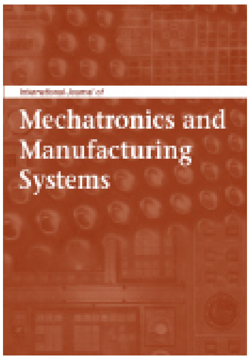

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Machine learning approaches towards digital twin development for machining systems

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Abstract: Machine learning (ML) and artificial intelligence (AI) have experienced an increased degree of applications associated with Industry 4.0. Their effective utilisation is elevated with readily available computational power and computerisation of production processes toward digital twin development. This paper begins with a review of the use of ML and AI Methods in machining applications, using examples from open literature, discussing the future perspectives for further utilisation of ML and AI techniques within the scope of machining, both in terms of research and industrial applications. Examples of computer-aided production (CAP) systems are presented and compared with a discussion on how ML and AI can be applied to improve applicability and performance of already established software solutions. Additionally, a software solution for numerically controlled (NC) toolpath optimisation is shortly presented. Finally, incorporation of machine learning method in a CAE software solution developed by the authors is discussed along with a case study.

Keywords: virtual machining; production; advanced manufacturing system; CNC; computer numerical control; machine learning; artificial intelligence; digital twin; Industry 4.0.

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1 Introduction

Industry 4.0 is seen as an opportunity to achieve higher levels of productivity through interconnected intelligent elements (machines, robots, sensors, etc.) inside the shop floor. The technology allows the remote sensing, real-time monitoring, control of devices, and cyber physical manufacturing elements across network infrastructures and, therefore, provide a more direct integration and synchronisation from physical to the virtual world. The digital technologies enable virtual product and process planning through simulation and optimisation tools to make them available for planning in real time. One of these simulation-based planning and optimisation concepts with great potentials in digital twin (DT) which is the real-time virtual replica of a physical object, process, or system.

Artificial intelligence (AI) is defined as the presence of certain traits in machines and computers that make them exhibit abilities and behaviours that the human perceives as indicative of intelligence. Numerous advances in the field of AI are based on machine learning (ML). ML is an area of AI that allows machines to learn and adapt to perform specific tasks using input data, without the need for being precisely programmed to perform a particular activity (Kim et al., 2018). For machine learning in machining modelling, often artificial neural network (NN) models or deep neural network (DNN) models are utilised. A DNN is a NN with multiple layers between the input and output layers (Hinton and Salakhutdinov, 2006).

In general, the machine learning process for machining modelling can be described as follows:

- First, the machining modelling problem is defined, and the ML method is selected. For example, when artificial neural networks are used, an appropriate method (i.e., supervised learning using DNN or convolutional neural network (CNN) (Hinton et al., 2012), or unsupervised learning using Restricted Boltzmann Machine (RBM) or Helmholtz (Ackley et al., 1985)) and a suitable neural network structure (Agarwal et al., 2020) are selected;
- Next, appropriate training data must be collected (for example by conducting experimental tests or gathering data from open literature) and processed into a form that can be used for machine learning purposes (for example, data is divided into inputs and correct outputs in case of supervised learning using neural networks with DNN or CNN type). Data processing can also involve elimination of errors/noise and normalisation to obtain more accurate results;

- Next, the machine is trained, and the results are evaluated. Then, the model is used for making predictions and these predictions can be used in a particular application (a machining-relevant example can be obtaining predictions of process performance indicators, such as surface quality or tool life for certain values of machining parameters without having to obtain them experimentally).
- Predicting tool vibrations and chatter can be attempted. Tool vibrations can be discretised, and each data point can be used to train the machine learning NN model. Alternatively, tool vibrations can be characterised with amplitude and frequency (mode) signals based on the each cutting condition tested (spindle speed, tool length, depth of cut, feed rate, wet, dry, MQL, etc.) These characteristics can be used as training dataset to train neural networks for capturing tool vibrations and tool vibration characteristics can be classified as stable, on the border, unstable etc. at the fully connected NN layer.

Machine learning methods can be divided into three main categories:

i supervised learning

ii unsupervised learning

iii reinforcement learning.

In supervised learning, the computer is trained using inputs and known correct outputs and classification. In unsupervised learning, known outputs are not provided to the system and the network is used to identify patterns using clustering for large input datasets. Reinforcement learning uses a reward/penalty signal that is used during training.

Industry 4.0 and computerisation have a significant impact on the machining industry, facilitating its development and evolution to meet new demands arising from increasing part complexity, quality requirements and the increased demand for parts made from difficult-to-cut alloys. Within the machining industry, the utilisation of computer techniques, including AI and machine learning, is associated with the concept of smart machining. Smart machining as an ability to monitor the machining process in real time to improve its performance and meet the target goals. This can be achieved by establishing relations between the physical machining tool, its sensors and monitoring equipment and the computer hardware/software that allows for process monitoring, digitalisation and simulation (digital shadow/digital twin) for process optimisation and adjustment of machining parameters, either in real time or for subsequent operations. Machine learning algorithms can be utilised here for a number of purposes, ranging from online process monitoring (be it in the aspect of machine health/performance or product quality) to process optimisation to improve productivity/workpiece quality. Examples include employment of ML techniques to predict surface roughness, cutting force components, workpiece defects or chatter occurrence. Specific examples of machining-relevant ML applications are given in the literature review section of this paper.

The paper aims to review and summarise the use of machine learning algorithms in machining applications and suggest future perspectives of utilising machine learning and AI in the machining industry. It attempts to outline the current available solutions for virtual machining and digital twin, discussing how machine learning and AI can be used to improve the functionality of available solutions. Also, it provides a discussion on the possibility of incorporating machine learning and AI techniques in a software solution developed for VM/toolpath optimisation – Optima NC.

2 Digital twin concept for manufacturing

The digital twin consists of a virtual representation of a production system that is able to run on different simulation disciplines that is characterised by the synchronisation between the virtual and real system (see definitions of digital model, digital shadow, and digital twin in Figure 1), thanks to sensed data and connected smart devices, mathematical models and real time data elaboration (see an example for machining system Figure 2) (Jones et al., 2020). The topical role within Industry 4.0 manufacturing systems is to exploit these features to forecast and optimise the behaviour of the production system at each life cycle phase in real time. The role of DT on the overall production systems will be to increase competitiveness, productivity, and efficiency in different manufacturing areas including production planning and control, maintenance, and layout planning (Wilhelm et al., 2021).

The analysis of the state-of-the-art of DT concept shows that the development of the DT is still at its infancy as literature mainly consists of concept papers without concrete case studies. However, a few applied case-studies already exist at the lower levels of integration (DM and DS). As shown in Table 1 from a recent survey reported, a main focus of recent research concerning the DT in manufacturing is dealing with manufacturing planning and control as it is a main data-sink within a manufacturing system that ties everything together.

Figure 1 Level of integration between physical object and digital object (Jones et al., 2020): (a) digital model (DM); (b) digital shadow (DS) and (c) digital twin (DT) (see online version for colours)

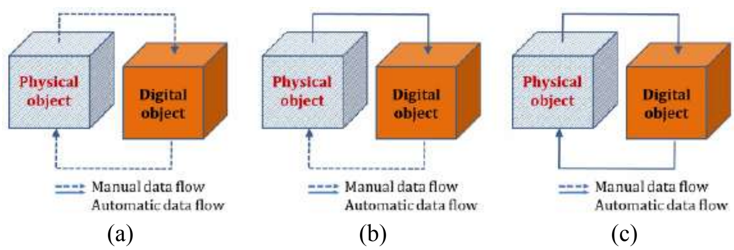
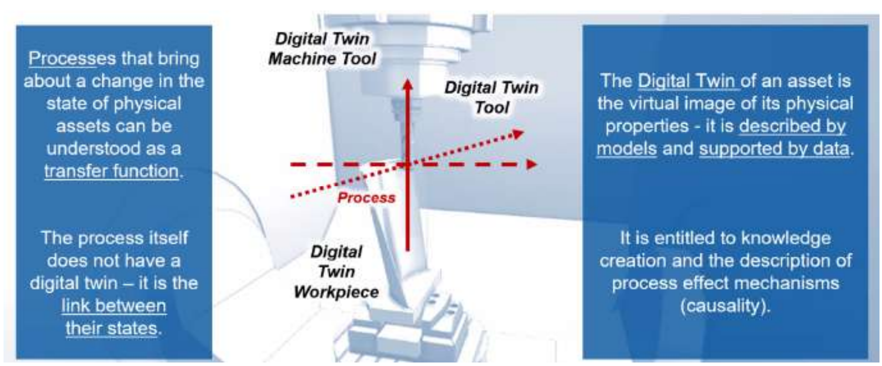


Figure 2 Digital twin and interaction of assets in the process (see online version for colours)



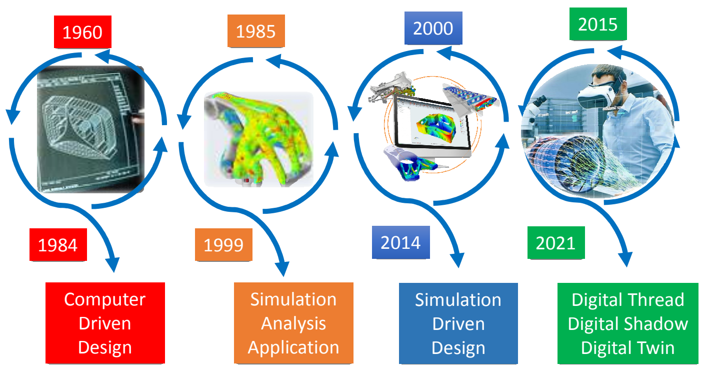
Source: Bergs et al. (2021)

Table 1 Survey on data integration level between the physical object and digital object

Integration level	*Concept* (%)	*Definition* (%)	*Review* (%)	*Case study* (%)
Undefined	11.9	0.0	2.38	4.76
Digital model	14.29	0.0	0.0	11.90
Digital shadow	26.19	0.0	2.38	7.14
Digital twin	2.38	4.76	9.52	2.38

Conceptualisation and complexity of DT has been constantly evolving over the decades, as depicted in Figure 3. Today, DT has been projected as the next disruptive technology which will reshape the production and manufacturing systems.

Figure 3 Concept evolution towards DT development (see online version for colours)



This underscores the fact that DT technology in its full essence is yet to be fully understood. Its depth and breadth are evolving. Moreover, myriad recent research on DT clearly highlight that DT cannot be bounded to unique definition. Rather, the definition will find its place where the digital twin is considered for filling a function similar to ‘twinning’. The level of integration in existing products/process design and complexity of practice determines its definition of DT in the context. While a lot of conceptual studies have been done for DT, few research papers have demonstrated practical implementation of DT till this date. This is a critical research gap, because the definition and functional properties of an evolving concept like DT should be directly linked to experimental outcomes reported in scientific literature.

There are a number of literature review conducted on the topic of digital twin including the work by Cimino et al. (2019), Tao et al. (2019), Negri et al. (2017) and Alexopoulos et al. (2020) They reveal that there are nearly 400 papers appeared in literature since 2015 when ‘Digital Twin’ in production systems in Industry 4.0 was first proposed. On the other hand, in 2019 alone, more than 200 papers, books or journals referring to DT have been published. This trend clearly shows a tremendous increase in interest to study digital twin.

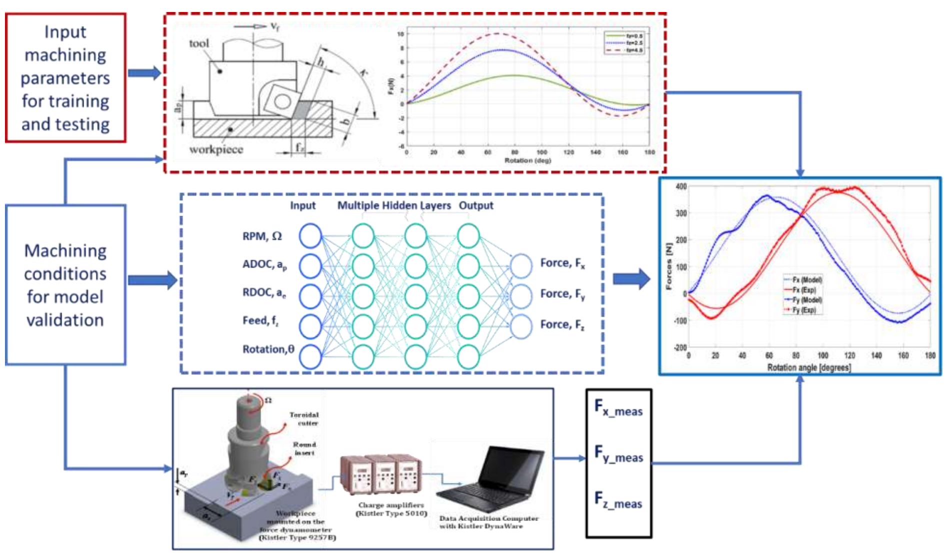
Generation, interpretation and processing, and universality in the exchanged data format. DT as a concept has been far more practical and executable for ‘systems-of-systems’ than it was coined in 2002. Advances in data transmission rate, resolution, and artificial intelligence/machine learning have made it possible for corporations to leverage

DT in reducing design lead times, managing gigantic ecosystems, dynamically re-calibrating and creating better production environment through software-driven devices. From the literature, it is clear to assume that in past two decades DT has gained lot of traction and sustained momentum towards digital transformation will play crucial role realising ubiquitous smart manufacturing platforms (Glaessgen and Stargel, 2012).

3 Digital twin and machine learning for machining applications

Many applications of Machine Learning algorithms applied to machining modelling can be found in in open literature. Several research studies have utilised a hybrid approach combining mechanistic modelling with neural networks for predicting milling forces. In this type of approach, multiple neurons in the input layer are often provided with radial depth of cut a_e, axial depth of cut a_p, feed per tooth f_z (or feedrate v_f) and tool rotation angle θ input data. Different NN structures are often tested to identify the most suitable NN architecture, ranging from a single hidden layer to multiple hidden layers with usually more neurons than the number of neurons in the input layer and as many as 50 neurons. During and after the network training process, data from testing and validation subsets was used to evaluate its performance. After the network was trained, its outputs (cutting force components, F_x, F_y, and F_z) are compared with experimentally obtained force data and classic mechanistic predictive modelling results. This approach of combining mechanistic modelling with neural networks is illustrated in Figure 4.

Figure 4 Combination of mechanistic force modelling and neural networks and for milling force predictions (see online version for colours)



For example, Vaishnav et al. (2019) have used a hybrid combination of NN training and a mechanistic force modelling approach for cutting force prediction in an end milling process. The authors have used supervised learning, providing the NN with training, testing and validation datasets. Overall, a good agreement of experimental and NN modelling results can be noted. The authors state that NN training with the use of supervised learning methods is a viable technique for cutting force predictions. In the discussed work, the neural network was trained with the use of mechanistic force modelling results instead of experimental data. A good agreement of NN predictions and measured real-life force values can be noted. This proves that input data from mechanistic force modelling can be used to obtain accurate NN training results without the need to perform costly and time-intensive experimental testing. Moreover, this greatly increases the flexibility of the approach proposed by the authors, as the mechanistic model can be easily modified for a range of tool/workpiece material combinations and cutting parameter values to provide plentiful data for neural network training.

Aralikatti et al. (2020) have used machine learning for tool condition monitoring in machining using experimental cutting force and vibration measurement results as input training data. The authors have performed a series of turning experiments, simulating four different tool conditions- namely a fresh insert, extended tool overhang, flank wear and tool chipping (tool breakage- catastrophic failure). Instead of classifying and processing gathered force and vibration data manually, a decision tree method was used to group the input data. A Bayesian algorithm was used to classify the data into four distinct groups corresponding to simulated faults. 66% the of measured data was used as a training set, while the remaining 33% of measurements were utilised as validation data. The algorithm performed remarkably better when provided with force data- 96.67% of the force results were classified properly, whereas only 70% of vibration signals were classified correctly. The potential application of this study is for online monitoring of cutting force signal for instantaneous detection of tool wear/failure or improper tool setup.

Afazov and Scrimieri (2020) have proposed a digital twin approach to process monitoring to ensure chatter free-machining. Cutting force data acquisition was used along with predictive modelling techniques to obtain a digital twin of a physical machining environment. The main goal was to use predictive modelling using data gathered in real time to ensure chatter-free conditions while maximising the material removal rate (MRR) while retaining a good machined surface quality. The process proposed by the authors can be divided into the following distinct steps:

1 creation of a digital twin of the process in a CAM environment, using it for toolpath generation

2 establishment of force and chatter prediction models with the use of gathered experimental data

3 detection of stable cutting conditions based on gathered data, adjusting the model based on data from machine sensors.

At the current stage of the work, the authors have focused on establishing an accurate predictive model for chatter and cutting force prediction, while also proposing how it can be used in a broader sense when coupled with a digital twin of a physical machine tool. The authors are planning to expand upon their digital twin concept in future research by conducting a case study in an industrial application. This is a promising approach, as the push for increased productivity (in terms of volume of removed material) can lead the technologists/machinists to increase the cut depth past the stable conditions threshold, resulting in chatter. This leads to decreased surface quality and tool breakage, increasing machining costs by generating defective workpieces and excessive tool costs.

A different approach to chatter prediction in turning was showcased by Cherukuri et al. in their recent work (Cherukuri et al., 2019). The authors have trained the neural network using data obtained with the use of an analytical model which was similar to the one used by Afazov and Scrimieri (2020). Therefore, this is another example of neural network training using simulation data instead of experimental results. A supervised learning method was used in this study. The inputs constituted spindle speed and maximum chip width. A single hidden layer with four neurons was used and the stable cutting conditions were predicted by the neural network. The simplicity of the approach proposed by the authors is noteworthy- the neural network requires inputs in the form of two parameters, and results from analytical modelling can be used instead of experimental measurements. A 10-fold cross validation method was used to evaluate NN prediction accuracy, which ranged from 0.8 to 1 when validated against a test dataset. Although the authors have not focused on a practical application in their study, this approach can be integrated into existing CAM/CAE/Virtual Machining solutions to help the technologist determine stable cutting conditions.

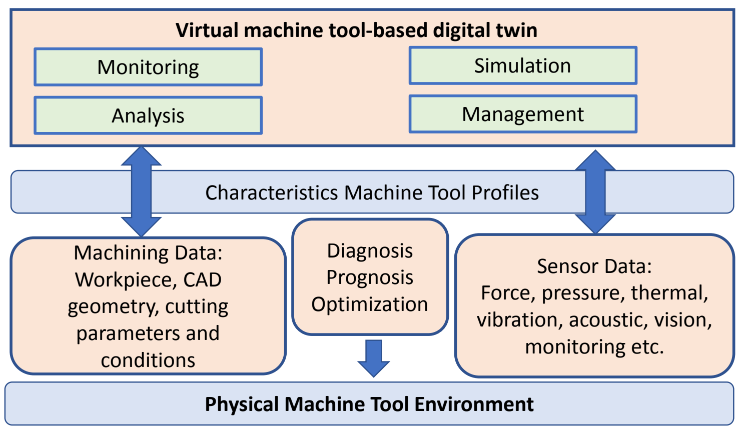
An interesting use of machine learning methods was showcased by Nassehi et al. (2015). The authors have utilised a genetic algorithm (GA) for toolpath generation based on a 3D STEP-NC part file. The main objective was to generate CNC milling toolpaths that would be optimal or near-optimal with respect to four selected objective functions:

- minimisation of cutting time
- maximisation of tool engagement time
- minimisation of tool/holder jerk
- combination of three first objectives.

In their work, an aerospace part model was used for the benchmark process. The toolpath was generated for a small portion of the part model. The generated toolpaths were evaluated regarding to total toolpath distance and percentage of tool engagement time. Examination of the generated trajectories reveals the presence of some redundant tool motions. The authors note that even for a simple benchmark process, the calculation time is extensive and requires substantial computational power. At this stage, no on-machine tests were performed by the authors. Nevertheless, the idea of toolpath generation using ML methods is interesting and noteworthy.

Cai et al. (2017) have developed a method to build virtual machine tools of physical machines for cyber-physical manufacturing by proposing the idea of integrating sensory data and manufacturing information. The authors use the case of virtual 3-axis vertical milling machine well-supported with manufacturing data and sensor data collected from actual vertical milling machine (Haas VF-2 3-axis CNC vertical milling machine), also discussing methods of this data collection, to back their theory. The Schematic of constructing the digital-twins virtual machine tool integrated with sensory data and manufacturing information is shown in Figure 5. The authors have used a vertical milling machine (Haas VF-2 3-axis CNC vertical milling machine) as a test bed for data collection. They also developed a CAD model of the same using SolidWorks. The manufacturing data was collected using an RS232 serial adaptor cable is connected between the controller of the CNC machine and the USB port of the desktop computer, which updates every 1–2 s. Two different sensors are mounted on the machine to capture change in current consumed by spindle and vibration induced between tool and workpiece with help of data acquisition device, with a predefined interval of 1 s. The authors also try to show data collection from face milling, pocket milling etc. by designing and manufacturing a test part. These data collections successfully record the fluctuations/inconsistencies in the data during different scenarios of process due to current consumption, tool involved, and such other factors. Overall, the authors take the development of a virtual three-axis vertical milling machine as an example to illustrate advantages of digital twin system in virtual manufacturing. The data collection techniques used in the process are a good starting point to this method. They also present evidence of these advantages by using the surface roughness example, which further states that this technique can be used to predict other such properties on manufactured part as well. Their take on the limitations of the method and future work related to improvements in data acquisition and speed of data transmission provides significant insight on the potential of this method.

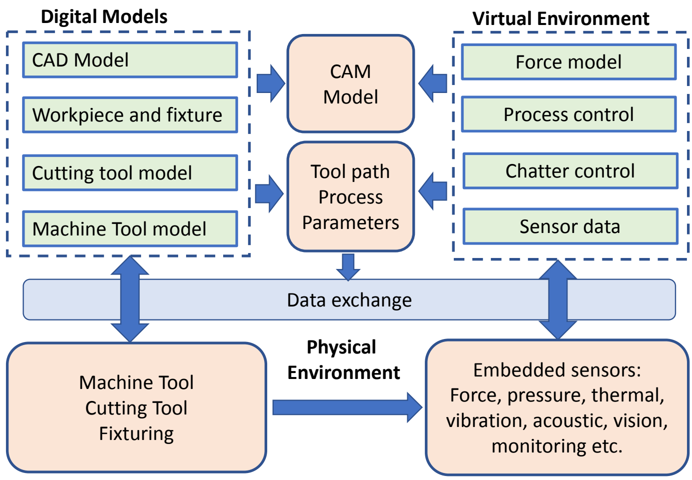
Figure 5 Illustration of constructing virtual machine tool-based digital-twins integrated with sensory data and machining information (see online version for colours)



On the other hand, open-source manufacturing technology is identified as a key metric for enabling automated machining solutions and digital twin developments. Damjanovic-Behrendt and Behrendt (2019) discusses that the enabling interoperability thereby reducing the costs for design and implementation of new smart machining solutions would be the major potential of open-source technology in smart manufacturing.

The reviewed literature indicates that the digital twin concept envisioned for machining process control, machine tool monitoring and control can be generally represented as depicted in Figure 6. In this vision for digital twin models for the CAD geometry, the workpiece and its work holding fixture, the cutting tool geometry, the machine tool configuration are used as inputs for the CAM system, then tool paths are generated, and appropriate cutting conditions/process parameters are selected. That information flows from digital software to the machine tools in the shop floor. In return, machine tool, cutting tool, and fixturing are equipped with embedded sensors to collected data from the process, the tooling, and the machine tool to be utilised in a virtual environment for uses in creating the CAM file, optimising the tool paths and related process parameters. Some of those models could be mechanistic force models, neural network models, thermal or analytical models, finite element analysis and so on. These pieces of the virtual environment however yet to be unified for successful creation and implementation of digital twins for machining systems.

Figure 6 Digital twin concept envisioned for machining process and machine tool control (see online version for colours)



Furthermore, tool chatter can be also modelled using ML and neural networks. The tool vibration measurements can be discretised as time-dependent, and each data point can be used to train the neural network model. Alternatively, tool vibrations can be characterised with amplitude and frequency (mode) signals based on the each cutting condition tested (spindle speed, tool length, depth of cut, feed rate, wet, dry, MQL, etc.) These characteristics can be used as training dataset to train neural networks for capturing tool vibrations and tool vibration characteristics can be classified as stable, on the border, unstable etc. at the fully connected NN layer. It is also possible to adopt a hybrid approach by combining mechanistic tool vibrations and chatter modelling with data-driven neural networks modelling where both can interact for cross-validation and correction purposes.

Based on the conducted literature review, the following conclusions and remarks can be made:

- Neural networks can be successfully trained using input data from conventional modelling techniques (such as mechanistic force modelling). This is a promising alternative to NN training using experimental results and greatly increases their flexibility and applicability.
- Machine learning can be used for online monitoring of tool condition, allowing for quick detection of tool wear/failure using measured cutting force and vibration signals. This allows for immediate adjustment of cutting parameters to prevent premature tool wear without interrupting the cutting process.
- Chatter-free cutting conditions can be predicted using supervised learning utilising analytical modelling results as input data. Such results are potentially useful for preliminary determination of stable cutting conditions before commencing trial/production runs.

- Machine learning methods can also be used for toolpath generation. This is a promising development. However, at the current stage, toolpath generation is extremely computationally intensive and burdened with errors and imperfections, limiting industrial applications.
- Predictive modelling can be integrated into a digital twin for online process control and optimisation in machining applications, for example to increase material removal rates while ensuring lack of chatter occurrence.

In this paper, research results regarding uses of machine learning in machining-related application were gathered, summarised and discussed to construct a literature review, which served as basis for further activity. Next, available commercial virtual machining/NC toolpath optimisation software environments were shortly discussed, particularly in the context of applying ML-based methods to enhance their functionality. The core part of this work was conducting a case study concerning the application of Neural Networks in cutting force prediction for a benchmark milling process, along with a short overview of proposed toolpath optimisation software and possibilities of application of ML-based methods as a part of an envisioned digital twin for virtual machining systems.

4 Virtual machining and CAM/CAE software solutions

4.1 Overview of available software solutions

The following section is devoted to a short overview of three select commercial software solutions for toolpath-level process optimisation/virtual machining (digital shadow), namely: VERICUT by CGTech, NCSIMUL by Spring Technologies and Production Module 2D/3D by Third Wave Systems.

4.1.1 CGTech VERICUT

The basic concept for VERICUT is the simulation of the machining process on a virtual machine tool comprised of complex and detailed 3D CAD models of its components, cutting tools and the workpiece. Visualisation of the machining process allows the end user to check for collisions, unnecessary tool motions, mistakes in CNC toolpath programming, excess machining allowances etc. Collision detection is not limited to tool-workpiece collisions – a common limitation for CAM software such as Edgecam or Mastercam. Thanks to the implementation of detailed 3D CAD machine tool models within the software, it is also possible to check for more serious and potentially significantly costlier collision, such as tool holder-spindle collisions. This feature is potentially very useful when taking into account the ever-increasing complexity of both CNC machine tools and machined workpieces, especially when considering that not every machine comes with a preinstalled collision avoidance system. VERICUT comes with a readily available library of 3D CAD machine tool models. Moreover, the users can import their own machine tool models into the program environment. This is a digital shadow-type system, as the software does not communicate with the machine tool- it serves as an environment for toolpath verification/optimisation by simulating the process on a digitalised version of the physical machine tool.

4.1.2 Spring technologies NCSIMUL

NCSIMUL is a CAE/Virtual Machining software package offered by Spring Technologies. Its functionality, area of application and basic working principles can be described as comparable with VERICUT. However, virtual machining capabilities of this software are more basic, as it only includes tool/spindle, workpiece and fixture models. NCSIMUL determines geometrical relations between different components of a virtual CNC machine tool, the cutting tools, and the workpiece on the basis of their 3D CAD models. This allows for collision detection. The machining visualisation module allows the user to check for excess tool motion and other toolpath errors. The CNC toolpath can be manually edited with the use of a built-in editor and evaluated again in the visualisation module. Moreover, the software possesses basic production planning/cost evaluation abilities, as it allows the user to calculate tooling/machine operation costs for the analysed NC machining process. This is also a digital shadow-type system, as there is no direct communication with the machine tool and all the changes to the process (such as new NC toolpath files) have to be transferred manually to the machine tool.

4.1.3 Third wave systems production module 2D/3D

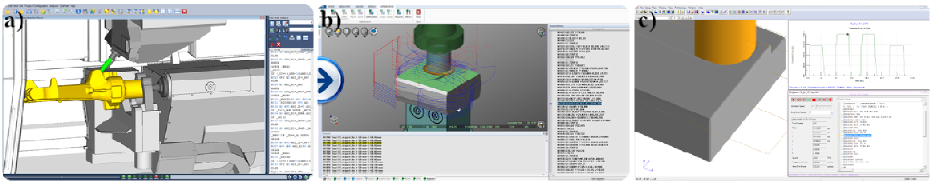
The production module 2D/3D (PM2D/PM3D) is a software package offered by third wave systems. The most important feature of the PM2/3D software is the inclusion of physics-based modelling of the cutting process. Thanks to this approach, the end user is provided with a plethora of information regarding process performance, such as cutting force components, spindle loads, cutting zone temperature, etc.

This software also includes 3D real-time process visualisation, albeit limited only to the workpiece and the cutting tool itself (no fixture, spindle/holder models). In addition, all output data is available in the form of graphs that are traceable in real-time. The software allows the user to view which NC toolpath line is executed at a given moment of the machining process, which can be helpful to identify lines responsible for excess tool motion and other toolpath errors. The software features a built-in CNC toolpath editor, which allows to correct the errors and re-check toolpath performance in the visualisation window. The process optimisation in production module works on a simple principle of changing the tool feed in agreement with user-defined criteria, such as: upper/lower limits of selected cutting force components, spindle load or cutting edge pressure. Limits can be determined on the basis of base process performance in workshop conditions and tool/machine manufacturer recommendations to avoid machine overload, tool breakage or inadequate workpiece quality.

It can be easily observed that production module focuses on a much more narrow aspect of simulating the machining process- namely the physics-based modelling of tool-workpiece interactions. Collision detection is absent from the software, which forces the user to rely on collision detection modules built within available CAM software. This can be seen as the major drawback of this software environment.

The graphical user interfaces (GUI) of discussed software packages are presented in Figure 7.

Figure 7 The graphical user interfaces of VERICUT, NCSimul, and PM3D systems (see online version for colours)



A comparison of described VM/CAE software solutions in this section is shown in Table 2, which summarises their features and capabilities. As summarised, VERICUT is more suitable for a digital shadow- type system. NCSIMUL has very basic VM capabilities and offers no machine tool-software integration. It is suitable for a digital shadow system. Third wave systems production module 2D/3D also has very limited virtual machining capabilities.

Table 2 Summary of selected VM/CAE software features and capabilities

Characteristic traits	*Advantages*	*Shortcomings*
	VERICUT	
• An industrially popular Virtual Machining solution • Allows importing of 3D machine tool models	• Extensive VM capabilities • Basic MRR-oriented toolpath optimisation	• Lack of information regarding cutting conditions before and after toolpath optimisation • Digital shadow- type system
	NCSIMUL	
• 3D Virtual machining simulations • Basic process planning/production analysis capabilities	• Built-in collision avoidance • Checking for coherence of workpiece geometry and cutting parameters between NC toolpath/CAD models	• Lack of force modelling capabilities • VM capabilities are basic • No machine tool-software integration (digital shadow)
	Third wave systems production module 2D/3D	
• Modelling-based NC toolpath optimisation • User-defined constraints for toolpath optimisation	• Plentiful information about cutting conditions • Allows the user to define their own material model	• Limited virtual machining capabilities • Lackluster GUI and high learning curve

4.2 Development and improvement with application of ML/AI

All presented software packages are digital shadow environments. A digital rendition of the machine tool is imported into the software, and there is no real-time communication with the machine tool. This means that every time the user wishes to improve the process, they have to run a simulation, evaluate the results, import the altered toolpath onto the machine tool, and run validation workshop tests. Two-way computer-machine tool communication could be employed and facilitated with the use of AI techniques, allowing for online process monitoring and appropriate adjustment of cutting parameters/toolpath strategy.

Machine learning methods could be utilised to extend software capabilities to prediction of cutting conditions based on data gathered from the machine tool. This data could then be used for neural network training purposes, allowing to predict process behaviour (with respect to cutting forces, process stability, tool life or spindle loads) when cutting parameters are altered. This could be applied to extend the capabilities of VM software that lacks force modelling capabilities (VERICUT/NCSimul). Neural Network training could also be utilised to obtain input data (in the form of cutting force coefficients) for force modelling in case of solutions that already possess predictive modelling abilities (PM2D/3D). A more detailed discussion on the subject is included in Section 5.2 of this paper, which discusses the potential of applying machine learning/AI in the proposed software solution.

5 Optima NC toolpath optimisation software

5.1 Overview

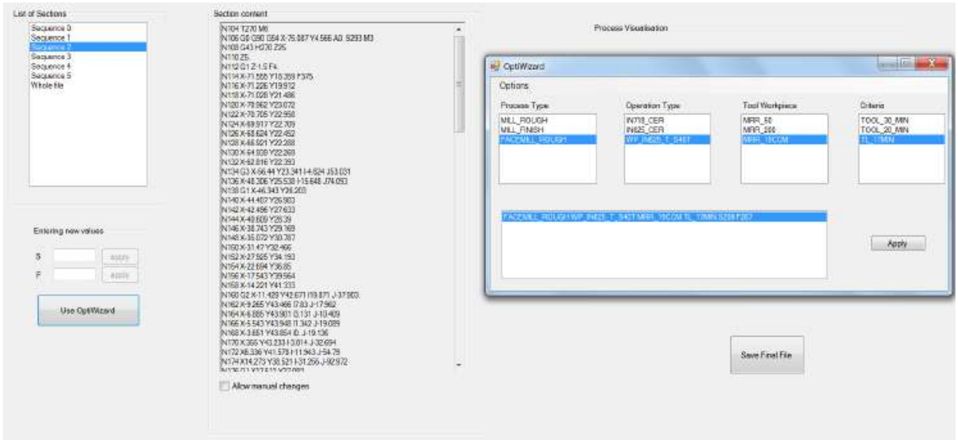
Optima NC is a work-in-progress NC toolpath optimisation/Virtual Machining/process modelling software package (Negri et al., 2017). The main design principle was to allow the use of results from prior experimental tests by including an open, user accessible library, where results can be entered, stored and annotated with proper descriptions to facilitate their utilisation in the future. The end user can utilise any results obtained during their own research/testing or available in open literature. The software possesses the ability to alter tool feed as well as cutting speed, which differentiates it from existing solutions, which focus on altering feed values in the NC toolpaths.

The software was designed to have a user friendly, window based GUI. The main window of the current stable version of the program and its built-in open library of cutting parameter values are shown in Figure 8.

The software divides the NC toolpath into separate subsequences, based on characteristic preparatory codes which typically signify the start or end of a distinct machining operation for a given postprocessor and operation type. This approach facilitates toolpath optimisation, as each machining operation can be optimised separately and with the use of different, case-appropriate optimisation criteria.

After specifying the desired values of spindle speed and feed per tooth/revolution (either by means of manual input or importing the results from the software library using the OptiWizard module) the program searches for appropriate lines within a subsequence and prompts the end user whether they want to substitute the speed/feed values within that line. This allows for full user control over toolpath optimisation. The function is also useful for optimising rapid and work feed motions separately. Optimised toolpaths are saved separately with an appropriate suffix to avoid overwriting base toolpath files and can be saved to an appropriate location, ready for workshop testing.

Figure 8 View of software GUI with main program window and built-in open library (see online version for colours)



Currently, the software consists of a core NC toolpath optimisation module that has been tested with popular postprocessors for CNC milling centers (Jarosz et al., 2019). This module is supported by an open library, where the user can enter values of optimum cutting parameters obtained in the course of prior modelling work/experimental tests and save them for future use. In the future, 3D machining process visualisation is planned, along with an implementation of a cutting force prediction model. 3D process visualisation should not concentrate only on the tool/workpiece interactions (like PM2D/3D), but rather take a holistic approach by employing a virtual machining environment in the style of VERICUT. This would also set up a stable base for a Digital Twin system.

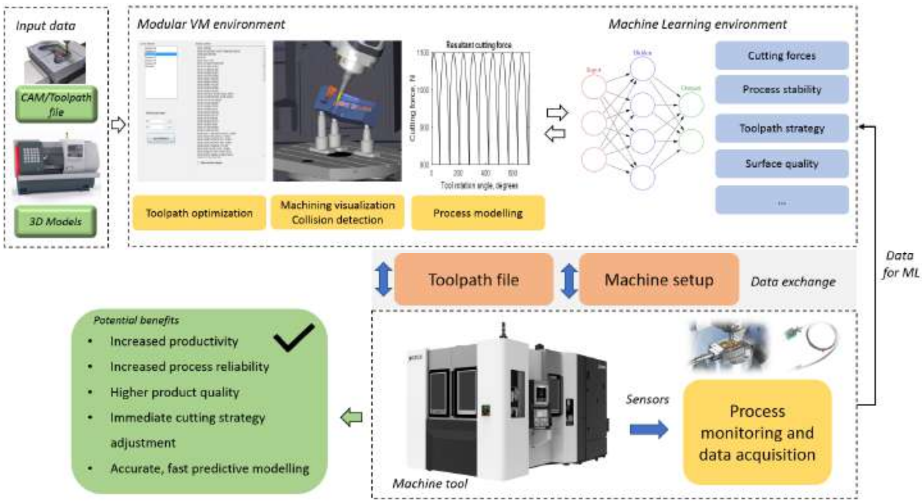
Another possible development path is the application of machine learning methods to enhance software capabilities. This is discussed in Section 5.2.

5.2 Development, improvement, and application of ML

As shown in the literature review section of this project report, machine learning techniques can be used for cutting force prediction, tool wear monitoring/detection of unstable cutting conditions and chatter prevention. This means that they can be used to enhance process performance and aid creating a comprehensive Digital Twin type Virtual Machining environment that would include not only process simulation, but also online monitoring, real-time adjustment of cutting parameters/toolpath strategy and fast, accurate predictive modelling. This concept is visualised in Figure 9.

The concept of a digital twin showcased in Figure 5 utilised a modular structure of the software, with reliance on constant machine tool-software communication and the utilisation of machine learning to improve process performance by using data acquired from online process monitoring. ML methods can be used for accurate modelling and constant adjustment of both the VM environment and the real-life process, to maximise process performance indicators that are deemed of importance by the end user, such as for example productivity, process stability, tool life or part quality. To explore the possibilities of employing Supervised Learning within the scope of the proposed approach, a case study that includes the use of both Neural Network training and incorporation of subsequent results with the use of Optima NC to modify the toolpath file is shown in Section 6.

Figure 9 Concept of a digital twin environment utilising machine learning methods (see online version for colours)

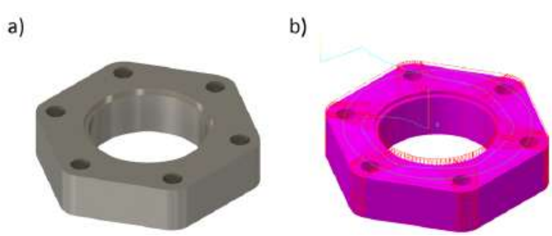


6 Machine learning application case study – results and discussion

Here, a manufacturing-relevant application of a chosen machine learning method (multi-layer neural network neural perceptron trained with backpropagation) is shown, based on the following case study:

An industrial partner is manufacturing a ducting flange from Inconel 625 nickel-based alloy, as shown in Figure 10. A Sandvik R300-050Q22-12H (cutter diameter $D_c = 38$ mm) indexable cutter with five round R300-1240E-PL ($iC = 12$ mm) coated carbide inserts is used here for the rough face milling operation. This example has been selected as digital model and machine learning-based approach can be demonstrated for advanced machining cases.

Figure 10 (a) 3D CAD workpiece render and (b) face milling toolpath generated by the CAM software (see online version for colours)



The technologist wants to increase the material removal rate for the rough face milling operation to improve process productivity. In this particular case, it is assumed that the cost per hour of machine labour significantly exceeds insert/tooling costs and rapid tool wear is of marginal concern, as the machine is equipped with a fast automatic tool changer, allowing for quick tool changes between batches. The only concern is retaining the stability of the cutting process.

Based on the machinist's expertise and prior observations of machine tool rigidity and capabilities, it was determined that an increase in the main (tangential) cutting force F_t above a threshold of approx. 1250 N may result in chatter occurrence. Therefore, cutting force values for proposed new values of cutting parameters (Table 3, sets 7&8) have to be determined. Normally, this is done through means of experimental testing. However, as the workpiece requires a special fixture (which is mounted on the milling center currently used to produce the part), conducting experimental tests would mean halting the production, which incurs additional costs, reducing profitability. Prior modelling results for previously used cutting parameter values are available (Table 3, sets 1–6) and have been validated. This is a potential area to apply machine learning methods to predict cutting force values and evaluate whether new proposed parameter values can be applied safely.

Table 3 Values of cutting parameters and corresponding cutting force values, used as NN inputs and correct outputs, respectively

	Inputs			*Outputs*	
No.	f_z (mm/tooth)	a_p (mm)	a_e (mm)	F_t (N)	F_r (N)
1	0.24	1.5	32	600.8	142.2
2	0.24	2.0	28	801.1	189.6
3	0.28	1.5	32	701.0	165.9
4	0.28	2.0	28	934.6	221.2
5	0.32	1.5	32	801.1	189.6
6	0.32	2.0	28	1086.0	252.8
7(T)	0.32	2.0	32	To be determined	
8(T)	0.32	2.5	28		

A supervised machine learning method was chosen to predict cutting force values. A multi-layer neural network was coded in MATLAB. Characteristics of the used neural network are as follows:

- three input nodes (f_z, a_p, a_e) and two outputs (F_t, Fr)
- four hidden layers with 60, 40, 20 and 10 neurons each, respectively
- Levenberg-Marquardt backpropagation (trainlm) training function.

Network structure, parameters, and training function were chosen basing on trial-and-error approach, for which various numbers of layers, neurons, different training functions and NN parameters were tested, until a close match with correct outputs was obtained. Inputs and correct outputs were normalised before NN training, as shown in Table 4. It should be noted that a neural network is not always suitable for such a small dataset and it may suffer from overfitting. It is recommended to collect more data for better NN training and test results.

Table 4 NN inputs and correct outputs after normalisation

	Inputs			*Outputs*	
No.	f_z (mm/tooth)	a_p (mm)	a_e (mm)	F_t (N)	F_r (N)
1	0.770	0.75	1.000	0.553	0.563
2	0.750	1.00	0.875	0.738	0.750
3	0.875	0.75	1.000	0.645	0.656
4	0.875	1.00	0.875	0.861	0.876
5	1.000	0.75	1.000	0.738	0.750
6	1.000	1.00	0.875	1.000	1.000

The Neural network training results when using datasets 1-6 as training data are shown in Figures 11 and 12.

Figure 11 Tangential cutting force prediction results against correct outputs (see online version for colours)

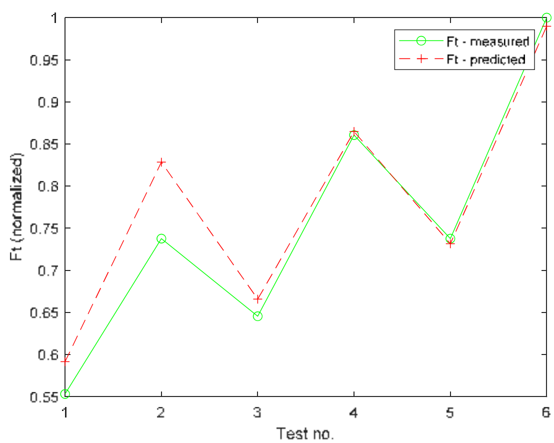
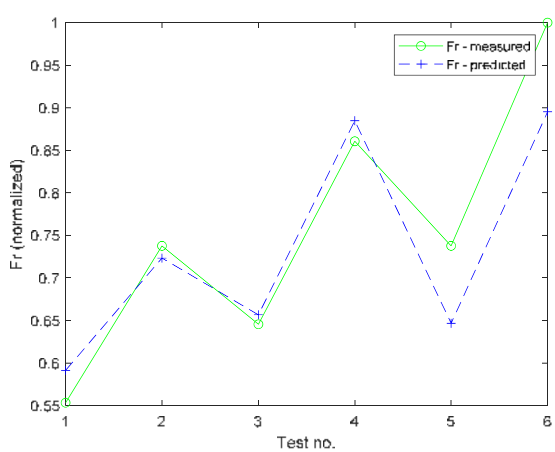


Figure 12 Radial cutting force prediction results against correct outputs (see online version for colours)



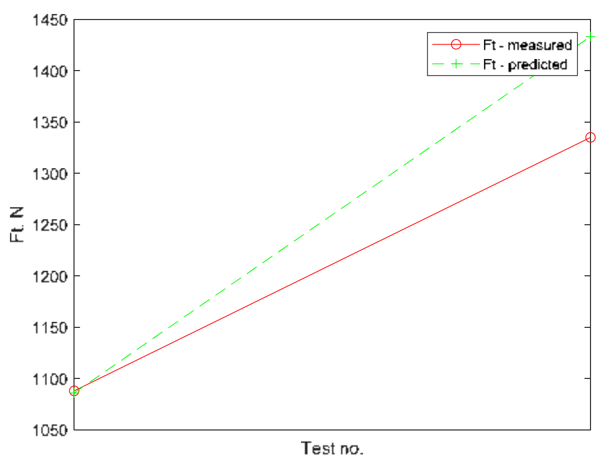
As shown in the graphical comparisons in Figures 11 and 12, the results of the neural network training can be deemed successful, with a close agreement of cutting force component predictions in relation to correct outputs.

After initial evaluation, the neural network was used to predict the values of cutting force components using new input values with no correct outputs provided. To allow for some form of validation, prediction results from a mechanistic force model were used as comparison data to evaluate neural network outputs, as listed in Table 5. NN prediction results plotted against mechanistic modelling results are shown in in Figures 13 and 14.

Table 5 Comparison of NN predictions with mechanistic modelling results

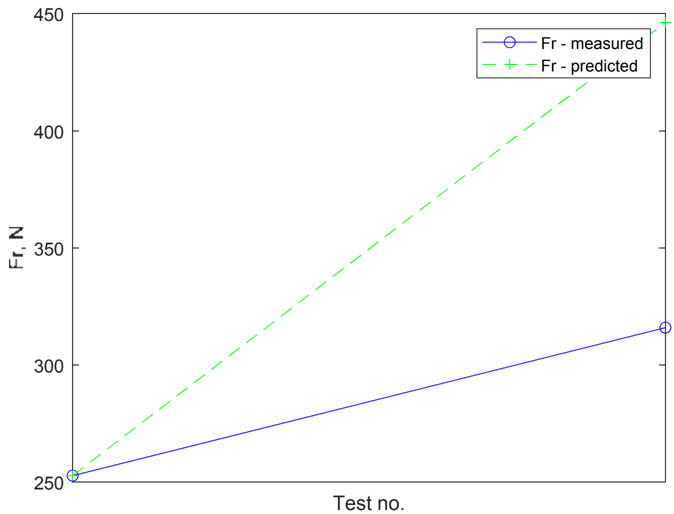
	Inputs			*Neural network outputs*		*Mechanistic model predictions*	
No.	f_z (mm/tooth)	a_p (mm)	a_e (mm)	F_t (N)	F_r (N)	F_t (N)	F_r (N)
7(T)	0.32	2.0	32	1089.0	252.6	1088.0	252.8
8(T)	0.32	2.5	28	1442.0	448.2	1335.0	316.0

Figure 13 Tangential cutting force prediction results against mechanistic modelling results for datasets 7&8 (see online version for colours)



As expected, results of neural network predictions and mechanistic modelling vary. Results obtained for Set 7 are nearly identical. However, notable discrepancies can be seen in case of Set 8, with better agreement of results observed for the value of tangential cutting force F_t, which was of main interest in this case study. Nevertheless, it can be easily observed that the F_t value exceeds the previously established safety threshold of 1250 N (by 192 N and 85 N for NN predictions and mechanistic modelling results, respectively). Therefore, the use of cutting parameters from Set 8 was not recommended and Set 7 was deemed a safer option that would allow to increase productivity while reducing the risk of losing process stability.

Figure 14 Tangential cutting force prediction results against mechanistic modelling results for datasets 7&8 (see online version for colours)



After parameter values from Set 7 are deemed safe to use thanks to NN predictions, the altered toolpath with new cutting parameter values is instantly prepared using Optima NC and production is ready to commence with increased productivity. The optimised NC toolpath for a presented test case was 286 lines long with a total of 5 subsequences, each correspondent to a distinct machining operation. The use of proposed software eliminates the need to manually alter the toolpath file or interfere with the existent CAM file to incorporate optimisation results.

7 Conclusions

This paper concerns the applications of machine learning (ML) methods in modern machining systems, with particular focus on predictive modelling with the use of Neural Networks and potential for application of ML in virtual machining and digital shadow/digital twin solutions. In addition to a literature review, the paper discusses the application of ML/AI in existing and future CAM/CAE/VM software solutions and a case study regarding the application of supervised learning in a machining application. The main takeaways, conclusions and remarks from this course project are as follows:

- Possibilities of applying machine learning (ML) methods in modern machining processes and systems are widely discussed in open literature, both in regards to theory and practical applications. This shows that the subject is important and industry relevant.
- Most existing commercial software solutions are Digital Shadow-type systems, and could benefit greatly from application of ML & AI methods. For example, a Digital Twin system utilising neural networks for process modelling could receive real-time force data from the machine tool, which would then serve as training and validation data for the neural network, greatly improving its accuracy.

- The presented case study shows that supervised learning can be applied for cutting force prediction, establishing potential directions for future development of all work-in-progress machining software solutions;
- Neural network prediction accuracy can vary every time the network is retrained, even when using the same NN structure, parameters and training function. This is to be expected when using such a small training set with an overfitting prone NN model. Therefore, one should always compare NN predictions against some form of correct outputs, be it experimental results or conventional modelling predictions;
- Despite the small dataset size, the chosen training function and network structure are relatively computationally intensive, even when using a high-end workstation. This increased computational cost comes with a payoff in the form of good prediction accuracy. Again, the small dataset provides a large potential for overfitting (i.e., good performance on training data, bad performance on unseen data).

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