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Hybrid Modeling for Condition Monitoring in Digital Twin Systems

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***Abstract*—Digital twin (DT) modeling is an emerging framework for modeling complex system which can improve modeling fidelity and accuracy. This improved modeling accuracy can be used to improve performance and reliability of these systems through performance optimization and condition monitoring (CM). One aspect of CM that can be potentially greatly improved is soft sensing, also known as virtual sensing or smart sensing, which is estimating the values of parameters or states without directly measuring them. Because a DT seeks to virtually replicate a system, it is necessary to model a great many parameters and states, and it is not economically feasible to directly measure each of them. To overcome this, soft sensing is used to estimate these using models. Because there is risk, uncertainty, and inaccuracy associated with relying on just one model, it is ideal to utilize multiple models. Hybrid modeling uses several models to improve the accuracy, precision, and reliability of these estimates. There are several approaches seen in the literature which can broadly be categorized as series, parallel , and combined models. Each has their own advantages and use cases, and they were each shown to improve CM capabilities of their respective systems. This work examines Hybrid modeling for CM in the context of DTs, and displays the effectiveness through examining existing literature applying the concept.**

***Index Terms*—Condition monitoring, Digital twin, Hybrid modeling, Soft sensing**

I. Introduction

Digital twins (DT) are an emerging technological paradigm in engineering system modeling. DTs are virtual representations of real life systems, processes, and objects. They utilize a high speed and fidelity connection to the physical asset to accurately model the system in real time. This up-to-date model can be used to improve system reliability and performance. Because it is not feasible to measure every possible system state it is necessary to implement soft sensing and other modeling techniques to predict or interpolate these measurements.

Modeling in a DT often occurs with either physics-based or data-driven approaches. Each method has their advantages and disadvantages that should be weighed and considered. Physics-based approaches rely on the physical phenomena, features, relationships, and parameters of a system to model its behaviour. Data-driven approaches on the other hand do not use understanding of the underlying system, but rather use statistics and probabilities to match system inputs to system outputs.

To overcome some of the disadvantages of each modeling approach, while maintaining the advantages, it may be ideal to implement hybrid modeling. Hybrid modeling uses two or more models to model the behaviour of a system, or integrates data-driven and physics-based approach. There are several ways to approach this, some methods use a series approach where one model feeds another, others use parallel models where 2 or more models estimate the same parameters or states, which are then combined using model fusion. By implementing hybrid modeling it is possible to improve system modeling accuracy and reliability.

Although hybrid modeling has been applied to many different fields such as chemical processing, energy generation, fluid dynamics, and biomedical modeling [1], this work will focus on applications of condition monitoring (CM) and soft sensing. This work examines hybrid modeling in DTs and how it can improve system modeling which can ultimately lead to improved system performance and reliability.

The remainder of the paper will be organized as follows: Section II will cover how DT is an advantageous platform for applying hybrid modeling to achieve CM and soft sensing. Section III will cover different types of modeling techniques. Section IV will cover different types of hybrid modeling strategies and their advantages. Section V will cover a few applications of hybrid modeling to CM scenarios. Finally, section VI will conclude the work and provide future work outlook.

II. Digital Twin Based Soft Sensing for Condition Monitoring

One of the primary applications of DTs is to CM. This is largely due to its property of frequent model state updates. This frequent update process means that the state of the system is constantly being measured or estimated, which lends itself well to CM. Although a typical DT system will have many sensors, it is simply not feasible, or even possible to measure every state. For example, on a machine tool if it desirable to measure tool wear, it is not feasible to take a direct measurement in process, as this would mean removing it and inspecting. This could be performed at infrequent intervals, but it is desirable to have a reasonable estimate of tool wear at any given time. To determine tool wear, or any other system state, it is desirable

TABLE I
ADVANTAGES AND DISADVANTAGES OF PHYSICS-BASED AND DATA-DRIVEN MODELING METHODS

Physics-based	Data-driven
Based on foundation of system's physics	Statistical relationship between input and output features
Advantages	
Gives insights into systems	Requires no understanding of underlying system
Can transfer knowledge to similar systems	Many different algorithms
Can be very accurate if system is well understood	Can be applied to many different types of problems
Disadvantages	
Computational complexity at runtime	Black box model
Susceptible to numerical instability issues	Can be biased based on data sampling
Cannot easily incorporate historical data	Training process can be time consuming
Sometimes requires simplifications or assumptions	Requires a large data set

to be able to estimate the system using some sort of model or soft sensing. As will be discussed further is section III, there are several approaches to do this.

Normally in engineering systems physical sensors collect data from physical quantities and convert them to interpretable signals [2]. The downside of these sensors is that they can be damaged during operation or from the environment (from radiation for example), each additional sensor increases costs and complexity, have sensors noise, and often require calibration. To overcome these issues it is worthwhile to implement virtual sensors, which are also known as soft sensors, smart sensors or estimators. These virtual sensors rely on accurate models for their predictions using other physical sensing data. Although one model alone may be adequate for estimating these states, more than one estimate can improve reliability, accuracy, and precision. Soft sensing also allows for immeasurable states, because of lack of sensor access, to be measured.

III. System Modeling

System modeling is often done using one of two approaches: Physics based, or data-driven. Each has their own advantages and disadvantages which have been listed in the Table I.

A. Physics-based Modeling

Physics-based approaches rely on the physical phenomena, features, relationships, and parameters of a system to model its behaviour. This approach is advantageous when a great deal of information of the system is know, but may be less useful as uncertainty increases. There are several approached to physics based modeling such as lumped mass modeling, finite element modeling (FEM) or computational fluid dynamics, and dynamic mechanical simulations. FEM is widely used across a variety application cases and fields of research. FEM can be used to model the stiffness, thermal, and vibration characteristics of systems which are useful features to track in CM. The main drawbacks of FEM are computational complexity and the fact that it relies on a good understanding of the underlying system [3]. Lumped mass models can reduce the degrees of freedom of a model so that it can be represented as a transfer function and make certain applications such as control, where this type of modeling if often applied, much more manageable [4]. The main disadvantage of lumped mass modeling is it requires a great deal of assumptions and simplifications.

B. Data-driven Modeling

Data-driven modeling is the process of creating a relationship between inputs and outputs without necessarily understanding the underlying mechanisms of the system. The advantage to this approach is that it does not require any underlying knowledge of the function of the underlying system, however this is also a disadvantage, as it is not possible to gather insight into the system through modeling as it is a black-box system. The most common type of data-driven modeling seen in DT modeling is machine learning. Machine learning uses statistical algorithms to make predictions on outputs based on a set of inputs. Supervised learning, which is the most common type, uses experimental data to train these models to make prediction on unseen data. One of the most common issues with data-driven approaches is that as the complexity of the model increases, so does the training requirement. One advantage of a DT based data-driven approach is the availability of data through its heterogeneous data stream. However, one problem that cannot necessarily be solved by using a DT is issues of data imbalance. Data imbalance may be an issue especially for fault detection, CM, and predictive maintenance as the amount of normal operating state data will far outweigh the faulty operating state.

IV. Types of Hybrid Models

Hybrid modeling is the use of several models, either in parallel, in series, or combined into a single model, to model a system, as seen in Figure 1. Many of these applications use both a physics-based and a data-driven model. There are advantages and disadvantages to each approach, so depending on the use case it is desirable to examine the merits of each.

A. Series Models

Series hybrid models use one or more models to generate output features, which are used as input features for other model(s). One type of series models is a sub-type of physics informed machine learning (PIML), physics-guided input feature augmentation, which uses accurate physics-based modeling, such as FE modeling to generate data to train NNs. This is very useful in the case where certain data may be difficult to come by normally, such as faulty conditions. Not all series models are used to generate synthetic training data, it can also be useful to augment the input features of a model.

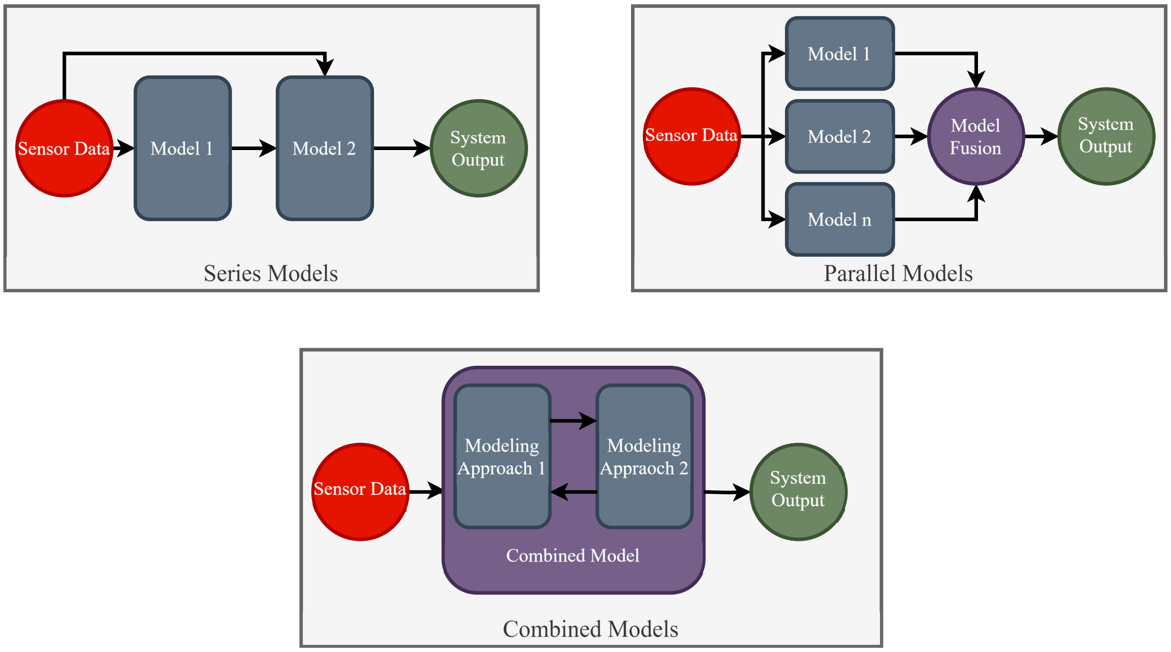

Fig. 1. Three types of hybrid models

One use case may be to generate features from temporal data via a recurrent neural network such as a long short term memory (LSTM) network to generate features for an atemporal model such as another machine learning methods like non-linear regression [5]. The two main advantages of this approach are creating a larger, more balanced dataset in the case of physics-guided input feature augmentation or by increasing the feature space and depth of the model, which can increase model performance.

B. Parallel Models

Parallel models are a common type of hybrid model. Parallel models use several models which are predicting the same state or parameter. These models may use all of the same, some of the same, or none of the same inputs to make this prediction. The main goal of this type of modeling is increased reliability, accuracy, precision, and generalizability of the estimated model. Similar to sensor fusion or estimation theory, this modeling approach seeks to decrease the uncertainty of the estimates by optimally combining and selecting model outputs as can be seen in Figure 2. Popular methods to do this are the particle filter [6], [7], Particle swarm optimization [8], [9], and Kalman filtering and its various extensions [10].

C. Combined Models

One final approach to hybrid modeling is combining several distinct modeling types into a single model. This could mean using a more complex model like FEM for a more important component, such as in the case with feed drive modeling where the ball screw is a critical component, and other less critical components as a simpler model, like a lumped mass model [11]. Another new type of modeling approach is physics

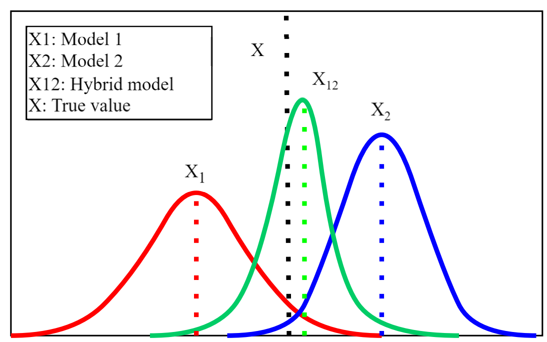

Fig. 2. Improved estimation accuracy and precision

informed neural networks. These are neural networks where the physical relationships of the system are built into the loss function. by doing this there is a lowered requirement for training data [12].

V. Applications

CM and predictive maintenance is a popular applications of hybrid modeling. The goal of CM and predictive maintenance is to identify the current state of the system and predict the remaining useful life so that maintenance can be done at effective intervals. Hybrid modeling can allow for the soft sensing of various states and parameters which can provide insight into the current state of the system.

Tool wear monitoring is a popular application case in machine tool CM, cutting tools are the primary interface between work pieces and the machine tools and experience a high degree of wear. Their level of wear can have a large impact on the quality of the parts being produced. It is also

TABLE II
EXAMPLES OF HYBRID MODELING FOR CM

Model Structure	Paper	Models	Application	Combining method
Series	Rai [13]	1. FEM (P) 2. Neural network (D)	Identify damage location on metal plates	-
	Xie [14]	1. FEM (P) 2. Neural network (D)	Thermal field prediction	-
	Seventekidis [15]	1. FEM (P) 2. Neural network (D)	Identify damage location in bridge	-
	Cai [5]	1. LSTM (D) 2. Non-linear regression (D)	Cutting tool CM	-
Parallel	Luo [6]	1. FEM (P) 2. Random forest regression (D)	Cutting tool predictive maintenace	Particle filter
	Zhuang [8]	1. Tool wear simulation (P) 2. SVM (D) 3. KNN (D)	Cutting tool predictive maintenace	Particle swarm optimization
	Yang [7]	1. Radial basis function SVM (D) 2. FEM (P)	Transmission wear	Particle filter
	Lu [9]	1. FEM (P) 2. LSTM (D)	Thermal error of a spindle	Particle swarm optimization
	Sicard [10]	Multiple lumped mass models (P)	Ball screw preload estimation	Kalman filter interacting multiple models
Combined	Sun [16]	1. Gated recurrent unit NN (D) with physical concepts integrated into loss function (P)	Crack identification and quantification	-
	Okwudire [11]	1. Lumped mass model (P) 2. FEM (P)	Improved positioning error estimation of feed drives	-

difficult to directly measure tool wear which makes it a good candidate for soft sensing. Cai et al. [5] used a series hybrid model to estimate the state of tool wear. Their model was a two layer system with the first layer being a LSTM NN which extracted features from temporal machine sensor data. Next, a second layer of a non-linear regression model which uses the output of the LSTM combined with production data such as depth and feed rate of a cut. Using this two layer model they could accurately (90%) predict tool wear using 2 test sets of data. Luo et al. [6] created a hybrid model to estimate cutting tool wear and apply predictive maintenance. Their model combined a data-driven random forest model and a physics-based tool degradation simulation in parallel. The estimates were combined using a particle filter, their hybrid model had improved RUL prediction accuracy compared to model based or data driven alone, prediction error was decreased from 10-20% to 3-6%. Zhuang et al. [8] Created a hybrid cutting tool monitoring scheme. Their model was a parallel model with a physical simulation of tool wear based on tool geometry and material, process parameters, and other factors. Their data-driven model was both a KNN for wear classification and a SVM for wear prediction. Each of the models is used to improve estimation reliability and accuracy. In addition to tool wear, it is useful to predict other high wear components. One example used parallel physical wear model, simulation based estimates, and a neural network (NN) prediction combined via a particle filter to estimate the wear of a transmission unit [7].

PIML can be used to overcome some of the potential deficiencies of data-driven or physics-based approaches. PIML has been used to generate synthetic data for fault detection. One examples is utilizing data from an FEM simulation to train a neural network to identify faults. In one work they utilized this method for identifying faults in a bridge. To validate their method they created an experimental setup with an identical fault to the synthetic data and they could correctly identify it with their NN trained on synthetic data [15]. A similar approach was taken in another work where FEM simulations were used to create a synthetic damage parameter database which was sued to train a NN which could detect damage to a metal plate with a high degree of accuracy [13]. Another application of PIML via a PINN is to detect cracks [16]. Because these cracks are a rare occurrence, it may be difficult to train a traditional NN with a limited dataset such as this. To overcome this issue by integrating the physical relationships of the system into the loss function. By doing this Sun et al. [16] improved the performance of their crack detection model by reducing quantification error by 80%.

Measuring thermal effects is common in CM applications, temperature fluctuations can have effects of system behaviour and performance, it is therefore worth monitoring. One application is monitoring of thermal effects in spacecraft, which encounters large shifts in temperature, which can effect navigation and structural integrity. One study [14] examined using a hybrid DT for temperature field estimation and attitude control.

They used a hybrid physics-based and data-driven method, combining a CNN estimate for the temperature field with a Modelica model of the attitude control system. Using this hybrid system they could accurately estimate temperature field and adjust both position and attitude accurately and efficiently. Another useful application is in machine tools where thermal expansion needs to be accounted for otherwise the dimensional stability of parts could be compromised. Lu et al. [9] created a hybrid method for thermal deformation prediction and soft sensing. Using sensors placed around the spindle unit both a FEM simulation and a LSTM model predicted the thermal error. By predicting the thermal error it can be better accounted for with compensation.

Hybrid modeling has been applied to CM of ball screw feed drives to combine the advantages of lumped mass models with finite element models. These methods often apply a continuous or finite element approach to the screw while applying a lumped mass approach to other components [4]. Okwudire et al. [11] created a hybrid modeling scheme for a ball screw driven feed drive. Their model combined lumped mass modeling and FEM. FEM was used for the ball screw, which is a critical component, and other components were considered lumped mass' or springs to decrease complexity. By doing this they could improve estimates on positioning error. Another application to ball screws was Sicard et al. [10], [17] who used interacting multiple models to predict the level of preload in a ball screw. Preload cannot easily be directly measured and so it is necessary to estimate the current level. By modeling several different levels of preload and predicting the model behaviour along sensor measurements of torque and position, the level of preload could be determined based on the likelihood function of the interacting multiple models algorithm.

VI. Conclusion

DT are an exciting new paradigm for modeling engineering systems. One of the most promising applications is CM, which can be improved by the capabilities enabled via a DT. DT technology can help to enable soft sensing which can allow the prediction of system states and parameters which can not be easily measured. Hybrid modeling can improve the accuracy, precision, and reliability of these predictions. Hybrid models can take several forms, including parallel models, series models, and combined models, each with their own advantages and application scenarios. Hybrid modeling has seen applications to solve many different issues such as cutting tool CM, damage identification, and preload monitoring. This is an emerging technology, and while this work covers some of the benefits of this approach as well as some examples, there are still much more literature to be examined as well as untested application scenarios. Additionally, there did not seem to be any papers that combined both a series and parallel approach, which could be an interesting avenue for future work.

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