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EXPLORING INTEGRATION OF SURROGATE MODELS THROUGH A CASE STUDY ON VARIABLE FREQUENCY DRIVES

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ABSTRACT

High-fidelity simulation models of variable frequency drives often incur expensive computation due to high granularity, complex physics and highly stiff components, hindering real-time Digital Twin Industry 4.0 applications. Surrogate models can outperform simulation solvers by orders of magnitude, potentially making real-time virtual drives feasible within practical computational limits. Despite this potential, current surrogate models suffer from limited generalizability and robustness. In this paper, we present an industrial case study exploring the combination of deep learning with surrogate modeling for simulating variable frequency drives, specifically replacing the induction motor high-fidelity component. We investigate the performance of Long-Short Term Memory-based surrogates, examining how their prediction accuracy and training time vary with synthetic datasets of different sizes, and how well the induction motor surrogates generalize across different motor resistances. This initial study aims to establish a foundation for further development, benchmarking and automation of surrogate modeling workflow for simulation enhancement.

1 INTRODUCTION

Dynamical systems theory aid in understanding the temporal evolution in physical systems (Legaard et al. 2023), essential for controlling advanced systems that depend on electronic circuits, fluid dynamics, and more. Engineering simulations facilitate decision-making in design optimization by virtually representing these complex systems and offering a cost-effective alternative to empirical analyses (Koziel and Yang 2011). Simulation-based design allows engineers to gain a deeper understanding of systems by exploring a wider range of design parameters and operating conditions in much shorter timeframes, without the need for expensive prototyping or testing facilities (Alizadeh et al. 2020).

Numerical simulations often incur significant computational costs across many research domains (Anantharaman et al. 2020; Rackauckas et al. 2022; Alizadeh et al. 2020). This high expense is largely due to the use of high-fidelity (HF) simulations during the design and development of complex dynamical systems. HF models typically involve large-scale representations consisting of nested or interconnected components, requiring high granularity and complex nonlinear physics to accurately capture behaviors of the modeled systems (Sun and Wang 2019). While lower-fidelity simulations are more cost-efficient, HF simulations are essential for capturing intricate dynamics and interactions within systems, ensuring that simulation models meet precision and accuracy requirements of the target application.

Moreover, the Industry 4.0 transformation, centered around digitalization and automation, demands computationally efficient HF models to enable real-time Digital Twins (DTs) (Rasheed et al. 2020). These HF models allow DTs to truly reflect real-world conditions and behaviors of their physical counterparts, thereby directly enhancing systems' representations in DTs and benefitting from most DTs' applications, like predictive maintenance and decision-making. Despite more computing power, advancements in simulation software, parallel computing, parametrization and downscaling of critical variables, computational overhead associated with HF simulation models remains a significant concern, preventing their use in real-time DTs (Anantharaman et al. 2020; Alizadeh et al. 2020; Koziel and Yang 2011).

Surrogate modeling (SMing) alleviates this computational burden by offering a possibility to trade fidelity for reduced simulation runtimes, aspiring to achieve fast yet reasonably accurate approximations of HF models, known as surrogate models (SMs) or “surrogates” (Rackauckas et al. 2022). SMing aims to accelerate simulations by replacing simulation solvers with simplified, data-driven representations. SMs are typically trained on a finite set of HF simulation outputs and encapsulate complex first-principles models in a black-box form, without explicitly solving the underlying equations (Koziel and Yang 2011).

Coupling SMing with the widespread success of machine learning (ML) across diverse domains, such as speech recognition, image classification, and natural language processing (Legaard et al. 2023), prompts exploration of ML's role in advancing the field of SMing and simulation to further enhance accuracy, efficiency and adoption of SMs. Recent research highlights the benefits of fusing knowledge and data-driven approaches by integrating physics expert knowledge into ML to enforce physical constraints in the models, enhance out-of-sample generalization (Karniadakis et al. 2021), allow for coarser datasets (Raissi et al. 2019) and increase models’ interpretability (von Rueden et al. 2021).

Current research on SMs often yields domain-specific solutions, lacks robustness and automation. These deficiencies, combined with the widespread success of ML, motivate us to explore how SMing can be automated, generalized and integrated with ML to enhance physics-based HF simulation models.

In this paper, we contribute to this exploration by presenting a practical application of ML-enhanced SMing through an industrial case study that involves first-principle simulations of variable frequency drives (VFDs). Our focus is on an induction motor (IM) component within a larger power conversion and control (PCC) model. The PCC model, a key contributor to the overall VFDs simulations during application development for controlling fans, extruders, pumps, conveyor belts and more, presents a significant computational bottleneck due to several HF components. The HF simulation model of the IM component serves as a suitable testbed for our initial case study due to limited complexity and the challenge it presents: the surrogate model must generate predictions that feed directly into subsequent simulation steps, effectively replacing the IM simulation in a black-box fashion.

This case study investigates the trade-offs involved in combining ML with SMing. We focus on component level SMs that can substitute HF IM simulation model in the broader PCC simulation of VFDs. We demonstrate that our data-driven SMs can accurately predict the transient behaviors of the IM component with total root mean squared error as little as 0.1446. While larger datasets lead to significant improvements in SM predictions, they come at the cost of prolonged trainings, leaving room for future work. We believe our findings provide a meaningful step towards the integration of ML with SMs for simulation acceleration and scalability.

The remainder of this paper is structured as follows: We first provide the necessary background concerning VFDs simulations complemented by introduction into surrogate modeling and deep learning for simulation enhancement and detailed description of our IM case study component (Section 2). Subsequently, we present our experimental setup followed by case study results and benchmarks (Section 3). Finally, we draw conclusions and provide an outlook on our future work (Section 4).

2 BACKGROUND AND RELATED WORK

2.1 Simulation of Variable Frequency Drives

VFDs control the speed and torque of electric motors by adjusting the power supply’s frequency and voltage (Mohan et al. 2003). Industry 4.0 transformation, particularly with emerging DTs, is shaping VFDs research and development. This technological evolution is driving enhancements in operational efficiency and energy management. To meet sustainability goals in industry, the green transition and electrification require improved electricity distribution management in the transmission grid to provide stable and reliable supply.

VFDs contribute to analyzing different scenarios in the electricity grid, such as new consumers, energy sources, electricity demand patterns or network upgrades. To assess the impact of these scenarios and monitor grid evolution, transmission system operators like Energinet in Denmark demand various simulation models of VFDs. These include stationary models for steady-state analysis, harmonic models for frequency response, electromagnetic transient models for dynamic behavior, and root mean square models that trade fidelity for faster computation (Commission Regulation (EU) 2016/1388, 2016, Article 21). This necessitates efficient HF simulation models of VFDs, deployable within DTs, known as virtual drives. Utilizing virtual drives is essential for both enhancing the design process with increased flexibility, reliability, and faster testing speed, as well as streamlining commissioning processes, improving energy efficiency, and ensuring safety during testing, thereby contributing to overall sustainability.

Our case study uses VFDs simulation model implemented in Simulink (Simulink 2024b User's Guide), a causal modeling environment, where (1) several configurations of software components can be tested in a controlled environment with specified input conditions and support infrastructure; and (2) the concept of model-based design is employed, which includes automatic generation of C++ code for control algorithms tailored to the targeted architecture. This concept allows simulation models to follow physical VFDs one-to-one in terms of application and control software. Additionally, the Functional Mockup Interface (FMI) (Blochwitz et al. 2011) standard allows each dynamic model to be exported as a component implementing FMI called Functional Mockup Unit (FMU), for execution of hardware-in-the-loop simulations or exchange with relevant stakeholders for classic or co-simulations. However, the HF requirements of some VFD applications significantly increase computational demands. The resulting simulation slowdowns are caused by highly stiff models in systems with oscillating behavior like insulated-gate bipolar transistors. Therefore, alternative execution models with at least real-time simulation speed are needed.

Current approaches in industry for accelerating VFDs' HF simulations primarily rely on reduced-order-models of components like converters or IMs (Thiringer and Luomi 2001). Faster simulations can also be achieved by limiting control choices, disabling unnecessary features, and later redefining component interfaces to pre-built nested component FMUs with their own solvers. While these approaches accelerate VFDs simulations, they sacrifice some of the detailed knowledge or functionality behind HF models which opens possibilities to employ SMing for simulation enhancement, on which we elaborate in the following.

2.2 Enhancing Simulations through Surrogate Modeling

SMing has emerged as an effective and highly popular tool for performing HF simulations within inexpensive timeframes (Alizadeh et al. 2020). This work aims to enhance simulation efficiency by enabling execution of substantially more simulations with the same computational resources, excluding other SM applications such as uncertainty quantification or feasibility analysis. According to Tahkola et al. (2020) and references therein, SMs are classified into three types: (1) hierarchical models that preserve the physics-based nature of the original HF models and trade execution speed for coarser meshes or neglecting some physical phenomena (often demanding years of expertise to fully grasp); (2) projection-based models, reducing the model order by iteratively projecting HF model onto subspaces which is intrusive and often insufficient in real-time applications; and (3) data-driven models, providing input-output mapping without knowing the underlying system. As presented in our recent review (Šturek and Lazarova-Molnar 2025), data-driven SMing includes various approaches relying on interpolation (radial basis functions and kriging); polynomials (surface regression or chaos expansion); and neural networks (support vector regression or artificial neural networks). Modern data-driven SMing combines SMs with machine/deep learning (DL) into architectures like Long Short-Term Memory (Hochreiter and Schmidhuber 1997), Continuous Time Echo State Networks (Anantharaman et al. 2020), Physics-Informed Neural Networks (Raissi et al. 2019), or Neural Ordinary Differential Equations (Chen et al. 2018) etc. In these approaches, the main idea is to forgo a large up-front cost associated with the model training to achieve rapid inference later. Subsequently, we discuss data-driven SMs that utilize deep learning (DLSMs) in more detail.

2.3 Deep Learning with Surrogate Models

Blending DL with simulations can help bridge the knowledge gap between these techniques by combining causal relationships from physics-based simulation models with DL's capability to uncover hidden dependencies that might still be present even in HF models. This way, simulation results can be given broader contexts, facilitate selective SMing, and more efficient parameter studies (von Rueden et al. 2020). Moreover, data-driven SMs empowered by DL provide predictions at a fraction of time (Legaard et al. 2023) and improve prediction performance with large scale problems and complex data patterns. Leveraging the universal approximation theorem, stating that there exists a neural network that can approximate any continuous function to the desired accuracy, research has explored different fields where DLSMs can be employed to advance HF simulations. These include fluid dynamics (Sun et al. 2020), gravitational wave astronomy (Khan and Green 2021), aerodynamic design applications (Sun and Wang 2019) or 340-fold acceleration with less than 4% error in dynamics of heating and air conditioning systems (Rackauckas et al. 2022). Additionally, DLSMs have also been used to accelerate simulations of solid mechanics (Haghighat et al. 2021), exothermic heat transfer (Amini Niaki et al. 2021), or finite element-based permanent magnet synchronous machines with 2000x speed up factor (Tahkola et al. 2020).

These successful applications motivate us to develop DLSMs for enhancing VFDs simulations. Electrical motors, as one of the several components contributing to VFDs simulations, have been the focus of research exploring the use of DL. Approaches in this area primarily target condition monitoring or detection and diagnostics of electrical or mechanical faults in stator, rotor and bearings (Zhang et al. 2020; Gangsnar and Tiwari 2020; AlShorman et al. 2020). From SMing perspective, a common objective is to optimize motor designs at reduced computation cost (Cheng et al. 2024) by predicting torque and current transients from finite element analysis simulation data (Keränen et al 2020; Takhola et al. 2022). In the following subsection, we outline the underlying network architecture used for DLSMs in this case study.

2.3.1 Surrogate Model Architecture

When selecting an appropriate DL architecture, we consider three key criteria: (1) the multivariate regression nature of the problem; (2) industry requirements on software toolchain allowing integration of SMs into existing VFDs simulation models; and (3) suitability and scalability of the architecture when automating SMing workflow in the future. For this exploratory case study, we choose Long Short-Term Memory (LSTM), a class of recurrent neural networks originally introduced in (Hochreiter and Schmidhuber 1997) and further improved in (Graves 2013). We select the LSTM architecture due to its capacity to retain temporal dependencies across sequences. This is achieved through its internal memory cells and specialized gating mechanisms, including input, output, and forget gates. These components enable LSTM networks to effectively capture long-term dependencies. Furthermore, they help mitigate common training issues such as vanishing and exploding gradients (Shiri et al. 2024).

LSTM-based surrogates are particularly well-suited to our application for several reasons: (a) they were shown to effectively handle multivariate regression problems across several tasks (Shiri et al. 2024); (b) they facilitate automation of SMing workflow with, e.g., automated ML (Baratchi et al. 2024), as they do not incorporate inductive biases from encoded physics, although doing so could enhance their fidelity and interpretability (Karniadakis et al. 2021; von Rueden et al. 2021) especially if used as component level SMs; and (c) they can seamlessly be integrated into the existing VFDs simulation workflow utilizing model-based design in the industry in the future (Simulink 2024b User's Guide).

Our SMs process batched sequences of multivariate input features matching the IM interface from the PCC model, which are passed through subsequent hidden layers. Specifically, we use SM architecture that stacks 4 LSTM hidden layers with hyperbolic tangent activation function, chosen for its support for cuDNN optimizations (Keras LSTM documentation). With deeper architecture, we aim to enable the learning of hierarchical representations, enhancing the understanding of intricate sequences. The first three LSTM layers contain 128 neurons each, while the final layer comprises 64 neurons, distilling essential information from data. For generating predictions, our LSTM surrogates employ a fully-connected regression output layer, with a size corresponding to the number of outputs in IM component, on which we elaborate next.

2.4 Induction Motor Component Basics

The IM model is one out of several power conversion and control (PCC) model subsystems shown in Figure 1(a), representing different functionalities like power conversion, motor and grid control, protections etc. Thus, setting up inputs of the PCC model from application software allows adjustment of the underlying control algorithms to control the plant model (compressor, fan, hydraulic pump etc.) or simulated load profiles connected to the IM model outputs. In our case study, we use a basic Simulink model of a three-phase IM as presented in (Holtz 1996), rated at 7.5kW, 50Hz, 400V, 14.6A, 1450Nm with power factor $\cos \Phi = 0.83$ and motor resistance $R_s = 0.7531$ that operates according to the mechanical speed input ω_m on three-phase pulse width-modulated stator voltages U_{Suvw} from converter.

From a control perspective, modeling IMs as direct current machines avoids time-varying steady state values in energy transfer. Thus, our HF IM model utilizes the well-known Clarke and Park transformations for three-phase stator voltages U_{Suvw} and currents I_{Suvw} among three-phase stationary (*abc)*, two-axes fixed (*αβ)* or rotating (*dq*) relative to stator, reference frames as illustrated in Figure 1(b). We refer the Interested readers to (O'Rourke et al. 2019) and references therein for more details on these transformations.

Our IM model further comprises calculations yielding stator currents and mechanical torque outputs, utilizing some intermediate results for monitoring purposes. These intermediate calculations are also shown in Figure 1(b) and include back electromotive force E_{uvw}, electromechanical torque T_e, motor fluxes in αβ and their corresponding vector argument θ_e. We use the "s" and "r" subscripts throughout this paper to distinguish between motor's stator and rotor respectively. Following this notation, the three-phase stator and rotor currents are given by Equation (1) with the motor fluxes by Equation (2), where mutual magnetization inductance L_m contributes to magnet coupling between stator and rotor to facilitate energy transfer. In the next section, we provide a detailed description of our VFDs case study.

$$I_s = \frac{U_s}{R_s} = \frac{d\bar{\psi}_s}{dt} \text{ and } I_r = \frac{U_r}{R_r} = \frac{d\bar{\psi}_r}{dt} \tag{1}$$

$$\bar{\psi}_s = I_s L_s + I_r L_m \text{ and } \bar{\psi}_r = I_r L_r + I_s L_m \tag{2}$$

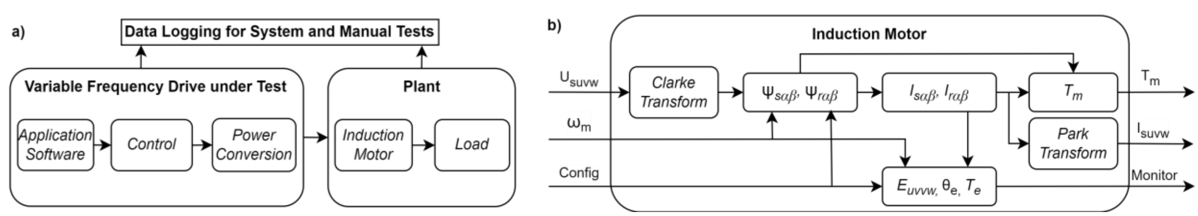

Figure 1: (a) A simplified block diagram of power conversion and control model with (b) a detail on calculations inside high-fidelity induction motor case study component not accounting for phenomena like magnetic saturation or temperature losses present in real induction motors.

3 CASE STUDY: VARIABLE FREQUENCY DRIVES

Our case study on VFDs begins with an investigation into the performance of the PCC model. Through several exemplary simulations, we observe the following: (1) The PCC model, when executed as co-simulation FMU, runs approximately 6 to 10 times slower than real-time. This significant slowdown prevents the efficient deployment of VFD simulation models inside near-real-time DTs (virtual drives). The slowdowns are primarily due to several HF model subsystems, such as inverters, rectifiers, loads, and fault detection mechanisms. (2) The control component, which includes pulse-width modulation responsible for controlling IGTBs, has the most significant impact on the overall model performance, surpassing the power conversion, load, and IM components, respectively. (3) The IM component allocates the majority of its execution time to numerical integrations for calculating motor fluxes. Thanks to the simplicity of the IM component within the entire VFD simulation of HF, we selected this component for our initial case study analysis and benchmarking and proceed by presenting an experimental setup.

3.1 Experimental Setup

With experimental setup, we describe the development of LSTM-based DLSMs for our IM case study component within VFD simulations. In the following, we outline the methodologies that we used to train the SMs and the techniques we used to generate synthetic datasets.

3.1.1 Synthetic Data Generation

Recognizing the inextricable link between DL and data, we first generate a synthetic dataset to represent the systematic behavior of the VFD. Thanks to the application of model-based design concept in HF simulations, any generated datasets exhibit a high degree of accuracy in representing the control performance of the real VFD. In this scenario, an IM is attached to a conveyor belt used for goods transportation in the food and beverage industry. We run forward simulations in MATLAB/Simulink, acting as black-boxes to produce data for our data-driven SMs. To ensure consistency, we keep IM-related parameters constant while varying only those influencing the IM operating conditions.

We define this variation in systematic behavior as a basic VFD motor control scenario, illustrated in Figure 2(b), as follows: (1) The VFD initially ramps up the motor to the reference frequency f_{ref} at zero load within the acceleration time t_{acc}, relative to the nominal motor speed. (2) Next, we simulate 10 step mechanical loads, applied in random order, with amplitudes ranging between 10% and 100% of the nominal mechanical torque T_m. The exact step torque profile is highlighted in green. (3) After the application of the last step load, the VFD ramps down the IM to zero speed within deceleration time t_{dec}.

To reduce the computational cost of HF simulations while still covering the design space uniformly, we employ Latin Hypercube sampling for design of experiments which offers high accuracy with less computation time invested (Alizadeh et al. 2020). We utilize 256 simulation sample runs instead of grid sampling, as shown in Figure 2(a). Note that the solutions of these simulations are obtained using a 4th and 5th order Runge-Kutta integration scheme with an adaptive step size. The number of samples obtained from each simulation varies due to the total adaptive simulation length determined by the reference speed at which the step loads are applied, and acceleration and deceleration times obtained from the design of experiments based on the design space from Figure 2(a).

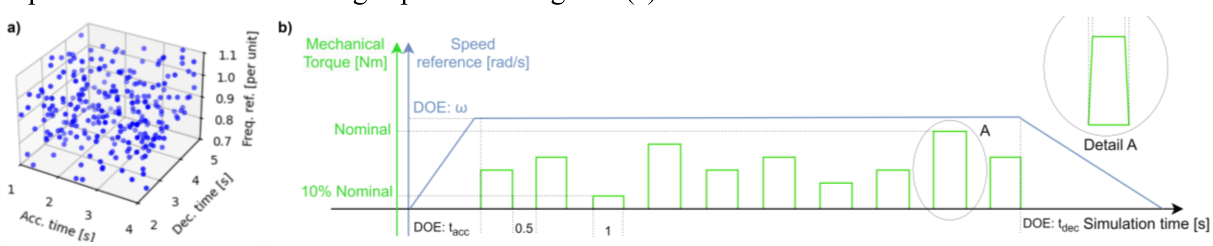

Figure 2: (a) Design of experiments (DOE) using 256 Latin Hypercube samples for determining reference speed ω_m, acceleration t_{acc} and deceleration t_{dec} times for induction motor control. (b) A systematic behavior of induction motor case study component (blue) controlled with variable frequency drive and applied exemplary mechanical torque T_m load profile (green) used to generate synthetic data.

To construct the dataset, we log time series data at regular intervals from each simulation run associated with the IM, consisting of simulation time stamps, values of voltages and currents in three phases, speed reference, and mechanical torque, visualized in exemplary simulation result in Figure 3. In total, the dataset comprises 64,514,048 data points for each logged variable. We refer to this dataset as D_{256} and use it for training and validation of our SMs throughout this paper unless stated otherwise.

To gain insight into how the prediction accuracy of SMs scales with data, we generate three additional synthetic datasets, each representing the IM's response to step loads. Using the same design space ranges from Figure 2(a), we systematically reduce the number of sample points in 25% decrements, yielding datasets D_{192}, D_{128}, D_{64}, where the subscript denotes the number of simulation runs.

Finally, we examine how prediction accuracy of SMs generalizes across different motor resistances and load profiles. To this end, we simulate conditions with ±20% motor resistance relative to the IM's rated value, using the last point from the design space covered by 256 simulations (D_{Rs}). In VFD applications controlling fans, the load profile is characterized by a quadratic relationship, where a small torque at zero speed progressively builds up to nominal torque at nominal speed. To simulate the fan conditions, we retain the original 256 sample points but apply a single fan load profile instead (D_{Fan}). All features in the five datasets are scaled between zero and one, a method proven to reduce training data size requirements, enhancing prediction accuracy, and improving training stability (Sun and Wang 2019). Subsequently, we proceed with training the SMs, which we elaborate on next.

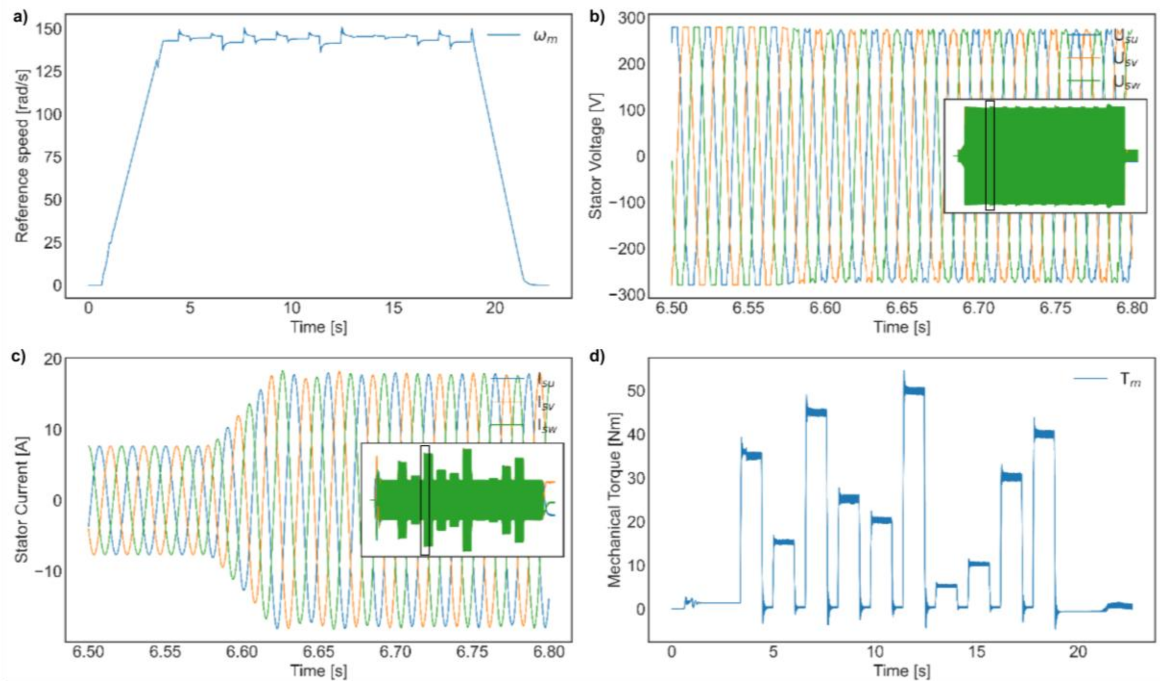

Figure 3: Exemplary simulation result of variable frequency drive controlling induction motor to the reference speed ω_m (a) by adjusting three-phase stator voltages U_{suvw} (b) to obtain corresponding stator currents I_{suvw}(c), and mechanical torque T_m (d) responses to the applied step load torques.

3.1.2 Training of Surrogate Models

As for the toolchain, we train our DLSMs in Python, leveraging TensorFlow 2.18.0 and Keras 3.7.0 API. To accelerate the execution of training algorithms, we exploit the parallel processing capabilities of an NVIDIA Tesla T4 GPU. Through experimentation with batch sizes and careful monitoring of GPU memory usage, we find an optimal batch size of 128, which we apply consistently across all SM trainings.

Besides D_{Rs}, which only serves for validation purposes, we split all remaining synthetic datasets into 85% training and 15% validation HF data, ensuring its distribution across the entire design space. We then proceed to training of LSTM surrogates on D_{64} to D_{256}, considering three distinct sequence lengths of 10, 32 and 64 samples denoted as $LSTM_{10}, LSTM_{32}, LSTM_{64}$. The training procedure utilizes the Adam optimizer with an initial learning rate of 1e-3 to minimize the mean squared error loss function for 50 epochs. To enhance training stability and mitigate overfitting, we employ a series of callbacks including:

(1) dynamic learning rate reduction, lowering learning rate of the optimizer by a factor of 0.25 when the validation loss plateaus for consecutive 4 epochs, subject to a minimum learning rate of 1e-6; (2) early stopping, terminating the training if validation loss doesn't improve for 5 consecutive epochs and restoring the best weights observed; and (3) training checkpoints, saving the model weights after each epoch if the model exhibits validation loss improvement, allowing us to retain the best-performing model. Next, we present the experimental results and benchmarks associated with our VFDs case study.

3.2 Experimental Results and Benchmarking

When benchmarking DLSMs and evaluating case study results, we base our analysis on the following key performance indicators: (1) the duration required to train the SMs; (2) the degree of accuracy retained in the surrogate predictions; (3) the impact of unseen data on the predictive performance of the SMs.

We first examine the implications of sequence length and dataset size on the associated training times as shown in Table 1. For example, utilizing 64 training sequences, as opposed to 10, resulted in nearly a two-fold increase in training duration when trained on the largest dataset. However, this trend diminishes in significance as the dataset size decreases. Training with less data thus allows for greater flexibility in enhancing the prediction accuracy of LSTM-based SMs by extending sequence length, while incurring smaller penalty in training duration. Examining the training times further reveals that doubling the dataset size results in a substantial increase in training duration but the relationship is not strictly linear. In the future, we intend to gather additional data to continue exploring its impact on the SM training duration.

Table 1: Experimental results for Long Short-Term Memory surrogates of an induction motor with different sequence lengths. The table details training times (subject to early stopping “ES”) and root mean squared errors (RMSE) calculated for synthetic validation data and distinct motor resistances. We only show the first phase if stator current predictions are similar across all three phases.

Surrogate Model	Training Dataset	Training Time (h)	RMSE on D_{256}			R_s	RMSE on D_{Rs}			
			T_m	I_{su}	Total		T_m	I_{su}	I_{sv}	I_{sw}
$LSTM_{10}$	D_{64}	7.91 ES	6.0738	1.7093	3.3835	-				
	D_{128}	33.85	3.7757	1.0624	2.1012					
	D_{192}	45.93	2.2706	0.6478	1.2705					
	D_{256}	60.99	1.0896	0.3332	0.6162	-20%	0.5297	0.6022	0.4403	0.5297
						rated	0.2735	0.2762	0.2704	0.2735
						+20%	0.4730	0.5118	0.4181	0.4730
$LSTM_{32}$	D_{64}	6.78 ES	3.3779	0.9676	1.8982	-				
	D_{128}	40.43	2.6796	0.8173	1.5408					
	D_{192}	64.18	2.6290	0.7673	1.4771					
	D_{256}	75.44	0.5480	0.1778	0.3143	-20%	0.6150	0.4919	0.5672	0.4095
						rated	0.1849	0.1876	0.1884	0.5842
						+20%	0.4006	0.4623	0.3621	0.8377
$LSTM_{64}$	D_{64}	8.68 ES	3.5745	1.1006	2.0316	-				
	D_{128}	54.92	3.9922	1.1951	2.2368					
	D_{192}	84.16	1.6007	0.5277	0.9087					
	D_{256}	110.77	0.2419	0.0911	0.1446	-20%	0.4599	0.4702	0.5537	0.3860
						rated	0.2516	0.0872	0.0860	0.0933
						+20%	0.3943	0.3520	0.4169	0.3127

Next, we evaluate the capability of SMs to mimic the HF behaviors. To enhance the interpretability of the results, we preserve the units of the original data by computing the root mean squared error (RMSE) metric between HF validation data from the IM component and LSTM surrogate predictions. As shown in Table 1, increased sequence length yields more accurate SMs, albeit at the cost of prolonged training times.

For all sequence lengths and the models trained on D_{256}, we conducted an analysis comparing worst and best-case simulation validation runs. Our findings revealed that these models had a common worst case simulation, with a 10-20% higher total RMSE compared to the second worst. Notably, the design parameters used for executing this simulation were not located at the corners of the design space depicted in Figure 2(a). We attribute this performance discrepancy to resonance within the system, where the control algorithms attempt to compensate through voltage drops, thereby inducing additional torque oscillations in the IM. These oscillations further challenge the prediction capabilities of the SMs.

Short sequences might lead to high frequency oscillations in SM predictions, particularly in regions where the IM undergoes load torque steps as illustrated in Figure 4(a-b). We speculate this can be attributed to the solver taking steps as low as 2e-14 around these locations to accurately capture the dynamics while we only log the simulation data at 1e-4 rate. Consequently, lower sequences may not provide the SMs with long-term memory needed to stabilize the predictions.

As the dataset size scales from 64 to 256 simulations, the design space becomes covered more densely, resulting in higher-fidelity LSTM SMs independently from sequence length, as shown in Table 1. However, each model enhancement in SMing incurs computation when evaluating HF model. In Figure 4(c), we show the encountered trade-off when aiming to improve fidelity of DLSMs. Each heatmap element shows the RMSE improvement percentage relative to the baseline at the smallest dataset size, where the risk of overfitting is highest due to constant validation data, evidenced by early stoppings. Negative RMSE improvement for $LSTM_{64}$ trained with 128 simulations indicates overfitting, potentially capturing broader patterns better suited to the validation set. Mitigation strategies could include simpler models, adjusted training or, e.g., logarithmic re-sampling of reference speed input to emphasize load step torque regions.

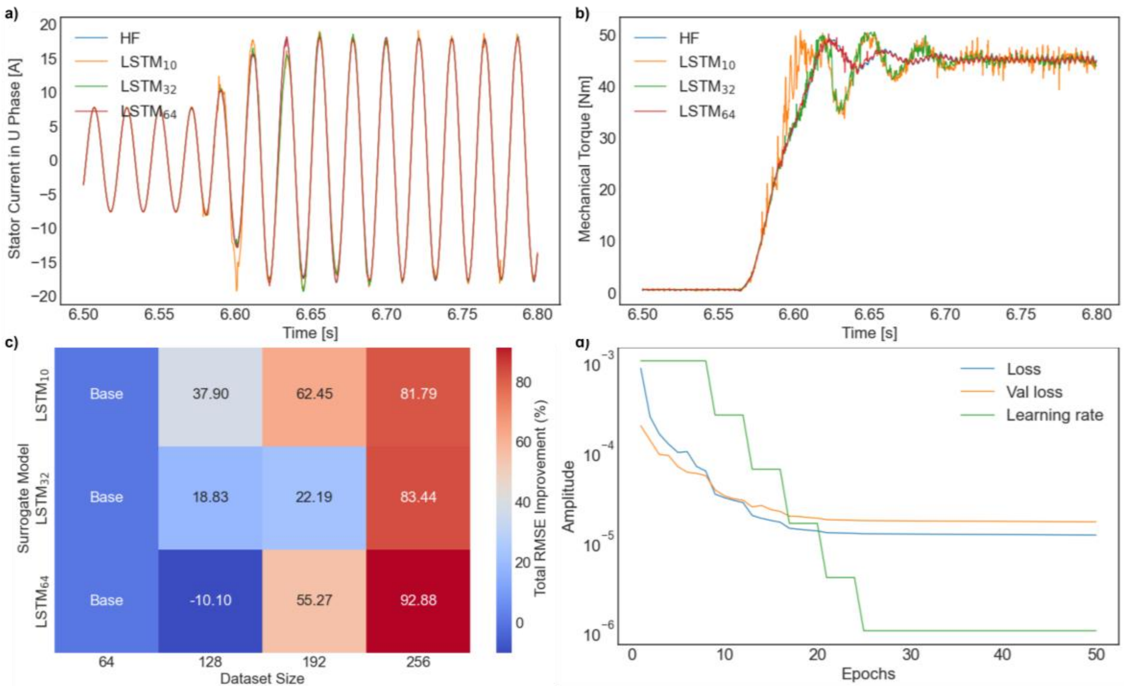

Figure 4: A comparative detail on high-fidelity solution and predictions from the surrogates where lower sequence lengths models exhibit oscillatory performance and struggle to accurately capture transitions immediately following load torque step in both currents (a) and mechanical torque (b). (c) Trade-off associated with training of surrogates with percentage improvement on total RMSE annotating heatmap elements and (d) logarithmic training history for $LSTM_{64}$ surrogate trained on 192 simulations.

While our IM surrogates could further benefit from more data points before RMSE improvement would plateau, we emphasize that these results will serve as a basis for our future work on developing SMs for VFD systems, rather than concentrating on individual components. The findings highlight the critical role of training data in SMs, enabling them to capture intricate relationships and boost fidelity. While Kaplan et al. (2020) demonstrated that increasing compute, model size and training data in tandem could further improve the prediction performance of DL-based Large Language Models, we leave an analogous analysis for SMs, also based on DL, to future work. We will also investigate automation of surrogate modeling simulation enhancement workflow for VFDs through generative artificial intelligence represented in multi agent-based framework such as AutoGen (Qingyun et al. 2023).

Building on the aforementioned insights, we evaluate the out-of-sample performance of our SMs under varying motor resistances and load torque profiles. Table 1 presents the key results of this analysis. Higher motor resistance due to temperature rise or load increase in IMs, affects mechanical torque build-up by reducing the efficiency of energy conversion. This often leads to slower torque response, which the IM may compensate for by increasing stator currents, thereby drawing more power and generating additional heat.

Generally, we observe that the predictive performance of our SMs on stator currents is more sensitive to lower motor resistances, with variations particularly impacting I_{sv} and I_{su} rather than I_{sw} predictions across all SMs. This underscores that designers need to be notified when using data-driven SMs outside their reliability region as the observed relationships can change drastically. Due to the lower frequency and amplitude of torque transients at higher resistances, LSTM-based SMs with longer sequences generalize better in these scenarios. Conversely, capturing the more oscillatory relationships induced by lower motor resistances is advantageous with SMs using shorter sequences.

In industry, VFDs are employed in a wide range of applications with unique operational demands, necessitating IM surrogates performing across different load profiles. Without exposing our SMs to any data associated with fan loads, we investigated if the surrogates trained on conveyor belt mechanical loads can generalize to fan load profiles. Although the SMs still could track the main behavior of stator currents, the associated RMSEs were notably higher. However, the SMs failed to capture the fan loads below approximately half the nominal speed during both phases when VFD either ramps down or decelerates the fan. To draw more meaningful conclusions and increase the scope of SMs for several VFDs applications, further work is needed in generating HF synthetic data across various load profiles and motor types. Hereby, we plan to reduce bias in SMs by drawing validation and test data from other design of experiment methods.

In future work, we will continue validating our SMs by coupling them inside existing VFDs simulation framework and running them alongside other HF components in PCC Simulink model to evaluate their predictive performance within a larger system. A key challenge to address is that the IM surrogates must provide predictions to be used as inputs for the control algorithms inside the PCC at each subsequent simulation step. This means minor prediction errors can be amplified through error accumulation across other VFD simulation components, potentially leading to substantial deviations in control algorithm inputs, thereby affecting the overall VFD control performance. To facilitate this investigation, we created a variation point in the PCC model structure, allowing seamless switching between HF and surrogate IM components, thereby enabling development, verification and validation of SMs in parallel to the original HF components inside the PCC model. Furthermore, we will determine speed up factors to explore whether our SMs can enable real-time VFDs simulations. We will export our SMs as FMUs and benchmark their execution speed against their HF counterparts. We dedicate the next Section to discussing potential avenues for future work and summarizing our main findings.

4 SUMMARY AND OUTLOOK

This industrial case study paper explores the combination of surrogate models (SMs) and deep learning (DL) for enabling real-time Digital Twin applications. We target high-fidelity (HF) induction motor (IM) component in larger power conversion and control model of variable frequency drives (VFDs) simulations.

We generated synthetic datasets using Latin Hypercube sampling to represent IM's behavior in conveyor belt applications. Next, we trained Long Short Term Memory-based SMs with varying sequence lengths and dataset sizes, analyzing prediction accuracy, training duration, and out-of-sample generalization. Our findings show that: (1) SMs achieve prediction accuracy with a total root mean squared error as low as 0.1446, while being sensitive to oscillations from suboptimal performance of control algorithms at specific operation points; (2) training duration exhibits a nonlinear relationship with dataset size, leading to significant improvements in accuracy; (3) SMs generalize well to varying motor resistances where lower values predominantly affect current and higher values torque predictions; and (4) SMs fail to capture mechanical torque transients when generalizing to fan load profiles unless more synthetic data is generated, indicating a need for further work.

These preliminary findings lay the groundwork for our future research, highlighting several key avenues for further development. Our future work will focus on coupling SMs in place of HF components to evaluate speed up factors, while generalizing the achievements from this case study by developing additional SMs, including architectures like Nonlinear Autoregressive Exogenous Gaussian Process or Neural Ordinary Differential Equations. Rather than creating multiple component specific SMs in VFDs simulations, we will prioritize system-level SMs, where the entire VFD is black-boxed and strictly parametrized in application software to serve specific applications under well-defined settings. Additionally, we plan to explore the automated creation of DL-based SMs, implemented in cloud-based workflow querying HF data from executing VFDs Functional Mockup Units. Developing this workflow will involve examining scaling laws related to model size, dataset size, and computation. Moreover, we will explore the use of generative artificial intelligence within an agent-based framework to automate the simulation enhancement workflow with SMs for VFDs.

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REFERENCES

Alizadeh, R., J. K. Allen, and F. Mistree. 2020. “Managing Computational Complexity Using Surrogate Models: A Critical Review”. *Research in Engineering Design* 31:275–298.

AlShorman, O., M. Irman, N. Saad, D. Zhen, N. Haider, A. Glowacz *et al*. 2020. “A Review of Artificial Intelligence Methods for Condition Monitoring and Fault Diagnosis of Rolling Element Bearings for Induction Motor”. *Shock and Vibration* 1.

Amini Niaki, S., E. Haghighat, T. Campbell, A. Poursartip, and R. Vaziri. 2021. “Physics-informed neural network for modelling the thermochemical curing process of composite-tool systems during manufacture”. *Computer Methods in Applied Mechanics and Engineering* 384.

Anantharaman, R., Y. Ma, S. Gowda, C. Laughman, V. Shah, A. Edelman *et al*. 2020. “Accelerating Simulation of Stiff Nonlinear Systems using Continuous-Time Echo State Networks”. *arXiv preprint arXiv: 2010.04004*.

Baratchi, M., C. Wang, S. Limmer, J. van Rijn, H. Hoos, T. Bäck *et al*. 2024. “Automated machine learning: past, present and future”. *Artificial Intelligence Review* 57(122).

Blochwitz, T., M. Otter, M. Arnold, C. Bausch, C. Clauß, H. Elmqvist *et al*. 2011. “The functional mockup interface for tool independent exchange of simulation models”. In *Proceedings of the 8th International Modelica Conference*, March 20th-22nd, Dresden, Germany.

Chen, R. T. Q., Y. Rubanova, J. Bettencourt, and D. Duvenaud. 2018. “Neural ordinary differential equations”. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems (NIPS'18)*, December 3rd-8th, Montreal, Canada, 6572–6583.

Cheng, M., X. Zhao, M. Dhimish, W. Qiu and S. Niu, 2024. "A Review of Data-Driven Surrogate Models for Design Optimization of Electric Motors". *IEEE Transactions on Transportation Electrification* 10(4):8413–8431.

Commission Regulation (EU) 2016/1388 of 17 August 2016 establishing a Network Code on Demand Connection (Text with EEA relevance), Article 21, C/2016/5239. http://data.europa.eu/eli/reg/2016/1388/oj, accessed 11th April 2025.

Gangsar, P. and R. Tiwari. 2020. “Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review”. *Mechanical Systems and Engineering* 144:106908.

Graves, A. 2013. “Generating Sequences With Recurrent Neural Networks”. *arXiv preprint arXiv: 1308.0850*.

Haghighat, E., M. Raissi, A. Moure, H. Gomez, and R. Juanes. 2021. “A physics-informed deep learning framework for inversion and surrogate modeling in solid mechanics”. *Computer Methods in Applied Mechanics and Engineering* 379(1):113741.

Hochreiter, S. and J. Schmidhuber. 1997. “Long Short-Term Memory”. *Neural Computation* 9(8):1735-1780.

Holtz, J. 1996. “State of the art of controlled AC drives without speed sensors”. *International Journal of Electronics* 80(2):249–263.

Kaplan, J., S. McCandish, T. Heninghan, T. B. Brown, B. Chess, R. Child *et al*. 2020. “Scaling Laws for Neural Language Models”. *arXiv preprint arXiv: 2001.08361*.

Karniadakis, G. E., Y. Kevrekidis, L. Lu, P. Perdikaris, S. Wang and L. Yang. 2021. “Physics-informed machine learning”. *Nature Reviews Physics* 3:422–440.

Keränen, J., M. Tahkola, P. Råback, A. González, V. Mukherjee, and J. Pippuri-Mäkeläinen. 2024. “Robust Development of Active Learning-Based Surrogates for Induction Motor”. *IEEE Transactions on Magnetics* 60(3):1–4.
Khan, S. and R. Green. 2021. “Gravitational-wave surrogate models powered by artificial neural networks”. *Physical Review D* 103(6):064015.
Koziel, S. and X. Yang. 2011. *Computational Optimization, Methods and Algorithms*. Berlin: Springer-Verlag.
Legaard, C., T. Schranz, G. Schweiger, J. Drgoňa, B. Falay and C. Gomes. 2022. “Constructing Neural Network Based Models for Simulating Dynamical Systems”. *ACM Computing Surveys* 55(11):1–34.
Mohan, N., T.M. Undeland, and W.P. Robbins. 2003. *Power Electronics: Converters, Applications, and Design*. 3rd ed., New York: John Wiley & Sons, Inc.
O’Rourke, C., M. Overlin, and J. Kirtley. 2019. “A Geometric Interpretation of Reference Frames and Transformations: dq0, Clarke and Park”. *IEEE Transactions on Energy Conversion* 34(4):2070–2083.
Qingyun, W., G. Bansal, J. Zhang, Y. Wu, B. Li, E. Zhu *et al*. 2023. “AutoGen: Enabling Next-Gen LLM Applications via Multi-Agent Conversation”. *arXiv preprint arXiv: 2308.08155.*
Rackauckas, C., M. Gwozdz, A. Jain, Y. Ma, F. Martinuzzi, E. Saba *et al*. 2022. “Composing Modeling And Simulation with Machine Learning In Julia”. In *Annual Modeling and Simulation Conference (ANNSIM)*, July 18th-20th, San Diego, CA, USA.
Raissi, M., P. Perdikaris, and G. Karniadakis. 2019. “Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations”. *Journal of Computational Physics* 378: 686–707.
Rasheed, A., O. San, and T. Kvamsdal. 2020. “Digital Twin: Values, Challenges and Enablers From a Modeling Perspective”. *IEEE Access* 8:21980–22012.
Shiri, F. H., T. Perumai, N. Mustapha and R. Mohamed. 2024. “A Comprehensive Overview and Comparative Analysis on Deep Learning Model”. *Journal on Aritficial Intelligence* 6(1):301–360.
Sun, L., H. Gao, S. Pan and J-X. Wang. 2020. “Surrogate Modeling for Fluid Flows Based on Physics-Constrained Deep Learning Without Simulation Data”. *Computer Methods in Applied Mechanics and Engineering* 361(4):112732.
Sun, G., and S. Wang. 2019. “A review of the artificial neural network surrogate modeling in aerodynamic design”. In *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering* 233(16):5863–5872.
Šturek, D., and S. Lazarova-Molnar. 2025. “Surrogate Modeling Approaches: A Review and Opportunities for Expert Knowledge Integration”. *Procedia Computer Science* 257(3):826–833.
Tahkola, M., J. Keränen, D. Sedov, M. F. Far, and J. Kortelainen. 2020. “Surrogate Modeling of Electrical Machine Torque Using Artificial Neural Networks”. *IEEE Access* 8:220027–220045.
Tahkola, M., V. Mukherjee, and J. Keränen. 2022. “Transient Modeling of Induction Machine Using Artificial Neural Network Surrogate Models”. *IEEE Transactions on Magnetics* 58(9):1–4.
The MathWorks, Inc. 2024. *Simulink 2024b User's Guide*. Natick, Massachusetts: The MathWorks, Inc.
Thiringer, T. and J. Luomi. 2001. "Comparison of reduced-order dynamic models of induction machines". *IEEE Transactions on Power Systems* 16(1):119–126.
von Rueden, L., S. Mayer, K. Beckh, B. Georgiev, S. Giesselbach, R. Heese *et al*. 2021. “Informed Machine Learning - A Taxonomy and Survey of Integrating Prior Knowledge into Learning Systems”. *IEEE Transactions on Knowledge and Data Engineering* 35(1):614–633.
von Rueden, L., S. Mayer, R. Sifa, C. Bauckhage, and J. Garcke. 2020. “Combining Machine Learning and Simulation to a Hybrid Modelling Approach: Current and Future Directions”. In *Advances in Intelligent Data Analysis XVIII*, edited by M. R. Berthold, A. Feelders and G. Krempl, 548–560, Cham: Springer.
Zhang, S., S. Zhang, B. Wang, and T. G. Habetler. 2020. “Deep Learning Algorithms for Bearing Fault Diagnostics-A Comprehensive Review”. *IEEE Access* 8:29857–29881.

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