Digital Twin of an Induction Motor: Fault Analysis and Predictive Maintenance

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***Abstract*—In this model, we basically present an efficient method to predict the fault in motors using digital twin and predictive machine learning models to estimate the fault in induction motor. The faults in an induction motor can be broken down into three different categories which are bearing faults, stator faults and unbalanced voltages and centricity. These faults have direct impact on two important parameters which are vibrational signals and stator currents, and these two parameters will be used in our predictive machine learning model for further analysis. All the other parameters are physical in nature and cannot be modelled using simulated motors. This includes using detection models on sensory thermography, oil analysis, and ultrasound data.**

***Index Terms*—artificial intelligence, digital twins, fault detection, predictive maintenance, induction motor, machine learning**

I. Introduction

Electric machines are essential to modern society, particularly in industrial settings. They are responsible for consuming 50 percent of the total energy produced globally and are used in a variety of devices such as pumps, fans, compressors, conveyor belts, and electric vehicles. The induction motor is the most commonly used electric machine in industry. However, these machines can experience mechanical, thermal, and electromagnetic stress during operation and may require maintenance to prevent disruptive failures.

To address this issue, the industry has begun adopting a predictive maintenance approach, also known as condition monitoring, in which manual inspections and repairs are performed based on the current state of the equipment. This allows for fewer disruptions when the equipment is in good condition and more frequent maintenance as the equipment approaches the end of its life cycle. Predictive maintenance requires continuous monitoring of the equipment with sensors to estimate its current state. The Internet of Things (IoT) and Digital Twin (DT) concepts, central to Industry 4.0, have positively impacted the technology of monitoring systems. In the Industrial Internet of Things (IIoT), sensors are connected to the internet and measurements are sent to the cloud, allowing maintenance personnel to remotely monitor the equipment in real-time [1].

The digital twin concept used in this model basically is the concept that we simulate a working model of an induction motor, and then we estimate the parameters of our motor such as reactance and resistance and number of poles by the data collected of the real world motor. Then we train our motor using Simulink model parameter estimation block and set the parameters exactly to the real world actual working model. Then our next step is to build a predictive machine learning to predict the faults in our model.

For this purpose, we follow the approach that we run a thousand simulations switch different faults and then train our model on the basis of the parameters extracted from those readings. Hence, when a fault appears in our real machine, we can predict the fault using the difference of the actual value and the predicted value of our digital twin.

II. Literature Review

Rasheed et al. [2] give a taste of what a state-of-the-art DT of an offshore oil platform looks like. The DT in the example study is continuously updated with sensor data in near real-time and can be supported by synthetic data generated from a virtual entity. In this case, DT does not only give the real physical entity real-time information for more precise control and decision-making, but may serve as pa prediction makers about how the asset will evolve or behave in the future.

Anton Rassõlkin et al. [3], used the concept of Digital Twin in creating and maintaining a digital representation of the real physical entity and supporting its performance utilizing simulation and optimization tools, which are fed with real data. Development and implementation of Digital Twin technology is a hot topic in many industry-oriented research projects.

Victor Mukherjee et al. [4], paper presents a saturable analytical model of induction machines, with a systematic approach for segregating the electromagnetic losses. The proposed model is based on the equivalent circuit of the machine, which has been augmented to account for different loss components. The segregation of different loss components in the stator and rotor has been improved by considering the loading, skin effect and field-weakening operation.

There have been several recent studies that have used Digital Twin (DT) and Internet of Things (IoT) technology for fault prediction in electric machines. These studies have employed machine learning techniques such as support vector machines, k-nearest neighbors, and random forests to identify and predict combined faults in a non-invasive manner [5]. Another study [6] proposed an IoT platform for real-time monitoring and remote visualization of power substations, while another used neural networks in a MATLAB/Simulink

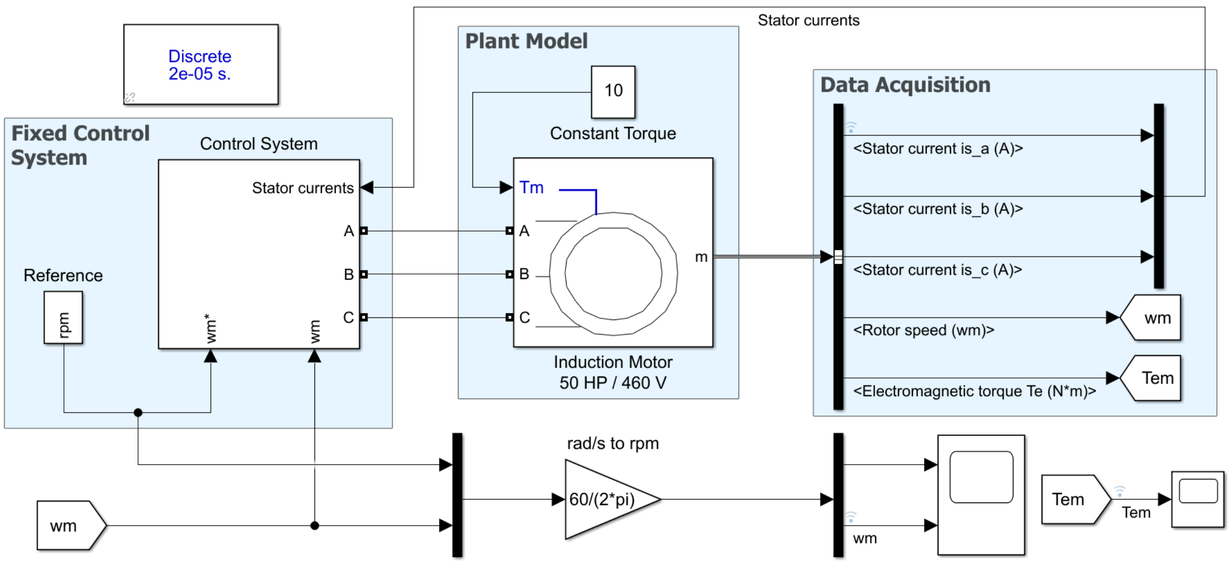

Fig. 1. Induction Motor Model on Simulink

software to monitor the performance and remotely predict the health of electric motors in real time through the cloud, using simulations with the finite element method. Another paper by the authors proposed a DT-based monitoring system that numerically models the monitored motor using only input current measurements and an IIoT system to provide motor parameters as input data for the computer simulation. This work also implemented improvements to increase the accuracy of the monitored variables and validate the results, including the analysis of resistive losses in the stator and rotor, simulated temperature analysis in the rotor and stator, and the analysis of the conductivity of the motor windings [7].

III. Model & Methodology

The digital twin of a machine is an internet-connected, 3D digital replica that has the same functionality as the original [8]. It can be used to predict and prevent machine failures, optimize maintenance, and enable new services. Digital twins are being used in many industries, including manufacturing, energy, transportation. It is a digital copy of a real-world object that can be used to predict its future behavior. The induction motor is one of the most used motors in industry today. It is an electric motor that works on the principle of electromagnetic induction, which means it uses magnetic fields to produce torque and rotation.

The most common sets of parameters representing an induction machine model consists of the following parameters: stator resistance R_s, rotor resistance R_r, stator leakage inductance L_s, rotor leakage inductance L_r, and magnetizing inductance L_m. The task is that to adjust these parameters in simulation to relate with real world induction motor. Digital twin induction motor makes it easier to relate simulation data with real time data. It works in a way that we must adjust the values of the simulation that are operating on ideal conditions to the real time data. So, when the parameters are correlated with each other, a Digital Twin induction motor will be obtained.

Figure 3 gives a high level abstract block diagram to a workflow of a digital twin.

A. Estimation of Model Parameters

The estimation of parameters was done by using the Simulink block, which basically carried out the task of aligning our simulated motor parameters with the parameters of the motor, whose data was collected through a number of iterations. The basic model was that it trained and estimated the parameters of the actual motor to our simulated motor to make the digital twin. This digital twin would now run a thousand different simulations with different faults such as bearing faults, stator faults and unbalanced voltages and will thus provide with different graphs which will be fed into our machine learning model to train with those parameters for future prediction of different faults.

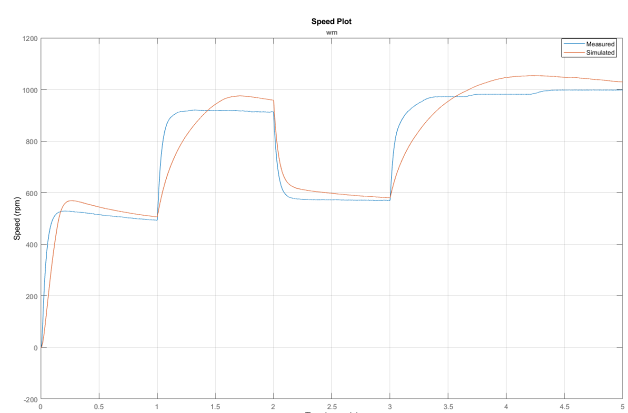

Fig. 2. Measured and reference speed before estimation

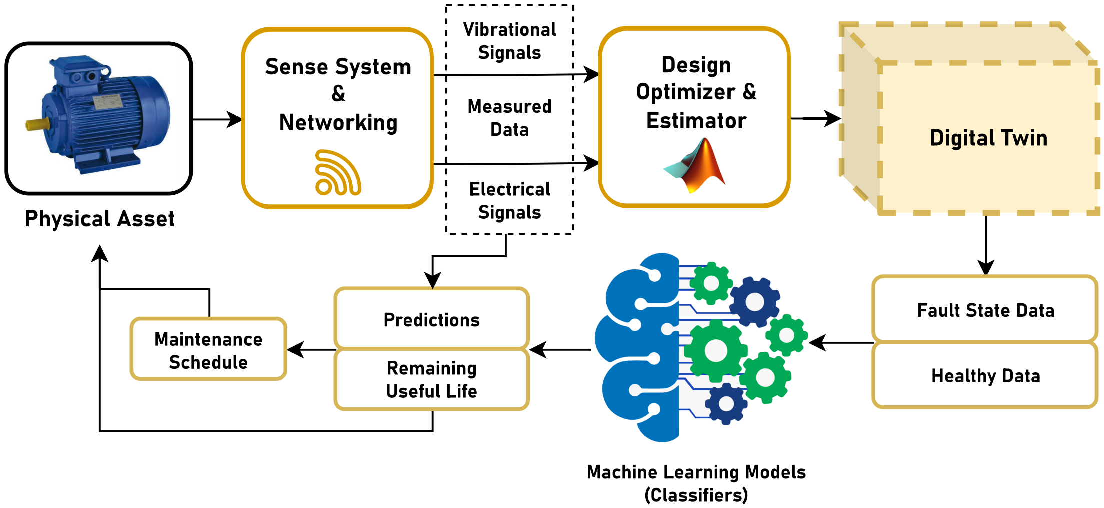

Fig. 3. Workflow for Digital Twin on an Induction Motor

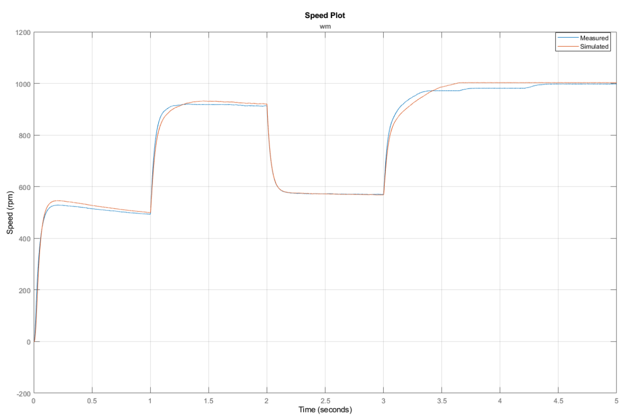

Fig. 4. Measured and reference speed after estimation

B. Machine Learning for Fault Detection

Next, we make our machine learning model to train on the results inferred by our digital twin, and then we use predictive analyses to predict further faults.The machine learning model used was KNN – K nearest neighbors. Although we tried different machine learning algorithms to test such as SVM, decision trees, Naïve Bayes, and neural networks.

SVM [9] stands for support vector machines and this machine learning technique works by mapping data to a high-dimensional feature space so that data points can be categorized, even when the data are not otherwise linearly separable. A separator between the categories is found, then the data are transformed in such a way that the separator could be drawn as a hyperplane.The next machine learning algorithm we used was decision trees.

A decision tree [10] is a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks. It has a hierarchical, tree structure, which consists of a root node, branches, internal nodes, and leaf nodes. Decision tree learning employs a divide and conquer strategy by conducting a greedy search to identify the optimal split points within a tree. This process of splitting is then repeated in a top-down, recursive manner until all, or most records, have been classified under specific class labels. Whether all data points are classified as homogeneous sets is largely dependent on the complexity of the decision tree. Smaller trees are more easily able to attain pure leaf nodes—i.e., data points in a single class. However, as a tree grows, it becomes increasingly difficult to maintain this purity, and it usually results in too little data falling within a given subtree. When this occurs, it is known as data fragmentation, and it can often lead to over fitting.

The deep learning networks [11] both wide and narrow over fitted the provided data because the data was too less as we ran 40 simulations, and the model was over fitting on that data.

The best prediction was made by KNN [12] which stands for K-nearest neighbors. The k-nearest neighbors (KNN) algorithm is a simple, supervised machine learning algorithm that can be used to solve both classification and regression problems. KNN works by finding the distances between a query and all the examples in the data, selecting the specified number of examples (K) closest to the query, then votes for the most frequent label (in the case of classification) or averages the labels (in the case of regression). We achieved an accuracy of 90 percent by using KNN.

IV. Results & Discussion

Using artificial intelligence (AI) to create a digital twin of an induction motor can provide several benefits and results, including:

- Enhanced accuracy: AI algorithms can be used to accurately model the complex behavior of an induction motor, allowing the digital twin to more accurately predict the motor's performance under various operating conditions.

- Improved optimization: AI algorithms can be used to optimize the design of the induction motor, finding the optimal parameters for the motor's operation.
- Enhanced control: AI algorithms can be used to develop and implement advanced control strategies for the induction motor, improving the accuracy and stability of the motor's operation.
- Predictive maintenance: AI algorithms can be used to analyze the data from the digital twin and the physical motor, helping to identify potential problems before they occur and enabling proactive maintenance to reduce downtime and costs.
- Overall, the use of AI in a digital twin of an induction motor can help in improving the performance, reliability, and efficiency of the motor, while also reducing costs and downtime.

KNN machine learning algorithm produced the best accuracy of 90%. Other algorithms did not perform well, such as decision trees that could only give an accuracy of about 80%. The Naive Bayes algorithm gave an accuracy of about 75% and the neural network gave a low accuracy of 77 to 80% due to lack of data, and they were over fitting. We observe that our machine learning models gives accurate predictions for faults in our machine on our test data.

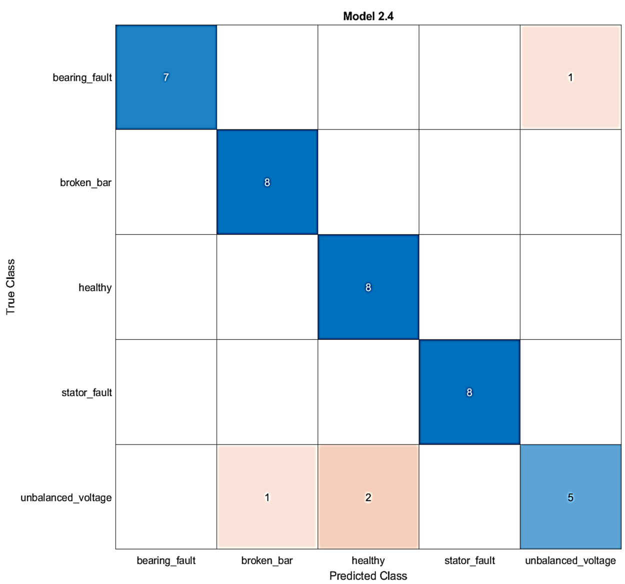

Fig. 5. Validation confusion matrix

V. Conclusion

Induction motors are one of the most crucial electrical equipment and are extensively used in industries in a wide range of applications, and our project is an attempt to better the workflow of induction motors, by predicting failure and analyzing faults. We conclude that we are able to use a digital twin as a virtual representation of a physical system and hence perform real-time analytics and get instant feedback.

In addition to that, we understand that digital twins can act as smart software drivers for physical assets via IoT (internet of things). By using an appropriate number of parameters, and by performing appropriate feature extraction, we can predict the future failures of the model. And hence reduce downtime by planning maintenance or repair accordingly. Moreover, by performing what-if tasks and using ML, we can train the model in such a way that it will effectively identify the issue with respect to the reading measured. In our project, we focused on measuring only vibrations and stator currents. However, we can improve our digital twin by adding more parameters.

VI. Contributions

A. Abubakar

Literature Review: *Researched existing literature*

B. Syeda Fatima Zahra

Induction Motor Model: *Modelled the induction motor*

C. Danial Ahmad

Parameter Estimation: *Created digital twin via design optimization*

D. Muhammad Umer

Fault Generation & Feature Extraction: *Created faulty data and extracted statistical features for training the classifier*

E. Muhammad Ahmed Mohsin

ML Model Training & Testing: *Trained the machine learning classifier and calculated the confusion matrix*

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