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Data-Driven Soft Sensors for Electrical Machines

Nada Sahlab[1], Arzam Kotriwala[1], Andrew Habib[1] and Victor Mukherjee[2]

Abstract: As electrical machines are widespread in industrial automation, operating them efficiently has significant potential to improve sustainability. Due to the complexity of electrical machines, obtaining direct measurement of energy consumption is challenging and cost intensive. Soft sensors are useful in inferring variables using available measurements in industrial processes. The data-driven approach to developing soft sensors requires a sufficiently large and diverse training dataset. Given the high cost to obtain voluminous sensor data, turning to simulation data as an additional data source is less expensive, although possibly inaccurate. With this motivation, we explore the need and benefit of combining measurement data from intelligent sensors with electrical machine simulation data for building soft sensors. We present an approach to leverage both, sensor measurements and simulation data to develop a soft sensor for energy efficiency. The soft sensor implementation results for an induction motor support the feasibility of the approach.

Keywords: Electrical Machine, Soft Sensor, Simulation, Data Augmentation, Machine Learning.

1 Introduction

Electrical machines are widespread in industrial automation systems – they play a critical role in the overall performance, cost-effectiveness, and energy efficiency of industrial processes. Three phase induction machines are used in various industrial applications due to their simple design and reliability. They provide mechanical power from electrical power to drive loads. As electrical machines need to be supplied with high amounts of energy and with the goal of increasing sustainability, strict regulations for transparency regarding energy efficiency for electrical machines are required. Operating motors efficiently has significant potential to improve sustainability, especially since around 60% of installed motors operate below their rated power [Ch16]. According to one estimate, the adoption of high-efficiency motor systems could cut global electricity consumption by up to 7% [FE11]. With the increased installation and application of electrical machines in the future, energy efficiency becomes increasingly important. In fact, energy costs (as opposed to purchase costs) make up most of a machine’s lifecycle costs. So, providing more transparency on energy efficiency helps fulfill both sustainability and economic goals.

To ensure efficient operation of induction machines, dynamic modeling approaches are needed to assess and improve their performance. Electrical machines can be modeled

[1] ABB Corporate Research Center, 68309 Mannheim Germany, first.lastname@de.abb.com
[2] ABB Motors and Generators, 00380 Helsinki Finland, first.lastname@fi.abb.com

using numerical or analytical approaches, each offering a trade-off between computational effort and accuracy. Using such models, machine parameters can be derived to estimate the output power and overall efficiency from the supplied electrical input power.

Complementary to modeling approaches, monitoring approaches are needed to include sensed real values in the estimations. Within the vision of Industry 4.0, miniaturized sensors with communication and processing modules (intelligent sensors) have enabled the acquisition of data and analysis of industrial assets during operation. However, continuously measuring some variables using intelligent sensors is not always feasible due to interference with critical processes or complex machine construction. For instance, measuring the mechanical power of induction machines is not directly possible and usually relies on estimation approaches based on measured values such as flux, speed, or vibration. Additionally, sensors used to measure these values are placed in industrial environments and therefore may be subject to faults thereby introducing inaccuracy and decreasing their reliability.

In this regard, soft sensors or virtual sensors are useful in inferring variables based on available measurements in industrial processes. The data-driven approach to developing soft sensors requires a training dataset that is sufficiently large and diverse e.g., encompassing the range of operation of an electrical machine. Given that measured data can be costly to collect in large amounts, it is natural to turn to other sources of data, e.g., simulation data, which is much less expensive to collect but might be inaccurate depending on model used to represent the machine.

With this motivation, this paper explores the need and benefit of combining measurement data from intelligent sensors with data generated using electrical machine simulation for the purpose of building useful soft sensors for electrical machines. In our work, we use data assimilation to model differences between measurements and simulation followed by data augmentation to generate additional corrected simulation data. In the context of soft sensors, we can leverage data augmentation techniques in several scenarios, e.g.:

- To compensate for inaccurate or insufficient sensor measurements,
- Where direct measurement is infeasible due to high intrusiveness or costs e.g., measuring the output torque of an electrical motor, which can either require costly sensors, commonly not present in industrial settings, or high intrusiveness.

The remainder of the paper is organized as follows. Section 2, presents the related literature on electrical machine modeling approaches for energy efficiency estimations and soft sensors for condition monitoring and performance optimization of induction machines. Section 3 presents our approach and Section 4 discusses the results. Finally, Section 5 concludes the paper and discusses future work.

2 Related Work

2.1 Electrical Machines Modeling

To monitor and optimize the performance of electrical machines, a modeling approach is needed. Generally, electrical machines can be modeled in a numerical or analytical manner. Numerical methods, e.g., finite element method, are classified as accurate, although computationally expensive. Analytical methods encompass equations based on the machine equivalent circuit.

Simulations implement models of electrical machines as a function of time. For the scope of industrial automation, a simulation model is a virtual representation of one or multiple aspects of a physical asset, which mimics its expected behavior when giving possible inputs to a virtual model. Simulation models differ in type and fidelity level and can be complex and costly to run for industrial assets.

Electrical machines simulators are designed and used to simulate the operations of electrical machines and to collect operational data such as speed, power load, magnetic field, and other data.

A high-fidelity simulation of an electrical machine using finite element method is commonly applied and requires a geometrical model as well as knowledge about its material and properties. The simulation time, given through a number of steps and a given period is transformed into discrete time steps. Furthermore, loading points of the machine can be given as an input to compute output values such as the output electrical values, power or the flux density distribution within the magnetic field. [TKS20]

2.2 Energy Efficiency of Electrical Machines

Energy efficiency of electrical machines is the ratio of electrical input power to the mechanical output power delivered to the shaft to drive applications. There are different approaches to measure energy efficiency of induction motors, mostly consisting of indirect measurements and estimations due to the non-linearities exhibited within the electromagnetic field and machine construction. The nameplate method for example, relies on motor ratings to estimate the machine's efficiency profile [Ar22], whereas indirect measurements of the external flux or speed can be used to derive a linearized speed curve. Estimating different power losses by the machine is a further common approach to estimate its energy efficiency. The equivalent circuit approach uses parameters of the machine's equivalent circuit to calculate its output power given technical data or relying on lab tests. [Sa19]

It can be noted that all mentioned approaches with their variations differ in their accuracy and intrusiveness level. No single approach is collectively deemed best. In recent years, approaches relying on artificial intelligence and data-driven methods have been increasingly considered.

In [AC23], a combination of a data-driven and physics-based model is used to rate the machine efficiency as part of its Digital Twin. In [Si23], search algorithms are compared and used to estimate parameters of the machine's equivalent circuit.

2.3 Soft Sensors

A soft sensor is an intelligent software module that uses existing physical sensors to generate similar data or derive new information by processing physically measured data using mathematical, physics-based, or data-driven approaches. It can be redundant to the physical sensor thus increasing its reliability, replace the physical sensor in case of high maintenance and calibration cost, or extend its functionality by deriving more information from raw measured data. One example is provided by [Li12], where an industrial soft sensor to measure nitrogen oxides based on process measurements was developed.

Data-driven soft sensors [KGS09], [SG21] apply data-processing and analysis techniques such as machine learning and artificial intelligence to measured quantities, obtained through physical sensors, to derive new data and information which are not directly measurable through the physical sensor.

The idea of data-driven soft sensors is already established. However, a key challenge of solely relying on historical data to train such sensors has been the difficulty in ensuring that a wide range of process states and/or conditions are sufficiently covered. This can be addressed by using adaptive soft sensing techniques [KGG10]. For instance, in our case, we leverage simulation data together with associated measurement data to account for any gaps in coverage of different operating conditions of electric machines.

Related to soft sensors is also the concept of surrogate models. They are simplified representations of complex systems or simulations. A common approach to obtain surrogate models is by fitting machine learning models on the input-output data resulting from simulation systems [TKS20], [TMK22]. Amongst the benefits of using surrogate models is to obtain instantaneous estimations, which would otherwise be more time-consuming. Moreover, they can be employed for various use cases, such as condition monitoring or as part of digital twin models. Surrogate models can be realized in a data-driven, hierarchical, or projection-based manner in which a high-fidelity simulation model is used as basis. Data-driven surrogate models using machine learning models can complement simulations for deriving output values of electrical machines. [TKS20]

3 Approach

We propose an approach that combines the use of sensor measurements and simulation data to develop soft sensors for electrical machines. Figure 1 shows an overview our approach to develop soft sensors for electrical machines. It can be used for different soft sensor applications e.g., speed estimation, motor health or fault detection, and energy efficiency estimation [Sa19].

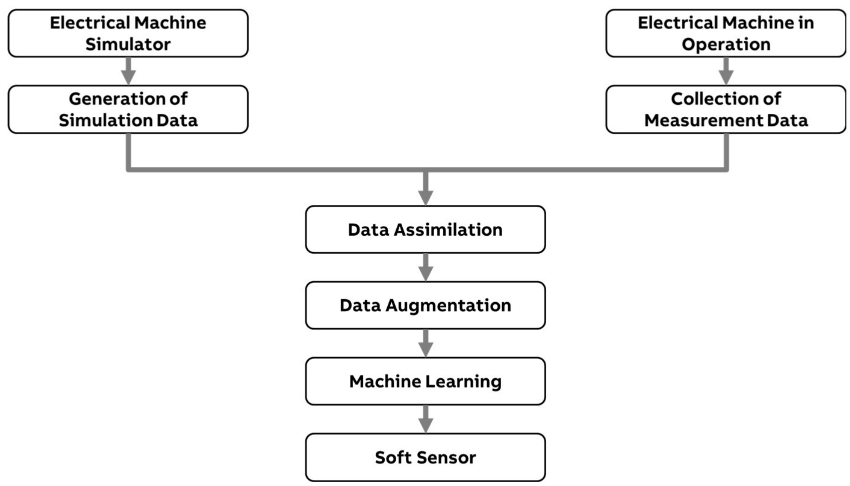

Figure 1: Workflow to develop data-driven soft sensors for electrical machines.

The approach consists of three steps for data collection and processing: gathering real data, generating simulation data, and assimilating and augmenting simulation data. Then, ML models are trained on the final dataset which consists of measurements and augmented simulation data. In the following sections, we provide more details on the proposed steps.

3.1 Collection of Sensor Measurements

We collect operational data, i.e. torque and speed in an experimental setup for an electrical machine. The data is collected using an external sensor attached to the operating motor. Section 4.1 gives more details about the data we collect in our experiments.

3.2 Generation of Simulation Data

We use a proprietary simulator for electrical machines to collect large amounts of simulation data. We generate data for the same operating conditions that were used while collecting the real data.

3.3 Data Assimilation

Based on the available measurement data, we first obtain simulation data for the same operating conditions. We seek to combine the measurement and simulation data such that the simulation data is adjusted to better match the associated real measurements. To this end, we employ "data assimilation" i.e., techniques to combine different sources of information such as integrating a numerical model with observations, with the goal of improving the forecasting capability of a given model [PVS22], [PVS22].

Different data assimilation techniques exist e.g., averaging values, applying priority rules to favor one source over another, or simply selecting the most recent data, fitting of error residuals and Kalman filter (see review of techniques: [PVS22]). We adopt a statistical data assimilation approach that has already been applied to the domain of machine learning for electrical machines (see [Bi24])

In particular, the error between recorded measurements at different loading conditions and associated simulation data for each model feature are computed. A normal distribution is then fitted to estimate the mean (μ) and standard deviation (σ) of the error for each loading point associated with each feature. Consequently, for any loading point, the simulator can be used to generate data, which can then be corrected using an estimate of the error from models fitted on the mean (μ) and standard deviation (σ) values.

3.4 Data Augmentation

Data augmentation refers to the process of creating variations of an existing data set for multiple purposes, e.g., fill gaps in data or increase the amount of data to enable the application of machine learning techniques. Examples of data augmentation approaches include oversampling, and synthetic minority oversampling technique (SMOTE).

In our work, data assimilation is a pre-requisite for data augmentation. Thus, once we have modelled the error between measurement and simulation data using data corresponding to the same operating conditions, we can then, also similar to [Bi24], use data augmentation to create new data that resembles measurement data, without needing to record additional measurements in a real setup.

This is done by generating simulation data for any number of additional operating conditions, and then correcting it to resemble real measurements. Not only is this beneficial because the effort to record additional measurements is eliminated but also because machine learning modelling typically benefits from datasets that are larger in size and variety of conditions.

3.5 Machine Learning

The data assimilation and augmentation approach helps create an arbitrarily large dataset encompassing a wide range of operating conditions, which is then used to train a machine learning-based soft sensor.

Our work differs from [Bi24] in that we tackle a different problem: predicting load levels of electrical machines as a regression problem whereas they classify the health status of motors and fault conditions such as broken rotors.

4 Results

We developed a soft sensor for motor output power as output power directly correlates to motor efficiency and would otherwise need to be measured intrusively during operation, for instance, attaching a torque meter to the motor shaft to record torque and rotational speed.

4.1 Experimental Setup

To collect measurement data, we use a setup similar to the one presented in a reference work [Bi24] i.e., a “deriving” motor is controlled to act as a constant load torque to our “test” motor. We use an IE4 15 kW, 50 Hz, 400 V delta-connected induction motor and increase the load in steps. At each load level, torque meter measurements are recorded along with corresponding magnetic flux sensor measurements.

4.2 Data Generation, Assimilation, and Augmentation

We increased the load in steps of about 10% from no load to 110% to collect a few measurements samples for each distinct load – we consider different samples at about the same load as a ‘loading group’. For each of these measurements, we use the simulator to generate equivalent data. For both, measurements and simulations, we computed a number of statistical features over a number of windows of the flux data. For each feature, we assimilated the simulation and measurements by computing the error of at each loading group and then estimating the mean (μ) and standard deviation (σ) of the error.

In order to validate our approach, we leave out one loading group at a time and use the remaining available measurement data for data assimilation and augmentation. For the loading group we leave out, we generate simulation data, compute the same statistical features and then correct them by adjusting the error estimated for the given loading point via data assimilation. This estimation and adjustment of error can be done an arbitrary number of times to augment the dataset. For instance, in our experiments, for every loading group, we have about 3 measurements, so we generated 5 augmented samples i.e., enough to increase the dataset but not so many that the machine learning model is biased by synthetic data in favor of real measurements.

4.3 Model Training and Validation

We trained machine learning models to learn loading from flux values, where loading denotes the ratio of output power to the rated power of the motor. The statistical features we used include mean, standard deviation, minimum, maximum, skewness, and kurtosis. We experimented with different modeling algorithms for regression such as linear models (linear and ridge) and ensemble models (random forest and gradient boosting). The best results we obtained were using gradient boosting regression with statistical features computed on both, X and Y components of flux.

Validation of our modeling was done by performing leave-one-group-out cross-validation [TAJ21], i.e., to determine how well our model would generalize to an unseen loading condition, we held out the measurements of that loading group. However, to realize the benefit of our data assimilation and augmentation, we included the simulation data we generated and corrected for the held-out loading group.

For each held-out loading group, the model predictions for each available measurement sample corresponding to the loading group are compared against ground truth torque meter measurements. The absolute errors are computed for these loading values and predictions and their mean values are plotted (see Figure 2).

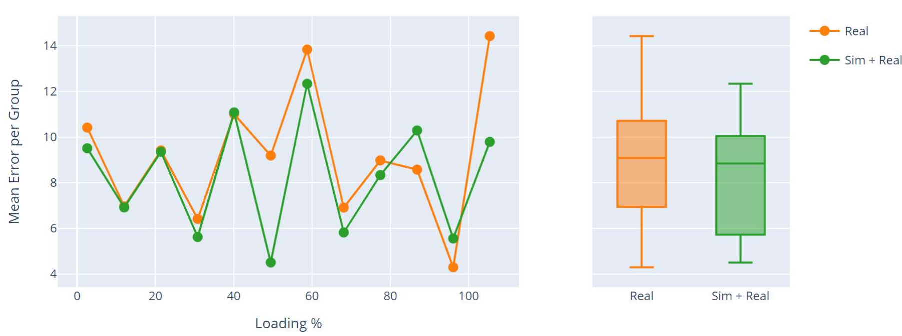

Figure 2 Comparison of modelling error distributions

The results show an overall error reduction when we use measurement data combined with simulation data ('Sim + Real') over only measurement data ('Real'). Most notable of these improvements include loading groups at the extreme ends. This is not surprising as machine learning models are naturally better suited for interpolation as opposed to extrapolation from the underlying training data distribution.

5 Conclusion & Future Work

Motivated by the need of transparency regarding energy efficiency of electrical machines and the challenges around respective data collection, an approach for developing data-driven soft sensors was pursued. The approach follows a 3-step process of collecting and processing data from both simulation and sensor measurements. We implemented the proposed data-driven soft sensor approach in a specific industrial application and our results support the feasibility and the promise of the approach.

Potential directions for further research may include investigating the relationship between data quantity and model performance as well as testing the use of such soft sensors for different applications. For instance, a soft sensor for machine losses may be trained using our approach, which could be used together with an optimizer to compute machine configuration parameters for a given set of operating conditions.

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