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A hybrid digital twin approach for proactive quality control in manufacturing

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Abstract

Quality control is a critical aspect in today's fast-paced and competitive business landscape. The increasing digital transformation of manufacturing companies allows for the implementation of even proactive quality control strategies. This, however, requires the proper integration and analysis of shop floor data, regarding monitoring, diagnosis, and prognostics. This is to support defect recognition and recuperation, along with potential system reconfiguration based on knowledge extraction and human experience integration. Digital twins, being virtual replicas of physical assets, support real-time monitoring, analysis, and optimization. However, quality-related aspects may not be related to monitored parameters, thus solely data-driven models may not be accurate enough for proactive quality control. In this work, a hybrid digital twin is proposed, where data-driven models are used to finetune the behaviour of the digital twin based on its physics model. A use case concerning an industrial asset and the heat transfer to a steel bar is investigated with the results presented and commented on.

Keywords: Digital Twin; Manufacturing; Proactive Quality Control;

1. Introduction

A digital twin is created by coupling real-world data with digital simulations and/or models of physical assets or entire systems. This approach in turn provides valuable insight into their behaviour. Thus, they provide a digital, cost-effective, and non-destructive, approach to replace the traditional electromechanical or physical test models used for

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the evaluation of an asset's behaviour under certain conditions [1]. Through proper modelling and synchronization of the virtual and real worlds, digital twins may provide a framework for manufacturers to identify problems in their products' design and production process. Using the digital twin as a basis and combining it with statistical or machine learning models may even support proactive decision-making achieving, for example, proactive quality control or even accurate configuration of machines resulting in reduced waste [2], [3].

Nevertheless, modelling the behaviour of even a relatively simple asset can be quite challenging. Apart from its characteristics, it includes the modelling of the phenomena and the behaviour of the asset when exposed to them under specific inputs and environmental constraints [4]. Mathematical models are traditionally used to model physical phenomena. However, they are usually rather generic and approximate a system's response, but they can provide an interpretation of its output and its dynamics [5]. Thus, decision-making based on such approaches may not be of high accuracy. On the other hand, nowadays, machine learning approaches, if high data availability exists, can provide highly accurate results, with little to no requirement for an understanding of a system's dynamics [6]. While such approaches may support better decision-making, by comparison, they reveal little about why the better decision was reached. Thus, little knowledge and insight are created for humans using the digital twin and the applications running on top of it.

Considering the complexity of its mathematical modelling, and assuming the availability of an adequate volume of data for a highly accurate machine-learning model, this study proposes the use of the data-based model for finetuning the physics-based model of the digital twin iteratively. As a result, using the accurate outputs of the data-based model, the physics-based model may be gradually updated, resulting in an accurate and explainable digital twin. In this process, the use of the expert's knowledge is needed to correlate the outputs of the data-based model with the unknown or uncertain parameters of the physics-based model. A prototype has been implemented and tested in a case study related to the heating of a steel bar in an induction furnace.

2. Literature review

The Digital Twin concept has its origins in the idea developed by the University of Michigan for the formation of a Product Lifecycle Management centre [7]. According to [7] and [8], the Digital Twin is defined as the set of integrated data into a physical representation of an entity from the micro-atomic level to the macro geometrical level. The Digital Twin concept model consists of the physical entity in real space, the physical entity in the digital space, and the data exchange between the real and digital entities [9]. The Digital Twin in the Industry 4.0 sphere undertakes the responsibility of real-time simulation, what-if scenario simulation, prediction, optimization, monitoring, controlling, and improving the decision-making process [10].

The core of the Digital Twin Is the approach followed in building the model which represents a real-world entity in the digital world. The Digital Twin's model can be data-driven, physics-based, or a hybrid of the two approaches [11]. Data-driven modelling has proven to be very effective in scenario-based capacity and in performance analytics, due to the high amount of available data in a manufacturing environment [12]. In [13], a data-driven approach was utilized to model the energy consumption behaviour of different machine states in the manufacturing sector. In [14], a systematic review was conducted of how data-driven models can be applied to Digital Twin simulation, by utilizing data-driven models for prediction. Furthermore, in [15] sensor data was utilized to enrich digital simulations coupled with motion recognition of human activities to optimize the planning of human-based production processes.

In contrast, physics-based modelling is more challenging than data-driven modelling [16]. In [17] physics models were utilized to build a physics-based Digital Twin for process reconfiguration. Combining both a data-driven and a physics-based modelling approach forms a hybrid Digital Twin. In [18] a hybrid approach was developed, which utilized physics information in an NN's loss function to form a physics-emended NN to accurately obtain the cutting force of a cutting machine. Another approach was laid out by [19], who proposed a strategy to develop a Digital Twin for discrete manufacturing workshops by utilizing real-time dynamic data in combination with the geometry, physics, and behaviour of the functional component.

Developing a realistic Digital Twin can prove challenging. In [20] a Digital Twin for carrying out what-if simulations was developed, to enhance the decision-making approach but this required significant time and computational resources to perform multiple simulations of different scenarios. In [21] the challenges posed by human resources and inventory levels in a system's performance were identified. In [22] it was identified that a key challenge when trying to integrate a Digital Twin in a manufacturing environment is the lack of an effective collaboration mechanism between manufacturing units thus, the Digital Twin is not able to optimize the overall manufacturing process dynamically.

Both data-driven and physics-based modelling present challenges. Data-driven modelling the need for high quality data required for modelling introduce significant challenges [23], [24]. In a similar manner, creating highly accurate physics-based models can be challenging due to the complexity of the mathematical equations required to describe a manufacturing process. However, physics-based models, when accurate, can provide precise information on future events which makes them a valuable tool in the decision-making process [16]. However, physics-based models, when accurate, can provide precise information on future events which makes them a valuable tool in the decision-making process. However, creating an accurate physics-based model can be challenging due to the complexity of describing a manufacturing process through advanced physics equations. To address this challenge, the current work proposes a hybrid modelling approach, where an industrial asset is modelled based on a mathematical model generated through physics equations that describe its investigated functionality and are then improved dynamically through data-driven models.

3. Approach

This work presents an approach to how to use a data-driven model to improve the performance of a physics-based model of an industrial asset. Physics-based modelling can be very complex. The complexity can increase exponentially when multiple physic processes occur simultaneously. The physics modelling of an industrial asset requires a good understanding of the physical processes which occur. To develop a physics model of an industrial asset the first step is to build the digital model of the asset under examination and establish the fundamental physical laws, principles, and equations which govern the behaviour of the system and create a set of mathematical equations that describe this behaviour. The next step is to determine the boundaries under which the model will operate. These boundaries will assist in defining the initial as well as the limits of the model. Most physics-based models of an industrial asset are very complex and require specific numerical methods to be solved. The identification of the numerical methods that will be utilized for solving the complex set of mathematical equations is the final step in creating the initial physics-based model. Lastly, during the steps of building the mathematical model that describes the industrial asset's behaviour, it is crucial to consider also the error of the model. The error will encapsulate all the performed assumptions during the construction of the mathematical model and the boundaries under which the model operates.

Data-driven modelling requires a large amount of data. A data analysis on the collected data is required and it is considered as the first step in creating a data-driven model. Through data analysis, correlations between feature variables and the target variable will be identified. By extracting the features with the highest correlation with the target variable, a Machine Learning or Deep Learning model can be built capable of predicting the target variable. Predicting the target variable can be done either through a regression model or a model that generates an equation that describes the relationship between the features and the target variable. This depends on the type of data and the type of correlations which has been observed between the data in the initial steps of building the model. However, in both cases, a thorough testing of the model's hyperparameters is necessary to achieve the best possible model performance. This can be done through grid searching to automate the process of fine-tuning the data-driven model's hyperparameters.

To improve the performance of a physics-based model using a data-driven model, multiple steps can be followed. The most crucial step is conducting predictions using the physics-based model to simulate its performance and acquire the prediction results. These predictions are fed to the data-driven model to be utilized as features to perform predictions. The next step is to introduce an additional parameter in the physics-based model which represents the error of the model. To correctly estimate the physics model's error the output of the physics-based model needs to be subtracted from the output of the data-driven model. This error is then passed to a human expert. The human expert through process knowledge adjusts the error and updates the physics-based model. The proposed approach is presented below in Fig. 1.

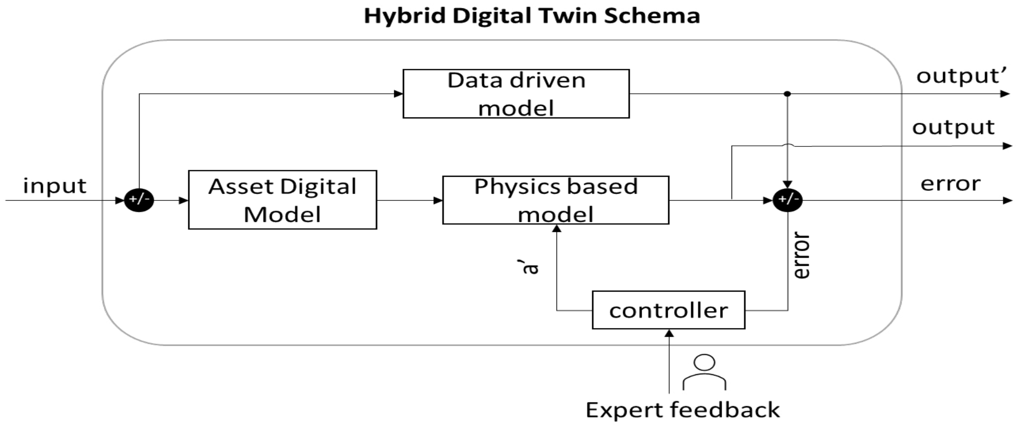

Fig. 1. The Hybrid Digital Twin

The input to the above schema consists of real-time and historical data from the production line. In the proposed approach the Digital Twin consists of three models. The data-driven model is responsible for providing predictions and data-driven behaviour using Machine Learning (ML) algorithms based on training with historical data, the physics-based model describes the behaviour of the asset using mathematical equations that derive from the physics laws the asset follows, and the digital model of the asset which provides the three-dimensional model of the asset. The input data is split, and the real-time data is fed to the digital model of the asset, the data-driven, and the physics-based model while to the data-driven model, historical data is also provided. Each of the models has an output signal. The data-driven model's output signal (output´) includes the data-driven behaviour and predictions generated by the algorithms, the output of the physics-based model provides the asset's state in real-time (output). Finally based on the subtraction of the physics-based output from the data-driven output the system also outputs an error (error). The error is then passed to the controller. The controller is responsible for evaluating the error and in conjunction with feedback from human experts, the error is adjusted (a´) and fed back to the physics-based model to improve its accuracy.

At this point, it should be noted, that the controller aims to implement a human-centred decision-making mechanism for finetuning and reconfiguring the process parameters described in the physics-based model. However, this part is still under investigation.

4. Implementation

The proposed approach has been implemented into a software prototype. The implementation (Fig. 2) consists of five components. These components include a MySQL database, the Node-Red tool, Python 3.9, a publish/subscribe communication interface, and the frontend visualization component.

The Node-Red tool has been used to create the data flow replicating the inputs and outputs measured upon the real product(s) (Fig. 3). In addition, python has been used to correlate the modelled asset and I/Os to their mathematical model, using the same tool. Python was utilized to create the data-driven model using process historical data. The data-driven model was developed using the pandas for data pre-processing. The TensorFlow library was used for creating the data-driven model and the model was saved using the Joblib library. Additionally, the handling of the mathematical model is also done in Python and its solving is done using the FEniCS PDE Solver Library. Furthermore, a MySQL database was used to store the real-world data used to test the implementations. The data communication was performed via a publish/subscribe communication interface. Finally, the visualization of the digital twin, its behaviour, and the prototype UI was implemented using JavaScript, and in particular the Three.js and the React.js framework respectively (Fig. 4).

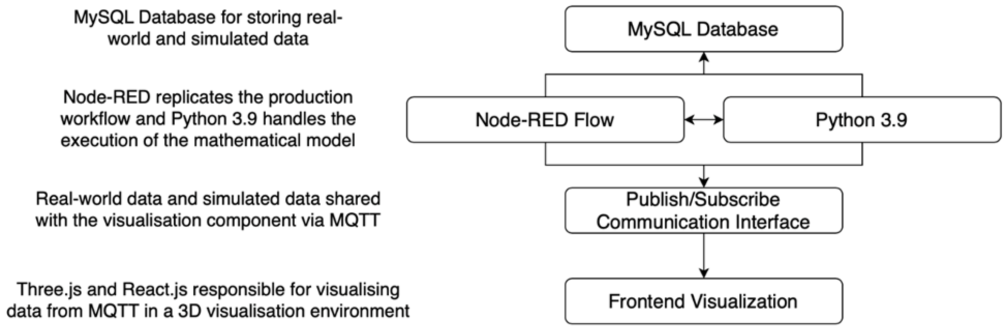

Fig. 2. The implementation's components

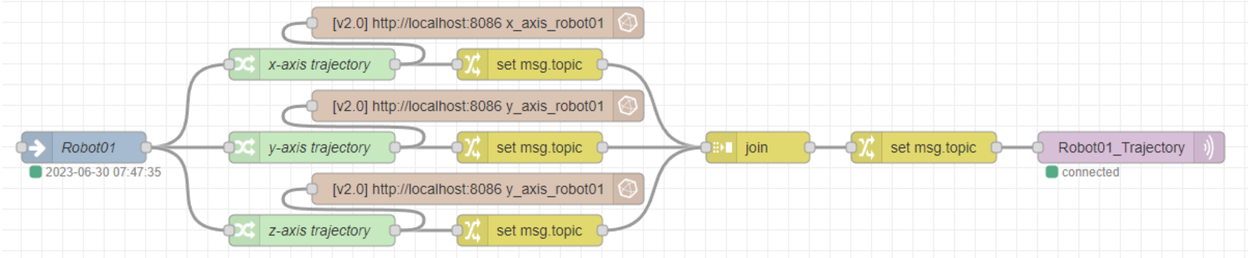

Fig. 3. The Node-RED implementation for replicating inputs and outputs of the robot.

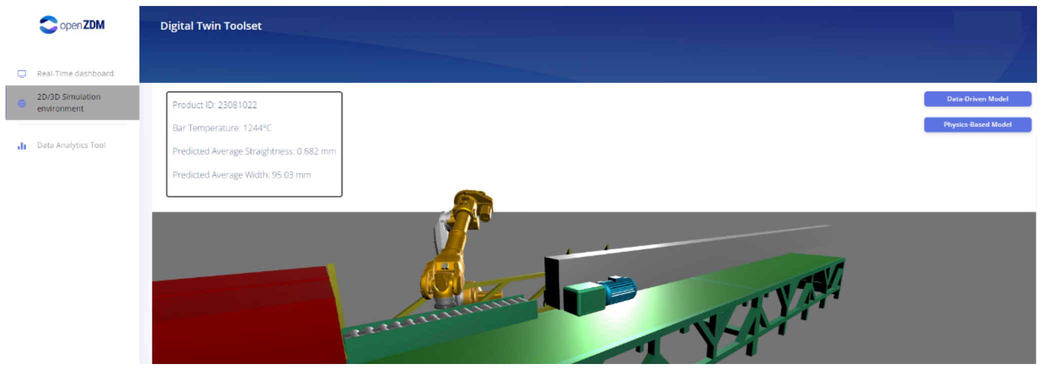

Fig. 4. The User interface of the implemented robot digital twin regarding the metal bar handling process

The prototype implementation allows for the process description of an asset and its characteristics using Node-Red workflows, the integration of real-time data, and on top of each node the addition of Python script either for the physics-based or data-based representation of the node's behaviour.

5. Case study

In the context of this study, an industrial induction furnace was selected, and a metal bar which is heated by passing through the furnace. The process was studied from the aspect of heating which occures inside the furnace. The focus was on the temperature distribution of the metal bar as it passes through the furnace and exits from it. Thus, by predicting the temperature of the bar at the exit of the furnace, predictive quality control can be ensured through monitoring the temperature and comparing to the desired temperature the bar should have at the exit and prescriptive quality control can be achieved in terms of making suggestions for alterations in the process parameters. The induction furnace utilizes the concept of induction heating to heat the metal bar. Induction heating is based on electromagnetic induction, where alternate current passes through the induction coils. This creates a rapidly changing magnetic field and the magnetic field can be approximated using Ampere's – Maxwell's law.

The magnetic flux results in an electromotive force which can be calculated with Faraday's law. The rapidly changing magnetic field creates Eddy currents in the metal bar as it passes through the field and based on Ohm's law the current density is calculated. Using Joule's law and the current density the generated heating power is calculated. Furthermore, the heat gets distributed inside the metal bar due to the heat conductivity of the bar. Based on the principle of energy preservation the temperature at a point of the bar in any given time is given by equation 1. Lastly, the induction furnace's power consumption was estimated using Ohm's law's electric power equation.

$$p(T)C_p(T)\frac{\partial T}{\partial t} = \nabla(k(T)\nabla T) + \frac{1}{\rho(\mathrm{T})}\mathrm{E}^2 + a \tag{1}$$

Where:

- E: The electromotive force (V),
- t: Measurement of time in sec,
- ρ: The electrical resistivity in Ωm,
- p: The density of the metal bar in $\frac{kg}{m^3}$,
- C_p: The specific heat capacity in $\frac{J}{kgK}$,
- k: The thermal conductivity of the metal bar ($\frac{W}{mK}$),
- T: The temperature of the metal bar in the Kelvin scale (K),
- a: The error of the physics-based model as a non-dimensional quantity.

For the data-driven model, a dataset of approximately 8 months, was created and the correlation between the process data and the temperature of the bar at the exit of the furnace was identified. An ML regression model was trained to estimate the temperature of the bar as it exits the furnace, using as input the measured temperature of the bar as it enters the induction furnace. A linear regression model was selected since the data presented a linear correlation with the temperature of the bar at the exit of the furnace. Thus, the ML model was able to predict the temperature of the metal bar with high accuracy.

The proposed approach was tested using synthetic data generated. The synthetic data was generated using the Node-RED flow and they replicate the actual data from the manufacturing line required to test the proposed approach of the hybrid model of the induction furnace. The foundation of the generated data are the historical data of 8 months obtained to train the data-driven model. Thus, the synthetically generated while different from the historical data, they bare a close resemblance to actual real-world production data.

By applying the proposed methodology in this case study, proactive quality control can be achieved. By utilizing the induction furnace's hybrid digital twin model, we can simulate the temperature of the metal bar passing through the furnace. Using this simulation, operators are notified through the digital twin's user interface errors in the heating process. Thus, further processing of the metal will not be performed, and proactive quality control will be achieved. Furthermore, the digital twin and its hybrid model can be utilized during the start-up phase of the machinery. During the start-up phase, any tests performed to adjust the runtime parameters of the furnace, which will be maintained in the steady phase, can be done through the digital twin.

6. Results

During the creation of the physics-based model, estimations were made regarding the construction and the characteristics of the coils inside the induction furnace. These estimations were used to calculate the rapidly changing magnetic field generated by the furnace, the electromotive force, and the power consumed by the furnace. The outputs of the power consumption model of the furnace were fed to the data-driven model to predict the temperature of the metal bar at the exit of the furnace. Based on the output of the data-driven model fed with the predicted power consumption of the furnace and after receiving feedback from furnace operators and field experts it was concluded that the error derives from the variation of the frequency of the current within the coils. The error of the physics-based model for predicting the temperature of the bar was estimated. The error was integrated into the physics-based model, manually, and in Table 1, a percentage difference between the output of the physics-based model and the hybrid model with the measured temperature can be found. Furthermore, in Table 2, statistical metrics of the hybrid model's outcomes can be found compared to the real-world measurement statistical metrics.

Table 1. Outcomes of the experimentation with the hybrid digital-twin model

Steel Bar	Temperature before	Temperature After	Deviation in the estimation
Real-world measurement	25ºC	1280ºC	-
Physics-based model value	-	825 ºC	64.5%
Data-based model value	-	1271 ºC	99.2%
Hybrid model	-	908 ºC	71.0% (6.5 % improvement over the physics-based model)

Table 2. Statistical metrics of the hybrid model's outcomes compared to real-world measurements

Statistical Metrics	Hybrid model	Real-world measurement
Mean temperature after the furnace	844 ºC	1265 ºC
The standard deviation of temperatures after the furnace	44.3 ºC	31.8 ºC
Minimum temperature after the furnace	783 ºC	1185 ºC
Maximum temperature after the furnace	908 ºC	1280 ºC

From the findings in Table 1, it is evident that the data-driven model is capable of high-accuracy predictions due to the large amount of high-quality data the ML model was trained with. From the findings of Table 1 and Table 2 it is evident that due to initial assumptions made during the creation of the physics-based model, the accuracy of the model was significantly lower. When implementing the proposed approach, the model's accuracy increases due to the introduction of a new error parameter, modelling the uncertainty of the physics-based model, which was calculated based on the proposed approach and based on the provided feedback by process engineers. However, the model's accuracy remains relatively low compared to the accuracy of the data-driven model and further refinement of the physics model is required. Moreover, it is evident that there are significant deviations between the real-world measurements and the hybrid model' predictions (Table 2). In comparison to the real-world measurements with a standard deviation of 31.8ºC, the hybrid model exhibites a larger variability in its predictions evident by a standards deviation of 44.3ºC. Although there are significant deviations in the presented results, the proposed approach for creating a hybrid model of a Digital Twin shows potential by improving the accuracy of the physics-based model at predicting the temperature of the bar at the exit of the furnace. In the context of proactive quality control in the discussed case study such high deviations are significant and it is emphasized that in order to ensure highly accurate predictions through the hybrid model and to gain insight to potential process parameters adjustments required to reduce generated defects, further refinement of the physics-based model is needed. However, through the expertise of operators and field experts, the hybrid model's predictions can be further calibrated with expert's feedback through the controller of the hybrid model which is the focus of future work.

7. Conclusions

While physics-based models can provide significant insight to the behaviour of the manufacturing process, their development can be challenging due to the complexity of mathematical equations required to represent the phenomena occurring. Furthermore, initial assumptions required for the numerical solving of the mathematical equations can hinder severly the performace of such models. Thus, the proposed approach of creating a hybrid model, which utilizes both physics and data, can improve the performance of only physics-based model while retaining the ability of the physics-based model to provide better insights and understanding of underlying processes and root causes.

Hence, an innovative mechanism which finetunes the parameters of the physics-based model of a digital twin using its data-based model is proposed by this work. In particular, the data-driven model is used to minimize the error in the representation of the physical asset with the physics-based model. In turn and using the physics-based model, the process configuration may adapt according to the objective, resulting, for example, in less energy consumption through finetuning the furnace parameters affecting the hearing process of the asset.

A prototype implementation was tested in a simulated use case with real-world data. The preliminary results showcase the potential for the proposed mechanism to be able to increase the accuracy of the physics-based digital twin. It is evident from the results that although the hybrid model is capable of increasing the accuracy of the physics-based model, refinement of the physics-model is still needed. Additonally, the controller depicted in **Error! Reference source not found.**, that aims to implement a human-centred decision-making mechanism needs further investigation. Moreover, further investigation and experimentation is needed, especially in the mechanism of updating the physics-based model along with the means to facilitate decision-making regarding dynamically adapting process parameters, based on the results of the digital twin. This is the main focus in future work.

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