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Digital Twin Enabled Asset Management of Machine Tools

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***Abstract*—Machine tools (MT) are essential equipment in modern manufacturing. They are a large investment which yields great returns to productivity and profitability. MTs enable the high throughput manufacturing of high precision components. Given their great importance, and their large cost, it is beneficial to implement asset management (AM) strategies such as condition monitoring, fault detection and predictive maintenance. Implementing these processes and methods can improve reliability and performance of MTs, while extending their lifetime and reducing operating expenses. Digital twins (DT) are an emerging technology within the Industry 4.0 landscape. They represent a connection between a physical system, object, or process and it's virtual representation. DTs can be leveraged for AM implementation in MTs. This work examines the potential benefits of applying DTs to AM, examples in the literature of applying AM methods to MTs using DT, and how advanced AM strategies can be deployed using DT. From examining the literature it was clear that DTs are well suited for AM in MTs. DTs enable improved data collection and processing, modeling and model retention, and historical analysis and trend prediction. DTs have been applied to a variety of application scenarios for MTs such as in cutting tools, spindles, and feed drives. DTs can additionally enable more advanced modeling solutions such as physics informed machine learning which can overcome some issues with traditional data-driven and physics-based modeling strategies. These advanced methods can improve overall AM across the MT's life-cycle and enable effective prognostic health management.**

***Index Terms*—asset management, condition monitoring, digital twin, fault detection, machine tool**

I. Introduction

Modern manufacturing relies on the use of expensive and complex assets. These assets improve productivity and profitability by increasing throughput, reliability, and part quality. There are several key assets common in manufacturing including: robotic arms, gantry cranes, automated vehicles, and machine tools (MT). Many manufacturing operations rely on the foundational support of MTs, which encompass various types such as mills, lathes, and grinding centers. These MTs contain intricate systems, comprised of numerous complex electro-mechanical, pneumatic, or hydraulic sub-systems. Some of these sub-systems include: the spindle, linear and rotary feed drives, tool changer, and cooling system [1]. To ensure the MTs are operating at peak capacity and returning maximum value to their owner it is essential to implement asset management (AM) strategies such as condition monitoring (CM), fault detection (FD), and predictive maintenance (PM) [2].

Implementing each of these AM strategies can ensure enduring and extended performance and reliability from MTs. The primary goal of CM is monitoring the system to get up-to-date information on the current state of the machine, FD seeks to identify any faults that occur so that they can quickly be addressed and compensated for, and PM ensures maintenance can be performed efficiently to maximize the effective lifetime, while minimizing associated costs. To implement these AM strategies there are two primary requirements. The first requirement is frequent data collection from a heterogeneous data stream. The second requirement is advanced, effective, and accurate data analysis and modeling methods. One possible solution for achieving these requirements would be the implementation of a digital twin (DT).

DTs are virtual representation of real life objects, systems, or processes. Their main feature is using dynamic model(s) which are constantly updated by collecting a heterogeneous data stream via multiple sensors [3]. This allows a constantly up-to-date model(s) which also contain a history of the system, as well as the ability to make accurate predictions about the future state of its associated real life object. This paradigm is well suited for AM as it solves the two primary requirements to implement CM, FD, and PM. It is then unsurprising that one of the primary applications in the literature for DTs is CM [4].

This work examines the advantages of using DT for AM. The existing literature on CM, FD, and PM for MTs using DT was examined to determine the state of current research. The proposed benefits of applying DTs to AM are examined, focusing on their ability to enhance data collection, modeling, and trend analysis. It was found that DTs have been applied in many different ways to several different sub-systems within a MT. Additionally, it will be discussed how DT can be used to implement an advanced modeling strategy known as physics informed machine learning (PIML) which could be extremely beneficial for AM in MTs by easing the constraints of data set size and balance. This work seeks to examine and present

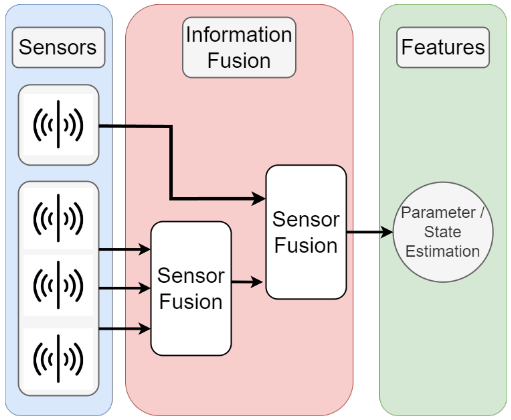

Fig. 1: Sensor fusion for parameter and state estimation

the state-of-the art of this technology and its applications to prognostic health management.

The organization of the remainder of this work is as follows: section II covers how DT can be used to augment AM, section III covers examples of using DT for AM of various components in a MT, section IV covers the use of DT to implement PIML, and finally section V concludes the work and provides potential issues, future work directions, and identifies gaps in the literature.

II. Asset Management Using Digital Twin

DTs are well suited for AM because their primary attribute is regular updates to their model(s). This update process, along with the storage of historical modeling information provides a good foundation for evaluating the condition of the machine, identifying faults, and applying PM. The life-cycle of the MT can be mirrored into a virtual representation which can enable improved decision making and system optimization [5]. Effective PM relies primarily on two factors: prediction accuracy and frequency of prediction, of which DT technology can improve on both. An important function of AM and PM is the ability to predict the remaining useful life (RUL), anomaly detection, and performance evaluation. This allows the optimal replacement of components which maximizes their life while minimizing the impact of poor performance, or the possibility of unexpected downtime. Prediction accuracy of PM is most often a matter of the quantity and quality of data, and the accuracy of analysis performed. It will be demonstrated that DT is an ideal candidate for accomplishing the goals and objectives of AM.

A. Data Collection

DTs can collect large heterogeneous data streams. For a MT this is often achieved via an Internet of Things (IoT) sensor network which consists of many different types of internal and external sensors, production data, and control system information [2], [6]. In addition to the quantity of data, the quality and accuracy of the data is also important. The quality of data can often be a matter of sensor quality, a restrictive factor that may be alleviated through the integration of multiple sensors and the application of sensor fusion techniques. Sensor fusion can be accomplished by fusing similar measurements from the same type of sensor taken at different positions, or by fusing different types of sensors. There are several different examples in the literature such as camera measurements and vibration measurements [7], or current and vibration measurement [8]. This process is illustrated in Figure 1. Applying sensor fusion can also improve measurement reliability. If one sensor fails or malfunctions it is still possible to collect data about that state via a secondary source as long as it is accounted for in the fusion algorithm [9]. For example if a vibration model is used to detect tool wear, a secondary vision system can be included in the case of false signals of failures [7]. Another case would be using a thermal camera as a back up option for a force measurement system for measuring tool wear [10]. Sensor fusion can also allow the ability to estimate unmeasured states via soft sensing [11]. Often it is too difficult or impossible to directly measure states. One example of this would be cutting tool temperature while cutting. A potential approach of soft sensing would be measuring various points on the spindle and using measured points to estimate tool temperature [12]. Using sensor fusion for soft sensing, improved reliability, or improved accuracy requires the implementation of a fusing algorithm of which there are several. Many of these algorithms can be categorized into probabilistic models, least-squares techniques, and intelligent fusion [13]. Two common methods which are utilized in many of the examples seen in section III are Kalman filtering and particle filtering.

Data collection via a sensor network combined with sensor fusion to improve data accuracy, reliability, and scope is an important step in ensuring that there is adequate data quality and quantity for DT based AM purposes. This data is used for parameter and state estimation which is used to create models of the system and a virtual life-cycle. This virtual life-cycle data can be used for model training and validation, and future projections described in sections II-B and II-C.

B. Modeling and Model Retention

Modeling in DT via up-to-date real time data is a key advantage of the approach. DTs often implement many different domains and modeling approaches to holistically represent the system such as electrical, mechanical, and thermal. DTs can enable more advanced modeling and analysis techniques through advanced simulation capabilities and model consistency retention methods, where model consistency retention is the process of constantly updating and validating the system model(s) [14], [15]. This process allows for a high accuracy model over the entire life-cycle as seen in Figure 2. This is often accomplished via building a model and comparing and validating against current and historical operational data. This is a desirable characteristic for AM purposes, as it is expected that the system will change throughout the life-cycle. It is

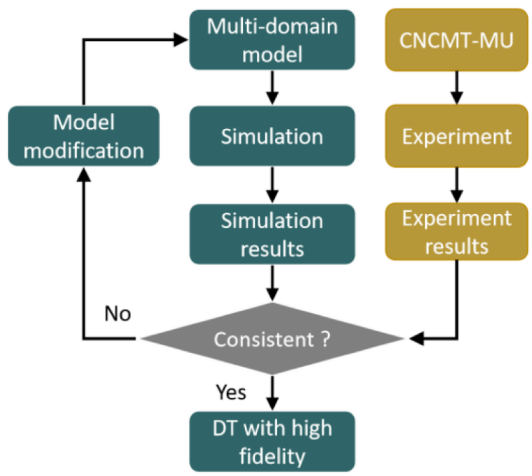

Fig. 2: Consistency retention / model update process [14]

useful to understand how it is changing and to be able to predict the change.

Most modeling in a DT system can fall under the category of data-driven, or physics-based modeling. There are possible advantages and disadvantages to each approach. Data-driven approaches can be advantageous because they do not require understanding of the underlying system, however, understanding the system can be advantageous in many AM applications. Common data-driven approaches to modeling seen in the literature include the use of artificial intelligence or machine learning. This is often implemented via a neural network (NN) which creates a mapping of input parameters and states to a set of outputs. Typically, past data collected into the virtual life-cycle is used to train and validate a model. NNs are one of the most common approach for data driven approaches which can be seen below in section III. Physics-based modeling is often best used when there is a great deal of understanding of the underlying mechanisms of the system. Physics-based solutions are typically accomplished using multi-domain simulation and modeling software such as MATLAB/SIMULINK [16], SiumulationX [17] or Modelica [18]. The most common approach for these is to build a model and tune and validate the parameters with incoming operating and condition data. ANSYS is another popular tool for physical modeling using finite element analysis (FEA) in DT applications [12], [14]. It is frequently applied to solutions examining thermal characteristics, stiffness, and vibration, where sensor measurements are often used for boundary conditions in these simulations. The main downside with physics-based modeling is that it may require assumptions and simplifications of the systems as it is impossible to fully accurately model the system, especially with limits to computational capabilities. In addition, physics-based models are designed based on existing scientific principles and equations. If the underlying system dynamics changes over time, such is the case in various PM tasks, the model is at risk of becoming obsolete over time.

Often there are parallel models used in DT systems which take many of the same inputs and produce the same or similar inputs, or models which are used to complement and reinforce each other. This hybrid solution of using multiple models and applying some sort of model fusion can be used to increase the accuracy and reliability of models similar to what sensor fusion can do for data, as discussed in II-A. Hybrid modeling is a popular approach for DT solutions to AM and PM problems [14], [17]. A special type of emerging hybrid modeling is PIML, which could also be the solution to the deficiencies of both physics-based and data-driven. PIML can further improve modeling accuracy and fidelity for CM as discussed in IV. Accurate and up-to-date modeling can help not just with current assessments of a machines condition, but also to project future behaviour.

C. Historical Analysis, Real Time Monitoring and Future Prediction

In the past CM was performed manually at certain intervals, which was very time consuming, expensive, required inspector expertise, and left large intervals between inspections. Equipment was often replaced at set intervals, which is wasteful as it ignores the current condition of the components and leads to unnecessary downtime [1], [2]. Real time CM is now a possibility due to advances in sensor network connectivity due to the IoT, as well as advances in computing power. Real time CM allows for improved decision making, and fault and anomaly detection. This real time CM can be achieved via the implementation of a DT [4]. Enabled by the improved automatic data collection and improved modeling described in the previous sections, real time analysis of the system can be performed.

One common theme among DT based solutions is the visualization of real time CM data [19]. This often is accomplished by creating a interface or dashboard which includes relevant information such as real time RUL or wear estimates [20], error warning alarms [21], current operating conditions [22], and performance metrics [19]. This enables the user to quickly determine the state of the machine or the process. DT based system visualization allows for quickly and easily interpretable CM which can be valuable for many stakeholders in the manufacturing environment.

One key feature and advantage of DTs is a model history, and the ability to predict future behaviour though accurate, validated modeling solutions as seen in Figure 3. Effective PM programs not only require information on the current state of the condition of the MTs, but also a history of past operating or performance data and the ability to make future predictions [23]. The data about historical condition of the machine allows for the building and validation of models. Future predictive capabilities afford the opportunity for strategic planning and forecasting, minimizing unforeseen events. Future projection in a AM and PM context using DTs usually involves RUL prediction [4] which can be used

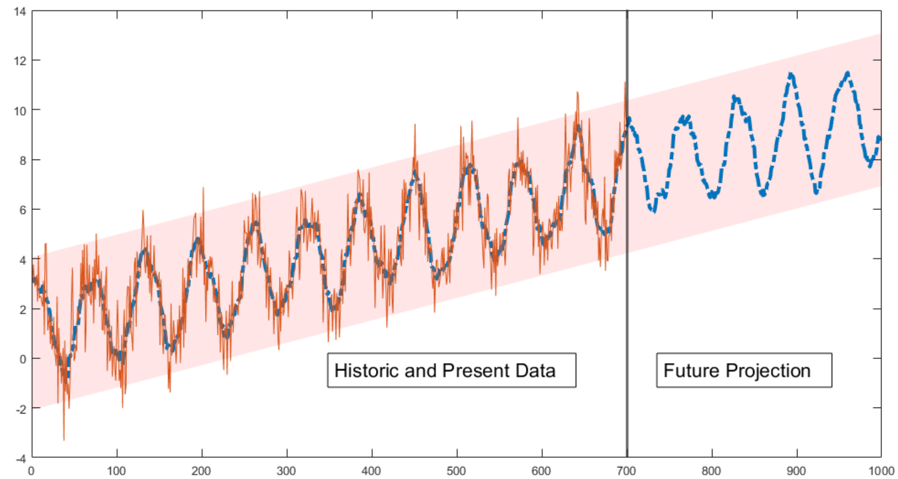

Fig. 3: Historic trend analysis and future projection using DT life-cycle

to efficiently replace components and to detect and avoid unexpected failures [23].

III. Applications to Machine Tools

Ensuring machine reliability is of key importance and as previously mentioned, one of the best ways to do this is to implement PM via CM and FD. CM ensures that MTs are working as intended. There as several examples in the literature of applying DT technology to MTs to improve AM capabilities such as a paper by Guo et al. [22] where the authors did research into designing a virtual MT. In this work the authors implemented their DT to simulation to avoid collision, as well as real time data monitoring and historical analysis. In other work by Davies et al. [24], they created a DT of a MT to optimize maintenance through the implementation of PM. They combined theoretical predictions of motor, spindle and feed drive RUL using multiple data sources which was used to create and accurate timeline for maintenance intervention. As previously mentioned, a popular approach with DT based CM is the implementation of a dashboard or web platform to monitor the MT. This was demonstrated in work by Wang et al. [19], who created a real time CM dashboard for a die cutting machine which had three primary functions: real time CM, production scheduling, and overall equipment effectiveness measurements. Parameters such as machine availability and productivity are constantly being updated and displayed for the user. Another example of a dashboard was Stan et al. [25] who built a web based platform to monitor the process of robotic de-burring. This platform would create error alarms and allow remote access and control by qualified personnel. Using this platform they hoped to optimize machine productivity and energy efficiency.

Entire MTs are often too complex of a system to create a DT at the current level of sophistication and development of the DT concept [26]. Because of this many examples in the literature apply DTs to sub-systems of the MT which can decrease development time while still providing useful analysis and modeling for PM. One possible approach to implement a DT would be developing smaller scale DTs and integrate them as development continues [27], [28]. Some key sub-systems that are worth implementing a DT for are the cutting tools, the feed drives, and the spindle.

A. *Cutting Tools*

Cutting tools are key components in most MTs because they are the interface for material removal, and therefore most often experience high levels of force and wear [29]. This wear can occur in several ways, such as flank wear, chip offs, edge deformation, and tool fracture. As a result of wear, surface finish can be diminished and the work piece will experience increased forces. Consequently, the diminished quality will result in increased load requirements for the various feed drives and the spindle [29].

There are several methods that are popular for cutting tool CM. One method involves direct monitoring, necessitating the measurement of wear through direct means or capturing visual data, such as photographs or videos of the tool. The issue with this method is that it requires breaks in production and therefore cannot be done in real time [10]. Another method is indirect measurement via using signals such as force or vibration, however, as a compromise, this approach is often less accurate than direct measurement [10]. Indirect measurement methods are popular in the literature. They often employ data-driven methods such as NNs or physics-based methods such as FEA, or both via hybrid modeling. There were examples of NN based methods [30], [31] for milling and turning cutting tool life prediction, as well as hybrid model methods [17] which found that the hybrid method using a particle filter performed better at predicting the replacement time than just a model-based or data-driven method. Direct measurements using cameras, regular or thermal, can be used to monitor the cutting tool as well as the work piece to detect any wear or poor machining performance. There are several approaches to direct measurement such as machine vision [20], thermal cameras [10], and visual inspection [7] which are used to estimate the RUL. Some methods combine direct and indirect measurement methods to create an improved and more reliable and accurate estimation model [7]. Ideally a DT AM framework for cutting tools would utilize multiple sensors and data streams in conjunction with some type of degradation model or simulation to estimate the RUL of the cutting tool in real time. There are a few examples in the literature for dashboards or updating processes for cutting tool health monitoring. For example, Xie et al. [21] created a framework for cutting tool degradation and a dashboard to display information about the condition of the tool. Another examples was Botkina et al. [32], who proposed a framework for a DT of a cutting tool through a method termed ”tweeting”, which periodically updates the model of the cutting tool to reflect the updated condition.

B. Feed Drives

Feed drives are very important components in most MTs. They are responsible for accurately positioning components during machining operation. It is important that they can accurately track their reference trajectory as well as maintaining appropriate velocities to maintain desired machining parameters. These machines will often encounter high forces by needing to move heavy axis platforms, as well as resisting machining forces. It is important that they maintain rigidity and minimize friction so that high performance can be maintained.

There is limited research on CM of MTs feed drives using DT compared to other components of a MT DT. A more popular application is trajectory planning. One possible way this can be adapted to a DF scenario would be to identify when anomalous behavior is occurring if it deviates from predicted behaviour or matched a model representing a faulty state. An example would be Sicard et al. [33] where ball screw preload levels were identified by matching current system behaviour to a fault state. Alternatively, Chaiprabha et al. [34] used a DT model of a linear feed drive to identify an obstruction anomaly event. Another popular use of DTs in feed drives that can be adapted for CM is in process parameter identification. Parameters such as stiffness, damping, and friction will change as the condition of the feed drive condition deteriorates [35]. RUL and degradation can be modeled to estimate the performance of the system [14]. Hybrid models can be used to fuse model-based methods such as FEA with data driven methods such as a NN.

C. Spindle

Spindles are a critical component in both lathes and mills, which are two of the most prevalent types of MTs. They are responsible for turning the work piece in the case of the a lathe, and the cutting tool in the case of a mill. They experience high loads due to rapid acceleration and deceleration, as well as machining process forces. Spindles also needs to be accurate, rigid, dissipate heat to operate under stable temperatures, and have the ability to dampen vibrations [36]. There are several qualities and faults that aught to be monitored in a MT spindle. Some of these include tool deflection, thermal error, balance, and the health monitoring of the various sub-components [37]. A great deal of this CM can be achieved via the implementation of a smart spindle [37] which integrates abilities of sensing, decision making and control. Smart spindles can be augmented with the implementation of DT technology which can further augment the capabilities .

DTs can be applied to more accurately monitor faults and the condition of the MT spindle. One characteristic that can be examined is spindle stiffness. One approach would be to build a spindle stiffness fault library to match with sensor data [38]. Another would be to measure the vibration and stiffness of the spindle and compare to DT generated data which could then be used to create a performance index [18]. One other common application of DTs in spindles is thermal monitoring. Thermal monitoring and estimation is necessary to predict levels of thermal deformation which needs to be compensated for, otherwise parts will be incorrectly sized. It is not possible to directly measure thermal elongation and deformation of a spindle or work piece and so it is often necessary to estimate the aforementioned elongation via simulations or by taking direct measurements further from the end of the spindle. A popular approach to this is hybrid modeling where a NN and FEA are combined to create thermal deformation estimates from spindle temperature readings. These hybrid methods often employ a NN to estimate boundary conditions for a FEA simulation [12], [16], or they create a parallel s which is combined to form a more accurate overall estimate [39].

IV. Advanced Condition Monitoring Using Physics Informed Machine Learning

Two issues with traditional data-driven AM strategies is the requirement for large data sets, and the black box nature of these models, where not much about the underlying mechanisms is known [40]. Large data sets, especially balanced ones, may be difficult to obtain. Given that fault conditions are inherently rare compared to regular operating conditions, there will tend to be highly imbalanced data sets [41]. To accommodate this issue there needs to be some sort of re-balancing or re-sampling to handle the imbalance. Another issue is the black box nature of many data driven approaches, especially NNs where the lack of understanding of the inner-workings of the method does not allow for critical analysis of the results from the system outputs. Physics-based modeling can also face roadblocks due to the requirement of needing to make assumptions or simplifications which can lead to an imperfect representation. The computational complexity that

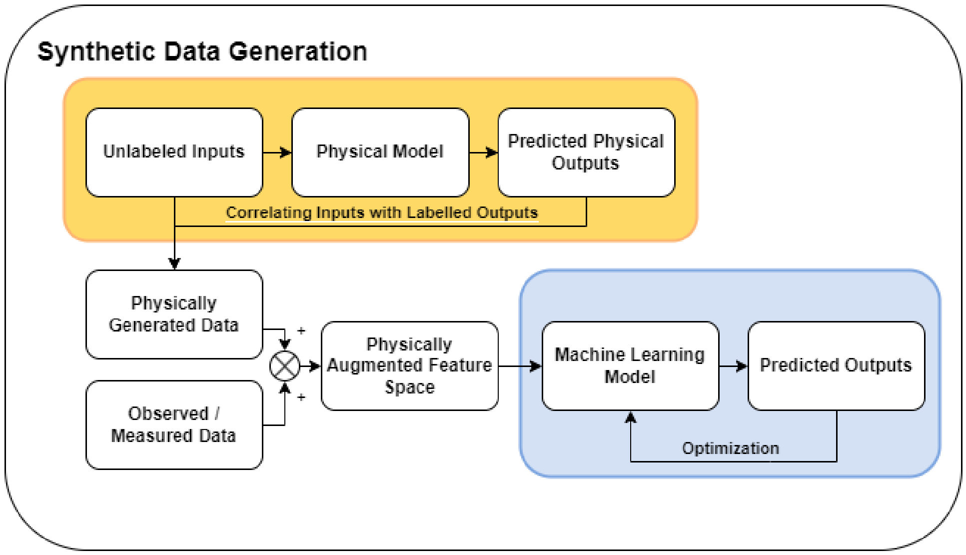

Fig. 4: Synthetic feature generation for PIML [40]

often occurs with these types of models can also prove to be an issue [40].

PIML is a set of emerging hybrid modeling strategies that combines the benefits of traditional physics-based modeling with data-driven modeling. Many other types of hybrid modeling use separate data-driven and physics-based solutions whose results are fused together. PIML integrates the two approaches into one solution. By doing this it is possible to obtain the advantage of both data-driven and physics-based approaches while minimizing the potential disadvantages of each. DT is a potential enabling technology for PIML as it often requires the ability to collect a data set and advanced simulation and physical modeling capabilities. Two of the possible ways of implementing PIML are using advanced simulations to generate data to train ML methods, or by embedding the physical relationships and constraints in the model loss function of NNs.

The first method uses synthetic data generated from an advanced simulation to train a NN which can be seen in Figure 4. This can be useful if it is desired to detect a fault which has not yet occurred, and therefor there is not data for. This is fairly often the case as faults, especially catastrophic ones, do not occur very often. One example of applying this method is work by Seventekidis et al. [42] who generated data for a fault condition where there was a notch in a structural beam. They then used this data to train a NN which could identify this fault in an experimental setup without using real experimental fault condition in its training data set. This approach could be incredibly useful for fault and anomaly detection as imbalanced data sets or lack of available data sets is often a key challenge. Many data-driven methods require a very large dataset which is another issue that can be solved by this method, as it would be possible to theoretically generate as large as a data set as desired by running many simulations.

The second approach, physics informed NNs, implement the physical principles and relationships that represent the system, such as ordinary or partial differential equations, into the training of NN. One proposed benefit of this method would be requiring less training data compared to traditional NNs [43]. This method works by using NNs to solve ODEs and PDEs using limited data [44].

PIML is an emerging method which could prove to be an exceptionally effective way of implementing AM and PM. Both PIML methods discussed are most effective when paired with a DT due to overcoming some of the weaknesses or challenges of both physics-based and data-driven modeling. Data set size and balance requirements are loosened which allows for quicker development and more accurate modeling.

V. Conclusion

After examining the literature it is clear that there are several features of DTs make it an effective approach to AM of MTs. DTs have many diverse data streams, usually collected via a sensor network which is often fused to improve the reliability and accuracy of these measurements. These measurements are then used to create accurate and up-to-date estimations of the systems parameters and states. There are many different types of models used in DT system, most of which are either physics-based, or data-driven. There are also many approaches which combine the results of several different types of models via model fusion. The system model(s) are constantly updated and refined using a process know as model retention which ensures that any modeling technique is accurately representing the system. These accurate system models can be used to implement real time CM which is often implemented via a user interface or dashboard which gives users and stakeholders access to key information in real time. Data collected with the system can be used to construct a system life-cycle that can be used to examine trends and create future projections.

DTs have been applied to whole MTs as well as several different components of the MT. The most popular applications were cutting tools due to the fact the cutting tools are highest wear component, and are the direct interface between the machine and the work piece and thus have possibly the largest affect of part quality. An under examined MT component was the MT feed drive which is essential for accurate positioning of the work piece in a MT and should be further studied. Overall, DT is an emerging topic in CM and has seen increased interest, but there still needs to be more application examples in the literature.

One exciting new technology that could be useful for AM would be PIML. PIML can be enabled by DT technology and could possibly help overcome the shortcomings of both physics-based and data-driven CM. Issues such as the requirement of advanced knowledge of the system or a large balanced data set respectively can be mitigated with this approach.

A few possible issues and challenges exist with DT based AM. One of these issues is that of data access privacy and security, as many of these systems rely on remote access to machines and their associated data. It is important that appropriate security and privacy measures are undertaken to ensure the integrity of the data of these machines. Another issue is the quantity of data collected, as well as the complexity of this analysis. Dealing with this data and analysis may require a great deal of computing power and data storage which may be expensive due to capital investment requirements or cloud computing costs. An additional challenge could be that due to the complexity and nature of FD and CM it may require extensive development time. Many of the examples in the literature are limited in scope and part of it is due to this limitation.

Overall it is clear that DT technology has been proven to be an effective approach to AM. It is important to further develop the literature by continuing to applying the DT concept to MTs and its various components, especially under explored components such as the feed drives. Additionally it is important to explore the full capability of what DTs are capable of for AM by continually applying new data collection, modeling, prediction, and visualization techniques.

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