Development of a Virtual Sensor for Torque Prediction in Electric Machines by Machine Learning Methods and Physical Modeling

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Abstract. The automotive industry is in a rapidly transformation process with the influences of the electric mobility and autonomous driving, which has also an impact on the knowledge of developers about the behavior of electric motors. In order to provide an accurate prediction of efficiency of electric motors and condition monitoring, it is essential to precisely determine the torque of an electric motor depending on various influencing factors. In response to this circumstance, this paper presents a methodology for the development of a virtual sensor for torque prediction. According the state of the art, virtual sensors are a good method to handle the challenge for a torque prediction.

In order to develop a realistic torque prediction, all possible influencing variables of the electric machine are recorded. In order to eliminate the influences of a test specimen, two asynchronous machines with the identical construction (440 kW nominal power) are braced against each other with a cardan shaft.

The electrical machines are equipped with a speed sensor on one side and a torque sensor on the other side of the machine rotor shaft.

In order to crystallize an optimal method for developing a virtual sensor, data-driven AI models were created and discussed in comparison to physical models. The results of the individual model approaches are compared with real data and discussed in this paper. The black box model has an optimized accuracy in the area of torque prediction.

The significance of this endeavor lies in its potential to revolutionize the field of electric vehicle engineering. Traditional physical sensors have limitations in terms of cost, complexity, and scalability. Our proposed virtual sensor offers a promising alternative, circumventing these constraints while delivering a specified torque prediction. This innovation represents a substantial step forward in the pursuit of efficient and reliable electric propulsion systems. Furthermore, the discussion and comparison between the physical and black box approach build up a good basement and shows the possibilities of the different methods.

Keywords: efficiency prediction, electric motors, machine learning, test rig, torque prediction, virtual sensor

1 Introduction

This chapter presents the motivation and potential for developing a virtual sensor for torque prediction.

1.1 Motivation

As the EU's Green Deal leads to a constant increase in the number of electric motors, the automotive industry is facing new challenges in the powertrain sector. [1] To meet new trends such as autonomous driving and e-mobility, new models and approaches are being rapidly developed in all areas. The use of AI is also increasingly being considered as a solution. Recent global patent applications indicate a growing trend in the field of AI. [2] Torque measurement methods are undergoing changes due to the challenges caused by high rotation speed in the field of electromobility. Additionally, measuring the loads of an electric power train is a new challenge for the automotive industry compared to measuring the torque of a combustion engine. [3] In these circumstances, precise torque prediction can be helpful. Early estimation of torque is essential for designing drivetrains, safety components, and other system-relevant parts. Real-time torque monitoring has been possible using costly and space-intensive sensors that must be installed at specific points. [4]

1.2 Problem definition

There are different approaches in the literature like the white box modeling and the black box modeling. This paper presents and discusses the data-driven modeling approach so called black box approach. In this approach, correlations are created based on collected data and tested cycles to either replace existing systems or create predictive models [5]. Physical test setups of the systems to be modeled are required in advance for this approach to create the respective database. Finally, it should be noted that importing data and training models for respective variable cases is necessary. [5, 6]

2 State of the art

This chapter presents the current state of the art in virtual sensor technology for electric motors. In addition, torque prediction is discussed. In [7], a method based on extended Kalman filters is proposed for sensorless control of asynchronous motors. The method aims to estimate the speed and torque with minimal error for steady-state and transient data across a wide speed range. The results demonstrate accurate parameter estimation for sensorless control of ASM. [7] The torque of an asynchronous motor drive can be estimated using the Model Reference Adaptive System (MRAS), as described in [8]. The results indicate that a good dynamic estimation is possible. However, the transient state is sensitive to torque changes. [8] Physical models require knowledge of the basic physical relationships to achieve good results. Empirical models provide accurate results without requiring knowledge of the relationships. In [9], a modern approach for predicting torque on permanent magnet synchronous motors is presented. The torque and the temperatures on a permanent magnet synchronous motor are estimated. The results show a mean square error of 0.0002. The presented work demonstrates successful torque estimation using white box models. Additionally, the prediction of synchronous machines with black box models also shows good results.

3 Materials and Methods

This chapter presents the resources and methods used to solve the stated problem.

3.1 Test bench

The test setup consists of an asynchronous machine (nominal: 1200 rpm, 3502 Nm, 440 kW) with an air-cooled rotor and water-cooled stator operating against an identical asynchronous machine. One machine is equipped with measuring equipment and is operated in motor mode, while the other is operated in generator mode. A cardan shaft is used to connect the two machines. This test setup allows for the complete power spectrum of the ASM to be run without any limitations imposed by a test specimen. The measurement equipment includes speed and torque sensors, which are also implemented at the test bench. Additionally, three-phase voltage and current signals are recorded on the motorized asynchronous machine using an external data logger.

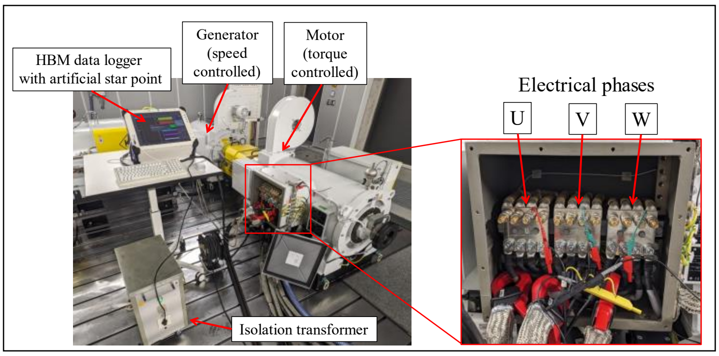

Fig. 1. Test bench setup

The load collective used for the experiments consists of 400 random load points. This collective is defined with the load points with limit values of 3000 rpm, 3000 Nm and 440 kW. Each load point is approached for 20 s and held for 50 s. The measurement is 30 s long and recorded during the end of the static area. This is necessary to avoid deviations of the control of the induction motors. In preliminary tests the time was determined and defined with a factor in security. The load points are run at random in order to minimize the influence of temperature and to prevent machine learning algorithm from recognizing patterns that could result from an ordered sequence of load points.

3.2 Data preprocessing

This chapter presents a review of the collected data in order to gain some initial insight into the interdependencies of the database. A correlation analysis is conducted to compare the measured variables including current, voltage, speed, electrical frequency, phase shift, slip, and torque. In addition, the correlation matrix is employed for purposes of data verification, with the objective of ensuring accurate assessment of the physical correlations. The input form of the mechanic data is a mean over each load point. The feature form of the current and voltage is an RMS value of the deep pass filtered data for each load point. The slip, phase delay and electrical frequency are the mean value of calculated measurement data as a result of the mechanic and electric raw measurements. The consideration of the phase delay and the slip are a result of the physical calculations on the basis of the power loss and efficiency. The results of the correlation analysis are shown in figure 2.

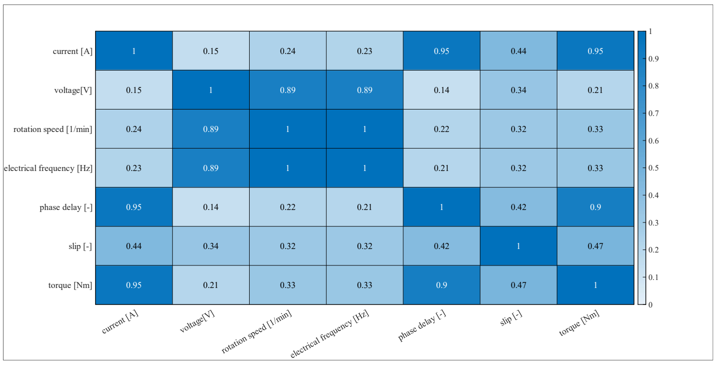

Fig. 2. Correlation matrix

The data shows a strong correlation between various variables. Specifically, the speed, electrical frequency, and voltage are closely related due to the mathematical relations. Additionally, the current heavily influences the torque to be predicted later, while the slip and phase shift also have a major impact. Although the voltage, speed, and electrical frequency have a reduced influence. Consequently, all these variables are used as input variables in the black box approach to predict torque, which is shown in the following sections.

A physical model will be employed to calculate torque, which is intimately connected to the formula for determining mechanical power. The mechanical power can be determined by calculating the power in the air gap, which results from the rotor losses. The calculation of electricity heat loss is dependent upon the number of strands, the resistance of the rotor, and the square of the rotor current. This implies that both mechanical power and torque are directly proportional to the square of the rotor current. These methodological approaches provide a comprehensive understanding of the underlying physical processes.

The machine learning system XGBoost, which stands for "Extreme Gradient Boosting", was originally developed by Tianqi Chen and described in a paper by Chen and

Carlos Guestrin. The way XGBoost works is to iteratively build models, with each new tree attempting to correct the errors of the entire previous ensemble of trees. This is achieved by minimizing a loss function that takes into account both the prediction error and the complexity of the model to avoid overfitting. [10]

In the model selection process, where the DecisionTreeRegressor, XGBRegressor and CatBoostRegressor models were trained on a training dataset, the XGBRegressor model proved to be the best performer when further analyzed on an independent test dataset. The XGBRegressor model uses the previous shown variables as input to predict torque as the target variable. The hyperparameter optimization with the following parameters is generated the best results: maximum depth of six, regression alpha of four, the number of estimators of 150 and a learning rate of 0.1 achieved the best result.

4 Results and Outlook

This chapter presents and discusses the results of the black box modeling approach. It concludes with an outlook for further in-depth steps.

4.1 Model discussion and result

The different white box model approaches in the state of the art with specified limitations can achieve a relative error in the area of 0.25 to 0.40. [11, 12] The black box model approach of this paper has a maximum absolute prediction error of 141 Nm. On average, the absolute error is 15.25 Nm, and the relative error is 0.026. Figure 3 shows the relative prediction error of the black box model against the real torque. It is evident that the relative error is high in the lower torque area and diverges rapidly with an increase in torque towards zero. The reasons for the high relative error values in the lower torque area is the low real torque and the challenges at the measurement and calculation of the slip and the phase delay as a result of the complex equipment and the high frequency changes of the electric values.

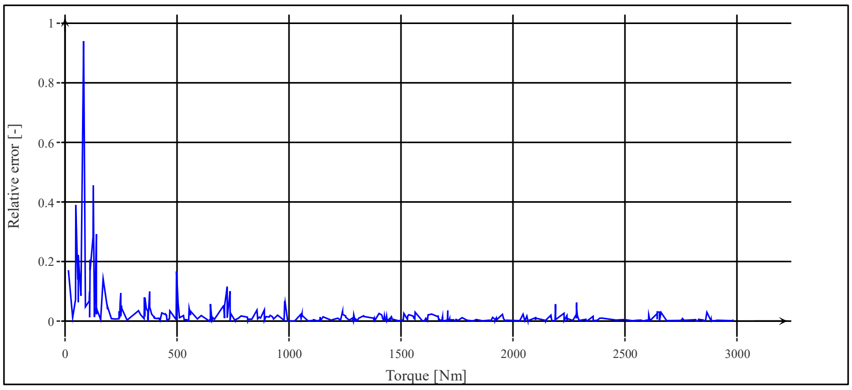

Fig. 3. Relative error of black box model

In addition, the predicted torque over the test torque is shown in figure 4.

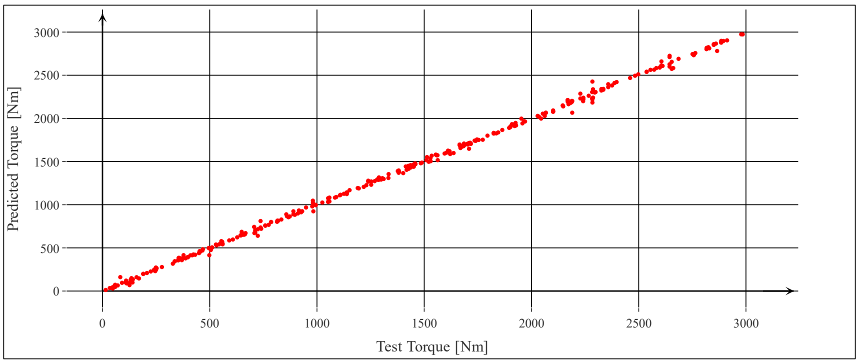

Fig. 4. Predicted torque over real torque of black box model

As described, the predicted torque follows a normal curve as an angle bisector. This shows the high accuracy of the prediction of the black box approach.

4.2 Conclusion and Outlook

This paper discusses the concept of virtual sensors and their implementation in electrical machines. It describes the test setup, sensor concept, and data pre-processing methodology. The paper concludes by comparing and discussing prediction errors based on various parameters and limitations of the white box and black box approach. The white box approach with specified restrictions can achieve a relative error between 0.25 to 0.40, while the presented black box approach can achieve 0.026.

The conclusion is, that the presented black box approach has a ten times smaller error in compare to the white box model. So, the presented virtual sensor can be an effective substitution or extension for physical torque sensors.

This approach can serve as a foundation for further research, including analyzing the adaptability of results to transient data conditions and optimizing the model's accuracy by using a broader database.

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References

[1] KBA, *Anzahl der Elektroautos in Deutschland von 2006 bis Oktober 2023.* [Online]. Available: https://de.statista.com/statistik/daten/studie/265995/umfrage/anzahl-der-elektroautos-in-deutschland/ (accessed: Feb. 3 2024).

[2] Stanford University and Center for Security and Emerging Technology, *Anzahl der Patentanmeldungen im Bereich KI weltweit in den Jahren 2010 bis 2021.* [Online]. Available: https://de.statista.com/statistik/daten/studie/1321367/umfrage/anzahl-der-ki-patentanmeldungen-weltweit/ (accessed: Feb. 4 2024).

[3] Mitchell Marks, *Drehmomentmessung im Wandel.* [Online]. Available: https://www.hbm.com/de/8435/drehmomentmessung-bei-hohen-drehzahlen-im-wandel/ (accessed: Feb. 3 2024).

[4] R. Mansius, *Praxishandbuch Antriebsauslegung: Grundlagen, Tools, Beispiele,* 2nd ed. Würzburg: Vogel Business Media, 2017.

[5] C. Neumann, "Modellbasierte Methoden für die Fehlererkennung und Optimierung im Gebäudebetrieb : Endbericht ; ModBen," Fraunhofer-Institut für Solare Energiesysteme, 2011.

[6] L. Bauer, P. Beck, L. Stütz, and M. Kley, "Enhanced efficiency prediction of an electrified off-highway vehicle transmission utilizing machine learning methods," *Procedia Computer Science*, vol. 192, pp. 417–426, 2021, doi: 10.1016/j.procs.2021.08.043.

[7] M. Barut, S. Bogosyan, and M. Gokasan, "Speed-Sensorless Estimation for Induction Motors Using Extended Kalman Filters," *IEEE Trans. Ind. Electron.*, vol. 54, no. 1, pp. 272–280, 2007, doi: 10.1109/TIE.2006.885123.

[8] Y. A. Zorgani, Y. Koubaa, and M. Boussak, "MRAS state estimator for speed sensorless ISFOC induction motor drives with Luenberger load torque estimation," *ISA transactions*, vol. 61, pp. 308–317, 2016, doi: 10.1016/j.isatra.2015.12.015.

[9] K. Bingi, B. R. Prusty, A. Kumra, and A. Chawla, "Torque and Temperature Prediction for Permanent Magnet Synchronous Motor Using Neural Networks," in *2020 3rd International Conference on Energy, Power and Environment: Towards Clean Energy Technologies*, Shillong, Meghalaya, India, 2021, pp. 1–6.

[10] T. Chen and C. Guestrin, "XGBoost," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco California USA, 2016, pp. 785–794.

[11] J. Stütz, L. Bauer, and M. Kley, "Stuttgarter Symposium für Produktentwicklung SSP 2019 : Stuttgart, 16. Mai 2019, Wissenschaftliche Konferenz: Intelligente Lastkollektivoptimierung für Erprobungen von elektrischen und hybriden Antriebsstränge," 2019.

[12] L. Bauer, Bauer Manuel, and M. Kley, "Stuttgarter Symposium für Produktentwicklung SSP 2021 : Stuttgart, 20. Mai 2021, Wissenschaftliche Konferenz: Modellbasierte Validierung der Prüfstandsdynamik zur Erprobung von Komponenten elektrifizierter Antriebsstränge mithilfe eines digitalen Zwillings," 2021.