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Review

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Review

Real-Time Simulation for Intelligent Fault Diagnosis and Condition-Based Monitoring of Electrical Machines

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Abstract

This article presents an overview of selected reserach focusing on digital real-time simulation (DRTS) with the primary aim of intelligent fault diagnosis (FD) and condition-based monitoring (CBM) of electrical machines. Conventional multiphysics offline digital simulations are widely utilized in the conceptualization and development phases of industrial product manufacturing and processing, particularly for virtual testing under both standard and extreme operating conditions as well as for aging assessments and lifecycle analysis. Recent advancements in data communication and information technologies, including virtual reality, cloud computing, parallel processing, machine learning, big data, and the Internet of Things, have facilitated the creation of intelligent physical and mathematical models. These models are distinguished by their ability to enable real-time bidirectional data exchanges with physical systems. This article highlights recent progress and key challenges in this emerging field, with particular emphasis on real-time multiphysics modeling to enhance the efficiency of FD and CBM of electrical machines, which play a crucial role in industrial applications

Keywords: condition monitoring; digital simulation; digital twins; electric machines; hardware-in-the-loop simulation, fault diagnosis; machine learning; predictive maintenance; real-time systems

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1. Introduction

Today, the design and implementation of industrial products are almost inconceivable without the initial phase of virtual prototyping supported by digital simulation (DS). DS enables the creation of a reference model that provides a precise description of a physical entity. This is commonly known as a digital twin (DT), which serves as a virtual representation of the product prior to physical prototyping [1–4]. This approach provides access to a broad range of variables that may not be directly measurable or may require sophisticated instrumentation. Using this method, industrial products can be developed more efficiently and cost-effectively through a comprehensive analysis of their entire life cycle. An important feature of the DS world is that every test and decision can be conducted and undesired conditions can be anticipated. This can facilitate tasks such as configuration, FD and CBM for preventive maintenance. Compared with real-world testing, DS offers significant time and cost savings while minimizing waste and reducing potential risks. Conducting experiments in a physical lab requires substantial time owing to the preparation and construction of experimental test benches. Additionally, laboratory testing is often constrained by facility capabilities, capacity limitations, and lack of flexibility when modifications are required. In a design process that involves multiple iterations, where each stage depends on the outcomes of the previous test, the resulting time delay can be substantial. Beyond saving time and cost, DS enables the exploration of a much wider range of variants. This gives product developers greater flexibility to innovate, test numerous combinations, and experiment with unconventional approaches, ultimately leading to a more refined and optimized

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solution. To accurately represent the physical world, DS must incorporate interactions across multiple physical domains, including electromagnetics, fluid dynamics, mechanics, thermodynamics, and materials science [5]. If DS results fail to accurately represent real-world conditions, they lose their value. Confidence in DS increases when its outcomes align with those obtained from physical tests and field experiences. Electrical machines are widely used in various industrial applications, including electric traction systems, hybrid and electric vehicles, wind and marine energy conversion, power generation, energy storage, shipboard systems, and aerospace electrification. To enhance their design and performance, digital offline simulation (DoS) is frequently used to optimize structural configurations, develop controllers, and analyze the dynamic behavior of innovative electrical machines [6].

The modeling of electrical machines can be broadly categorized into two main approaches: physics-based (PHYB) and data-driven. PHYB models primarily rely on the observation of physical phenomena and aim to represent them using mathematical formulations, which are then solved, either analytically or numerically. By contrast, data-driven models require large amounts of data during the training phase, which can be generated from partial PHYB models or experimental measurements [7]. The multiphysics modeling of electrical machines can capture various fields of physics, including electromagnetism, mechanics, vibro-acoustics, and thermal phenomena, and can be composed of several interacting PHYB or data-driven models [8–11]. Focusing on the electrical and magnetic aspects, literature commonly reports both simplified PHYB models using circuit-oriented lumped-parameter (COLP) approaches and detailed PHYB (DPHYB) models for electrical machine modeling [6]. The first relies on an electrically and magnetically coupled circuit, which is typically used for analyzing dynamic behavior of electrical machines and electromagnetic transient studies. It assumes perfect symmetry in both the field and construction, a constant air gap that is small relative to the rotor radius, a linear magnetic system, and omission of hysteresis effects. In contrast, the second method considers complex geometry, magnetic saturation, eddy current and hysteresis effects in detail and is employed for design purposes [6,12]. Clearly, the DPHYB models offer greater accuracy than the COLP models, but this comes at the cost of an increased computation time. The COLP model includes the dynamic ‘abc’ and ‘dq0’ reference frame models and the dynamic voltage-behind-reactance model in which the variables of the stator are described in the ‘abc’ reference frame and the variables of the rotor are given in the ‘dq0’ reference frame [12,13]. The ’dq0’ reference frame model can be derived from the ’abc’ reference model using Park transform, which eliminates time-varying inductances in the ’abc’ frame and simplifies the voltage equations in AC electrical machines. Self and mutual inductances of ’abc’ reference model is commonly determined based on the Winding Function Approach (WFA) or modified WFA (MWFA) when some data regarding the geometry of the machine is known [14]. Another approach is to perform basic experimental tests, through which it is possible to obtain these parameters for a simplified internal equivalent circuit model [15].

DPHYB models encompass both finite element method (FEM)-based and analytical models. In FEM-based models for electrical machines, Maxwell’s equations must be solved numerically for each mesh element, whether in 2D triangular or 3D tetrahedral configurations. Conversely, analytical models rely on explicit solutions of Maxwell’s equations and are widely employed to aid in design and analysis, particularly when an accurate calculation of the magnetic field distribution across various machine regions is essential. The accurate modeling of electric machines often relies on the FEM. However, finite element analysis (FEA) can be highly time-consuming, particularly during the initial design stages when conducting parametric studies. Two commonly used analytical models for design purposes are magnetic equivalent circuits (MEC) which relies on a permanence element network and models derived from the formal resolution of Maxwell’s equations in regions with constant permeability [16,17]. In an MEC-based model, the mesh network must be carefully designed to achieve an accuracy comparable to that of a FEM-based model. When considering the effect of iron magnetic saturation, the differential equation governing the MEC-based model transforms into a nonlinear representation of magnetic scalar potentials. To solve this, the Newton-Raphson method is typically employed, often in combination with an adaptive simulation time-step [18].

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Data-driven modeling has gained significant attention owing to the development of advanced open-source machine learning (ML) and artificial intelligence (AI) tools, user-friendly and affordable computational resources, and extensive training materials. Unlike PHYB models, this approach operates under the premise that data encapsulates both explicit and implicit physical behaviors. Therefore, when trained on sufficiently large datasets, data-driven models can independently uncover underlying physical relationships. In particular, deep learning has enabled models to achieve near-human or even superhuman performance in tasks once considered out-of-reach by computers. These models can typically be categorized into six types: supervised and unsupervised linear models, supervised and unsupervised nonlinear models, and unsupervised deep learning approaches [19]. Although the performance of data-driven models depends on the widespread availability of large-scale/big data, the proposed methodology seeks to address the limitations of relying solely on either PHYB or data-driven modeling techniques. This integrated approach, known as hybrid modeling, combines the clarity, theoretical grounding, and insight of PHYB models with the precision, computational efficiency, and pattern recognition capabilities of advanced ML and AI methods. Hybrid modeling can be conceptualized as existing at the intersection of large-scale/big data, physics-informed modeling, and data-driven techniques, as illustrated in Figure 1 [7,20]. For example, instead of relying on computationally intensive FEA, a deep neural network (DNN) is employed as a surrogate model. The DNN was trained in a supervised manner using a large dataset generated from precomputed FEA results. During inference, the outputs of network intermediate are utilized as inputs for the PHYB post-processing step, which computes characteristic maps and key performance indicators. This hybrid strategy demonstrates a significant reduction in computational time while preserving flexibility within the simulation workflow of electrical machines [21].

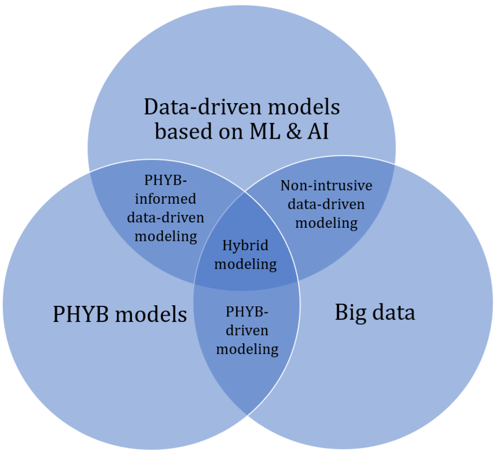

Figure 1. Scheme for hybrid modeling at the intersection of PHYB models, big data, and data-driven models [7].

The DoS concept has been widely applied in the development of fault diagnosis (FD) and condition-based monitoring (CBM) strategies for electrical machines. This approach primarily focuses on creating models that accurately incorporate various fault types, including bearing defects, static, dynamic, or mixed eccentricity, open or unbalanced circuits, short circuits in stator or rotor windings, insulation degradation, damage to rotor bars and end rings in squirrel-cage induction machines (SCIM), and demagnetization in permanent magnet synchronous machines (PMSMs) [22–25]. DoS enhances the clarity of fault signatures in physical variables that are often influenced by noise and the inherent imperfections of sensors used in experimental test setups. This makes it possible to effectively analyze early stage faults. A digital real-time simulation (DRTS) corresponds to a DoS that must operate within real-time processing constraints. In other words, the discretized model must be sufficiently swiftly computed to synchronize with real-world timing [26]. Therefore, the selected solver must be optimized to resolve the system equation within a specified time-step. DRTS is more advantageous than DoS because it can be linked to external equipment for design, test control, and robustness analysis in a hardware-in-the-loop (H-i-L) framework. H-i-L systems have been essential

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in the aerospace industry and in flight simulations for several decades [27,28]. Their application has expanded significantly in various fields, including powertrain modeling for electric vehicles, energy management in microgrids, power and energy systems, and the dynamic performance analysis of power electronic devices. Recently, this concept was proposed for the development of advanced fault diagnosis methods for electrical machines [15,29–31]. DRTS contributes to the FD and CBM of electrical machines by incorporating technologies such as virtual reality or DT, data analytics, large-scale/big data, Internet of Things (IoT), and machine learning which have been widely adopted in Industry 4.0 revolution. DT, which defines adaptable mapping of a physical system to a virtual replication [32], is a powerful and emerging technology that enables the representation of the state of health of complex systems and facilitates CBM [33,34]. This article provides an overview of selected papers on the topic of multiphysics DRTS in the context of DT for intelligent FD and CBM of electrical machines. Section II reviews the definition of DT, its emerging concepts, and the various levels and scales at which it is applied. Section III discusses the main challenges of DRTS as an enabling tool within an electrical machine DT platform. Section IV explores whether multiphysics RTDS can contribute to intelligent FD and CBM of electrical machines. Finally, the conclusion summarizes the key points and offers perspectives for future research in this domain.

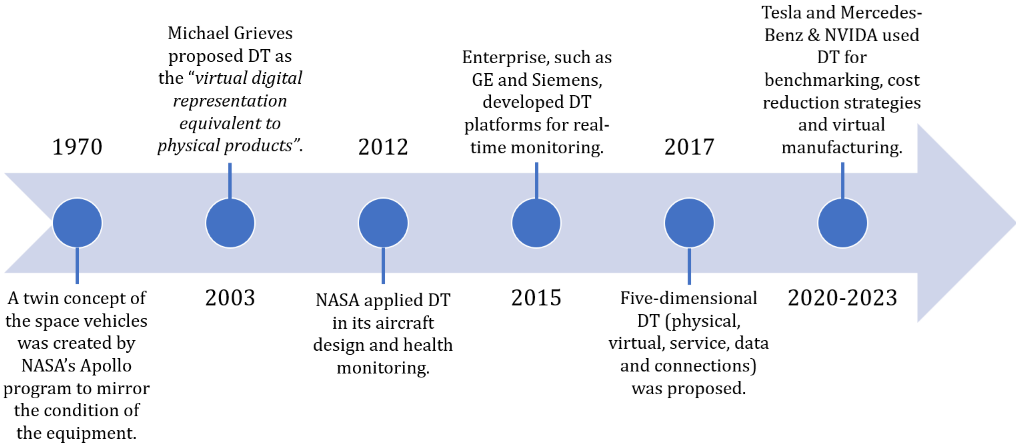

Figure 2. Timeline of DT evolution [35,36].

2. Electrical Machine Digital Twin

2.1. Digital Twin Definition

The notion of a DT can be traced back to NASA in the 1960s, when it emerged as a dynamic representation of Apollo missions. Following the explosion of an oxygen tank and damage to the main engine during Apollo 13, NASA employed several simulators to investigate the root causes of malfunction. They enhanced their physical model of the spacecraft by incorporating digital elements, creating an early version of what is now known as DT. This system allows for continuous data input, supporting both forensic analysis of the incident and the planning of subsequent actions [37]. Since its initial development, the concept of DT has gained significant attention from both academia and industry. Figure 2 illustrates the timeline of DT evolution, starting from its inception [35,36]. Numerous reviews and state-of-the-art articles have focused on enabling technologies, existing challenges, and methodologies for leveraging DT in product lifecycle management and innovation [35,38–40]. Scholars and institutions have proposed various definitions and interpretations of DT, comprehensive discussions can be found in [19,35,39–41]. For instance, Vrabic et al. [42] characterized DT as a digital counterpart of a physical asset or system, enhanced with integrated simulations and service-related data. The digital model aggregates data from multiple sources throughout the product lifecycle, which is regularly updated and represented in different formats to forecast both current and future states in design and operational contexts, thereby supporting improved decision making [39]. According to Tao et al. [38], a DT can be characterized as a high-fidelity simulation that integrates multiphysics

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and multiscale modeling, incorporating probabilistic elements. It dynamically mirrors the state of its physical counterpart using a combination of historical information, real-time sensor inputs, and physical modeling. Similarly, Rasheed et al. [7,19] defined DT as a virtual model of a physical system that utilizes real-time data and digital simulations to enable monitoring, control, optimization, prediction, and informed decision-making. Unlike traditional digital models or digital shadows, DTs are distinguished by a fully bidirectional data flow between their physical and digital counterparts that allows any change in the physical system to be immediately reflected in its digital representation [39]. More recently, Rasheed et al. [19] presented a comprehensive survey of emerging applications of DT technology in the wind turbine industry. This study presents widely recognized definitions of DT from leading organizations and researchers, including Gartner, NVIDIA, IBM, DNV, GE Digital, Siemens, Oracle, Microsoft, the Digital Twin Consortium, Trauer et al., Grieves & Vickers, and the Industrial Digital Twin Association. Table 1 summarizes these recent definitions based on key aspects: 'Things,' which indicates the scope of application covered by each definition; 'Representation,' which refers to the realization space of the digital model; 'Data,' which outlines how information is utilized; and 'Purposes,' which identifies the primary objectives of DT development.

Table 1. Summery of most popular DT definitions [19].

	Things	Representation	Data	Purposes
Gartner	*Process, physical object, organization, person, or any abstraction*	*Encapsulated software*	*Information from several DT can be collected to provide a unified perspective of real-world objects*	*Simulating an entity in real time*
NVIDA	*Real-world physical things, people, system*	*Virtual*	*Information collected from connected sensors, processed through edge computing, enables the replication of physical equipment behavior*	*Enables the autonomy of systems through the machine learning*
IBM	*Object, system*	*Virtual*	*Two-way flow of information*	*Decision-making based on simulation, machine learning, and reasoning*
DNV	*Asset, system*	*Virtual*	*Provide system information through a unified modeling and data solution*	*Offer guidance for decision-making throughout the asset lifecycle*
GE Digital	*Physical asset, system, process*	*Software*	*Real-time analytics*	*Enhance business outcomes through proactive detection, prevention, prediction, and optimization*
Siemens	*Physical product, process*	*Virtual*	*Data is used throughout the product lifecycle to simulate, predict and optimize the product before any prototyping*	*Undrestand and predict the physical counterpart's performance characteristics*
Oracle	*Physical asset, device*	*Digital*	*Updated with operational data and can be combined with physics-based models*	*Virtual sensor, detect anomalous behavior and prevent anomalies*
Microsoft	*Object*	*Digital exact replica*	*Data from monitoring devices for real-time view of asset*	*Improve the real-life version*
Digital twin consortium	*Real-world entities and processes*	*Virtual that is synchronized at a specified frequency and fidelity*	*Use real-time and historical data to represent the past and present*	*Transform business, simulate predicted futures*
Trauer et *al.*	*Physical system*	*Virtual dynamic*	*Bidirectional information exchange, and the connection along the entire lifecycle*	*Improvement of product development by refining requirements, easing troubleshooting, or supporting after sales*
Grieves, Vickers	*Physical manufactured product*	*Virtual equivalent from the micro atomic level to the macro geometrical level*	*Link between physical system and its replica*	*Understanding system behavior*
Industrial digital twin association	*Asset*	*Digital*	*Updating throughout the lifecycle based on real-time data*	*Emulation, simulation, integration, testing, monitoring, and maintenance*

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The definition of DT can fall within its capabilities and levels, which are classified as standalone, descriptive, diagnostic, prescriptive, and autonomous [19]. Standalone DT represents the foundational level, primarily utilized during the design phase. It relies on a DoS approach to enable cost-effective system evaluation prior to physical construction. At the descriptive level, a CAD model combined with real-time sensor data is used to reflect physical assets. This setup relies on a precise PHYB, that supports data interpolation in the targeted areas of interest. At the diagnostic level, powerful ML tools can be applied to data to support FD, and CBM. Using insights from diagnostic DT, human experts can intervene early to make necessary adjustments, prevent minor issues from escalating into major problems. Unlike standalone, descriptive, and diagnostic DTs, which do not offer foresight, the predictive DT continuously deliver updated predictions by leveraging real-time data streams from the physical entity. Prescriptive DT are valuable for optimizing asset control, as it generates recommendations based on what-if scenarios, risk assessments, and uncertainty analysis. This capability is especially beneficial for decision support systems, offering guidance to experts who then determine the appropriate course of action. In the final stage, DT and its physical counterpart engage in continuous two-way communication. The physical asset updates the DT in real time, whereas the twin, in turn, issues control commands to steer the physical system toward optimal performance. This enables rapid decision-making without requiring human intervention. Referred to as autonomous DT, this fifth level requires a high degree of technological maturity, particularly for deployment in safety-critical applications [19]. Industrial platforms such as General Electric's 'Predix,' Siemens' 'MindSphere,' and 'ThingWorx' support the development of DTs by leveraging Internet of Things (IoT) technologies. IoT extends digital connectivity into the physical environment through widespread use of radio-frequency identification (RFID) chips embedded in real-world devices [43]. Although IoT offers significant benefits, it also presents major challenges related to IT infrastructure, connectivity, data privacy, security, trust, and data management [39]. In this context, data analytics plays a critical role in collecting, cleaning, and processing data for further analysis. The data cleaning stage particularly through imputation techniques is essential for addressing errors or missing values, ensuring the quality and reliability of the data before analysis.

2.2. Electrical Machine DT Realization

Drawing from the diverse range of existing DT definitions, the authors proposed a predictive level framework with the following vision for the DT design of an electrical machine in the service phase [34,38,41]:

- The DT of an electrical machine is a synchronized, ultra-fidelity replica of it, incorporating multiphysics, multiscale, and probabilistic modeling.
- An automated, bidirectional, real-time flow of data occurs between the DT and the electrical machine through appropriate instrumentation and the IoT platform.
- The twin encompasses data from the service stage of the electrical machine's lifecycle and remains connected to this phase through to the retirement stage.

Figure 3 represents the scheme of electrical machine DT realization based on IoT and cloud-computing technologies for FD and CBM. The physical electrical machine in this configuration is fully instrumented using RFID smart sensors to collect data on voltage, current, vibration, acoustics, temperature, speed, and mechanical torque. Quantities such as the active, reactive, and apparent power can be computed based on the measured stator voltages and currents. The implemented sensors describe the conditions of the electrical machine supplied by an electrical drive. The last device adjusts the operating point of the electrical machine according to its health state. The RFID smart sensors and electrical drive are connected via an IoT infrastructure to a cloud-computing platform, as shown in Figure 3. The cyber layer of this structure enables secure bidirectional data transfer among smart sensors, electrical drive and cloud-computing platforms. In the next section, the DRTS challenges are discussed, as they are considered a fundamental stage for the predictive level framework for the DT design of electrical machines in the illustrated configuration (Figure 3).

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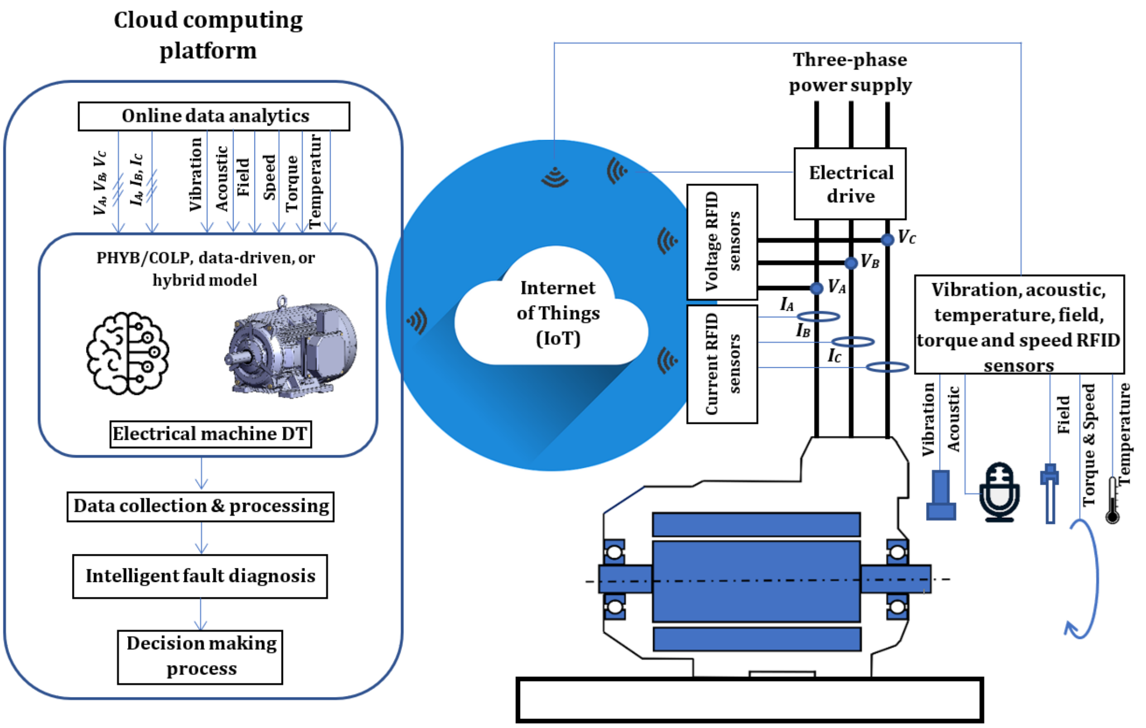

Figure 3. Scheme of electrical machine DT for intelligent fault diagnosis [4].

3. Electrical Machines DRTS Challenges

3.1. Electrical Machine Models

In addition to DT, other terms have been introduced to clarify its workings in the real world, including physical entities, physical objects, physical things, physical assets, physical processes, physical products, real-world entities, physical systems, and physically manufactured products, as well as its workings in the digitally generated virtual world, including virtual entities, virtual dynamics, virtual representations, digital representations, and digital exact replicas (Table 1). DPHYB, COLP, data-driven, or a combination of these models can be used to build the DTs of electrical machines. As mentioned in the introduction, data-driven models, despite exhibiting stable behavior after the training process, require extensive historical data (big data), that can be obtained from the collected information. They are simpler to configure, typically do not require detailed physical entity parameters, and can operate faster than real-time models. However, they operate as black boxes and the presence of biased data can manifest in the model, resulting in unpredictable errors and uncertainties. The PHYB and COLP models have significant advantages, because they operate based on a solid physics foundation, resulting in estimated errors and uncertainties which are important criteria in fault management systems. Hybride modeling as shwon in Figure 1 can be considered as a good alternative but this approach is rarely used for modeling of electrical machines [21,44].

The PHYB and COLP modeling approaches can be categorized into experimental and numerical models. Experimental modeling involves conducting reduced or full-scale experiments to determine the main parameters of the electrical machine model [15,45]. To enhance the physical authenticity of a DT, it is necessary to solve the governing equations obtained from the physical modeling. In some cases, analytical solutions can be derived for simplified equations. However, owing to their complexities, numerical solutions are often obtained using computers [7,46,47]. The main aim is to analyze quantities that are commonly difficult or costly to measure directly. These models can subsequently be employed within the context of Figure 3 as the DTs for electrical machines. The traditional approach involves creating a COLP dynamic 'dq0' reference model for AC electrical machines [48,49]. The estimation of model parameters can be used for fault diagnosis. Although several techniques have been proposed for the identification of AC electrical machine parameters, they are commonly performed offline, limiting their application to DT realization. Another approach relies on residual computation using parity

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equations, state observers, or state estimators. This technique has been used extensively in sensor fault detection and diagnosis systems. Such dynamic models are simple enough to be used in DRTS and DT realizations, as presented in [12]. However, they omitted the magnetic saturation effect and assumed a sinusoidal winding distribution. Moreover, the machine is assumed to be perfectly symmetrical. The 'dq0' reference frame models are commonly preferred for simulating electromagnetic transients because the 'abc' reference frame models have time-varying inductances. This means that, to solve the governing equations, the inductance matrices must be inverted at each time-step during the digital simulation, in addition to the computational burden of each digital simulation step [12]. Despite the aforementioned inconvenience, the 'abc' reference frame has the advantage of being easily applicable for modeling multi-phase electrical machines, regardless of asymmetry in both stator and rotor circuits, and can account for all space harmonics in the electrical machine [50–52]. In this regard, it is possible to include certain inherent asymmetries in the physical electrical machines in the model. Induction machines (IMs) that are broadly utilized in the industry are good examples [53].

Table 2. COLP modeling of various fault types in the 'dq0' reference frame.

Fault types	References
Broken rotor bar and end ring	[54–59]
Stator/rotor windings unbalance	[60]
Stator/rotor windings short circuit	[14,55,56,61–64]
Static, dynamic or mixed eccentricity	[55,65]
Ball bearing and race	[66]
Magnetization-related	[67]

The equations representing the dynamic of a p-pole, three-phase, wye-connected IMs in the 'abc' reference frame is given by [68]:

$$\begin{bmatrix} \mathbf{v}_{abcs} \\ \mathbf{v}_{abcr} \end{bmatrix} = \begin{bmatrix} \mathbf{r}_s & 0 \\ 0 & \mathbf{r}_r \end{bmatrix} \cdot \begin{bmatrix} \mathbf{i}_{abcs} \\ \mathbf{i}_{abcr} \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} \boldsymbol{\lambda}_{abcs} \\ \boldsymbol{\lambda}_{abcr} \end{bmatrix} \tag{1}$$

with

$$\begin{bmatrix} \boldsymbol{\lambda}_{abcs} \\ \boldsymbol{\lambda}_{abcr} \end{bmatrix} = \begin{bmatrix} \mathbf{L}_s & \mathbf{L}_{sr}(\theta_r) \\ \mathbf{L}_{sr}(\theta_r)^T & \mathbf{L}_r \end{bmatrix} \cdot \begin{bmatrix} \mathbf{i}_{abcs} \\ \mathbf{i}_{abcr} \end{bmatrix} \tag{2}$$

$$T_e = \left(\frac{p}{2}\right) \mathbf{i}_{abcs}^T \frac{\partial}{\partial \theta_r} \left[\mathbf{L}'_{sr}(\theta_r)\right] \mathbf{i}'_{abcr} \tag{3}$$

where $\mathbf{v} = [\mathbf{v}_{abcs}\ \mathbf{v}_{abcr}]^T$, $\mathbf{i} = [\mathbf{i}_{abcs}\ \mathbf{i}_{abcr}]^T$ and $\boldsymbol{\lambda} = [\boldsymbol{\lambda}_{abcs}\ \boldsymbol{\lambda}_{abcr}]^T$ denote the voltage, current, and flux linkages, respectively. The subscripts *abcs* and *abcr* denote the variables related to the stator and rotor circuits, respectively. $\mathbf{r}_s$ and $\mathbf{r}_r$ represent the stator and rotor resistance matrices in the diagonal form, respectively. $\mathbf{L}_s$ and $\mathbf{L}_r$ denote stator and rotor windings inductances, respectively. θ_r is the angular separation of the stator's *as* and the rotor's *ar* axes. $\mathbf{L}_{sr}(\theta_r)$ represents the mutual inductance between the stator and the rotor windings. The superscript $'$ is the representation of variables refers to the stator windings. The relationship between the torque and rotor speed is defined as

$$T_e - T_l = J \cdot \frac{d}{dt}\omega_m + B \cdot \omega_m \tag{4}$$

where J is the moment of inertia (Kg.m^2), B denotes the viscous friction (N.m.s), and $\omega_m = \frac{2}{p} d\theta_r/dt$. The governing differential algebraic equations represented by (1) and (2) can be reformulated into a first-order ordinary differential equation (ODE) (5) for the digital simulation of the IM model in the 'abc' reference frame [13]:

$$\frac{d}{dt}\mathbf{i} = \mathbf{L}^{-1}(\theta_r)\left\{\mathbf{v} - \mathbf{r} \cdot \mathbf{i} - \omega_r \cdot \frac{d}{d\theta_r}\mathbf{L}(\theta_r) \cdot \mathbf{i}\right\} \tag{5}$$

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with

$$\mathbf{L}(\theta_r) = \begin{bmatrix} \mathbf{L}_s & \mathbf{L}_{sr}(\theta_r) \\ \mathbf{L}_{sr}(\theta_r)^T & \mathbf{L}_r \end{bmatrix}, \; \mathbf{r} = \begin{bmatrix} \mathbf{r}_{abcs} & 0 \\ 0 & \mathbf{r}_{abcr} \end{bmatrix} \tag{6}$$

The relations (1) and (2) can be considered a baseline for modeling various types of faults, such as broken rotor bars, end rings, and stator winding ITSCs in IMs. For instance, a COLP model of a three-phase IM can be developed, to include an ITSC in one of its stator windings [61] (Figure 4). Main parameters of the three-phase IM that are modified in (1) and (2) due to a stator winding ITSC are the stator-related matrices: $\mathbf{r}_s$, $\mathbf{L}_s$, and $\mathbf{L}_{sr}$. In these matrices, the parameters corresponding to the faulty segment are separated from those of the remaining winding. The proposed model can be extended to study simultaneous occurance of ITSC faults in the stator windings of an IM [14]. To investigate broken rotor bar or end-ring defects in squirrel-cage induction machines (SCIMs) using the COLP modeling approach, the rotor structure can be represented by the configuration shown in Figure 5. In this model, $\mathbf{r}_r$ accounts for the resistance of the rotor bars and end-ring segments, while $\mathbf{L}_r$ includes their self, leakage, and mutual inductances. Additionally, $\mathbf{L}_{sr}$ denotes the mutual inductances between each rotor loop or end-ring segment and each phase of the stator winding [69].

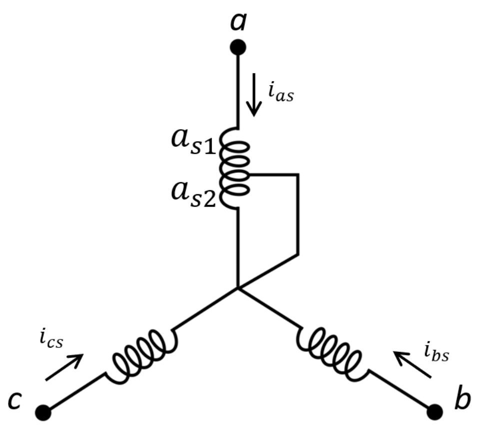

Figure 4. Stator windings of an IM with an ITSC fault in phase 'a' [61].

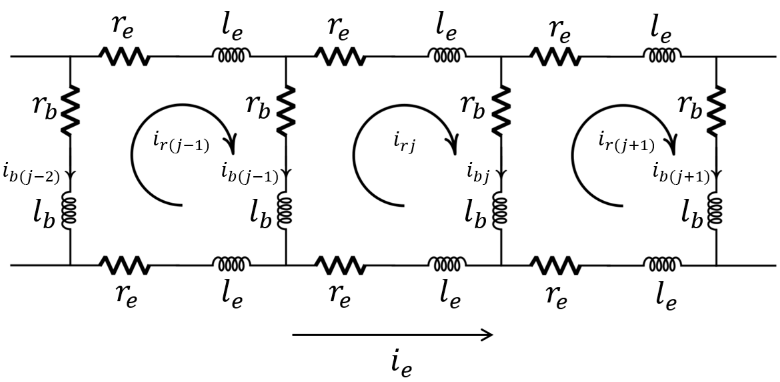

Figure 5. Equivalent circuit of a squirrel-cage rotor showing rotor loop currents [69].

Table 3. COLP modeling of various fault types in the 'abc' reference frame.

Fault types	References
Broken rotor bar and end ring	[70–77]
Stator/rotor windings unbalance	[15,31]
Stator/rotor windings short circuit	[14,70,78,79]
Static, dynamic or mixed eccentricity	[80–83]
Ball bearing and race	[84–86]
Magnetization-related	[87]

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The COLP modeling approach was initially developed for multi-phase winding structures of IMs, designed to operate even in scenarios where one or more of the stator phases are open-circuit, as discussed in [51]. The winding function approach (WFA) for computing self- and mutual inductances, which considers all space harmonics in a multi-phase IM, is presented. The proposed model includes asymmetry resulting from inter-turn faults in the stator phase windings, as well as any issue and number of failures in the rotor bars and end rings [52]. This type of modeling is crucial for fault diagnosis in AC electrical machines, where in many cases, space harmonics are required for efficient fault identification [88]. A universal mathematical model for a five-phase IM, encompassing the influence of higher space and time harmonics in the air-gap field, is presented in a similar manner. Given the significant role of space harmonics in AC electrical machines with more than three phases, mathematical relations for computing the self- and mutual inductances are derived [89]. To simplify the DRTS of the 'abc' reference frame model of the IM based on (5), both $\mathbf{L}^{-1}(\theta_r)$ and $\frac{d}{d\theta_r}\mathbf{L}(\theta_r)$ are described through look-up tables as a function of θ_r [90]. This modeling approach can be extended to other electrical machine classes, such as permanent magnet synchronous machines (PMSM) [31]. In this regard, the classical 'abc' reference frame models of the IM and PMSM can be utilized for the DRTS of stator windings asymmetry fault. This illustrates the efficacy of such simple representations in detecting winding imbalance faults, as demonstrated in [14,15,91,92].

The use of PHYB models, especially FEM-based models that incorporate spatial and nonlinear aspects, as well as non-sinusoidal windings distribution phenomena inside the machine, can enhance fault detection performance. These models provide comprehensive information regarding the health state of a machine using residual signals. However, the computational intensity of these models and their size and time-step limitations render them unsuitable for DRTS applications. MEC-based models are generally considered to be a middle ground between FEM-based and COLP models in terms of their computational performance [6]. The concept of MEC-based modeling relies on the analogy between the electric and magnetic circuits. A deeper analysis of the electric and magnetic fields revealed that magnetic circuits typically function in a saturated, nonlinear mode, whereas the majority of the elements in electric circuits exhibit linearity. In this regard, the machine's 2-D or 3-D structure must be divided into small elements that describe the MEC. Each element of the MEC model includes voltage and current sources and reluctances, which can be expressed as

$$\Re_m = \int_0^l \frac{dx}{\mu(x)A(x)} \tag{7}$$

where l represents the length of the flux tube and A denotes its cross-sectional area. μ denotes the permeability of the magnetic material. Figure 6 represents the 3-D MEC reluctance-based network and the circuit model of its elements. The voltage source, F_{ij} represents the magnetomotive force (MMF) and the current source, ϕ_{PM-ij} represents the flux of the permanent magnet. This network must be solved to obtain magnetic scalar potential, u, at each node. Based on the Figure 6.b it is possible to derive the following [6]:

$$\Re_{ij} \cdot (\phi_{ij} - \phi_{PM\text{-}ij}) = (u_i - u_j - F_{ij}) \tag{8}$$

Once the permeance and MMF are computed, the MEC relations can be determined based on the classical circuit nodal analysis.

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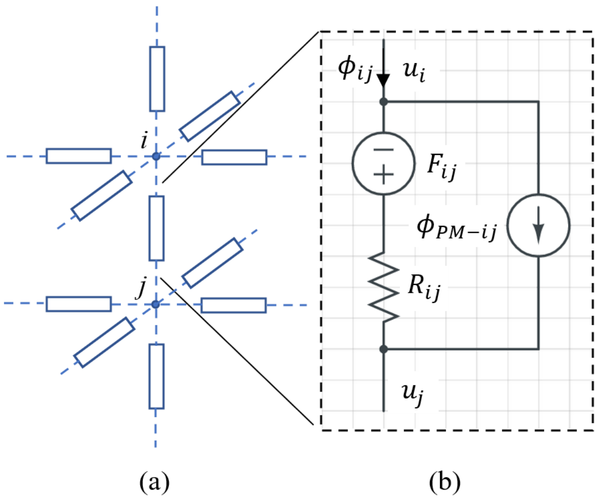

Figure 6. Scheme of MEC model: (a) 3D reluctance network and, (b) equivalent circuit of each element of the network [4].

Flux tubes serve as the foundation for MEC modeling techniques. A flux tube constitutes a geometrical region where all flux lines are perpendicular to their bases and no flux lines cut their sides. This requires knowledge of the machine geometry, including the effects of stator and rotor slots, skewing, winding connections, and magnetic nonlinearity of the electrical machine cores. Consequently, it produces more accurate results than the COLP modeling technique. For instance, permeance network and nonlinear MEC-based models have been introduced for real-time simulation of IMs [93,94]. A DRTS model was developed for PMSMs with shaped poles utilizing the analytical solution of field equations incorporating space harmonics in the air-gap flux density distribution. This model was constructed under the assumption of linear superposition [95].

Table 4. MEC modeling of various fault types.

Fault types	References
Broken rotor bar and end ring	[96–98]
Stator/rotor windings ITSC	[99–101]
Static, dynamic or mixed eccentricity	[102]
Ball bearing and race	[103,104]
Magnetization-related	[105–111]

3.2. RTDS Hardware Platforms

A Real-time simulation is defined as a process in which computational tasks are completed within the same time interval as the physical processes that represent. This section explores the main aspects of practically implementing RTDS across various hardware platforms, emphasizing constraints, trade-offs, and architectural capabilities. RTDS assumes that the state of a system changes only at fixed discrete time-steps, synchronized with a real-time clock. The execution of RTDS involves three critical stages: receiving/sending signals through input/output (I/O) interfaces, executing computations particularly solving the ODEs that define machine behavior and finally, transferring data between processing units and memory. To preserve real-time behavior, all these processes must be completed within the simulation time-step. In this regard, among the various implicit and explicit numerical integration methods Runge-Kutta (RK), backward Euler (BE), forward Euler (FE), and trapezoidal rule (TZ) are more widely used in power system simulations, including electrical machines. When selecting an integration method, the key factors include the numerical precision, computational time, and resource usage. Higher-order methods like RK4 offer better precision but demand more computational resources. In contrast, the FE method is faster and simpler but less accurate, especially for larger step sizes [6,112,113].

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There are two types of RTDS: H-i-L and S-i-L, in the context of electrical machine DT design. In the H-i-L configuration, a physical component interacts with simulated components on a hardware platform, whereas in S-i-L, all components are simulated digitally on the same platform, ensuring signal integrity and computational flexibility. H-i-L is advantageous for testing in high-risk or inaccessible environments, whereas S-i-L allows pure software validation [10,114]. The Simulation fidelity is governed by the time-step size. A small time-step ensures higher accuracy but increases the risk of overrun if computations cannot be completed in time. This is particularly challenging for high-frequency simulations such as those involving PWM drives, which may require nanosecond-level precision.

Hardware platforms can be categorized into chip single-core processor units (CSPUs), chip multiprocessor units (CMPUs), computer clusters, field-programmable gate arrays (FPGAs), and graphics processing units (GPUs). Each platform presents a unique set of advantages and trade-offs in terms of execution speed, resource usage, scalability, latency, and programming complexity. CMPUs or multicore CPUs include several processing cores within a single chip. Each core executes instructions in parallel using multithreading. CMPUs support shared memory and offer high clock speeds, making them suitable for medium-complexity simulations. Their advantages include user-friendly programming with tools like MATLAB/Simulink, cost-effectiveness and wide availability, and effectiveness for models like 'dq0' and MEC [94,115–119]. Their limitations include high I/O latency owing to PCI bus delays, difficulty handling time steps smaller than one microsecond, and suboptimal performance for high-frequency simulations [120,121]. Computer clusters consist of multiple interconnected computers (nodes) each with multiple CPUs. They are scalable and suitable for simulating large-scale electric systems such as wind farms. Their architecture is based on a master node that manages the simulation, while slave nodes execute parallel computations; nodes communicate via high-speed Ethernet or Infiniband links. Challenges include high communication latency, complex programming models involving message-passing interfaces (MPI), and node synchronization, which can become a bottleneck. Computer clusters are widely employed in RTDS of electrical machines [115,122–125].

The FPGAs consist of configurable logic blocks, interconnection resources, and I/O interfaces. These platforms allow deterministic execution and very fine time-step control, making them suitable for real-time simulation of electric machines and drives. Key features include low-latency I/O interfaces without PCIe, parallel or pipelined architectures for high performance, and support for both fixed-point and floating-point arithmetic operations. The development approach is based on either textual programming languages (e.g., VHDL and Verilog) or schematic/block-based tools, such as the Xilinx System Generator. Limitations include limited hardware resources, need for expertise in digital hardware design, and high costs when scaling with multiple FPGAs. These are widely used in the DRTS of electrical machines and drives [68,93,95,126–134]. Multiple interconnected FPGAs or pipelining schemes can be considered for high-order RTDS models [6,49]. Graphics Processing Units (GPUs) are well-suited for handling large-scale numerical simulations owing to their highly parallel architecture and strong floating-point processing capabilities. They consist of numerous cores arranged in blocks and grids, with threads executing instructions in a Single Instruction, Multiple Data (SIMD) manner, and working alongside a central host CPU. These features make GPUs particularly effective for speeding up FEM simulations and managing models with thousands of ODEs. Additionally, they offer high computational throughput and can be programmed using languages such as Compute Unified Device Architecture (CUDA) or Open Computing Language (OpenCL). However, GPUs have drawbacks such as significant initialization and data transfer overhead, and tend to be less efficient when applied to small-scale or rapidly changing models. Owing to their inherent parallel processing capabilities, GPUs are being adopted in various numerical analyses related to electrical engineering. Their applications include the numerical field analysis and simulation of electric machines [135–139]. In comparison, CMPUs provide adaptable but moderately performing solutions with higher latency; computer clusters offer scalability but require complex coordination and programming; FPGAs deliver

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fast, low-latency performance but are constrained by limited resources; and GPUs excel in processing large models, although they are less optimal for high-frequency operations.

4. Intelligent FD and CBM of Electrical Machines

Multiphysics modeling of electrical machines integrates various physical domains, including electromagnetics, thermal dynamics, mechanics, and acoustics. For instance, lumped models (LMs) are typically used to represent magnetic, electrical, electronic, and thermal components, whereas analytical models are applied to describe vibro-acoustic and mechanical behaviors of a PMSM. Although such coupled modeling approaches are commonly used during the design phase of electrical machines, their applications to FD and CBM remain limited [8,140]. In particular, the resistances in the COLP model presented in [140] were defined as functions of the supply frequency and winding temperature, allowing for improved accuracy. The frequency effect accounts for both skin and proximity effects. A multiphysics model of the induction machine is shown in Figure 7 [141]. This model comprises five interdependent sub-models. All these sub-models are either analytical or semi-analytical to achieve a good compromise between computational speed, accuracy, and flexibility. The core of this approach is the electromagnetic model, which provides key insights such as the induction in the air gap, radial forces acting on the stator, and current distributions. The output of this model can be utilized in two ways. First, they serve as inputs for mechanical vibration and acoustic models, which are designed to predict the vibration behavior of the machine and the resulting electromagnetic noise emissions. Second, the electromagnetic model outputs are fed into the loss model, which quantifies the various losses that occur within the motor. The calculated losses were subsequently used in an aerothermal model to simulate the evolution of internal motor temperature over time. A dynamic interaction exists between the electromagnetic and aerothermal models: the temperature predictions from the aerothermal model influence certain electromagnetic parameters, which in turn affect the loss estimations, that is, the same losses that act as heat sources in the aerothermal analysis.

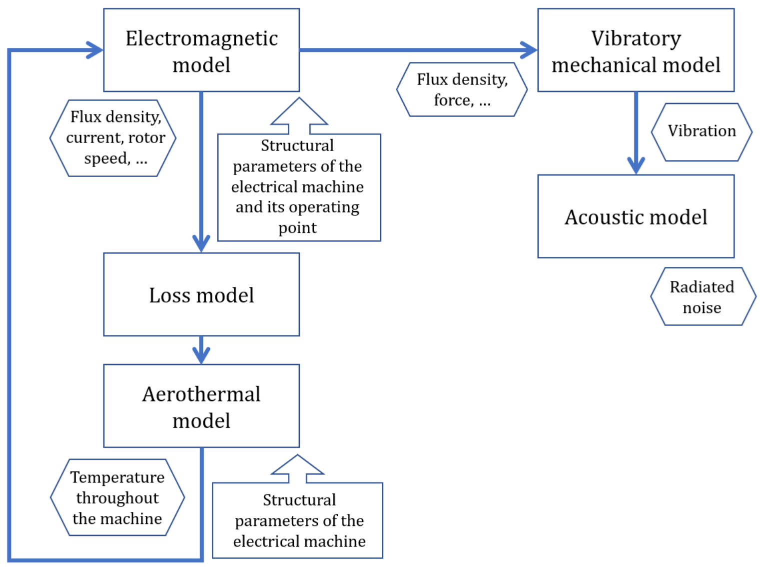

Figure 7. Schematic of a multiphysics model of an induction machine [141].

In this regard, the DT design procedure for FD and CBM of complex systems is well defined in [142]. In the first stage, it is essential to establish a high-fidelity reference model (DT) for electrical machines. Table 5 summarizes the advantages and disadvantages of PHYB/COLP compared with data-driven models for DT development [7,47]. A multiphysical model that considers all important aspects of the electrical, mechanical, and thermal behaviors of a physical entity enables the reference model to provide a wide spectrum of signals. Although data-driven models have weaknesses in representing all aspects of complex systems, they can be combined with PHYB/COLP to optimize

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and solve the ODE governing the model [143,144]. In the second stage, an IoT infrastructure must be built to facilitate the evolution of DT through available data from sensors installed on a physical electrical machine. In the final stage, DT data are fused with well-known data-driven models for further processing, FD, and CBM [145]. The main features of the DT of an electrical machine that contribute to intelligent FD and CBM are highlighted as follows:

- DT parameters can be updated in real time based on voltage, current, vibration, acoustic, field, speed, and temperature measurements.
- DT can be supplied by the measured phase (V_A, V_B, and V_C) or the line (V_{AB}, V_{BC}, and V_{CA}) voltages.
- DT provides a wide range of inaccessible signals that commonly require sophisticated instrumentation.
- More clear fault signatures can be detected in physical variables of the DT.
- Intelligent FD and CBM become possible through processing of DT data outcomes.
- Remote monitoring and control become feasible via the IoT infrastructure.

To achieve a high level of DT performance, it is crucial to adopt a strategy based on multiphysical modeling and the integration of the main fault types (Figure 8). This approach involves coupling all physical phenomena that contribute to life-cycle analysis, including thermal, mechanical, electrical, and chemical aspects. These factors have rarely been investigated in the literature for DT development in the context of FD and CBM of electrical machines.

Table 5. Comparison of PHYB/COLP Modeling Techniques with Data-driven Approaches for Electrical Machines DT Design [7,47].

PHYB/COLP	Data-driven
+ Solid foundation in physics	– Black-box concept
– Need partial or entire geometric data of the electrical machine	+ No need for any knowledge about the electrical machine
+ No need data for training	– A lot of data needs to be provided for machine learning
– Need optimization algorithms for continuous updates of model parameters	+ Neural network update
– Numerical instability of the model	+ Stable for a trained model
+ Less prone to bias	– Bias in the data can be reflected in the model
– Difficult to assimilate extensive historical data	+ Integrate easily the extensive historical data
+ Developed model can be used for similar electrical machines	– New model needs to be trained for each electrical machine
+ Several variables are available from the developed model	– Only the trained variables are available

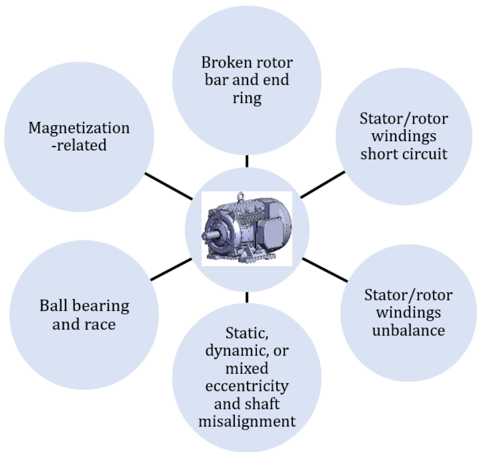

Figure 8. Integration of the main fault types into the DT of an AC electrical machine.

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5. Conclusion

This paper presents a summary of articles focusing on DRTS in the context of emerging DT technologies for intelligent FD and CBM in electrical machines. A predictive level framework with the following vision is proposed DT design during service phase:

- The DT of an electrical machine is a synchronized, ultra-fidelity replica of it, incorporating multiphysics, multiscale, and probabilistic modeling.
- An automated, bidirectional, real-time flow of data occurs between the DT and the electrical machine through appropriate instrumentation and the IoT platform.
- The twin encompasses data from the service stage of the electrical machine's lifecycle and remains connected to this phase through to the retirement stage.

Based on the above definition, achieving an ultra-fidelity replica requires multiphysics modeling approach with online parameter updating, whether PHYB, data-driven, or hybrid. Furthermore, implementing intelligent FD and CBM requires simulation of key fault scenarios using the DT of an electrical machine, which offers a wide range of variables. The model must also operate in real time to ensure proper synchronization and bidirectional data flow with the physical system through the IoT infrastructure. In this context, hardware platforms such as GPUs, FPGAs, PC clusters, and CMPUs, which are commonly used in RTDS for electromagnetic transient studies of electrical machines, are well suited to support this requirement.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating Current
COLP	Circuit-Oriented Lumped-Parameter
CBM	Condition-Based Monitoring
CMPU	Chip MultiProcessor Unit
CSPU	Chip Single-core Processor Unit
CUDA	Compute Unified Device Architecture
DNN	Deep Neural Network
DoS	Digital offline Simulation
DRTS	Digital Real-Time Simulation
DS	Digital Simulation
DT	Digital Twin
FD	Fault Diagnosis
FEM	Finite Element Method
FPGA	Field-Programmable Gate Arrays
GPU	Graphics Processor Unit
H-i-L	Hardware-in-the-Loop
IM	Induction Machine
IoT	Internet of Things
MEC	Magnetic Equivalent Circuit
ML	Machine Learning
MMF	MagnetoMotive Force
MPI	Message Passing Interface
MWFA	Modified Winding Function Approach
ODE	Ordinary Differential Equation
PHYB	PHYsics-Based
PMSM	Permanent Magnet Synchronous Machine

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RFID	Radio Frequency IDentification
RTDS	Real-Time Digital Simulator
PMSG	Permanent Magnet Synchronous Generator
SCIM	Squirrel Cage Induction Machine
SIMD	Single Instruction Multiple Data
WT	Wind Turbine
TSR	Tip–Speed Ratio
MPPT	Maximum Power Point Tracking
P-H-i-L	Power-Hardware-in-the-Loop
H-i-L	Hardware-in-the-Loop
P-i-L	Processor-in-the-Loop
S-i-L	Software-in-the-Loop
WECS	Wind Energy Conversion System
WFA	Winding Function Approach

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