The 11th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications
22-25 September, 2021, Cracow, Poland

Extending the Multiphysics Modelling of Electric Machines in a Digital Twin Concept

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Abstract— **The digital twin is a trending technology that has been applied to different fields. In this work, the use of the digital twin of electric machines in a life cycle perspective is investigated. It presents a literature review of the main concepts and applications of the digital twin in the field. In addition, it discusses the methodological approach to obtain the digital twin of a static electric machine by using its multiphysics model in a reduced order model, to improve the maintenance scheme and estimate the lifetime of its insulation system based on the machine's temperature profile.**

Keywords—digital twin; multiphysics; FEM; remaining lifetime; electric machines

I. Introduction

The digital twin is one of the most trending technologies, being nominated in 3 consecutive years as top 10 strategic technology trends [1]. It extends the simulation in a specific domain or physical asset to the complete lifetime. By this way, engineering simulation may support decision making through the entire life-cycle of products and processes.

The advances of computer hardware and software have allowed the design process of electric machines to become more sophisticated, enabling accurate multiphysics models, saving costs and time. Also, the ability to use a variety of sensors to monitor several parameters allied with the advances of the Internet of Things (IoT) and Big Data allowed the development of new technologies.

Considering the above mentioned technologies, the digital twin seems like a natural step in the industry. According to Hartmann and Auweraer [1], it is expected that the digital twin becomes imperative in the industry, thus the enterprises must not fall behind it.

Due to the fact of the electric machines have a highly non-linear behaviour, depending, for instance, on environmental data and load conditions, the "dynamic" modelling provided by the digital twin concept is able to reduce costs over the lifetime and favour optimized control of industrial drive systems.

This work is structured as follows: section II presents a literature review of the main concepts of digital twin and the works that apply a digital twin in the context of electric machines; section III proposes an approach to develop a digital twin for electric machines and section IV concludes the paper and outlines the future work.

II. Literature Review

The digital twin is a technology that has been receiving more attention in the past years in different fields of study, mostly applied to manufacturing, aircraft, and healthcare. The beginning of the digital twin concept traces back to Michael Grieves in 2002, which was initially called "Conceptual Idea for Product Lifecycle Management", but it aggregated all the key concepts of the digital twin [2].

Almost 20 years have passed and there are still misconceptions about the digital twin definition; as pointed out by [3], it is necessary that both industry and academy work toward presenting a definitive and more clear definition of a digital twin. In Grieves words, *the digital twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level* [2]. The digital twin also brought other terms to facilitate its understanding and operation, such as a physical entity, a virtual entity, a physical environment, and a virtual environment. According to [4] the physical entity is the real-world object, while the virtual entity is the computer-generated representation of the physical entity. The physical environment is the setting where the physical entity is placed, and the virtual environment is an environment that imitates the physical environment to fulfil the purposes of the digital twin.

To develop a digital twin, it is necessary to obtain a virtual model of the physical entity, which can be physics-based modelling or data-driven modelling. Physics-based modelling uses analytical or numeric methods to solve the governing equations of the related physics phenomena that occur in the entity's geometry. The finite element method (FEM) is a good example of a numeric method used to model physics phenomena. The data-driven models exploit the availability of a variety of sensors to capture the information and process it with modern computer techniques; this approach is particularly useful due to advances on the IoT and Big Data. Table I shows the main advantages and disadvantages of both approaches.

This work has been supported by FCT - Fundação para a Ciência e Tecnologia within the Project Scope: UIDB/05757/2020.

Methodologies aggregating both modelling approaches are also possible, for instance, using data-driven models to calibrate the physics models.

TABLE I. PHYSICS-BASED MODELLING VS DATA-DRIVEN MODELLING. ADAPTED FROM [5].

Physics-based modelling	Data-driven modelling
+ Solid foundation based on physics	- Works like black-boxes
- Difficulty to assimilate long historical data	+ Assimilates long historical data and experience
- Sensitive to instability (convergence errors, boundaries conditions, etc.)	+ Very stable after the training process
+ Errors/uncertainties can be bounded and estimated	- Errors/uncertainties cannot be bounded
+ Less susceptible to bias	- Bias in data is reflected in the model
+ Can handle new problems with similar physics	- Cannot handle unseen problems

The digital twin has been applied in different areas such as manufacturing [6], healthcare [7], and logistics [8]. In the context of electric machines, the digital twin has also been applied, but the published works are still scarce. A summary of the works regarding electric machines and digital twins are presented hereinafter.

The work presented in [9] exploits the digital twin of the power inverter system of an offshore wind turbine for maintenance purposes, thus it does not develop the digital twin for the generator, which could be also used for monitoring and predictive maintenance. A real-time simulation of a wind farm is developed in [10], which is implemented into a field-programmable gate array (FPGA) and it is focused on the control aspects of the generator. The work developed in [11] is focused on the mechanical aspects of a wind turbine, handling the structural stress and mechanic loss of the system, also there are several sensors installed in the system, and the digital twin uses both physical and data models.

The work developed in [12] derives an electromagnetic FEM model of a large hydro generator to be used as a digital twin. As the FEM model showed its capability to perform reliable simulations in several conditions, e.g., no-load, rated load, and overexcited, the digital twin based on this model should aid the diagnosis and maintenance scheme of the generator, which is helpful and convenient for large machines.

The work performed in [13] develops an electromagnetic model of an induction machine that is based on FEM allowing it to be used for a digital twin; the model shows good results, but it only models electromagnetic phenomena and it is not able to calculate the iron loss. In [14] it is achieved an analytical electromagnetic model based on an equivalent circuit that is capable to estimate the iron loss of the machine, presenting results similar to the FEM model.

Aircrafts have high standards of safety and maintenance, making them excellent applications for digital twins. Thus, in [15] it is developed a digital twin of the electrical generator of an aircraft, which predicts faults based on the temperature of the oil that is cooling the generator. As the model is data-driven it was necessary to obtain enough data from the generator, and classify it correctly, which was proven to be not an easy task.

A data-driven digital twin of a 3 kW permanent magnet synchronous motor (PMSM) employed in an electric vehicle prototype is developed in [16]. Two methods were applied, artificial neural network (ANN) and fuzzy logic; both methods have three inputs, the motor's speed, running time, and the casing temperature. The health of the motor relates to the temperatures of the windings and permanent magnets, which are estimated through the casing temperature measurements. When compared with theoretical results, the ANN digital twin presented a lower deviation margin than the fuzzy logic digital twin.

Power transformers are simple static electric machines, but they play a key role in power systems, and they can take advantage of the digital twin technology. Within this subject, [17] outlines an architecture that can be used for a smart power distribution system, which will monitor the status of the transformers and will take action for an abnormal operating condition. However, it is not explicit how the transformer is modelled. Several sensors are to be placed in the transformer and will feed the model, which will enable the monitoring of the transformer and improve the predictive maintenance.

The work presented in [18] develops a tool that is approximately a digital twin of a power transformer. With the measurements of the temperature sensors placed in the transformer's tank, the software tool is able to estimate the status of the transformer.

An important aspect of the digital twin is the ability to obtain information about the physical entity, which can be difficult sometimes. For instance, it is easier to measure the current and voltage on one side of the transformer than on the other side. To surpass this difficulty, Moutis and Mousavi [19] developed a digital twin of a power transformer that uses only the measurements obtained on the medium voltage side. This was accomplished with an analytical model of the transformer that is implemented in MATLAB, allowing the monitoring of the harmonic components and possible faults or abnormal conditions. The digital twin presented good results when compared with the real measurements.

In [20], it is developed a digital twin of a power transformer based on a data model that uses machine learning techniques, resulting in an accurate prediction of the transformer status. Reference [21] also develops a data-driven model of a power transformer, which uses multi-source and heterogenous data to evaluate the transformer status. In order to obtain a real-time simulation of a power transformer, [22] uses an FPGA enabling to monitor and diagnose the transformer, with a maximum delay of 1.1 ms.

III. METHODOLOGICAL APPROACH

Without a doubt, the digital twin has been gaining attention in the context of electric machines, but there is still a lot of research to be developed under this topic. Thus, this work aims to exploit the methodological approach for a digital twin of electric machines based on the multiphysics FEM model. FEM approach to obtain multiphysics modelling is a well-established methodology, considering the improvements in software development and computer processing capacity, and it has been obtaining popularity [23]–[26]. Its use brings several advantages for the design process of the machine, resulting in a better, faster, and cheaper process since it reduces the need for several prototypes. It is necessary to put a lot of effort to obtain a good multiphysics model, collecting several materials properties, modelling different physics phenomena and coupling them. Therefore, this model can be extended for the entire lifecycle of the machine, instead of being used only in the design process. Despite the nowadays software and computer hardware, a multiphysics FEM model cannot be used for a real-time digital twin since it can take at least several minutes to simulate all the physics phenomena related to the machine.

To address this problem, it is necessary a post-processing model that is based on the results of the FEM modelling but does not require a long simulation time, thus applying to a real-time simulation. This framework uses model order reduction techniques that can be described as the intersection of physics-based simulation and data-driven models [5]. Using a reduced order model (ROM) allows a real-time simulation of the machine by trading the accuracy of the model with real-time outputs. Thus, it is necessary to ensure that the ROM provides the accuracy required by the application.

Different techniques can be applied to obtain a ROM from a FEM model, varying according to the physics solution characteristics of each model. Proper orthogonal decomposition (POD) is an example of these techniques, which is completely data-dependent not requiring any prior knowledge of the process that generates the data, and if the original model has nonlinear characteristics the POD model will also be typically nonlinear [27]. The data for the POD method is gathered by running the original model, original FEM model, considering the inputs of different scenarios and taking snapshots of the results for these scenarios which are stored in a snapshot matrix. Thereafter, the singular value decomposition (SVD) is applied to the snapshot matrix obtaining the modes of the POD. The modes of the POD can be evaluated concerning the energy content in the least square sense [28], allowing to choose an appropriate number of modes to achieve an efficient model, combining good accuracy and fast solution time. In [28] this technique is applied to the electromagnetic model of a PMSM, whereas the developed ROM has as inputs the rotation angle of the machine and the angle and magnitude of the current. A total of 150 different scenarios were used to fill the snapshot matrix and 63 POD modes were selected, which reduced the simulation time by half, from 0.18 s to 0.09 s. The ROM presented an average relative error of 2,5% showing that it is capable to calculate the solutions for scenarios not included in the snapshot matrix. POD is not the only technique being applied in the context of electric machines. In [29] the ROM of a PMSM is developed considering its application to refined real-time control of the machine, which is accomplished through the orthogonal interpolation method (OIM). An advantage of this method is its capability to evaluate input values up to 20% beyond the upper and lower range with acceptable precision.

Sancarlos *et al.* [30] point out that the employment of the proper generalized decomposition (PGD) techniques in electromagnetism problems is a very active research area at the moment. It applies the PGD method to obtain a magnetostatic solution of a PMSM, which presented an error below 2% when compared to the FEM solution. The authors of [31] use the PGD technique which resulted in an improvement of the solution time by about 900 when compared to the original FEM model, despite the torque estimation being in general agreement with the FEM model it presented some noticeable errors because it is calculated through the virtual work principle. In addition, the work developed in [32] shows the possibility to express deviations within the PGD framework, which is an interesting feature because these deviations can represent external disturbances and even the difference between the predictions and measurements. This possibility allows the development of a more robust and accurate digital twin that could be crucial for control purposes.

Focused on the condition monitoring of induction machines, the work developed in [33] uses a different approach to obtain a model that is accurate enough and that is capable to run in real-time in hardware in the loop configuration. An induction machine can suffer from a variety of faults with different levels of severity, so it is unreasonable to obtain FEM solutions able to cover all ranges of faulty conditions. To overcome this difficulty, the authors use a sparse subspace learning (SSL) strategy. The SSL is used to obtain a parametric solution that is used to initialize the FEM solution since the prediction is close to the actual solution the process becoming a much faster method than a usual FEM. This strategy was implemented to monitor induction motors considering only the static eccentric fault and the measured current as input of the model. The obtained results presented a small error when compared with the traditional FEM method and with a 99.92% boost in the solution time.

Moving towards the thermal model, the authors of [34] use the thermal ROM to obtain an accurate and detailed thermal model of an electric traction motor. The model considers the detailed geometry and material characteristics of the windings and the contact resistances between the different parts of the motor. As the machine is self-ventilated the convection coefficients vary according to the motor's speed, thus it is used computational fluid dynamics (CFD) to obtain the coefficients considering the speed range of the machine. The results obtained from the ROM presented a deviation in the range of 0.5% to 5% when compared with the temperature measurements, which is impressive because the ROM computed the whole transient duty cycle in less than 1 s.

By using the ROM approach, and keeping in mind the objective of an improved maintenance scheme based on the insulation system monitoring of an electric machine, it is possible to develop a 3D virtual temperature sensor that is capable to estimate the critical temperatures of the machine, which can lead to significantly reduced costs [35].

In a previous work [36], the coupled electromagnetic and thermal FEM model of a low power transformer has been developed using the Ansys software suite. In this coupled approach, the losses obtained by the electromagnetic model are used as the heat generation input in the thermal model, which allows calculating the temperature distribution of the machine. Conversely, the temperature output of the thermal model is used as input to the electromagnetic model, considering the temperature dependence on the electromagnetic parameters. This interaction between the electromagnetic and thermal models runs iteratively until the variation of temperature between the two last iterations is lower than a defined threshold, meaning that the temperature and losses variation is minimal. This model was able to estimate the steady-state temperature of the windings within an error of 7% when compared with the measured temperature.

It is known that thermal stress is one of the main causes of insulation system deterioration in electric machines. Thus, the ability to estimate the temperature of the windings can be leveraged to improve predictive maintenance schemes and estimate the lifetime of the insulation system. Based on the guidelines provided by the IEEE standard C57.96 [37], which uses Dakin's method [38] to handle the deterioration of the insulation in view of the chemical rate phenomenon, the expected lifetime, in hours, of the insulation is calculated by

$$t_{life} = a \times \exp\left(\frac{b}{T}\right) \qquad (1)$$

where a and b are constants that are defined by the material characteristics, and T is the absolute temperature of the windings, that are to be integrated into the methodological approach.

This method will enable the monitoring of the lifetime of the transformer's insulation considering its real operation conditions, allowing to predict failures and manage the maintenance of the device. Besides, this method can be expanded for other electric machines, enabling better and more efficient maintenance and monitoring of electric machines.

On one hand, similar concepts have been already done, such as [39], where it is used fiber Bragg grating temperature sensors embedded into the stator coils, allowing to measure the temperature of the windings in different spots. With the information from the temperature sensors, it is possible to estimate the insulation health in real-time. Also, in [40] the leakage currents are used to estimate the insulation degradation through an ANN to obtain the insulation system health status.

On the other hand, the digital twin approach is a technique under development, that has an enormous potential to be exploited. The digital twin technology expands the "static" models providing an accurate description of the machine over time. It is possible to accurately forecast the degradation of insulation systems, perform data-based predictive maintenance, support online fault diagnosis, and reduce operating costs, instead of having to work with empirical estimates which are, typically, overestimated.

IV. Conclusion

The digital twin is a trending technology, transversal to several fields, objectives, and applications. This work introduced a systematic literature review and discussion on the use of digital twins in electric machines. The research and application of the digital twin to electric machines is still evolving and its penetration in the industry is not mature yet. Under this scenario, the paper proposes and discusses the methodological approach to define a digital twin of a static electric machine, obtained by the ROM of the multiphysics FEM model used in the design process. This digital twin will provide the information necessary to estimate the remaining lifetime of the insulation, which will assist the monitoring and maintenance schemes.

Further work will include the evaluation of the multiphysics ROM as a digital twin. If the ROM proves to be adequate, the digital twin should be evaluated considering different conditions, which will prove if it can be used as a monitoring and maintenance tool.

References

[1] D. Hartmann and H. Van der Auweraer, "Digital Twins," *SEMA SIMAI Springer Ser.*, vol. 5, pp. 3–17, 2021.

[2] M. Grieves and J. Vickers, "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems," in *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches*, Springer, Cham, 2016, pp. 85–113.

[3] A. Fuller, Z. Fan, C. Day and C. Barlow, "Digital Twin: Enabling Technologies, Challenges and Open Research," in *IEEE Access*, vol. 8, pp. 108952-108971, 2020.

[4] D. Jones, C. Snider, A. Nassehi, J. Yon and B. Hicks, "Characterising the Digital Twin: A systematic literature review," *CIRP J. Manuf. Sci. Technol.*, vol. 29, pp. 36–52, 2020.

[5] A. Rasheed, O. San and T. Kvamsdal, "Digital twin: Values, challenges and enablers from a modeling perspective," *IEEE Access*, vol. 8, pp. 21980–22012, 2020.

[6] S. R. Chhetri, S. Faezi, A. Canedo and M. A. Al Faruque, "QUILT: Quality Inference from Living Digital Twins inIoT-Enabled Manufacturing Systems," in *Proceedings of the International Conference on Internet of Things Design and Implementation (IoTDI '19)*, 2019, pp. 237–248.

[7] M. Joordens and M. Jamshidi, "On The Development of Robot Fish Swarms in Virtual Reality with Digital Twins," in *2018 13th Annual Conference on System of Systems Engineering (SoSE)*, 2018, pp. 411–416.

[8] F. Coelho, S. Relvas, and A. P. Barbosa-Póvoa, "Simulation-based decision support tool for in-house logistics: the basis for a digital twin," *Comput. Ind. Eng.*, vol. 153, 2021.

[9] K. Sivalingam, M. Sepulveda, M. Spring and P. Davies, "A Review and Methodology Development for Remaining Useful Life

Prediction of Offshore Fixed and Floating Wind turbine Power Converter with Digital Twin Technology Perspective," *Proc. - 2018 2nd Int. Conf. Green Energy Appl. ICGEA 2018*, pp. 197–204, 2018.

[10] Y. M. Alsmadi, L. Xu and A. Wang, "Development of a computer twins-based wind farm testbed," *2015 IEEE Energy Convers. Congr. Expo. ECCE 2015*, pp. 1005–1012, 2015.

[11] F. Tao, M. Zhang, Y. Liu and A. Y. C. Nee, "Digital twin driven prognostics and health management for complex equipment," *CIRP Ann.*, vol. 67, no. 1, pp. 169–172, 2018.

[12] C. Moussa, K. Al-Haddad, B. Kedjar, and A. Merkhouf, "Insights into digital twin based on finite element simulation of a large hydro generator," in *Proceedings: IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society*, 2018, pp. 553–558.

[13] S. Bouzid, P. Viarouge and J. Cros, "Real-time digital twin of a wound rotor induction machine based on finite element method," *Energies*, vol. 13, no. 20, 2020.

[14] V. Mukherjee, T. Martinovski, A. Szucs, J. Westerlund and A. Belahcen, "Improved analytical model of induction machine for digital twin application," in *Proceedings - 2020 International Conference on Electrical Machines, ICEM 2020*, 2020, pp. 183–189.

[15] F. Boulfani, X. Gendre, A. Ruiz-Gazen and M. Salvignol, "Anomaly detection for aircraft electrical generator using machine learning in a functional data framework," *Proc. 2020 Glob. Mosharaka Congr. Electr. Eng. GC-ElecEng 2020*, pp. 27–32, 2020.

[16] S. Venkatesan, K. Manickavasagam, N. Tengenkai and N. Vijayalakshmi, "Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin," *IET Electr. Power Appl. Res.*, vol. 13, no. 9, pp. 1328–1335, 2019.

[17] G. Zhang, C. Huo, L. Zheng and X. Li, "An Architecture Based on Digital Twins for Smart Power Distribution System," in *2020 3rd International Conference on Artificial Intelligence and Big Data*, 2020, pp. 29–33.

[18] I. E. Kolesnikov, A. V. Korzhov and K. E. Gorshkov, "Digital Program for Diagnosing the Status of a Power Transformer," in *Proceedings - 2020 Global Smart Industry Conference, GloSIC 2020*, 2020, pp. 315–321.

[19] P. Moutis and O. Mousavi, "Digital Twin of Distribution Power Transformer for Real-Time Monitoring of Medium Voltage from Low Voltage Measurements," *IEEE Trans. Power Deliv.*, vol. 8977, no. 797451, pp. 1–1, 2020.

[20] P. Zhou *et al*., "Research on Mining of Transmission Grid Assets of Heterogeneous System Based on Digital Twin," *2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2)*, 2020, pp. 3051-3056.

[21] Y. Yang *et al.*, "State Evaluation of Power Transformer Based on Digital Twin," *Proc. - IEEE Int. Conf. Serv. Oper. Logist. Informatics 2019, SOLI 2019*, pp. 230–235, 2019.

[22] J. Xiong, H. Ye, W. Pei, K. Li and Y. Han, "Real-time FPGA-digital twin monitoring and diagnostics for PET applications," *2021 6th Asia Conference on Power and Electrical Engineering (ACPEE)*, 2021, pp. 531-536.

[23] G. Du, W. Xu, N. Huang, X. Cheng and X. Xiao, "Rotor Design of High Power High Speed Permanent Magnet Machine Considering Multiphysics Constraints," *2019 22nd Int. Conf. Electr. Mach. Syst. ICEMS 2019*, vol. 1, 2019.

[24] Z. Huang and J. Fang, "Multiphysics Design and Optimization of High-Speed Permanent-Magnet Electrical Machines for Air Blower Applications," *IEEE Trans. Ind. Electron.*, vol. 63, no. 5, pp. 2766–2774, 2016.

[25] Y. Yasa, M. Elamin, Y. Sozer, J. Kutz, J. S. Tylenda and R. L. Wright, "Acoustic noise mitigation for high pole count switched reluctance machines through skewing method with multiphysics FEA simulations," *2017 IEEE Energy Convers. Congr. Expo. ECCE 2017*, vol. 2017-Janua, no. 1, pp. 738–744, 2017.

[26] C. Yan, Y. Wei, C. Xu and B. Zhang, "Experimental verification and electromagnetic-mechanics-acoustic field coupling analysis of transformer pressure relief valve malfunctions due to external short-circuit faults," *IEEE Trans. Magn.*, vol. 55, no. 6, pp. 9–12, 2019.

[27] M. Rathinam and L. R. Petzold, "A new look at proper orthogonal decomposition," *SIAM J. Numer. Anal.*, vol. 41, no. 5, pp. 1893–1925, 2003.

[28] M. Farzamfar, A. Belahcen, P. Rasilo, S. Clénet, and A. Pierquin, "Model Order Reduction of Electrical Machines with Multiple Inputs," *IEEE Trans. Ind. Appl.*, vol. 53, no. 4, pp. 3355–3360, 2017.

[29] M. F. Far, F. Martin, A. Belahcen, P. Rasilo and H. A. A. Awan, "Real-Time Control of an IPMSM Using Model Order Reduction," *IEEE Trans. Ind. Electron.*, vol. 68, no. 3, pp. 2005–2014, 2021.

[30] A. Sancarlos, C. Ghnatios, J. L. Duval, N. Zerbib, E. Cueto and F. Chinesta, "Fast computation of multi-parametric electromagnetic fields in synchronous machines by using pgd-based fully separated representations," *Energies*, vol. 14, no. 5, 2021.

[31] L. Montier, T. Henneron, S. Clenet and B. Goursaud, "Proper Generalized Decomposition Applied on a Rotating Electrical Machine," *IEEE Trans. Magn.*, vol. 54, no. 3, pp. 16–19, 2018.

[32] F. Chinesta, E. Cueto, E. Abisset-Chavanne, J. L. Duval and F. El Khaldi, "Virtual, Digital and Hybrid Twins: A New Paradigm in Data-Based Engineering and Engineered Data," *Arch. Comput. Methods Eng.*, vol. 27, no. 1, pp. 105–134, 2020.

[33] A. Sapena-Bano, F. Chinesta, M. Pineda-Sanchez, J. V. Aguado, D. Borzacchiello and R. Puche-Panadero, "Induction machine model with finite element accuracy for condition monitoring running in real time using hardware in the loop system," *Int. J. Electr. Power Energy Syst.*, vol. 111, no. March, pp. 315–324, 2019.

[34] L. Boscaglia, A. Boglietti, S. Nategh, S. Member, F. Bonsanto and C. Scema, "Numerically Based Reduced-Order Thermal Modeling of Traction Motors," *IEEE Trans. Ind. Appl.*, vol. 57, no. 4, pp. 4118–4129, 2021.

[35] A. Barnard and S. Zistl, "Virtual Sensor opens a World of Efficiency for Large Motors," Siemens, 2018. Accessed: June 2021. [Online]. Available: https://new.siemens.com/global/en/company /stories/research-technologies/digitaltwin/virtual-sensor-opens-a-world-of-efficiency-for-large-motors.html

[36] G. Mendes, Â. Ferreira and E. Miotto, "Coupled Electromagnetic and Thermal Analysis of Electric Machines," in *MATEC Web of Conferences. Vol. 322*, 2020, p. 01052.

[37] IEEE Guide for Loading Dry-Type Distribution and Power Transformers, *IEEE Std C57.96-2013 (Revision of IEEE Std C57.96-1999)* , 2014.

[38] T. W. Dakin, "Electrical Insulation Deterioration Treated as a Chemical Rate Phenomenon," *Trans. Am. Inst. Electr. Eng.*, vol. 67, no. 1, pp. 113–122, 1948.

[39] K. Tshiloz, A. C. Smith, A. Mohammed, S. Djurović and T. Feehally, "Real-time insulation lifetime monitoring for motor windings," *2016 XXII International Conference on Electrical Machines (ICEM)*, 2016, pp. 2335-2340.

[40] A. S. Guedes, and S. M. Silva, "Insulation protection and online stress agent identification for electric machines using artificial intelligence," *IET Electric Power Applications*, vol. 13, no. 4, pp. 559-570, Apr. 2019.