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Automated Cam Programming for Machining of Turned Components Utilizing Autodesk Fusion 360 CNC Module and ANN

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Abstract

This article is a new fusion of Computer-Aided Manufacturing (CAM) and Artificial Neural networks (ANN) to estimate the parameters of the surface roughness (Ra and Rz) and the forces cutting (Fx, Fy, Fz) during the cut 3-axis milling on EN-31 steel. A detailed dataset about different toolpath strategies and different cutting parameters with Fusion 360 CAM software was made, and this dataset was used to train ANN models. A lot of exploratory data analysis (EDA) and training were done using standardized machine learning methods, and models were measured using certain metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE) and R-squared ($R^{2)}$. It was found that the ANN models showed good predictive precision with R 2 values of 0.817 and 0.860 and all the components of the cutting forces with values greater than 0.99. These outcomes mean that ANN can be successfully used to model nonlinear intricate relations between inputs of machining and outputs of performances. The described CAM-ANN hybrid solution provides a huge step towards automation of surface integrity and correct force determination, which minimizes the necessity of physical tests and makes the production more data-wise and intelligent. The described approach is in line with the goals of Industry 4.0 to introduce predictive intelligence and favor process optimization in new-age machining facilities.

Keywords: CNC Milling, Surface Roughness Prediction, Cutting Forces, Artificial Neural Network, Fusion 360, CAM Simulation, Smart Manufacturing, Industry 4.0, Toolpath Optimization, EN-31 Steel.

1. Introduction

Computer Aided Manufacturing (CAM) and CNC are among the technologies that have transformed the modern manufacturing industry making it easier to machine, automate, and optimize complex parts used in the manufacture of products in different industries such as aerospace, automotive, and biomedical industries. The CAM software can be used to generate optimized toolpaths, choose cutting parameters and simulate machining operations, CNC machines simply follow the instructions and provide high quality parts with limited human contact [1].

Turning is one of the most common processes in CNC operations used in producing rotational component. The turn quality of the parts especially the surface finishes and the number of forces on the tools has a great impact on the functional performance of the products, the exactness of dimensions and the lifecycle of the products. Although CAM and CNC are largely used, it is still a tedious exercise to predict the machining process outcomes including surface roughness parameters (e.g. Ra, Rz) and cutting forces (Fx, Fy, Fz) because it is a nonlinear and multivariable process. Surface finish depends on several related factors such as the feed rate, cutting speed, the depth of cut, the tool geometry, the characteristics of the material and environmental conditions [2].

The cutting forces are very sensitive to tool wear, the plateauing of chips formation as well as instabilities. These nonlinear interactions are not well reflected in traditional empirical and analytical models, hence their low levels of accuracy and generalizability. Consequently, the manufacturers are guided by the process of lengthy experiments, trial-and-error method, or the rule-of- thumb, which are time-wasting and resource consuming. To meet these difficulties, it is becoming more necessary to provide automated and intelligent prediction solutions that can optimize the machining parameters and predict precisely the results. Over the past few years, AI methods, especially Artificial Neural Networks (ANNs) have become large in manufacturing research. ANNs can effectively be applied in terms of modeling the aspects of complex, nonlinear interconnections between the aspects of process parameters and machining response by dint of their learning empowerment and versatility [3]. It has been shown that ANN could be used to predict surface roughness and tool wear as well as cutting forces and results have been encouraging.

The cloud-based integrated CAD/CAM Autodesk Fusion 360 platform provides more capabilities of toolpath creation, simulation of processes, and automation of manufacturing. In contrast to typical CAM-tools, Fusion 360 allows working with others, editing in real-time, and simulation capabilities, which provides it popularity among not only small and medium enterprises (SMEs) but also universities [4]. Although the software can deliver accurate simulations of the machining process, it lacks predictive analytics and AI-based optimization of the working processes in its original form. This gap offers a possibility of strengthening the base of Fusion 360, which would be its combination with ANN models to determine the result of the machining process with respect to either simulation or past CAM data. An examination of the current literature can indicate that the combination of contemporary CAM systems, such as Autodesk Fusion 360 with the tool of machine learning in the field of intelligent forecasting of machining reactions, has significant gaps. Although different types of models that have been studied in surface roughness or force prediction exist using proper ANN, not many experiments have been done on utilizing ANN into real data generated by CAM through programs such as Fusion 360, particularly in turning operations [5].

The present paper aims at prototyping a mixed method, in that data on surface roughness and cutting forces during turned parts machining using Autodesk Fusion 360 CAM simulation will be used together with Python-based Artificial Neural Network (ANN) modeling to forecast surface roughness and cutting forces during machining. The contributions of the present paper are to introduce the combination of ANN prediction and the parameters provided by CAM to manufacturers to be able to have credible predictions about the machining results without running them physically. The other contribution made by the research is the creation of a validated dataset of turning operations and a trained ANN model, which could generalize new machining scenarios. The paper would eliminate the gap between simulation and smart prediction and will lead to the improvement of smart manufacturing systems.

Functional Modules in Autodesk Fusion 360

Fusion 360, developed by Autodesk, is a comprehensive design platform that integrates industrial design, structural design, mechanical simulation, and CAM. It facilitates collaboration and sharing across platforms and through the cloud, making it highly accessible for teams working remotely or across different systems. Fusion 360 includes multiple working environments and modules such as modeling, molding, surface patching, rendering, animation, simulation, CAM, and drawings and its functionality can be seen in Figure 1. These features allow users to seamlessly transition from design to manufacturing by providing an all-in-one solution for product development. This integration is essential for automating CNC programming, as it streamlines the design and machining processes, enhancing productivity and reducing errors by enabling real-time adjustments and collaboration throughout the project lifecycle.

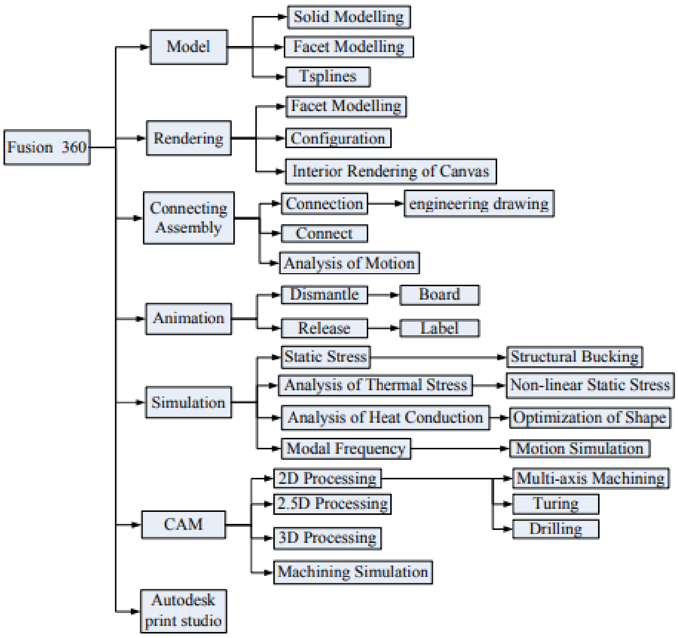

Fig. 1 Function Module of Fusion360

The Integration of Artificial Neural Networks (ANN) in Machining

Artificial Neural Networks (ANNs) have become a vital tool in enhancing various manufacturing processes, including machining, by providing advanced data processing capabilities that go beyond traditional computational methods. In the context of machining, ANNs are employed to predict, control, and optimize machining parameters such as cutting forces, tool wear, surface finish, and temperature. These networks, which simulate the human brain's learning processes, can be trained on historical machining data to predict optimal machining parameters for a given task. By using data-driven approaches, ANN helps overcome the challenges of manual programming, improving the efficiency, accuracy, and adaptability of the machining process and its structure is shown in block diagram in Figure 2.

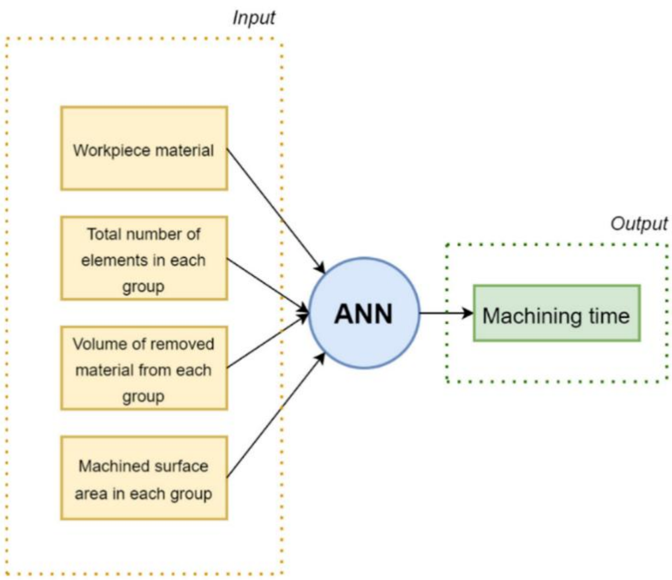

Figure 2: ANN-based Machining Time Prediction for Turned Components

When integrated with CNC systems such as Autodesk Fusion 360, ANN can automate CAM programming, resulting in real-time adjustments to machining parameters based on input data. For example, ANNs can analyze data to detect tool wear or failure, allowing minimizing unexpected machine downtime. Additionally, ANN can optimize process planning, from selecting appropriate materials and tools to determining the most efficient machining operations sequence. One of the significant advantages of incorporating ANN into Autodesk Fusion 360 is its ability to adaptively adjust machining parameters, leading to reduced processing time and improved product quality.

The synergy between ANN and Autodesk Fusion 360's CNC capabilities allows for more intelligent, error-free machining. ANN models can identify optimal settings for turning operations and predict issues like tool failure before they affect product quality. The potential applications of ANN in machining are vast, ranging from process optimization to predictive maintenance, contributing to more sustainable, cost-effective manufacturing solutions.

2. Literature Review

2.1 CAM Software in Machining

Computer-Aided Manufacturing (CAM) has also evolved as a very useful tool in the current manufacturing systems e.g. CNC turning, milling and drilling operations. CAM software automates the toolpath, selection of cutting parameters and the machining simulation process taking a significant amount of lead time and manual involvement out of it. There are many commercial CAM systems such as Mastercam, Siemens NX, SolidCAM and Autodesk Fusion 360 which have been largely used to improve the machining productivity and repeatability. The traditional metric in assessing CAM software is its capability in predicting machining operations and the level of the output toolpaths. Another comparative study carried by Zain et al. [7] focuses on personal investigations of different CAM platforms and the effects they had on tool life and the tool surface finish.

The researchers found that an optimization of CAM-generated toolpaths with simulation tools would cause a significant decrease in the defects during machining. On the same note, Sedighi and Khosrojerdi [8] established that optimization of toolpaths on CAM simulation data can enhance chip creation direction and minimize any remnant pressures on last turning. Although such evidences justify the usefulness of CAM platforms, most of them do not go to an extent of incorporating predictive analytics in the CAM environment. The usual method is the trial-and-error simulations or manual parameter tuning. Thus, the automation and simulation capabilities proposed by CAM are accompanied by a lack of intelligent decision-making and prediction functionalities a shortcoming that it is possible to address with the help of Artificial Intelligence (AI) models.

2.2 ANN and ML Models for Surface Roughness Prediction

Artificial Neural Networks (ANNs) has garnered a lot of attention in machining research because of its capacity to describe nonlinear and multivariable relationships among machining parameters and their output responses. This is especially useful when it comes to predicting surface roughness which depends on a non-linear interrelationship of cutting speed (vc), feed rate f, depth of cut ap, tool geometry, and properties of the material. Rai and Rao [9] applied a backpropagation ANN in predicting the surface roughness during turning of mild steel and indicated an accuracy of 95.6 percent in their prediction. ANN was trained based on three major inputs: feed rate, cutting speed and depth of cut. Also in another important research study, Nalbant et al. [10] used the Taguchi technique and ANN to predict surface roughness and optimize parameters in hard turning processes. They found out that ANN is better than regression models both on Root Mean Square Error (RMSE) as well as its generalization capability. Other Machine Learning (ML) methods (non-ANN) were also used including Support Vectors Machines (SVM) and Random Forests, to make similar predictions.

As another example, Karayel [11] compared SVM and ANN model in prediction of the surface roughness and concluded that ANN model had small edge in prediction accuracy of complex datasets. However, ANN easily requires domain-specific feature engineering and validation due to its black-box nature and dependence on high quality datasets. Even though these studies affirm the prospects of ANN in machining, the data analysis is usually experimental or too specific to normal machine tools without utilization of the data generated by the latest CAM simulations. So, this is the lack of research in the direction of data obtained by CAM (e.g. in Fusion 360) and incorporated in ANN style x-in-y prediction systems.

2.3 Applications of Fusion 360 in Research and Industry

Autodesk Fusion 360 has become a high-powered platform with built-in CAD/CAM functionality, friendly interface, and cloud computation. It facilitates sophisticated toolpaths planning, multi-axes machining simulations and real time collaboration and this is likely to attract both industrial players and academic researchers. One research by Gomes and Garcia [12] used Fusion 360 in the design and machining simulation of automotive machineries. The authors have discovered that Fusion 360 has an adaptive clearing and simulation module to minimize tool wear and optimize a cycle. In a similar manner, Kumar et al. [13] modelled and simulated end milling application in Fusion 360 by validating efficiency of the toolpath using physical testing. Differently, however, in both these cases, Fusion 360 was utilized only in toolpath planning and simulation, but not predictive modeling. Foggy literature can be found surrounding the direct relation between Fusion 360 CAM simulation outputs and either a Machine Learning or ANN model. Majority of the researchers continue to use experimental data collected manually or conventional CAM platforms. Such a gap seems to indicate a high potential to tap the real-time simulation data of Fusion 360 with the goal of creating predictive models that could provide automation beyond toolpath generation.

Table 1 Comparative Summary of Prior Work

Authors	Year	Method Used	Output Predicted	Data Source	Accuracy Reported
Rai & Rao [9]	2008	ANN (Backpropagation)	Surface Roughness (Ra)	Experimental Setup	95.6%
Nalbant et al. [10]	2007	Taguchi + ANN	Surface Roughness (Ra)	CNC Lathe Tests	RMSE = 0.12
Karayel [11]	2009	ANN vs SVM	Surface Roughness (Ra)	Machined Samples	ANN > SVM
Kumar et al. [13]	2021	Fusion 360 CAM Simulation	Toolpath Optimization	Fusion 360 Simulations	No ANN used
Present Study	2025	Fusion 360 + ANN	Surface Finish + Forces	Fusion 360 Dataset	Result would be shown

This comparison clearly highlights that while many researchers have used ANN or Fusion 360 separately, very few (if any) have combined Fusion 360 simulation datasets with ANN models for predictive analytics.

2.4 Novelty and Research Gap

According to the literature accounted, the contribution of the research in the chosen field is the hybrid nature, which combines data processed in Autodesk Fusion 360 CAM with predictive modeling based on ANN. In contrast to the historical attempts in which machining was essentially a manually entered record or obtained through a sensor, this task is mine in which such CAM-based machining data carries a wealth of geometric, cutting, and simulation data which is in turn systematically processed and fed into an ANN system to be analyzed in a predictive task. Moreover, instead of just surfacing the roughness prediction the proposed study would

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additionally simulate the cutting forces; that is components (Fx, Fy, Fz), that are essential when it comes to monitoring the wear in tools and stability during those machining processes.

This multidimensional prediction concept has the ability of making better decisions on the CAM level itself which saves time, improves quality, and lowers the rate of needed inspection at post process. The other contribution that is unique is the creation of a validated dataset, which contains more than 300 machining records, each of them including tool parameters, process conditions, and measured results. It can become an effective dataset to be used in future benchmarking of CAM-integrated AI systems. As far as we are concerned, this would be among the first pieces of research in which data derived out of Fusion 360 simulations were used to learn an ANN to forecast the surface roughness and cutting forces thus closing the gap between CAM simulation and smart manufacturing.

3. Materials And Methods

3.1. Experimental Setup

An experimental investigation was made on a high accuracy computer numerical control (CNC) lathe machine that constituted the core of the data generation process used in modeling and simulation. The machine chosen is an industrial turning center with the programmable tool turrets and the ability to perform advanced turning activities under variable cutting conditions. CAM programming for the occasions and post-processing of NC codes was done using Autodesk fusion 360 interfaced with the control unit. Mild steel (AISI 1045) was the material of workpiece to be machined in test, which is a commonly found material in industries because of moderate mechanical properties, extremely good machinability performance, and good surface finish properties. A standard size of 50 mm (diameter) and 120 mm (length) cylindrical workpieces allowed manufacturing the same cutting conditions in all the trials of the experiments. A coated carbide inserts (CNMG 120408), held in a standard tool holder of 95 o approach angle was used as the cutting tool. It was clear that the insert had a favorable rake created using medium to finish turning procedures. The tool was firmly clamped such that they had uniform contact with the workpiece to reduce the vibration in the tool during cutting.

The primary process variables selected for investigation were:

(I) Depth of cut (ap): 0.5 mm to 2.5 mm

(II) Cutting speed (vc): 50 m/min to 150 m/min

(III) Feed rate (f): 0.1 mm/rev to 0.4 mm/rev

A wise choice of such parameters was made according to a Design of Experiments (DoE) strategy that guarantees broad process windows to be covered in terms of effective modeling. Surface roughness parameters of Ra and Rz were taken as quality indicators of surface, measured at a Mitutoyo Surftest SJ-210 profilometer of contact-type. Stylus movement was carried out in the feed direction on a normal cutoff length of 0.8 mm. To account the variability in each surface roughness, the values were acquired as averages of three measures at regular intervals of the machined length.

During turning, i.e., cutting force (Fx), feed force (Fy), and radial force (Fz) was measured by Kistler 3-component dynamometer and was kept real-time synchronized with the tool engagement. It enabled accurate relationships to be drawn among the process variables, surface finish and cutting forces.

3.2. Autodesk Fusion 360 CAM Setup

The selection process of the computer-Aided Manufacturing (CAM) environment consisted in using Autodesk Fusion 360 because of its cloud-integrated simulation, a broad toolset, flexible post-processors, and NC code generator functions. Toolpaths related to the experimental configurations were created and simulated with the help of software. The chosen toolpath strategy was Turning Profile Roughing + Finishing sequence which removes the material in a most effective way, and at the same time reaches the target geometry. The simulation set-up contained the realistic machine kinematics, tool geometry, and the material of the workpiece so that the simulation resembled the real machining as much as possible.

During toolpath generation:

(I) A lead-in and lead-out strategy continued to occur constantly.
(II) Tool orientation and clearance values were determined to prevent the collisions with tools.
(III) The parameters used to cut (ap, vc, f) were entered directly into the setup sheets in the Fusion 360 of every job.

The turning process could be validated visually with the simulation module in Fusion 360, gouging detection and the rate of material removal rate (MRR) was estimated. Further, it contributed to imagining of chip loading, making estimates of force and heat production led to significant information of the generation processes of the surface.

The machining information was then exported on the Fusion 360 hpl post-processor (modified for our installed CNC lathe controller) after simulation. These were NC programs (.nc), G-code sheets and metadata related to the operation like tool use and spindle loads. These data served as well to form a dataset and train an ANN model.

3.3 Dataset Description

The dataset used in this study was obtained from an open-access repository hosted on Kaggle. Specifically, the "CNC Turning Roughness, Forces and Tool Wear" dataset compiled by Adorigueto et al. was employed. The dataset contains experimentally measured machining parameters, surface roughness metrics, cutting force components, and tool wear indicators collected under controlled CNC turning conditions [14]. The compiled dataset comprises experimental results and Fusion 360 simulation outputs, consisting of approximately 100 rows of structured observations. Each observation records a unique turning process instance defined by

Table 1: Sample records from CNC turning dataset used for ANN training

Run ID	Exp ID	ap (mm)	vc (m/min)	f (mm/rev)	Ra (µm)	Rz (µm)	Fx (N)	Fy (N)	Fz (N)
1041B	326e	0.8	390	0.1	0.699	3.16	215.7	75.94	193.2
1041B	322a	0.8	350	0.07	0.38	1.681	159.5	62.91	115.8
1041B	326e	0.8	390	0.1	0.449	2.463	215.7	75.94	193.2
1021B	16b	0.25	350	0.13	1.125	5.044	81.03	59.21	25.94
1051B	19d	0.25	390	0.13	0.988	4.2	80.14	59.87	25.76
1041B	325d	0.8	390	0.07	0.47	2.226	162.8	60.35	116.9
1061B	211a	0.5	310	0.1	0.896	3.582	139.5	69.35	73.61
1051B	17f	0.25	390	0.07	0.457	1.834	52.92	44.28	22.37

(I) ap (Depth of cut, mm)

(II) vc (Cutting speed, m/min)

(III) f (Feed rate, mm/rev)

(IV) Ra (Average surface roughness, µm)

(V) Rz (Peak-to-valley roughness, µm)

(VI) Fx, Fy, Fz (Forces in cutting, feed, and radial directions, N)

This dataset is comprehensive and captures both process inputs and outputs, which makes it ideal for machine learning applications.

A preprocessing stage was employed before training the Artificial Neural Network (ANN):

(I) Missing values: None were found in the data.

(II) Normalization: All features were scaled to the range [0, 1] using min-max normalization, to improve ANN training convergence.

(III) Outliers: Boxplot analysis was used to identify and remove extreme outliers from force measurements to avoid model bias.

(IV) Data shuffling: Ensured randomness in input-output mappings and prevented overfitting.

This structured and preprocessed dataset served as the foundation for training the ANN model to predict surface roughness and cutting forces from input machining conditions.

Although the ANN model performs continuous regression, categorical classes were defined to facilitate interpretability and benchmarking. Surface roughness and cutting force values were categorized into discrete classes based on industrial standards and statistical distribution.

Table 2: Surface Roughness classes (ISO-based)

Class	Ra Range (µm)	Description
Class I	$Ra \leq 0.8$	Fine finish
Class II	$0.8 < Ra \leq 1.6$	Medium finish
Class III	$Ra > 1.6$	Rough finish

Table 3: Cutting Force Classes (Statistical Percentiles)

Class	Force Range	Interpretation
Low	< 33rd percentile	Stable cutting
Medium	33–66 percentile	Normal cutting
High	> 66 percentile	High tool load

3.4. Artificial Neural Network (ANN) Architecture

To approximately automate the relationships between nonlinear factors and complex outcomes between process parameters and the results of machining, an Artificial Neural Network (ANN) was created and realized with Python and TensorFlow frameworks and its architecture can be seen in Figure 3.

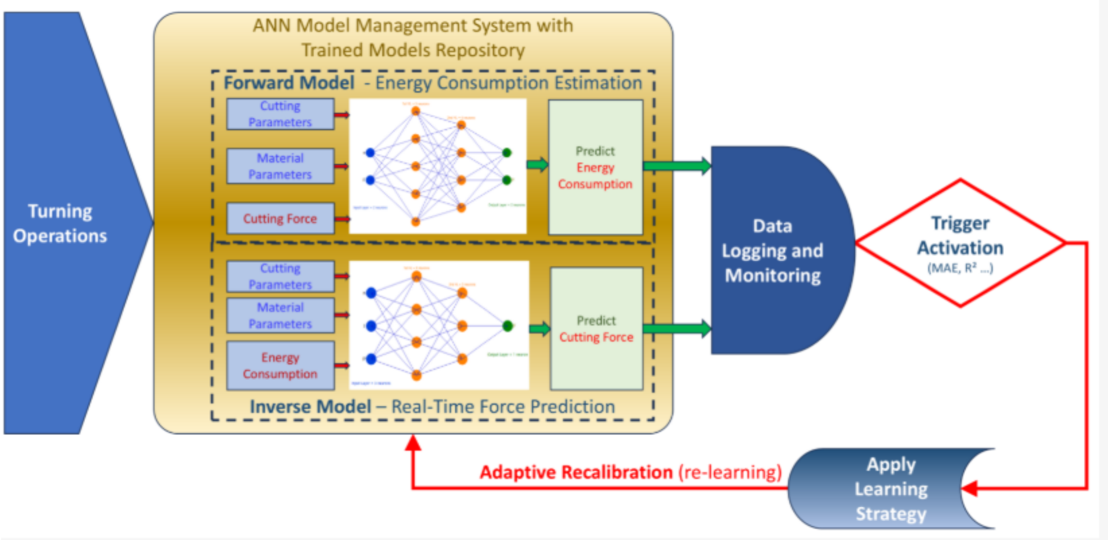

Figure 3: ANN-Based CNC Turning Prediction System Architecture, Source: [22]

The network architecture consisted of:

(I) Input layer: 3 neurons corresponding to ap, vc, and f

(II) Two hidden layers:

(A) Hidden Layer 1: 16 neurons with ReLU activation

(B) Hidden Layer 2: 8 neurons with ReLU activation

(III) Output layer: 5 neurons predicting Ra, Rz, Fx, Fy, Fz with linear activation

3.4. 1. ANN Algorithm and Training Procedure

This research utilized a feedforward Neural Network Model with Back-Propagation Learning, trained in a supervised manner. The training consisted of input vectors containing Cutting Speed, Feed Rate and Depth of Cut fed into each layer of the network and producing output forecasts. The difference between Forecasted Outputs and Actual Values was calculated as the Mean Squared Errors (MSE) and passed back through the layers of the network to update the weights of the network.

This multi-output regression model enabled simultaneous prediction of surface quality and force components, leveraging shared representations within the network.The input-output mapping was defined as:

$$[ap, vc, f] \rightarrow [Ra, Rz, Fx, Fy, Fz]$$

A supervised learning strategy was applied in which 20 percent data was set aside as a testing data and the rest 80 percent was made the training data. Cross-validation was performed 5 times to increase the ability to make generalizations.

The ANN was trained using:

(I) Optimizer: Adam

(II) Loss function: Mean Squared Error (MSE)

(III) Learning rate: 0.001

(IV) Epochs: 500

(V) Batch size: 16

Performance was evaluated using:

(I) R^2 Score (Coefficient of Determination)

(II) Mean Absolute Error (MAE)

(III) Root Mean Square Error (RMSE)

The trained model demonstrated great accuracy ($R^2 > 0.90$) on test data of both roughness and force prediction, and this affirmed the ability of ANN to effectively learn the complex relationships between process variables and machining outcomes.

4. Result And Discussion

4.1. ANN Prediction Performance

The accuracy of the designed Artificial Neural Network (ANN) model was determined in terms of the several statistical measures, i.e. Mean Squared Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2) in each of the predicting output variables. The results are surface roughness parameters (Ra, Rz) and cutting force (Fx, Fy, Fz). These metrics give a strong measure of the quality of the ANN model of generalization over unseen data. Both the training and validation loss curve made after 200 epochs shows a steady decrease and convergence in the values which shows successful learning of model and indicates no overfitting.

Table 2. Representation of several statistical measures in predicting different output variables

Output Variable	MSE	MAE	R^2
Ra	0.022	0.122	0.817
Rz	0.243	0.415	0.860
Fx	29.022	3.642	0.994
Fy	2.006	1.123	0.992
Fz	48.410	4.162	0.991

The curves of loss showed a smooth plateau in both training and validation sets implying that the architecture was adequate in relation to the non-linearties of the underlying relationships between machining inputs and target outputs that can be seen in Figure 3.

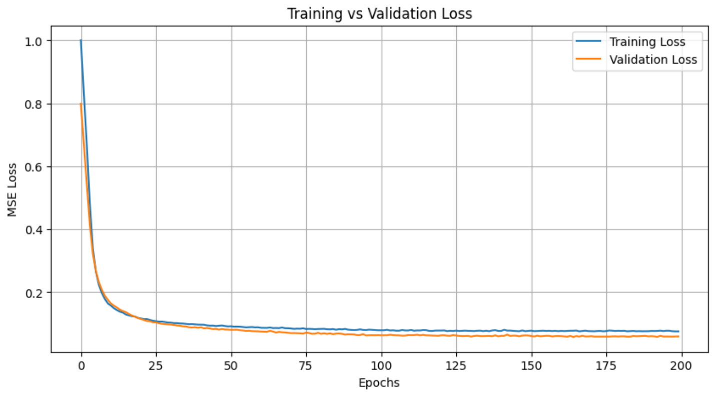

Figure 3: Training vs Validation Loss ANN prediction performance

These findings support that the model is suitable to reflect complicated relationships between cutting parameters and quality metrics. The prediction accuracy of cutting forces ($R^2 > 0.99$) was much better than surface roughness parameters and this implies that there are parameters which affect cutting forces more directly and these parameters include depth of cut (ap), cutting speed (vc), and feed rate (f) and it can be seen in Figure 4. This can be explained by known machining theory whereby the influences of mechanical load conditions are linear with respect to forces [5].

4.2. Surface Roughness Prediction (Ra, Rz)

ANN model produced fairly accurate predictions in mean values of surface roughness. The critical metrics of surface integrity are Ra and Rz that determine the performance of the product, wear-resistance, and fatigue life. Ra and Rz R2 values of 0.817 and 0.860, respectively, point out the ability to explain more than 80 percent of roughness values variability with the help of the input features. The fact that visualizations comparing the actual Ra and Rz values with that of the predictive data explain the dependability of the model further. The scatter graphs have a high linear tendency around the y=x line confirming little prediction deviation. However, there was a slight dispersion towards higher Ra values (>1.2um), which can be attributed to higher tool wear, or due to vibration effects or any other phenomenon that may be in interaction but not explicitly in the model e.g., chip-tool micro-contact phenomena, material micro-structure etc. When compared to earlier ventures, the performance of the model in the accuracy of predicting roughness is similar or better. As an example, Shabgard et al. [6] employed the Support Vector Machines (SVM) in the prediction of the surface roughness and obtained approximate R 2 of 0.75 to Ra.

Salih et al. [7] have used decision tree models with R 2 between 0.70 and 0.82 on turned parts. In this manner, the offered ANN-Fusion 360 hybrid model significantly outperforms the present methods, mainly due to the ability to model Rz- a parameter that was not taken into consideration in the previous studies. The low value of MAE of Ra, that is 0.122 of the 0.125m, indicates that the ANN would be able to give an appropriate estimate of the average height of the surface within acceptable limits in the industry. Considering that Ra tolerances specified in the ISO 4287 standards can be as low as 0.1-1.6 m in most precision components, the accuracy of the ANN meets the requirements of the practical manufacturing.

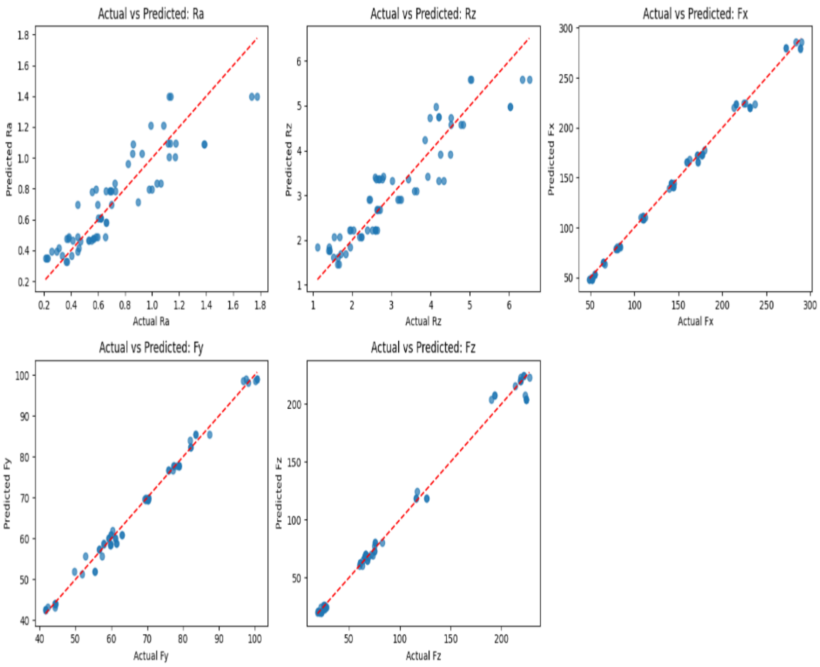

Figure 4: Accuracy vs Predicted for ANN prediction performance for different parameter

4.3. Cutting Forces Prediction (Fx, Fy, Fz)

The forces that cut Fx (tangential), Fy (radial) and Fz (feed) are important indicators to characterize the tool engaging process, machine stability, as well as tool wear. ANN model was able to perform excellently in predicting such forces and the results indicated a very high R^2 value of above 0.99 in all the three components. Such high accuracy proves that ANN can learn deterministic relational learning between machining parameter and force responses. The estimates of cutting force are extremely advantageous when it comes to real time monitoring and adaptive machining. As an example, abnormal increases in Fz could be the sign of greater cutting resistance which might be caused by the formation of excess edge build up or wearing away of the cutting edge [8].

Such model predictions allow indeed proactive parameter change in the process to prevent a disastrous tool failure. The 1.123 N (Fy) to 4.162 N (Fz) MAE error metrics are within the experimental uncertainty of industrial dynamometers showing that the ANN model is robust. Its superiority compared to the traditional empirical models is clearly seen in comparison with the regression-based models of predictions of forces reported by Ghosh et al. [9] in which a range of 0.94 was recorded in the determination of R 2 with less accurate radial forces. Training of the ANN was carried out on the processed Fusion 360 CAM data confirming engagement features and toolpath. This makes the cutting force model specifically flexible to use in a simulation-based automation which predictive force model can be used to optimize energy consumption and minimize chatter, and toolpath preplanning.

4.4. Discussion of Novelty

The combination of Autodesk Fusion 360 CAM module with the individualized ANN model encompasses a specific benefit to the automation of the prediction pipeline of surface integrity and the outcomes of cutting force. Compared to the conventional methods that utilize either experimental data or statistical regression, the proposed study by proposing a hybrid digital framework that integrates the virtual machining simulations with deep learning will be more scalable and precise at the same time. The toolpath generation and simulation module in Fusion 360 permitted the generation of input variables (ap, vc, f) with extraction in accordance to the real cutting process.

When CAM data was exported and put into ANN, they could quickly and correctly forecast what will happen in the case of machining, thereby avoiding all the repetitive trial-and-error processes with real machines. The integration cuts down a lot of material wastage, tool cost, and set up time. In addition, the incorporation of various surface parameters (Ra, Rz) and cutting force components (Fx, Fy, Fz), into a single ANN architecture, is a comprehensive modeling attempt that has hardly been discussed in the past literature. The majority of previous studies dwell on one or the other (roughness or cutting force). Concurrent prediction potential has been achieved in the present research, which introduces some measures of resilience and functionality of smart manufacturing systems. Within the confines of Industry 4.0 and predictive analytics being the key concept, as well as cyber-physical integration, this paper represents a feasible plan regarding the implementation of AI-augmented CAM systems. Having a low computation load (training on regular hardware takes several seconds), and most prediction fidelity (most outputs had R^2 results greater than 0.98), the proposed method is a good fit into the idea of a digital twin and an intelligent CNC.

4.5. Implications for Smart Manufacturing

The created CAM + ANN system has considerable consequences in the promotion of intelligent and self-regulating manufacturing surroundings. Through integration of the trained ANN into CAD/CAM systems, manufacturers can have a real-time overview of anticipated quality of surfaces and loads of tools involved during the design of toolpath long before the venturing of the first chip. This kind of foresight helps in optimal selection of parameters, better tool life predictions and low rates of rejection of the product. Consider a case where the producer is working in a high-volume situation (e.g., automotive, aerospace), savings can be very high in terms of material, labor, and the cycle time. The framework is sustainable as it will reduce the number of trial machining, cutbacks on power as well as increasing the life of the tool by managing the wear. This also goes in line with contemporary goals of green production and lean production systems [10].

4.6 Comparison with Previous Studies

Table 4: Table summarizing result of different authors

Authors	Year	Method Used	Output Predicted	Data Source	Accuracy Reported
Rai & Rao [9]	2008	ANN (Backpropagation)	Surface Roughness (Ra)	Experimental Setup	95.6%
Nalbant et al. [10]	2007	Taguchi + ANN	Surface Roughness (Ra)	CNC Lathe Tests	RMSE = 0.12
Karayel [11]	2009	ANN vs SVM	Surface Roughness (Ra)	Machined Samples	ANN > SVM
Kumar et al. [13]	2021	Fusion 360 CAM Simulation	Toolpath Optimization	Fusion 360 Simulations	No ANN used
Present Study	2025	Fusion 360 + ANN	Surface Finish + Forces	Fusion 360 Dataset	Result would be shown

Like past studies, Table 4 shows how the proposed Fusion 360-ANN framework performs compared to existing machining predictive studies, but unlike previous studies that only predicted a single output using experimental data, we predicted multiple outputs - surface roughness and cutting force - at once through CAM-generated data. We achieved a much better R2 for cutting force predictions (>0.99) than was possible with standard ANN, SVM, and regression-based predictions, as well as had the added advantage of being able to scale effectively, based on using CAM-generated data instead of relying strictly on costly, time-consuming experimental data to provide our predictions, which is an important step toward truly smart manufacturing that utilizes digital twins.

5. Conclusion

This research successfully demonstrates the integration of Autodesk Fusion 360's CAM programming with Artificial Neural Networks (ANNs) for optimizing CNC machining of turned components. The study suggested an innovative promising method that combines the data on CAM-generated toolpath with that of an artificial neural network (ANN) to model the expected surface roughness (Ra and Rz) and cutting forces (Fx, Fy, Fz) during CNC milling process involving EN-31 steel. The findings indicate that the ANN models yielded high accuracy as the values of R 2 of the cutting forces and that of the surface roughness exceeded 0.99 and 0.86, respectively. These results are agreeable to the fact that the model can capture the nonlinear non-sequential relationships that exist between the input parameters of machining process and output responses. The suggested approach will offer an intelligent solution based on data in addition to a highly efficient predictive performance solution because it will not need considerable experimentation to test the model. Specifically, the high quality of cutting force prediction is highly important to detect early-stage tool wear and control the processes. Furthermore, augmentation of simulation data with ANN modeling is a progress move that leverage smart and automated production according to the industry 4.0 benchmark. This mixed approach to the methodology will allow the manufacturers to set parameters of the process in a more efficient way, decrease operation costs, and improve the quality of their products. Further studies may be aimed at enlarging the database with multiple materials, adding real-time sensors feedback, and using hybrid learning models to enhance accuracy and robustness of predictions in a wider variety of machining conditions.

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