Cognitive dynamic digital twin: Enhancements for digital twin platforms based on human cognition

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ABSTRACT

Manufacturing has entered the fourth industrial revolution. Modern manufacturing is reliant on assets such as robotics and computer numerical control (CNC) machine tools. To optimize the performance and value of these assets it would be wise to implement digital twin (DT) technology. DT technology has the ability to provide valuable services to owners of machine tools and other manufactruing assets. The current issue facing DTs is that they currently exist at a lower level of sophistication, meaning they are incapable of implementing more complex services. Cognitive dynamic systems (CDS) are a type of smart system based on human cognition which can augment the performance of many engineering systems. This paper proposes a framework of implementing aspects of CDSs to enable DTs to exist at a higher level of sophistication called the cognitive dynamic digital twin (CDDT). Examples exist in the literature of implementing cognitive based methods to improve DT services, they primarily implement artificial intelligence and estimation based methods. Most of these methods implement only one aspect of cognition at a time. In this work the CDDT framework was implemented to build a DT machine tool wear prediction service. The service was shown to be accurate at predicting the levels of wear in cutting tools. This service utilizing the CDDT framework used each of the aspects of human cognition to augment its performance. This framework can be used by many different sorts of DTs to improve their level of sophistication.

Keywords: Artificial intelligence, Cognitive systems, Condition monitoring, Digital twin, Smart systems

1. INTRODUCTION

The world has advanced into the fourth industrial revolution (4IR) also known as Industry 4.0. Many industries across the globe have begun to embrace the 4IR and its technologies. Several key driving technological trends and paradigms have emerged during this time. These trends and paradigms include: Internet of things (IoT), artificial intelligence (AI), machine learning (ML), smart sensor networks (SSN), and virtual and augmented reality (VR/AR). The technologies of the 4IR are becoming very closely integrated with physical systems and objects,[1] and are affecting many sectors of our lives in ever increasing ways. Many industries are working towards digital integration. An emerging concept within the 4IR that embodies cyber-physical integration is the digital twin (DT). DTs along with other 4IR technology can improve efficiency, interconnection, visualisation, and flexibility in many different industries and sectors. The DT was first presented as a concept by Michael Grieves in 2003 in a lecture about life cycle management. Grieves later published a white paper codifying his ideas.[2] However, a similar concept was used earlier in the 1970s when NASA would mirror the conditions of one of their rockets in their lab. They had essentially created a physical twin of their rocket. In 2010 NASA published their technology road map.[3] They proposed that core technologies of DT: modelling, computing, simulation, and information processing are rapidly advancing technologies and are key to accomplishing their mission objectives. DTs could therefore substantially improve aerospace technology. Many definitions of DTs exist, but a common understanding among these is that a DT is the virtual representation of a physical object or system. A true DT will also evolve over time as the physical twin and its environment evolve. DTs have a few proposed benefits, including: real time state monitoring, system optimization, visualisation, and informed decision making. Generally speaking, DTs are a platform or tool for data collection, data analysis, and informed decision making that is applicable across many different sectors.

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Table 1: Levels of sophistication of digital twins.

Type of twin	Characteristics
Pre- twin / prototype twin	Digital model not connected to real life asset
Low level	Digital model
	Manual data connection
	Multi-domain simulation and modeling
	Limited pool of data to draw from
Mid level	Digital shadow
	Moderate amount of data to analyze
	Connection to persistent data
	Some predictive capability
	Interconnection between many different applications and users
	Analysis of operational state and performance
High level	Digital twin
	Wide range of data from various data sources including external sources.
	Adaptive UI/UX based on different needs of user
	Future scenario analysis
	Two-way data integration
	Continuous self-updating
	Autonomous operation
	High level and accurate predictive capability
	Unsupervised machine learning
	Horizontal or vertical integration with other twins

DTs exist across a spectrum of complexity and sophistication. One way to categorize a DT is by how data is transferred between the physical and virtual object. Under this lens of categorization there are three types of DT: digital model, digital shadow, and digital twin. Under this method of categorization a true DT requires automatic two way flow of data between the physical and virtual twins. Another method of categorization that is popular in the literature was presented by Madni et al.[4] Their method for categorization is a 4 tier system from pre-DT up to an intelligent DT. Various important industry leaders such as SNC Laval,[5] Autodesk,[6] and Arup[7] have presented their own framework for categorization. An overview of common features and themes of these frameworks can be seen in Table 1. Implementing a DT, especially one of a higher level of sophistication, requires the collection and processing of large quantities of data. A DT will need to access past and present data to make accurate predictions about future states. This can become very costly or simply impossible to do effectively if methods are not implemented to efficiently collect, manage, and analyze this data. An effective framework is required to build DTs that can manage the the quantiy of data and complex services required for a high level of complexity. An emerging framework that could possibly be adapted for this purpose which is used in engineering systems is cognitive dynamics systems (CDS).

CDS's are a type of smart system envisioned and proposed by Simon Haykin.[8,9] This framework for engineering systems is based on Fuster's paradigm for cognition[10] which has five key components: (1) Perception, (2) Memory, (3) Attention, (4) Intelligence, (5) Language. CDS's are governed by a perception-action cycle (PAC). The perceptor perceived the environment by processing incoming stimuli, the actuator controls the perceptor via the environment based on feedback information. Haykin applied this paradigm to radio,[11] radar,[12] control,[13] and other engineering systems. This paradigm has a high degree of potential in its application to DTs. Other papers have previously proposed similar concepts of DT augmentations. The concept of integrating cognitive capabilities in a manufacturing system DT was proposed in a paper by Al Faruque et al.[14] Papers by Maschler et al.[15] and Talkestani et al.[16] proposed "intelligent digital twins" which are DTs augmented with ML and AI. A concept often cited in the literature called a cognitive twin was proposed by Lu et al.,[17] however, it is primarily concerned with the semantic connection between virtual models. To differentiate the DT augmented with cognitive capabilities from the concept proposed by Lu et al. it will be henceforth be referred to as cognitive dynamic digital twin (CDDT).

One of the most popular sectors of research for DTs is manufacturing. One of the largest sectors of manufacturing, and one that is increasingly growing[18] is computer numerical control (CNC) machining. Machine tools are becoming increasingly complex, and as a result, more expensive. It is in the best interests of machine tool owners to maximize the return on these large investments. A DT implementation is one method in which even greater value can be gained from these machines. This work will focus on the application of the CDDT framework in a machine tool DT. This work seeks to contribute to the literature of DTs, CDS, and machine tools. First, this paper proposes a framework to augment DTs in order to reach higher levels of sophistication. Higher levels of sophistication provide much greater value but are often not achieved in industry or the literature. Second, this work provides an overview of the literature where machine tools were augmented using digital twin and/or CDS related methods such as AI or estimation theory. Additionally an example of a cognitive augmentation in a condition monitoring case study will be presented to display the value of cognitive enhancement. The case study will show improvements to memory management, and utilize a neural network to accurately predict levels of tool wear. A DT visualization tool will be used to present tool wear data to the user in real time. The goal of this work is to provide a framework that can be used by others in both academia and industry to augment their DTs to a higher level of sophistication to generate more value from it.

The rest of this paper is organized into several sections. Section 2 provides an overview of machine tool DTs and the benefit of their implementation. Section 3 proposes a framework for the CDDT and how it can be used to improve DTs. Section 4 shows the application of the framework to a condition monitoring DT service for Machine tool cutting tools. The results of the condition monitoring service and how it was augmented using the CDDT framework is shown in section 5. Finally the paper is concluded in section 6, which also provides recommendation for future work and how the framework can be expanded upon.

2. MACHINE TOOL DIGITAL TWIN

A machine tool is a complex system comprised of many inter-dependant and interacting subsystems.[19] Mechanical, electrical, pneumatic and hydraulic subsystems exist within most machine tools. Each of these components on any level of the hierarchy in a manufacturing system could have a DT associated with it. The DT would be unique and mapped to a single object or system. Over the course of its lifetime, from initial installation to the end of life, the components will accumulate data and have several updates to it's model(s). The main advantage to implementing a DT in a machine tool would be the use of services which can provide useful functionality and data analysis. DTs leverage large quantities of data and accurate dynamically updating models to implement these services. Some services that may be useful in a machine tool include: condition monitoring, making future projections, improved control using a dynamic model, and data visualization. A DT for the same asset may look different between implementations based on which services the asset owner desires. There are three properties of a machine tool DT that are especially desirable: scalability, extensibility and modularity. It is desirable to have the ability to scale up or down the services being used in a DT service. Often DTs will start by offering a limited amount of services which are less complex, and will collect a smaller stream of data. As demands for the DT system increase, it may be desirable to add data streams, increase number of services, or increase the complexity of services. It may also be desirable to increase the scope to higher levels of the hierarchy, or to increase detail on sub systems. The three aforementioned properties make this scaling possible. A roadblock to higher levels of sophistication is often the lack of these properties. The framework proposed in the section below will help to ensure a DT system that is scalable to higher levels of sophistication. A framework for implementing and using a DT for CNC machine tools was presented by Luo et al.[20] Several key abilities were identified: Precise simulation, self-sensing, self-adjustment, self-prediction, self-assessment. Several examples exist in the literature of leveraging DT technology, and implementing one or more of the abilities listed above. The advantages of using a DT in a machine tool application can be broadly grouped into three categories as seen below.

2.1 Improved Modeling

Several studies used DT to improve modeling. Improved modeling and model updating is important in DTs as they progress through their life cycle. This is even more important in machine tools, where having an accurate system model is often critical for accurate control to create high accuracy parts. In a paper by Zhang et al.[21] they were able to improve dynamic modeling of a ball screw and other rolling joints using a neural network (NN) augmented DT. Wang et al.[22] proposed a non-intrusive method using in-process CNC data for model estimation. Wei at al.[23] developed a method for consistency retention using vibration data. This method ensures the digital model's parameters closely match the physical system. Real-time accurate modeling is very useful and is often used as a backbone by many other services such as improved control and condition monitoring as discussed below.

2.2 Improved Control / Process Optimization

DTs can also be used for improved control and process optimization. It is often used to compensate for some sort of error. Liu et al.[24] proposed a method for predicting and compensating for time varying error which could improve machining tolerances. Armendia et al.[25] examined DT control in an aerospace and automotive machining application. They found that it was possible to improve process control using real time comparison of measured data to simulated data. Several papers utilitzed DT technoloy to imporve surface finish in machining processes. Tong et al.[26] applied a DT framework to improve the tool path in a 5-axis milling machine by compensating for measured disturbance. As a result the surface finish was improved and tracking error was decreased. Ma et al.[27] used a short term long term NN to compensate for thermal error and improve machining tolerances. Cai et al.[28] used a hybrid method for accurate on-line and off-line prediction of surface finish in a vertical missing operation. DTs can also be used to detect errors as well as optimizing a machining process. Guo et al.[29] created a DT based method for collision detection to avoid work piece collision with work holding for turning operations. Using simulation tools Stan et al.[30] were able to reduce power consumption for a robotic deburring process. In a paper by Shen et al.[31] they were able to determine parameters of a grinding procedure and optimize grinding wheel selection to reduce process time. DTs have been used in many applications to improve the performance of machine tools by implementing advanced control and process automation. By improving performance, manufactured parts with improved machining quality can be produced at a higher rate.

2.3 Condition Monitoring / Fault Detection

Condition monitoring and visualization are helpful for operators to determine if the machining processes are functioning as intended. Several papers created dashboards containing real-time data for process monitoring. In a paper by Guo et al.[29] they created a real time virtual twin dashboard containing information such as spindle speed, operating temperature, and currently running CNC code. Xie et al.[32] created a framework for cutting tool degradation and a dashboard to display information about the condition of the tool. Wang et al.[33] created a real time condition monitoring dashboard for a die cutting machine. Parameters such as machine availability and productivity are constantly being updated and displayed for the user. Stan et al.[30] built a web based platform to monitor the process of robotic de-burring. Botkina et al.[34] proposed a framework for a DT of a cutting tool. They proposed a method of "tweeting" which periodically update the model of the cutting tool to reflect the updated condition. Several studies used a DT platform for condition monitoring and remaining useful life (RUL) prediction. Weckc et al.[35] monitored clamping force to estimate tool wear and to ensure proper clamping of the work piece was maintained during operation. Xue et al.[36] built a model library of various fault states to diagnose faults in a machine tool spindle using ML. Hybrid data and model based solutions for prediction of performance degradation and RUL were proposed by Yang et al.,[37] and Luo et al.[19] They both found that the hybrid method performed better at predicting the replacement time than just a model based or data based method. Baig et al.[38] implemented an artificial neural network (ANN) to predict tool life in turning operations using vibration data and cutting parameters. DTs are an effective platform for condition monitoring. It is especially important in machine tools to monitor their condition as their value relies on them being in good working condition and having high system up-time.

3. COGNITIVE DYNAMIC DIGITAL TWIN FRAMEWORK

The following CDDT framework aims to provide a model for improving the level of sophistication of DTs. Each of the five elements of cognition discussed in Fuster's paradigm for cognition[10] are used to augment DT systems. Each of the cognitive processes are closely entwined with each other. Fuster explains in his work that:

> "... perception is part of the acquisition and retrieval of memory; memory stores information acquired by perception; language and memory depend on each other; language and logical reasoning are special forms of cognitive action; attention serves all the other functions; intelligence is served by all; and so on."[10]

Due to this fact there may be some overlap as to how each component of cognition can augment the system. An overview of the CDDT framework can be seen in Figure 1. Each of the functions of cognition and their relation to DTs and specifically machine tool DTs will be explained in the following subsections.

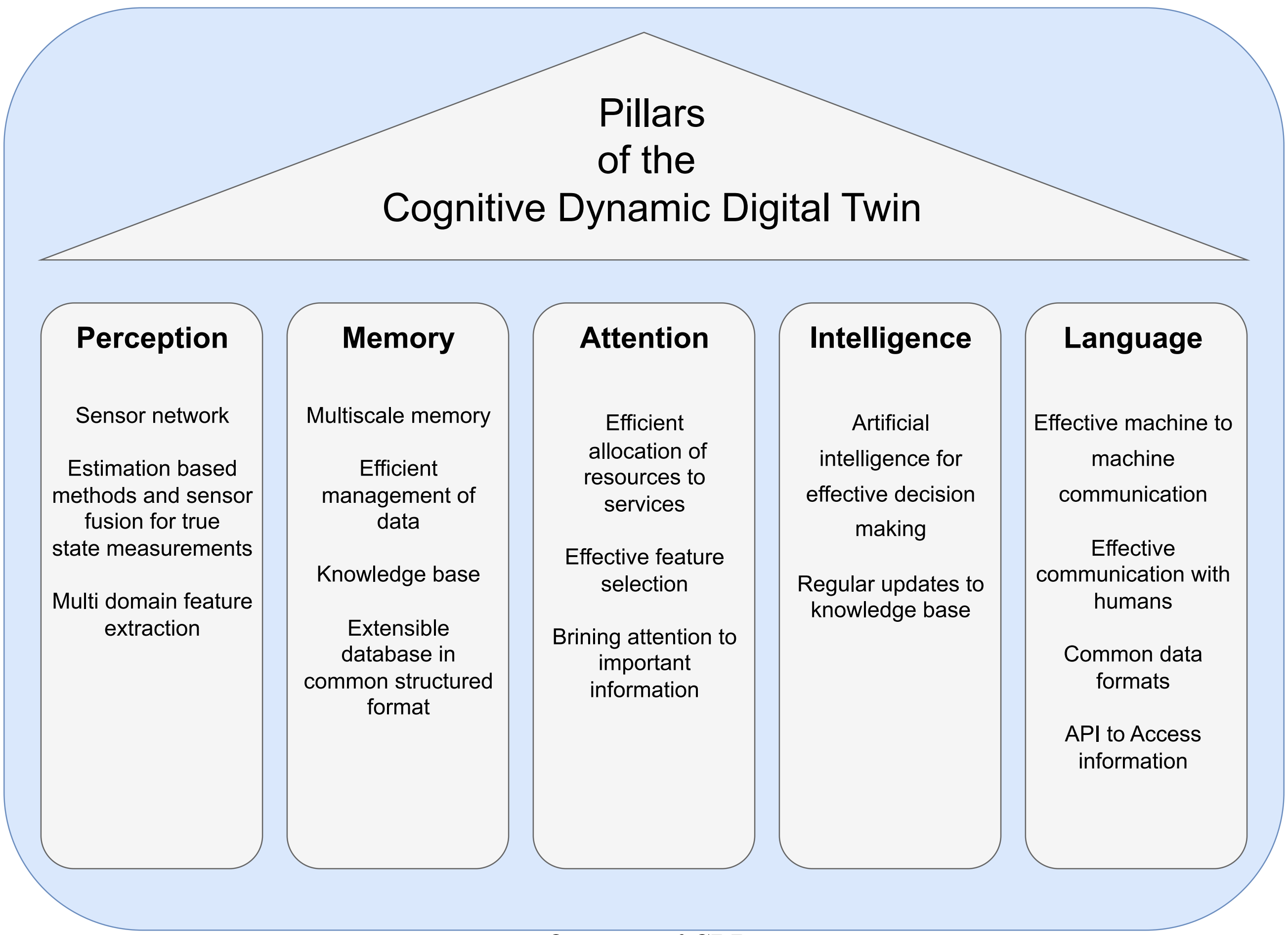


Figure 1: Overview of CDDT system

3.1 Perception

Perception is often confused with sensing, however they are two separate actions. Sensing is the process of receiving information from the environment, perception is the process of interpreting and organizing information from the environment so that it can be understood and reacted upon. Perception relies on both sensing, and and accumulated knowledge. The updating process of a DT is a process similar to human perception. A DT is constantly taking information from its environment and interpreting it to update its state and model information.

3.1.1 Sensing

Perception relies on sensing. A sensor network collecting many different types of measurements can help maximize the information available to process. For machine tools there are many measurements, sensors, and locations to mount these sensors. Papers by Sicard et al.[39] and Butler et al.[40] provide An overview of a few possible state measurements, sensors, and sensing locations in their papers on condition monitoring in machine tool feed drives. Large quantities of measurements can be extracted from these sensors. Extracting useful information from the large quantity of sensed data can be accomplished using various perception methods. Following the process of collecting the data (sensing), the data will need to be processed (perceiving) to extract useful information. An overview of the perception and update process can be seen in Figure 2. Several perception methods exist including the following: Estimation based methods, sensor fusion frequency domain analysis, statistical analysis.

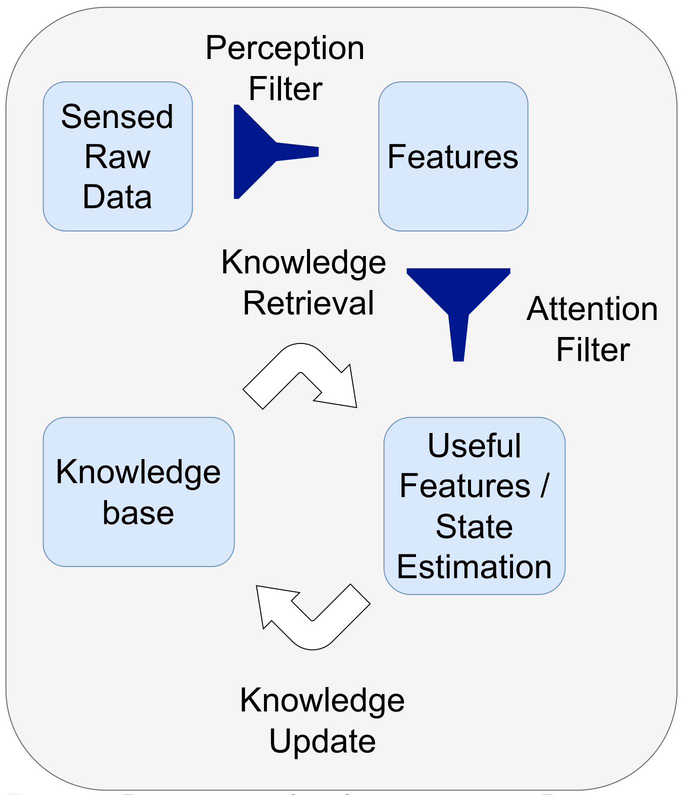


Figure 2: Perception and update process in a DT system.

3.1.2 Estimation theory and other perception methods

Many estimation based methods such as Kalman filtering draw from the systems knowledge base (system model) and data obtained from sensing to make estimations of a systems state that are more accurate than the model or sensed data alone. Several studies used Kalman filters (KF) to improve machine tool condition monitoring and control. Möhring et al.[41] introduced a sensory machine tool which uses a KF for sensor fusion of a sensing fixture and spindle. In a study by Schwenzer et al.[42] they used ensemble KF to improve modeling of process forces for their model predictive control of a milling operation. Sadhukhan et al.[43] and Niaki et al.[44] used the UKF and extended Kalman filter (EKF) respectively to estimate cutting tool flank wear in inconel 718 turning operations. This model was used for online tool wear monitoring. They found their method improved estimation accuracy of tool wear compared to deterministic methods.

Sensor fusion makes use of multiple data streams to reduce the uncertainty of state estimations compared to using a single data stream. Both methods can be used to maximize information gained from sensed information about the environment. Particle filtering has been used in several applications for model fusion. Yang et al.[37] and Luo et al.[19] improved their degradation and RUL models respectively using a particle filter and found that it had substantially smaller prediction error than both the data and model based methods. Cai et al.[28] used particle filtering to improve surface finish estimations in milling processes. Skordilis et al.[45] used particle filtering for updating their state space model for their deep Reinforcement learning (RL) model. Wang et al.[46] used a KF for sensor fusion to improve compensation for thermal error.

Raw sensor data is often not very useful on its own. It is often necessary to extract useful information from raw data. Often frequency domain methods such as fast Fourier transform (FFT)[47] and wavelet decomposition[48–50] are used to process signals and extract features, particularly vibration signals. A data stream can be separated into the contributions of signals of different frequencies. Statistical analysis can be used to extract useful features such as mean, range, and variance. Features extracted from the data using these methods will be more useful for intelligent analysis than raw data.

3.2 Memory

When considering memory in a DT system it may be useful to categorize it into 3 categories: (1) raw data, (2) features and state estimates (short term memory), (3) a knowledge base and memory base (long term memory). This model can be mapped to the update process as seen in Figure 2. These categories are similar to that of Atikinson and Shiffrins model of memory[51] which can be seen in Figure 3. It is important to effectively manage memory in a DT system. DT systems require the storage of historical information as well as regular updates to its knowledge base (models). If too much data is stored in long term memory it may be difficult to manage the sheer volume of data, this could cause additional costs to store the data. Additionally, some data may obfuscate the knowledge update process. Storing too little data could make updating the knowledge base difficult as there are too few features to perform intelligent analysis.

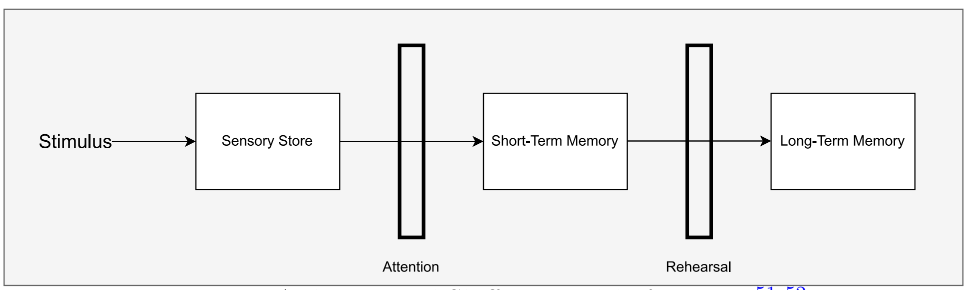


Figure 3: Atikinson and Shiffrins model of memory[51,52]

Often DTs will deal with many data streams, some of which will be sampling at a high frequency. It will be untenable to store and manage such a large quantity of data. Raw sensor data will often only exist in very short term memory, being discarded as soon as useful features are extracted. It sometimes may be valuable to store some raw sensor data to periodically re-calibrate the perceptual filter. In machine tools many sensors sample at rates of kHz, meaning thousands of data points are generated each second. Extracted features are stored in short term memory. These features are used in conjunction with the knowledge base to create estimates about the states. These states can be used by DT services for control, future projections, or condition monitoring applications to name a few. In the next time step of the update process useful features and state estimates are passed to long term memory storage.

Long term memory has 2 components: a knowledge base and a long term memory store. A knowledge base is able to create intelligent prediction of states based on incoming features. The process of updating and retrieving the knowledge will be further discussed in section 3.4. The long term memory store serves as a history of the object represented by the DT. It is ideal to not store redundant information, for example if the max and minimum value of a signal is stored, the range isn't necessary to be stored as it can be calculated from these two values. It may be worthwhile to store long term memory external to the object itself. An external database or cloud storage can facilitate easier storage of large quantities of data as well as enabling access to the data from other users. It is also desirable to store the data in a common structured format. This enables easy access to the data from multiple services as well as ensuring extensibility of the database.

3.3 Attention

Attention is the ability to allocate limited available resources to certain targets. Attention in the context of DTs can be thought of in three different ways. First, DTs offer many services such as condition monitoring, improved control, what-if simulations, system visualization, and many others. It is unlikely that all the services could be running simultaneously, therefore, it is necessary to properly allocate resources to theses services based on their importance at any given moment. For instance it would be recommended to run what-if simulations, or update the knowledge base when the machine is not running so that resources could be allocated to services such as improved control capabilities or condition monitoring while it is running. Second, attention could be considered in the context of relaying, or bringing attention to important information. A DT system should be able to notify users of important information so that they may take immediate action. For operators an adaptive user interface could be implemented that only provides the user with necessary and helpful information. Third, it is important to have a method to filter out features which could obfuscate intelligent analysis. Methods such as heat maps of correlation can be used to filter features.

3.4 Intelligence

Intelligence is the most important function of cognition. An intelligent system must be able to identify intelligent choices in uncertain environments. AI methods such as ANNs , recurrent neural networks (RNN) and RL can be used to facilitate decision making. Intelligence in the context of digital twins relates to how DT services can utilise AI for autonomous decision making and state estimation. Advanced condition monitoring, fault detection, control and other autonomous operation algorithms require intelligent decision making. AI in CDS is often implemented as either ANNs, RL, or dynamic programming. ANNs mirror how intelligence is thought to occur in human brains. A network of neurons can be used to make predictions based on seeming unrelated data. NNs have been successfully applied to many different tasks such as classification or regression (curve fitting). RNNs are a type of neural network especially useful in time series data. It can be used to predict trends in data. NNs have been proven to be effective when used as a predictor for condition monitoring. Dynamic programming and RL can be utilized to implement intelligent decision making. Both methods seek to optimize the reward from a Markov decision process (MDP). The primary difference between the two being that RL does not require a mathematical model of the underlying MDP. Both must consider weighing current versus future rewards. Q-learning, a popular reinforcement learning method uses a table (knowledge base) to make decisions based on a given state.

Applying NNs to estimate tool wear is popular in the literature. Several studies examined tool wear in turning operations[38,48,53–55] using inputs such as the cutting parameters (depth of cut, feed rate, etc.), force signals, acoustic emission signals, motor current, and vibration data. One paper[54] also used a thermal image as an input. Salinas et al.[55] found that an ANN had much improved classification of wear compared to conventional empirical-analytical methods. Many studies also examined tool wear and RUL in milling operations.[49,50,56–58] They used most of the same input parameters used in the papers looking at turning operations. Besides monitoring tool wear there were a few other applications of neural networks to machine tools. Ma et al.[27] used a Long short-term memory NN to compensate for thermal error and improve machining tolerances. Baig et al.[59] created an ANN based on thrust force, cutting speed, spindle speed and feed to predict the number of holes that have been drilled. With this, the estimated amount of wear could be deduced. Zhang et al.[21] found stiffness and damping parameters of rolling joints using first six order natural frequencies of their system in a Deep NN. RL wasn't as common as NN for machine tools. It is often applied to production and maintenance scheduling tasks. Skordilis et al.[45] used deep RL for a decision making framework for maintenance replacement that could generate warnings while the system was running. Ding et al.[60] Used Q-learning for fault detection in bearings and a pump system. They were able to detect faults with a very high degree of accuracy.

Each of the discussed AI methods use some sort of knowledge base. In the case of ANN, neurons in the network are given different weights which will lead to certain outputs given certain inputs. In Q-learning for example a table of state and actions will be used for decision making. For both of these methods training is required to update these knowledge bases. ANN use labeled data to create a model for prediction, Q-Learning uses an iterative process of exploring and optimization to create an optimal policy. Due to the dynamic natures of real life systems regular re-training needs to occur. A Q-learning based scheduling service that may have been accurate before may become inaccurate as cycle times change. Re-training might also be valuable due to an increase in available information, for example if a tool condition prediction service using a ANN had access to a larger database of labeled data, it could likely retrain to make more accurate prediction across a larger array of tools. Continuous knowledge base updates need to occur to effectively use AI based methods in a DT.

3.5 Language

Language is necessary for cognitive beings to communicate with each other. It facilitates passing along information from one person to another. There are two key acts in language, producing speech and comprehension of speech.[10] In the case of DTs it may be necessary for DTs to communicate with many other things. DTs can communicate with databases, other digital twins, operators, owners, and others. Primarily two types of communication should be considered: the communication between DTs and humans and the communication between DTs and other machines or software. And for each of these types of communication it is important to consider both the producing and comprehension components of language.

Effective communication with databases, software, and other DTs necessitates a common language. Data should be organized in a common data structure, ideally an object oriented framework[24] that can be extended and built upon for use in many different types of machine tools. Common data interchange formats such as XML, JSON, or CSV should be used for maximum interoperability. DTs require the ability to transform data to formats readable by other programs.[61]They should be built with an application programming interface (API) to facilitate communication between DT services.[62] Appropriate considerations for privacy and access privileges needs to be considered so that sensitive information is not access by the wrong people.

A critical level of communication is the DT's communication with humans. There is bidirectional communication, with the DT communicating information via a user interface, and the Human communicates information via entering commands through various control methods such as mouse and keyboard, control panel, voice commands, and others. The DT needs to be able to communicate effectively with users via an intuitive user interface, and ideally one that is adaptive to the users needs.[63]

4. APPLICATION OF FRAMEWORK TO TOOL WEAR MONITORING

Monitoring tool wear is important in machine tools as increased tool wear can lead to increased vibrations, surface roughness, and required cutting forces.[47] Several types of wear can occur such as flank wear, crater wear, fracture, and edge deformation.[47] The 2010 PHM data challenge is a data set where the goal is to be able to predict the wear on the flutes of a 3-flute ball end mill. Tools that are excessively worn can be replaced at efficient intervals to minimize tooling cost and minimize quality issues that arise due to worn tools. The goal of this experiment is to create a DT service based on the CDDT framework that can predict tool wear in a machine tool. Implementations of each of the 5 components of cognition will be used and shown to be of benefit to the service.

The experimental setup that produced the data can be seen in figure 4 from a paper by Li et al.[64] The machine spindle speed was 10400 RPM; the feed rate was 1555 $\frac{mm}{min}$; Y depth of cut (radial) was 0,125 mm; Z depth of cut (axial) was 0.2 mm. Data was acquired at 50 KHz. There are three data sets available, each containing data about vibration, force, acoustic emission, and the corresponding flute wear for each flute across 315 cuts.

4.1 Feature Extraction

The seven types of data collected and their units of measurement from the setup are the following: Force (N) and vibration (G) in the X, Y, and Z direction, and acoustic emission RMS (V). From this data we will need to be able to predict the level of tool wear. Looking at the flute wear from the data set we can see the wear somewhat follows expected wear patterns as seen in Figure 5a. There is an initial period of rapid wear, followed by a steady increase in wear, finally a period of severe wear occurs as the tool enters the end of its useful life. In

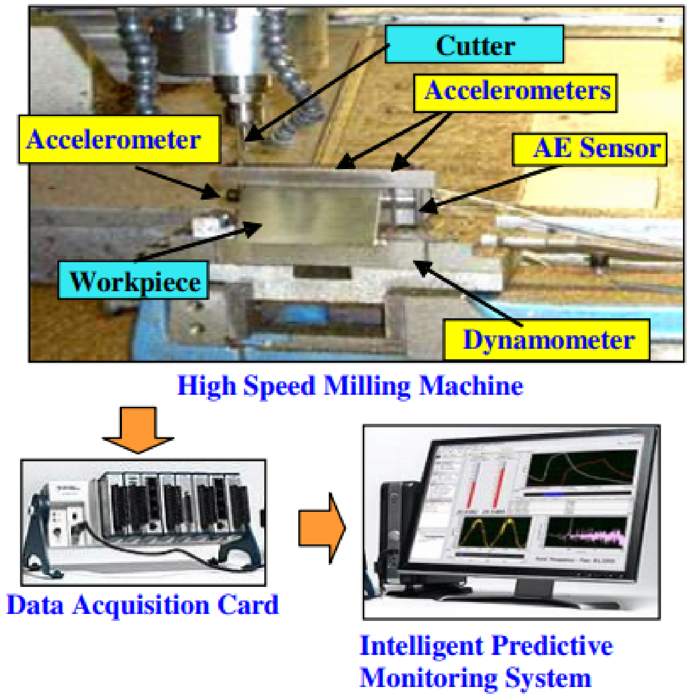
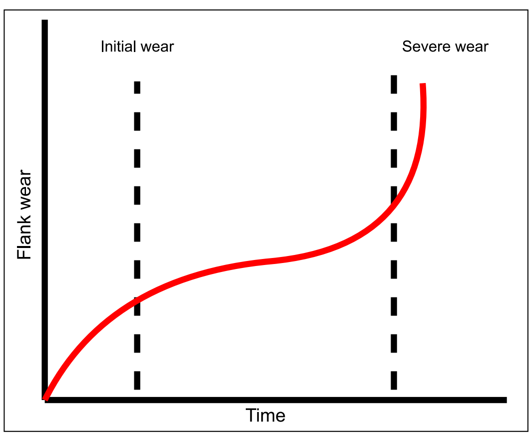
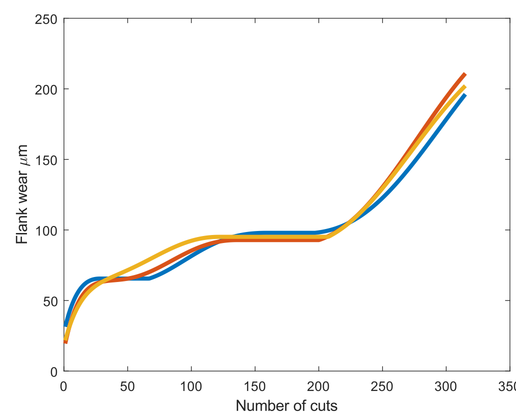


Figure 4: Experimental setup from paper by Li et al.[64]



(a) Wear curve of cutting tools[65]



(b) Wear of flutes from c4 data set

Figure 5: Comparing expected wear to actual wear of cutting tools

figure 5b we can see the same pattern emerge, cuts 1-30 are the wear in stage, cuts 30-210 are the steady wear, and cuts 210-315 are the rapid end of life wear.

Several methods were used to extract 70 features. Statistical numerical measures were extracted from the raw sensor data. Common measures such as max, min, range, mean, variance were calculated. On top of the common measures kurtosis, shapefactor, root mean square (RMS) were also calculated for each. Many of the statistical measures had positive correlation with the level of tool wear. From the time domain 55 statistical measures were extracted. In addition to these features the total cumulative feed of the cuts was recorded. FFT was used on the force sensor data to extract and separate information about forces acting at different frequencies. Upon analyzing the power spectral density (PSD) the largest components of the force signal seemed to be the DC components and at 521 and 1042 HZ. Given the spindle frequency of 173 and there being 3 flutes it was observed that the

1st and 2nd harmonic of the flute cutting frequency had the largest magnitude after the DC component. Each of these three frequencies increased in magnitude throughout the cuts as the cutter wear increased. Vibration data showed a similar trend with the 1st and 2nd harmonic of the flute cutting frequency increasing as the wear increased. The DC component of AERMS seemed to increase as tool wear increased following a similar trend of rapid initial increase, steady state, then rapid increase. From the frequency domain the following features were extracted: DC value of signal for all force signals and AE, 1st harmonic for force and vibration signals, 2nd harmonic for force and vibration signals.

For one tool this represents a decrease in the size of data from 2.88 GB of raw sensor data to 322 KB of feature data, or approx 0.01% of the original size. It is critical that historical data about the tool be saved as extracted features so that memory can be effectively managed. Extracted features are normalized between 0 and 1. A key is included with the normalized data to de-normalize the data to reflect the true values. The key will also be used to normalize incoming data that will be inputted into the neural network.

4.2 Building a Neural Network

To create more training data, wear for each of the individual flutes as well as the average wear of the flutes was used to create data sets. In total 12 data sets were created from the initial 3. Of theses data sets, the wear of the individual flutes was used for training and the average wear was used for testing resulting in a split of 75%/25% training to testing split. The NN regression model was created using the "fitrnet" function in matlab. The NN would use a variable size of input features to make a prediction of the level of wear. A summary of the final parameters of the NN model can be seen in Table 2. The level of wear could be between 0 and 1, where 0 was no wear, up to 0.25 would be initial wear, between 0.25 and 0.65 was steady wear and 0.65 and above was considered severe wear. Using the parameters seen in Table 2, prediction results can be seen in Figure 6. The prediction made using neural network is quite accurate. The RMSE for wear level predictions ranged from 0.013 to 0.113 for the C6 and C4 mean wear prediction respectively.

Table 2: Intial parameters for NN creation

Parameter	Value
Number of inputs	22
Number of hidden layers	1
Layer width	# of inputs
Activation function	sigmoid
Maximum number of iterations	$1e^3$

5. DISCUSSION OF RESULTS

Using the tool wear prediction NN a dashboard was created which with each successive cut will produce an updated prediction of tool wear as can be seen in Figure 6. The dashboard will communicated the level of tool wear as well as informing the user to replace the tool if it has entered into the "severe wear" zone. The blue line was included to indicate the true level of wear for visualization purposes but obviously in a real implementation would not be there as it would be unknown. As can be seen in Figure 6, the system can effectively and accurately predict levels of tool wear. The RMSE for wear level predictions for each of the three cuts was 0.0285, 0.111, 0.0144 for the C1, C4, C6 data sets respectively. The C1 and C6 data sets were more similar than they were to C4, it is understandable that the error for the c4 data set is much greater than the other 2. Ideally a real world implementation would have a larger pool of data to train and test the network. The wear profile of three tools performing the same cut is unlikely to produce a generalized neural network that can accurately predict wear using a different type of tool, cutting a different material or cutting with different parameters such as depth or feed.

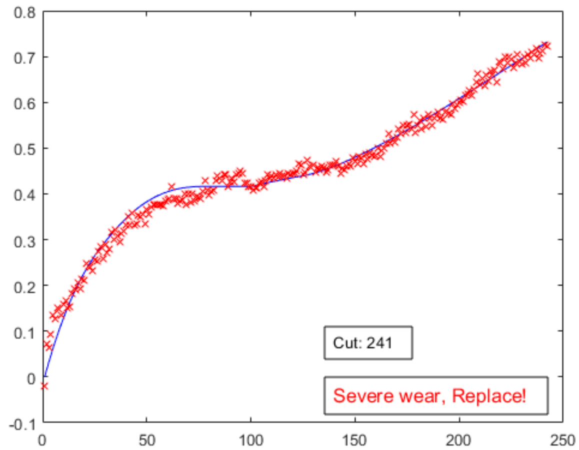


Figure 6: Wear prediction dashboard for c1 data set

Beyond just looking at the results of the accuracy of prediction of the neural network, it is important to look at how each of the five components of the CDDT framework were applied. Table 3 demonstates how each of the five components of CDDT were applied to this service and how they were of benefit.

Table 3: Implementation of framework

Component	Implementation	Benefit
Perception	Sensor network Multi domain feature extraction (time domain and frequency domain)	Large quantiy of data to select features from Large pool of features to build service from
Memory	Effective management of data Use of knowledge base to implement AI	Decreased data volume substantially Knowledge base can be continually be updated to improve prediction capabilities and generalization
Attention	Feature selection using correlation matrix to reduce dimensions of ANN UI that informs user of state of tool	Reduced complexity of NN to ensure quicker training User is made aware of current state of tool and when it should be replaced
Intelligence	Use of neural network for tool wear prediction	Neural network can effectively predict level of tool wear without reuiring a model
Language	Adaptive UI to inform user of state of tool Common data exchange format used to store and transport information (.CSV)	The dashboard gives users a history of the tool wear and the current state of wear Data can be accessed by other services as well as external programs

6. CONCLUSION AND FUTURE WORK

This paper has provided a possible direction for this development of DT technology to implement higher sophistication DTs. The primary contributions of this work are as follows:

1. Provided a framework to build more sophisticated DTs
2. Explored the current literature on machine tool DTs, and cognitive systems technology as applied to machine tools

3. Demonstrated the application and value of the CDDT framework to a machine tool DT condition monitoring service.

The proof of concept presented in this paper has demonstrated the utility and advantage of a cognitively enhanced machine tool DT service. Other examples in the literature have implemented aspects of cognitive systems, but this paper has shown the application of each of them and the value provided. Beyond the work performed in this paper there are several avenues for possible future work on this subject. Similar to machine tool DTs, DTs in other fields often exist at lower levels of sophistication. It would be worthwhile to apply the framework to these other fields to potentially augment their DTs performance. More research could be done on the application of the memory, attention, language portion of the framework, as the focus of the literature review was on the intelligence and perception components of cognition. The application of this framework was limited to a computer simulation using a relatively small data set. Ideally this application could be tested on additional real world data using different types of cutting tools, with different cutting parameters, and cutting different types of materials. This implementation also was limited to a single DT service for a single component, ideally future work could implement the framework in multiple services across several different components or layers of the manufacturing hierarchy.

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