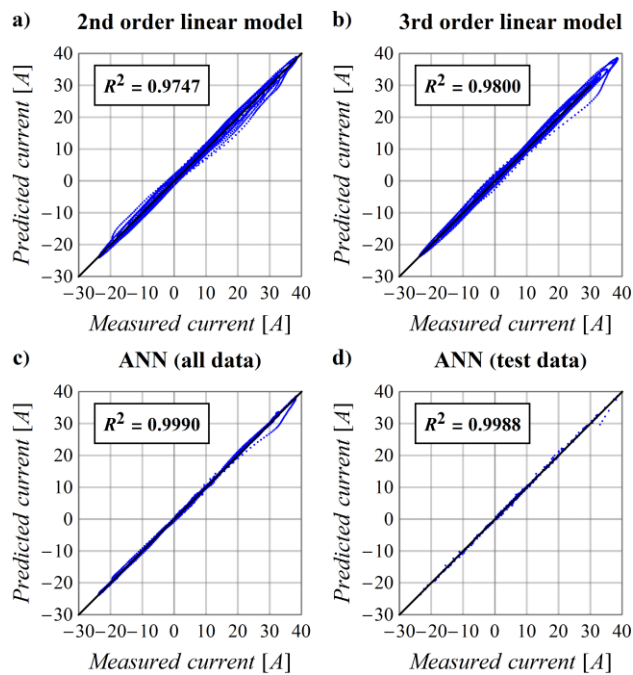


Figure 6 Comparison of fitted predictive models (Z-axis)

It can be noticed that training the neural network with only acceleration values yielded relatively good results, with R^2 values ranging from 0.90 to 0.95. In contrast, using only velocity did not provide any successful predictions. However, the ANN-based predictive model is most effective when velocity and acceleration are used jointly as input parameters.

3. Experimental validation

To validate the developed predictive models, additional experimental measurements were performed. Since the conditions during rapid traverse movements closely resemble those used to generate the training data, nearly perfect agreement was observed between the measured and predicted values in these tests. Consequently, only the test involving a complex trajectory with feed motion is presented in the following.

For the validation experiments, a butterfly-shaped tool path was selected, which is commonly used to evaluate CNC machine tool movements [16] [17] [18]. The programmed

feed rate was 6000 mm/min (100 mm/s). However, due to the sharp changes in feed direction, the actual feed rate decreased locally in some areas. The evolution of the X-axis' velocity is illustrated in Fig. 7a, where the strong fluctuations in the axial velocity are clearly visible. Fig. 7b compares the measured current value with predictions obtained from the third-order linear and ANN-based models. This comparison is further elaborated in Fig. 7c, which focuses on the central one second interval of the measurement.

Fig. 7 shows that the linear model alternately underestimates and overestimates the measured values, whereas the ANN-based model consistently yields close predictions, with slight deviations visible only during changes in direction. When these differences are quantified, the average absolute error of the linear model is 0.68 A, compared to only 0.24 A for the ANN-based model. This corresponds to relative differences of 12.8% and 4.5%, respectively, when normalised by the maximum current value. In conclusion, the ANN-based model demonstrated superior predictive performance in the validation experiment.

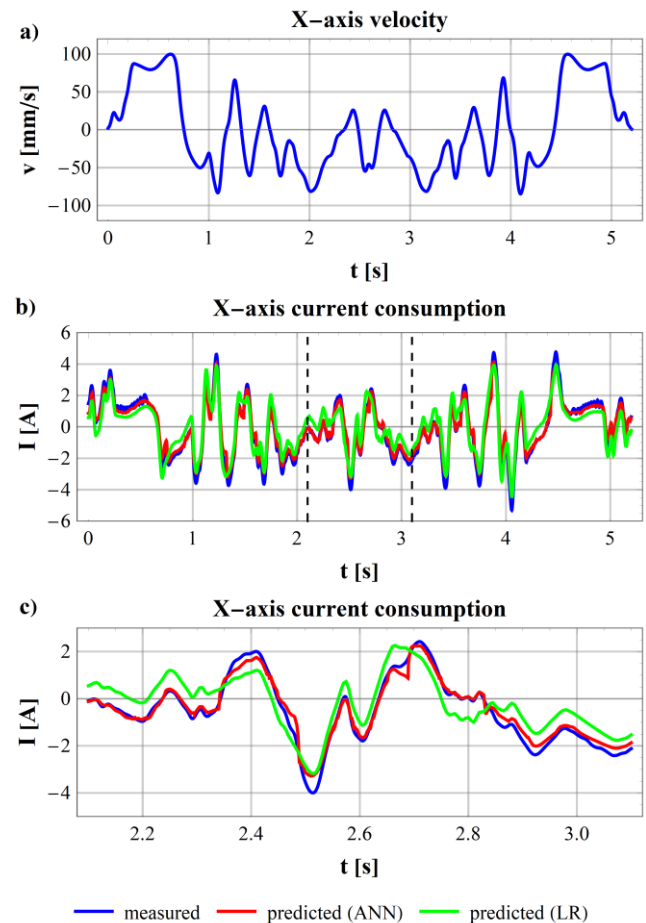


Figure 7 Validation experiment by traversing a complex trajectory

4. Conclusions and future outlooks

This paper presented a systematic procedure for data collection and an artificial neural network-based data-driven predictive modelling method that accurately describes the power demand of feed drives, taking into account the velocity

and acceleration state of the machine tool's sleds. In summary, the following results can be highlighted:

- The instantaneous velocity and acceleration of the axes are necessary and sufficient parameters for the accurate prediction of the feed drive's current consumption.
- By appropriately selecting circular and rapid positioning movements, a large number of velocity and acceleration combinations can be generated for model fitting in about one minute per axis.
- The developed fully-connected feed-forward neural network-based model, with 3 hidden layers and 64 neurons each, significantly outperformed the traditional second- and third-order linear regression models in accuracy and reliability, ensuring a near-perfect (above 0.999) coefficient of determination without overfitting.
- The validation experiment with a complex trajectory demonstrated that the developed model can make accurate predictions in general, maintaining a relative error limit of less than 5%.
- The proposed methodology enables accurate energy estimation of feed drives without the need for additional sensors, relying solely on the internal data of the CNC control, making it suitable for energy-aware tool path optimisation and digital twin applications.

Similar approaches can be employed to model the spindle's current consumption. By integrating cutting force models, the energy demand of the entire machining process can be modelled and optimised. In addition to optimising the machining parameters and tool path, modelling and monitoring of power consumption can also be used for process monitoring and preventive maintenance purposes by detecting abnormal operation in time. With support from digital twin technology, monitoring the feed drives' power consumption is expected to become an integral part of CNC machine tool operations in the near future.

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