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Review

Design and Optimization Technologies of Permanent Magnet Machines and Drive Systems Based on Digital Twin Model

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Abstract: One of the keys to the success of the fourth industrial revolution (Industry 4.0) is to empower machinery with cyber–physical systems connectivity. The digital twin (DT) offers a promising solution to tackle the challenges for realizing digital and smart manufacturing which has been successfully projected in many scenes. Electrical machines and drive systems, as the core power providers in many appliances and industrial equipment, are supposed to be reinforced on the verge of Industry 4.0 in the fields of design optimization, fault prognostic and coordinated control. Therefore, this paper aims to investigate the DT modelling method and the applications in electrical drive systems. Firstly, taking the high-speed permanent-magnet machine drive system as an example, multi-disciplinary design fundamentals and technologies, aiming at building initial mechanism and simulation models, are reviewed. The state-of-the-art of DT technologies is figured out to serve for high-precision and multi-scale dynamic modelling, by which a framework for DT models of electrical drive systems is presented. More importantly, fault diagnosis and optimization strategies of electrical drive systems in the decision and application layer are also discussed for the DT models, followed by the conclusions presenting open questions and possible directions.

Keywords: permanent magnet synchronous motor (PMSM); electrical drive system; system-level optimization; digital twin (DT); data-driven modelling; industry 4.0

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1. Introduction

The fourth industrial revolution (Industry 4.0), first introduced by German scholars, has brought increasing opportunities and challenges to manufacturing, energy, construction and other industries, which refers to the use of the cyber-physical system (CPS) to digitize and make intelligent the manufacturing and business information in supply chains, and finally achieve rapid, effective and personalized industrial system architectures [1]. In recent years, still in the early stages of Industry 4.0, a remarkable diversity of new concepts and multi-disciplinary technologies has visibly blossomed, such as smart manufacturing, distributed factories, Made in China 2025, advanced technologies including sensors and data transmission, machine learning and artificial intelligence, cloud computing, data storage, etc. [2,3]. However, how to aggregate their value and shape the future manufacturing thoroughly in the context of reduced costs, efficient automatic production and affordable services has triggered broad reflections and interactions.

Meanwhile, the rising concerns on digitalization, networking and intelligence in Industry 4.0 have contributed to the great attention to the digital twin (DT) technique from industry and academia areas due to its deep integration of new-generation information and digital models [4,5]. The DT technique, known as the dynamic mapping from physical space to virtual space, can realize the closed-loop interaction between humans, machines and the environment throughout the product entire lifecycle. This technique aspires to mirror the real-time operating status synchronized with the physical entity via mass data, allowing analysis, deduction and control via the data-driven models in the digital space, to thus implement more accurate modelling, performance optimization, rational decisions as well as improved production efficiency [4–6].

Nowadays, DT has shown achievements in many fields, such as aerospace, urban management, medical treatment, agriculture, etc. NASA first applied DT to monitor and predict the status of space vehicles to optimize subsequent operations [7]. Then, DT technology was introduced to urban construction and the medical industry for decision making and human health tracking [8,9]. In electrical engineering, scholars worldwide are also trying to apply DT technology to the new-type power system. In [10], Pu et al. reviewed the key technologies and the research prospects & challenges of digital twin used in power systems. In [11], Song et al. proposed a state estimation method based on DT, which can be used to not only monitor but also predict the power grid state according to possible future events. In [12], a DT design method for fault diagnosis of a distributed photovoltaic system is proposed, and the feasibility of DT utilization for fault diagnosis of electrical equipment was verified by simulation. In [13], an ultra-short-term prediction method for PV power generation using the DT-optimized genetic algorithm (GA)—back propagation (BP) neural network was put forward, which effectively improves the prediction accuracy. Considering the cyber-physical system as an important supporting technology for building a DT system, in [14], a CPS-based DT model information-physical system was constructed, which can alleviate collaborative false data injection and network attack by interacting with the control system to guarantee safe operation. Although lots of efforts have been made towards development of the DT technique, seldom have further technical routes and general construction frameworks been presented systematically and comprehensively yet, even in some leading manufacturing sectors. Moreover, the application and usage of DT in other involved industries should be emphasized and rapidly developed as well.

Electric machines and their drive systems act as the main power source role in many developed and developing powered devices, such as machine tools, flywheels, centrifugal compressors, distributed power generation systems, as well as road, rail, marine and aerospace transportation; as such, in the future context of big data, artificial intelligence and the Internet of Things (IoT), it is of great significance to make an attempt towards the DT development of electrical drive systems. However, the DT technique implemented in electrical drive systems is still in its infancy, and has been seldom leveraged to date.

Therefore, this paper aims to survey and summarize the research trends & development of the DT technique and its application to the design optimization of electrical drive systems. By the DT definition [15], 'twin' means that the physical entity and its mathematical model have 'the same gene'. In other words, they have the same physical laws and operating mechanisms. Considering that the physical process of an entity is usually observable with fixed mathematical models, and that the analytical model can be applied with less computational cost, a comprehensive overview of the design fundamentals and technologies for electric machines and their drive systems is firstly conducted to support the theoretical foundation for the DT modelling. The high-speed permanent-magnet (PM) machine (HSPMM) is regarded as a typical example due to the distinct characteristics of multi-disciplinary and broad industrial potential. Then, the state-of-art of involved DT technologies are summarized, followed by the proposed overall framework for the DT models of electrical drive systems. At the same time, considering the specialized objectives of the DT decision-making layer served for electrical drive systems, the fault diagnosis and optimization methods are also outlined, including demagnetization fault caused by high temperature and system-level optimization algorithms. The outcomes of this work strive toward accelerating the transition of motor drive system industries and providing theoretical reference, adhering to the 'informatization, digitalization and interaction' concepts.

The rest of this paper is organized as follows. Section II reviews the design fundamentals and technologies of HSPMM drive systems. Section III reflects the state-of-art of DT concept and the general guidelines for DT modelling of electrical drive systems. In Section IV, two major services in the decision-making layer are investigated. Conclusions including application prospects and future work are illustrated in Section V.

2. Design Technologies of HSPMM and Drive Systems

Compared with conventional electric motors, the high-speed motors possess unique merits and a wide range of application prospects in hybrid electric vehicles, flywheels, machine tools, centrifugal compressors, and distributed power generation systems [16], fulfilling the requirements of future or smart manufacturing. The major merits include the following aspects: (a) the high speed motors operate with higher frequency, resulting in a compact and light-weight structure; (b) they are capable of being connected directly with a prime mover or a mechanical load without additional transmission systems, leading to reduced gear costs, maintenance expenses, power losses, mechanical vibration and noise; and (c) the high-speed motors feature a fast dynamic response thanks to the small moment of inertia [16–18]. For the electric motor drives, permanent-magnet synchronous motors, induction motors, and switched reluctance motors are usually chosen in high-speed situations. Among the different motors, the HSPMM is often considered as the favorite thanks to its advantage of high-power high-torque densities, low torque ripple and relatively simple configurations.

To design and analyze an HSPMM, fundamental electromagnetic theories are still applied. However, the high-speed operation condition with minimized space and weight may cause a series of electrical, mechanical or thermal constraints. These issues have become the major challenges that motor designers need to address. Moreover, the basic physical layer in the DT model has desired the multidisciplinary models to mirror the entity to the digital space. It is noted that just the DT model cannot completely replicate the current state of physical entities yet, but it is necessary to have the knowledge of basic design technologies to guarantee the scientific relationships between physical quantities.

Therefore, in this section, the computational models for the stator iron loss (SIL), stator copper loss (SCL), rotor eddy-current loss (RECL), air-friction loss (AFL) and control system loss (CSL) are firstly overviewed. Then, the motor control strategies including the traditional field-oriented control (FOC) and the modern adaptive robust control are illustrated. Considering that effects of high working temperature on the power loss in HSPMMs are not trivial, various computation methods are investigated for calculating the temperature rise and distribution as well as different cooling approaches. The status on studying the HSPMM mechanical characteristics, such as the dynamic behaviors, rotor material strength and bearing support are also summarized.

2.1. Power Losses

HSPMMs feature high-speed high-frequency operation, high power density and a low thermal dissipation area. The power loss density is relatively large, which may cause a temperature rise and lower motor operation safety and stability. In order to acquire a good design, e.g., the motor temperature rise being within the limit, substantive research works have been carried out for more accurate calculation of HSPMM power losses, such as the SIL, SCL, AFL and PM REL.

The SCL is the power dissipated in stator and rotor windings caused by the copper wire resistance. Normally, the DC resistance is used in the calculation [19,20]. However, this method is not accurate for the HSPMM as the high speed causes high current frequency and the AC effect on the resistance becomes non-negligible. The high frequency stimulates the increase of skin and proximity effects and the decrease of effective area of current flowing, which then enhances the SCL. For calculating the copper losses, analytical models such as Dowell and Ferreira's have been applied and the effectiveness has been verified. However, the accuracy does not meet the requirement as some structural assumptions are made and nonlinear factors are ignored [21]. To address these problems, a finite element model (FEM) may be applied, which can not only accurately determine the copper loss, but also calculate the current density and magnetic flux density distributions in the motor. Some approaches have been applied for reducing the skin and proximity effects such as: (a) the copper wire is made with a few thin strands in parallel, (b) the wire radius is chosen to be smaller than the skin depth at the highest operation frequency, (c) the number of parallel strands for a certain frequency is optimized, (d) the current waveform harmonics are reduced, and (e) proper slot-openings are designed [20,21].

The SIL refers to the power loss in a magnetic core caused by the varying magnetic flux. Because an HSPMM works with a high-frequency magnetic field, high temperature rise and large mechanical stress, its iron loss can be much higher than that in a conventional motor. The generating mechanism of SIL, however, is quite complex. In general, the SIL calculation development process can be described as Figure 1. It can be seen that several millstones about the SIL calculation models include the simplified magnetic circuit model, Bertotti's classical three-term model [22], Zhu's model considering the effect of rotating magnetization [23], and orthogonal decomposition model [24]. These models are developed to consider the effects of both the alternating and rotating magnetizations, but the skin effect has not been included, which may cause large SIL calculation errors in the HSPMMs. In [25], Tumberger et al. studied the mechanism of how the skin effect may influence the SIL in HSPMM, but the effect of various magnetizations was neglected. In [26], the authors' team presented an improved model for predicting the core loss in an interior PMSM, in which the effects of pulse-width modulation (PWM) carrier harmonics, slotting harmonics, temperature rise and mechanical stress were all considered.

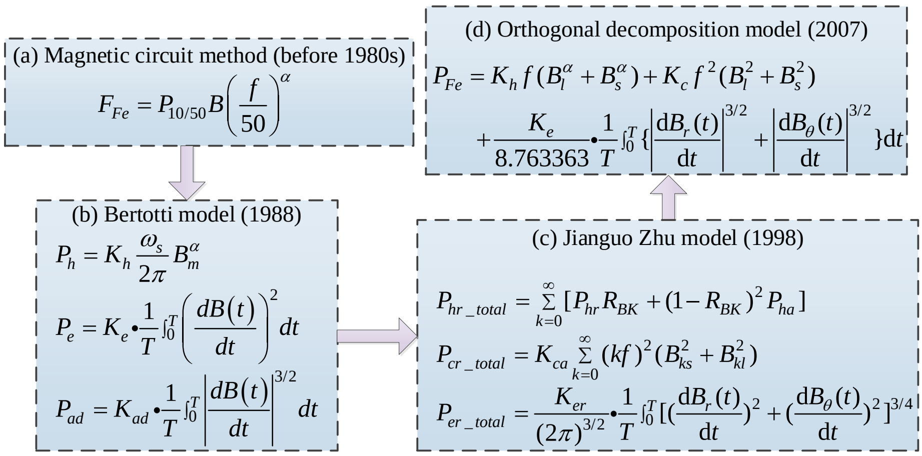


Figure 1. Development process of iron loss calculation models. Note: P_h is the hysteresis loss density, P_e the eddy current loss density and P_{ad} the additional loss density. The detailed explanations can also be found in the listed reference [22–24].

The RECL is basically due to the time harmonics and space harmonics of stator winding magnetic flux and slot openings. Compared to conventional motors, the RECL in HSPMMs would have a significant increase because it is proportional to the square of the magnetic flux frequency. On the other hand, non-contact bearings are extensively used in high operating speeds, which may reduce the rotor heat dissipation capability and increase the motor temperature rise, resulting in deteriorated PM characteristics. The RECL can increase significantly [27,28].

To predict the RECL, analytical models and FEMs are usually applied. The advantages of analytical models include a very short calculation processing time with reasonable accuracy, as well as acting as a bridge to illustrate the relations between the motor dimensions and electromagnetic parameters. The properties of the rotor materials such as conductivity and permeability, however, may vary with the operating conditions and deviate far from the model assumption. The analytical models often neglect the effects of core saturation, flux leakage and hysteresis, so the calculation accuracy may not meet the requirement. Therefore, FEMs are often applied for improving the RECL modelling accuracy. In [27], 2D FEM was applied for calculating the RECL of a surface-mounted PMSM with concentrated winding. The 2D FEM modelling has very short computation time, but the end effect and axial segmentation effect cannot be considered. To handle these, 3D FEM has been applied for the RECL analysis. Zhao [28] et al. calculated the RECL in sleeves and magnets of a surface-mounted PMSM by building a 3D FEM. The accuracy of the proposed methods is verified by the experimental results.

To reduce the RECL, the PM sleeve material and motor structure can be optimized, e.g., reducing the stator slot width, increasing the air gap length and using appropriate protective sleeve material. Recently, inserting a thin non-magnetic shielding ring between the sheath of the rotor and PM was studied. Taking advantage of the shielding effect of eddy current, the RECL in shielding rings and sheath can be effectively reduced [28,29].

Because a violent friction may happen between the rotor surface and air in HSPMMs, the AFL can be significantly higher than that of a conventional motor. Usually, the AFL on the rotor radial surface and axial end surface can be computed by (1) and (2) [30].

$$P_{Af\_rad} = k_f C_f \pi \rho_{air} \omega^3 r^4 l \tag{1}$$

$$P_{Af\_end} = \frac{1}{2} C_f \rho_{air} \omega^3 (r_2^5 - r_1^5) \tag{2}$$

where k_f is the rotor surface roughness coefficient, C_f is the air friction coefficient of radial surface, l is the rotor axial length, ρ_{air} is the air mass density, r, r_1 and r_2 are respectively the average, internal and external radius of the rotor end surface, and ω is the motor angular speed, respectively.

However, the air in the HSPMM gap may be in the turbulent state and it is difficult to accurately calculate the friction coefficient. Hence, the empirical formulae need modification, e.g., with the help of computational fluid dynamic (CFD) simulations. Research shows that the AFL is mainly related to the rotor size, surface roughness and rotating speed. It is effective to reduce AFL in HSPMMs by inserting non-magnetic conductive filler material into the stator slot, smoothing the initial air flow and reducing the fluid resistance [30].

2.2. Thermal Design

The following factors determine the highest operating temperature in an HSPMM: (1) if the insulation temperature exceeds the rated value, the motor life expectancy would decrease significantly, (2) irreversible PM demagnetization may happen due to the high temperature, and (3) the thermal stress in relevant components may increase and the rotor sleeve strength, especially composite sleeve, may decrease due to high winding temperatures [31,32]. All the above-mentioned issues reveal that thermal field analysis is necessary in HSPMM and the corresponding heat dissipation should be well designed to limit the temperature rise. Commonly, three types of models are applied for the thermal analysis in HSPMMs, which are the lumped-parameter thermal-network (LPTN) model, FEM and CFD models [31–34].

The LPTN method features merits like high calculation speed and hence it is effective for predicting the motor temperature rise at the design stage. However, the LPTN needs huge effort to determine the heat dissipation coefficient and equivalent thermal resistance. Furthermore, a lot of assumptions and estimations may be required in the LPTN and these would increase the calculation error [31]. In practice, the FEM, combined with the LPTN, is often conducted for the 2D and 3D thermal analysis. With the FEM, the machine can be divided into finite elements loaded with different power losses and thermal conditions, which are capable of solving detailed temperature rise distribution inside the motor.

However, the FEM may suffer from the same problems as the LPTN, i.e., the thermal conditions at each boundary still need to be determined with the help of empirical formulas and CFD simulations. Furthermore, the FEM is much slower than the LPTN in terms of parametric analysis [31,32]. To handle this problem, the FEM may be used to enhance the accuracy of equivalent thermal resistance, which is then used in the LPTN or to study the temperature distribution details at the local parts of the motor such as the windings. On the other hand, FEM can be considered as a convenient tool for complex geometries, which cannot be solved by using the LPTN.

In addition, according to the finite-volume technique, modern CFD algorithms can solve the Navier–Stokes equations complemented by a selection of validated and proven physical models, and then accurately solve the 3D laminar and turbulent flows and the heat transfer. The CFD can jointly model and solve the heat transfer in the whole motor, the external and internal cooling fluids, as well as the internal temperature rise distribution. In this case, the LPTN or FEM temperature rise modelling methods can be completely replaced. Furthermore, there is no need to determine the convective heat transfer coefficient of each part with the help of the empirical method, so more accurate and detailed results can be obtained. Despite the advantages, the CFD also has advantages such as long modelling and calculation time [33]. Recently, it has become an application trend to combine all the methods and use their respective advantages for motor thermal analysis. In [34], the temperature rise of a 30 kW, 60,000 r/min HSPMM was computed by combining the FEM and CFD. The heat transfer coefficient of air gap and the heat dissipation coefficient of the motor surface were calculated by the CFD and then the coefficients were assigned to the FEM. This can avoid large amount of calculation while the motor temperature rise distribution can be accurately obtained.

In summary, with the continuous advancement of computer hardware and software technologies as well as the continuing pursuit of higher HSPMM power density and efficiency, the employment of CFD technology in thermal analysis has become very popular. The temperature directly affects the PM working state and power losses. To accurately predict the temperature rise and working state, the coupling of power losses and thermal field analysis should be taken into account [33,34].

It is noted that, in order to keep the motor to operate within the allowed temperature rise, a proper design of the cooling system for the HSPMM is requested, particularly for high-power HSPMMs. The machines may employ the air cooling, oil cooling, water cooling and hybrid cooling approaches. In [35], different cooling approaches for the high-speed motor were investigated. It is found that compared with the air-cooling approach, oil cooling can reduce the loss of rotor surface ventilation, so as to reduce the temperature rise of the rotor effectively. However, the oil cooling equipment occupies a large space, and its design is quite complicated. Considering the disadvantages of oil cooling, the air- and water-cooling approaches are usually applied in rotating electrical machines. The air-cooling system has the merits of a simple structure, low cost and easy management and maintenance, but it needs large amounts of power, and its cooling effect and efficiency are poorer than the water cooling. Compared with air cooling, the water-cooling approach has higher effectiveness, higher efficiency and lower power consumption thanks to the large specific heat capacity of the water. However, the water-cooling system is featured with high cost caused by the complex structure. Therefore, a specific cooling approach is designed according to the actual temperature distribution of the motor, and the hybrid cooling approach may be the best for high power density motors.

2.3. Mechanical Characteristics

As for HSPMMs, the mechanical characteristics, especially the rotor material strength, bearing support and dynamic performance, are also important issues to consider in the design and optimization process. Generally, the requirements for rotor strength and bearing support can be easily satisfied based on the empirical design, while the dynamic performance requires special attention for most motors with high working speeds. In the dynamic analysis, the natural frequencies and dynamic responses are the most important issues to be addressed and are critical for the operating safety and stability of HSPMMs.

The permanent magnet materials employed in HSPMM have a low tensile strength, which indicates that the rotor may be broken without difficulty through the centrifugal pressure or thermal stress induced by the excessive velocity and temperature rise. Therefore, it is essential to be certain that the permanent magnet and matching shielding sleeve can stand up to the allowable stress by means of inspecting the rotor strength in static and excessive velocity dynamic working conditions. So far, the internal stresses of permanent magnets and sleeves can be calculated through different methods with analytical models or FEM [36]. Taking advantage of these achievements in the rotor strength prediction, the motor rotors can be designed and optimized to obey the listed prerequisites in terms of (i) the stresses inside all rotor components are limited in the safe range, (ii) positive pressures are always maintained between the parts in fit, (iii) compressive stresses always exist in the permanent magnets for various operating conditions, and (iv) no considerable changes should happen for the internal stress of protective sleeves even under changing speed and temperature conditions [36].

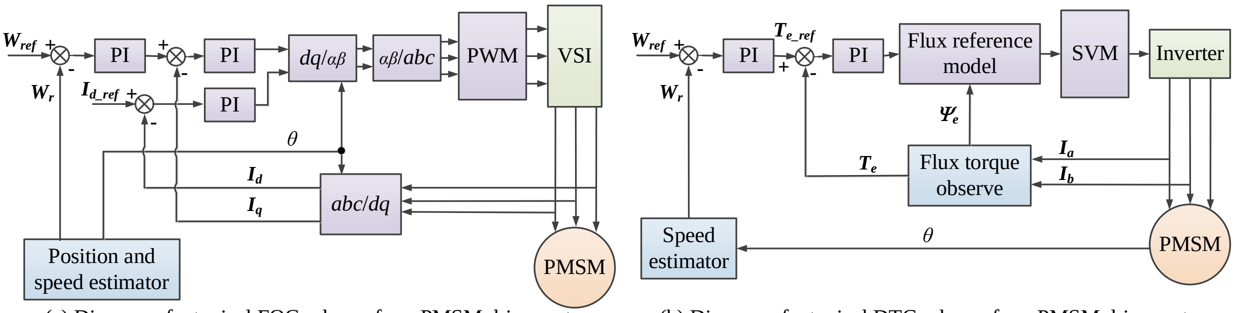
The dynamic behaviors and operating stability of HSPMM rotors rely significantly on the bearing support quality. In the machinery industry, the ball, oil-filled, air and magnetic bearings are usually selected for supporting the rotor in HSPMMs [37]. Meanwhile, based on the collected data [37], it is convincing that ball bearings are more suitable for HSPMMs with low-rated power, while air bearings and magnetic bearings have better functions used in electrical machines with high rated power and speed. In recent years, the concepts of bearing-less electrical motors were presented, in which the rotors can be suspended by the electromagnetic force. Academic institutions such as the Swiss Federal Institute of Technology in Zurich [38], Darmstadt University of Technology [39], Jiangsu University [40] and Nanjing University of Aeronautics and Astronautics [41] have received preliminary achievements concerning bearing-less electrical machines.

Dynamic behavior is an important characteristic for rotating machinery, and the dynamic analysis is helpful to solve the stability features, key frequency calculation and unbalance response for an HSPMM. The stability mandates the motor to return to stable working status after experiencing external disturbances. The key frequency calculation can be finalized to extenuate the noise/vibration aroused by the rotor unbalance and to avoid resonance. The unbalance analysis requires studies on the sensitivity of noise/vibration to the imbalance extent, thus to provide solutions for rotor unbalance [37,42]. The transfer matrix methods and FEM are usually employed for rotor dynamics and FEM has relatively higher accuracy. Through extensive studies, it can be concluded that factors including shaft length/diameter, bearing stiffness/position have a great influence on the natural frequency of the rotor. Despite the achievements in rotor dynamics, the nonlinear factors, bearing stiffness matching, parameter sensitivity and dynamic physical experiments are still difficult and more efforts are required for the design and optimization of HSPMMs.

2.4. Control Methods/Strategies

Control strategies play an essential function in the determination of dynamic- and static-state performances of electrical drive systems. Substantial efforts have been put forward for the development and application of various control algorithms in commercial drive systems, including traditional methods as the field-oriented controller (FOC), direct torque controller (DTC) and constant voltage–frequency (V-F) ratio controller [43–48], as well as modern control strategies as sensor-less controller (SLC), sliding mode controller (SMC), adaptive robust controller (ARC) and model predictive controller (MPC) [49–58].

Among the traditional control methods, the FOC decouples the stator current into excitation component and torque component in the d-q coordinate system, so that the control of the AC motor can be equivalent to that of separately excited DC motor [43–45]. FOC, proven to have superiorities concerning good control precision, wide speed regulating range and fast response speed, has been commonly applied in sorts of electrical drive systems [43–45]. Figure 2a shows the schematic diagram of a FOC control scheme used in a PMSM drive system. The DTC abandons the decoupling idea of FOC, which calculates and directly controls the flux and torque of the motor in the stator coordinate system, as shown in Figure 2b. It is distinguished by the merits of fast dynamic response, simple structure (thus low cost) and strong robustness against motor parameter variation. However, the torque and flux ripples reduce the performance in low-speed conditions, and the excessive acoustic noises restrict DTC application [46,47]. The V-F control is a kind of open-loop control, such that it can hardly complete the real-time control of machines [48].



(a) Diagram of a typical FOC scheme for a PMSM drive system (b) Diagram of a typical DTC scheme for a PMSM drive system

Figure 2. Control diagrams of typical FOC and DTC for PMSM drive systems. Note: I_d and I_q stand for the *d*- and *q*-axis currents, respectively. *Ye* is the flux, *Te* the torque. For FOC, the *d*-axis current is set to zero for achieving the maximum torque per ampere. The current/torque loop and speed loop are set as feedback loops to keep the reference speed W_{ref} as well as to make a smaller *d*-axis reference current I_{d_ref}.

The ever-developing modern industry has contributed to the widespread investigations of modern control strategies, among which the SLC, SMC, ARC and MPC are the most studied and widely used methods. To save costs and reduce the impacts of external disturbances on sensors, SLC was proposed to obtain the rotor position through calculation instead of sensors. So far, estimation methods using an open loop, fuzzy adaptive algorithm and observer can be used for rotor position when the machines work at relatively high speeds, while high frequency signals are often employed to predict the rotor position in low-speed conditions [49,50]. SMC, originally proposed by Utkin [51], possesses excellent features including simple algorithm derivation, a fast response speed and strong robustness for handling parameter uncertainties and external disturbances, which has been widely used in many plants. To guarantee and convergence properties and to relieve the chattering phenomenon, fractional calculus can be integrated into SMC for PMSM control [52,53]. Results in [52,53] showed the improved control performance of SMC, especially for dealing with the uncertain and nonlinear system, i.e., electrical drive systems. In combination with the functions of adaptive control in handling unstructured uncertainties and robust control in attenuating disturbances, Yao and Tomizuka presented ARC [54,55] and proved that it could handle both structured and unstructured uncertainties. In [56], Yin et al. presented an adaptive robust backstepping controller with an extended state observer, as shown in Figure 3, for the speed regulating drive system of a new-type hybrid drive wind turbine. Experimental results illustrated the excellent control performances under disturbances from both wind wheel and power grid ends. Taking advantage of the development of artificial intelligence, MPC with an advanced predictive algorithm was investigated and applied to electrical machines. This kind of control strategy does not need the fixed control model but has three basic parts. These are model prediction, iterative optimization and feedback correction. MPC has the merits of good robustness and dynamic performance used in complex industrial processes, but requires improvements in terms of stability, anti-interference ability and model adaptability [57,58].

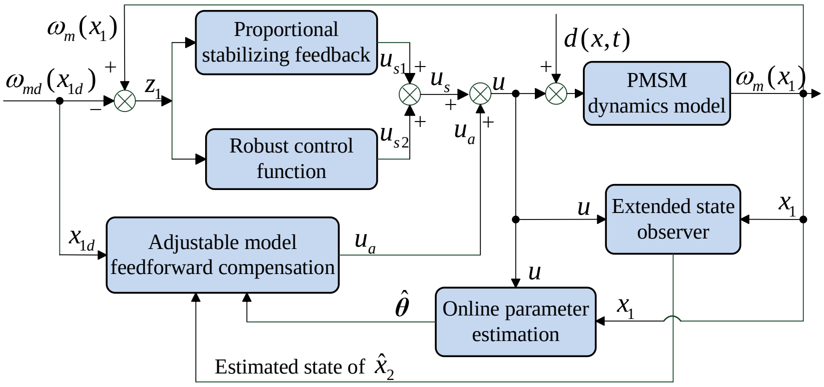


Figure 3. Control diagrams of ABC with ESO for PMSM drive systems [56]. Note: $x_1 = \omega_m$, $x_{1d} = \omega_{md}$, $\boldsymbol{\theta} = [\theta_1 \quad \theta_2]^T = [k_t/J \quad B/J]^T$. $d(x, t) = T_L / J$ and represents the lumped disturbances. ω_m is the PMSM rotor angular velocity, T_L the load torque or lumped disturbances, B the viscous friction coefficient, J the rotational inertia. $kt = 1.5\, p\psi_f$, and p is the number of poles, ψ_f the flux linkage of permanent magnet.

In industrial application, engineers should choose the control strategy and the matching processors according to the machine characteristics and operating scenarios to guarantee the best control performance and price/performance ratio. Meanwhile, more and more innovative control methods for PMSM drive systems will be presented based on the development of modern control theory, which will break through the limitations of traditional controllers and achieve parameter identification & control more easily by using artificial intelligence algorithms.

3. Digital Twin

The DT, first proposed by Grieves for product lifecycle management [15], can realize the complete mapping of the physical entity of electrical drive systems to the virtual space in real-time, which provides a simulated test and evaluation environment for the mechanism model, so as to carry out the simulation, calculation, analysis, decision making, and feedback optimization. So far, DT technique has shown achievements in manufacturing, urban management, medical treatment, agriculture, etc. [10–14]. NASA firstly applied the DT to monitor and predict the status of space vehicles to optimize subsequent operations [7]. Then, DT technology was introduced to the urban construction and medical industry for decision-making and human health tracking by Barricelli and Dang et al. [8,9]. The DT technique is showing a thriving development trend and may have great benefits to the electrical drive systems. However, although there are general guidelines for DT model design, there is no specific standard procedure. Therefore, more effort should be paid to receive a deeper understanding for the design and optimization of electrical machines based on the DT models. This section focuses on key technologies for developing the overall framework of the DT models for electrical drive systems.

Existing achievements have shown that DT technique possesses characteristics such as data-driven, real-time interaction and closed-loop feedback, which provide great advantages for application to electrical drive systems in the aspects of online analysis, real-time monitoring, state prediction, coordinated control, and design optimization, etc. As given in Figure 4, there are four key parts in the DT modelling process of the electrical drive system, including the physical entities, a perception layer for data collection, middle layer for data processing and decision layer for human–computer interaction. Generally, the data perception layer comprehensively collects the motion drive data, action signals, status data, command data, etc. in the workshop, the middle layer completes the manufacturing modeling, production process modelling and production system modelling in the workshop, and the decision layer maps the information of entity areas to digital area to realize the synchronous operation functions between digital models and physical spaces [59].

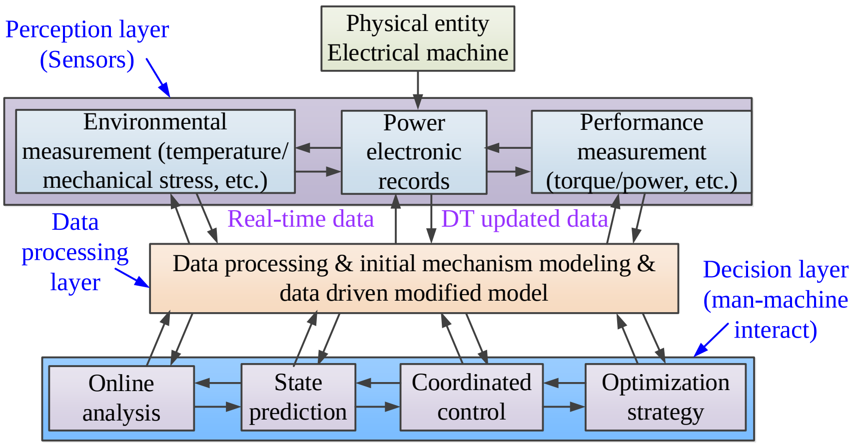


Figure 4. Framework of electrical machine DT modelling process.

3.1. System Physical Entity Layer

An electrical drive system mainly comprises a power source, an inverter with control devices and an electric motor. In order to drive this system, the circuits between the power supply and the motor must be connected, in which two key pieces of equipment, a motor controller and power converter, are needed. The motor controller is managed by using the battery administration system, while the power converter is managed via the motor controller. Therefore, to realize the motor drive, we need to firstly manage all controllers at low voltage to ensure the regular operation of a number of controllers. Then, the battery administration machine judges the charging status of the battery and completes the manipulation of the electrode. Finally, the motor controller completes the management of the power converter, which determines the quantity of cutting-edge flow to the motor and adjusts the pace of the motor [60].

3.2. Data Perception Layer

The data perception layer is based totally on the backside layer of the physical bodies for data collection, transmission and communication. Affected by factors such as environmental changes and equipment aging, there may additionally be mistakes in the model built up in accordance with the system theoretical knowledge and simulation requirements. In order to comprehend the real-time monitoring and accurate evaluation of the operation states of the electrical drive system, it is so vital to establish a number of sensing devices to finish the comprehensive perception of its state quantity in all aspects, such as temperature, stress, current or voltage, torque, speed, etc., as well as the programmable logic controller [61]. The parameters and states of DT models will depend on the data collected through the sensors, and will be always up to date in an iterative and incremental manner, such that the quality of the digital model can be consistently improved. At present, with the deep penetration and integration of optics, chemistry, biology, electronics and other disciplines, multi-sensor fusion has more and more emerged as a vitally important research hotspot around equipment sensing devices in order to reap high fault tolerance, great complementarity and intelligence [62].

Aiming at electrical drive system, the important challenges confronted with the data perception layer are as follows.

(1) Developing highly reliable advanced sensors for complex working conditions and environments. When the electrical drive systems operate at conditions of excessive temperature or excessive pressure, the sensors should nevertheless maintain the

traits of miniaturization, low power consumption, little delay in communication and high-precision time synchronization, etc.

(2) Realizing multi-faceted and overall in-depth monitoring. An electrical drive system is a multi-coupling system in the fields of electricity, magnetism, heat, force and sound. Many parameters can be difficult to observe or measure directly, such as magnetic field distributions and losses.

(3) Improving the accuracy of collected data. Due to the different sensor types and working environments, the current and voltage records gathered with the aid of the sensor are prone to harmonic interference with large noise. The low-quality data will cause the system to misjudge or pass over the operating state, affecting the accuracy of the DT models. The accumulated online statistics have to be similarly processed via data cleaning and other operations to enhance the information amount and supply a dependable statistics foundation for the building of DT models.

3.3. Data Processing Layer

Depending on the data obtained from the previous step, this layer plays an important role in further processing the data. It mainly includes abnormal data judgment, data eliminating, data completion and data fitting [4,59].

Based on the historical data of abnormal sensor devices, we can train and construct intelligent classifiers or extract key statistics. We can also usually use the method of offline online data mutual verification to realize the evaluation. Based on the technique of multi-criteria fusion, the sensor devices in abnormal operation can be discovered in time. In practice, due to the external environment and human factors, the data will have some missing values, mutation values, etc. Although this part of abnormal data accounts for a small proportion of the overall data, it will additionally have an effect on the reliability of the model. Therefore, it is necessary to clean this part of abnormal data, then mine effective information and improve data quality, which involves data completion and data smoothing technology. The optimal data set used to build the DT model of the system is then obtained by data fitting.

For the data fitting, knowledge-driven methods represent the deterministic, linear and representable parts in the modelling process while data driven methods represent the non-deterministic, non-linear, and non-representable parts. The specific ideas are as follows. A massive quantity of data-driven statistical correlation models generated by the operation of electrical drive systems under multi conditions is used to represent the uncertainty, and then for every condition, the knowledge driven differential algebraic mechanism model is used to calculate the certain parameters. In the end, the simulation consequences of all conditions are built-in to comprehend the integration of the two models, in which the probability distribution of random variables is calculated based totally on the differential algebraic mechanism model, and the knowledge driven deterministic algebraic mechanism model is transformed into the knowledge driven probability distribution function model to realize the fusion of the two models [63].

3.4. Decision-Making Layer

After obtaining the real-time operation data of all sorts of sensors, we can carry out the synchronous operation and interactive assessment of the equipment in physical space and virtual space, and realize the fault diagnosis, operation control parameter setting and optimization, as well as cluster management, by means of obtaining access to the PMSM drive system-DT model which integrates the mechanism model and data drive model, and combining the environment data, equipment process manufacturing data, equipment offline test, operation and maintenance data, fault case data, etc. [64]. In Section 4, two types of the most commonly used applications are introduced, in which the faults caused by temperature rise and system level optimization methods are investigated.

3.5. General Technique Route

The specific steps for building a DT for electrical drive systems are concluded below.

(1) The DT is initialized with the current state of the physical entity of electrical drive systems, so that the initial conditions of the DT and the physical entity are consistent. By customizing various working conditions according to research needs, simulation software is used to provide unobservable training and test data for intelligent algorithms. The initial training data set can then be obtained after data preprocessing, feature attribute selection and dimension reduction.
(2) The processed data are introduced into the neural algorithms to train the models. In addition to the data-driven statistical correlation models, the differential algebraic models (mechanism models) also need to be integrated into the DT models, because the genes of DTs and physical entity are consistent.
(3) Then, the physical entity is always in changing and developing, and constantly corrects its own structure and parameters in accordance with the real-time records from the sensors, in order to accurately reflect the state of the physical model in the virtual digital space.
(4) The objectives of DTs in short term are predicted, while the optimal control strategies are selected simultaneously.
(5) The optimization results obtained from the simulation are fed into the test entity to control the device, while the DTs will be improved simultaneously by using the updated running state data of electrical drive systems.
(6) Another optimization and control strategy can be conducted in this section with the stakeholders' advice. The same process as (5) will occur.

4. Fault Diagnosis and Optimization Strategy

The DT technology enhances the cognition and regulation of electrical drive systems through coupled dynamic and accurate digital modeling driven by data, knowledge and experience. The following is a combination of two typical applications of DT based on the requirements of the electrical drive system.

4.1. Fault Diagnosis

PMSM fault diagnosis can be divided into several types mainly including electrical faults, mechanical faults and permanent magnet faults, which are shown in Figure 5. Judging from the existing literature, a number of achievements have been received in PMSM electrical faults, while the research on permanent magnet fault diagnosis started late [65].

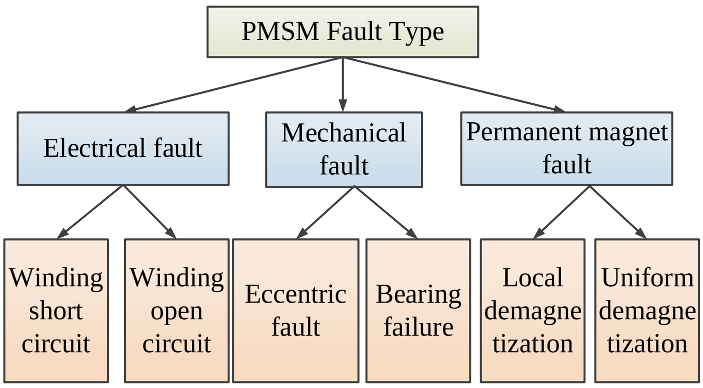


Figure 5. PMSM fault type.

Among them, the demagnetization fault is a relatively serious fault. For permanent magnet materials, when their stability is challenged by comprehensive factors such as temperature, external magnetic field, acid-base corrosion, manufacturing defects and natural life, the magnetic induction intensity is prone to amplitude reduction or distortion, forming a uniform demagnetization or local non-uniform demagnetization failure mode [66]. Sintered rare earth materials, such as samarium cobalt (SmCo) and neodymium boron iron (NdFeB), are typically used to manufacture rotor permanent magnets of high-performance applications. These materials are susceptible to cracking and corrosion under excessive humidity or heavy dew. During the installation of the motor, the permanent magnet exposed to mechanical pressure may produce small cracks, resulting in disassembly under high-speed operation. In addition, metallurgical changes in magnet materials caused by high temperature, corrosion and oxidation may lead to irreversible permanent magnet demagnetization failures. Direct impacts on the motor may additionally damage the permanent magnet, resulting in local loss of excitation.

After the motor stops, the reversible demagnetization can be restored as long as the working point of the permanent magnet is not lower than the maximum demagnetization working point. However, if the working point of the permanent magnet is below the maximum demagnetization working point, the magnetic flux cannot return to the initial value after the motor is cooled, which will lead to the irreversible permanent demagnetization and thus the unbalanced distribution of electromagnetic force, as well as the increasing of electromagnetic vibration and noise [67]. The mechanical torque will be greatly reduced, and catastrophic failures may even happen. Therefore, in order to realize the efficient and stable operation of the PMSM drive system, the health status of the permanent magnets must be monitored and diagnosed in real time.

The special requirement of PMSM demagnetization fault diagnosis is to seek a simple and reliable fault eigenvector to realize the real-time fault diagnosis of the motor. At present, according to the literature, the demagnetization fault diagnosis strategies are primarily developed from four aspects: the direct analysis method, model analysis method, signal processing method and artificial intelligence method.

(i) Direct analysis method

The traditional demagnetization fault detection of PMSM is generally judged by specialists or professional equipment. A Gauss meter is mostly used to directly measure the magnetic field axis and magnetic field distribution of permanent magnets [68]. Although this method can precisely diagnose the local demagnetization and uniform demagnetization fault of a permanent magnet, this technique ought to be disassembled in fault diagnosis such that it cannot become aware of the PMSM state in real time. Therefore, this method is mostly used for design stage rather than online fault monitoring and diagnosis.

(ii) Model analysis method

In the model diagnosis method, an accurate demagnetization fault model needs to be established starting from the operating mechanism and the internal electromagnetic relationship of PMSM. However, this method depends on the ideal conditions. Once the motor fails and the model establishment conditions do not exist, it needs to be remodeled and the model accuracy cannot be guaranteed, which greatly increases the difficulty of online fault diagnosis. Therefore, there is less literature reported on the PMSM demagnetization faults with parameters or mathematical models. The finite element model is not limited to this condition. Some satisfactory results have been achieved through the study of the magnetic field and the output data in the simulation environment. In [69], Wang et al. used the finite element analysis technology to build the motor model for simulating the demagnetization fault state, and then made use of the wavelet transform technology to extract the fault feature vector from the current data under the fault. In [70], Ruoho et al. found the relationship between machine parameters and permanent magnet demagnetization by simulating the motor operating state under different temperatures and loads. They also established an accurate mathematical model through this connection, so as to diagnose the motor demagnetization faults.

Although the finite element modeling can directly acquire the magnetic field distribution of a permanent magnet and analyze the influence of the internal electromagnetic field and motor output characteristics caused by the demagnetization fault, it is a physical model, with which it is difficult to comprehend the grafting with the control system, and can only be analyzed offline. The level of calculation is too large, and it is mostly used to furnish the groundwork for the optimal design of the PMSM rotor structure.

(iii) Signal processing method

This method is the most widely used in motor fault diagnosis. Scholars have found that when a PMSM has a demagnetization fault, some acquired signals have specific harmonic content, from which the feature vector can be extracted for determining the demagnetization faults [71]. However, the accuracy of this method is affected by factors such as inverter, vibration and load fluctuation. Based on the fault feature information contained in the branch current spectrum, in [72], Ruschetti et al. quantified the demagnetization degree of the permanent magnet and realized the demagnetization fault detection of the motor. Ruiz et al. used continuous wavelet transform to analyze the stator current to judge the demagnetization fault.

(iv) Artificial intelligence method

In recent years, researchers have utilized artificial intelligence algorithms to study the demagnetization fault in the context of industry 4.0. At present, only a small range of literatures use artificial intelligence algorithms for fault diagnosis of PMSMs, and there are even fewer studies on demagnetization faults based on artificial intelligence. Several scholars have combined neural sensor networks with signal analysis techniques such as wavelet analysis and empirical modal analysis. However, there are many problems with these algorithms, such as large training samples, large calculation burden, over-learning and complex parameter space [73]. This is also the future focus of research on artificial intelligence diagnosis. In [74], the Vold–Kalman filter order was delivered to track the order of the PMSM torque ripple to extract the characteristic parameters. The dynamic Bayesian network (DBN) was employed to detect and predict the demagnetization fault. The reliability of the proposed method was verified by experimental case studies.

However, most of the modern-day demagnetization fault prognosis techniques are based on the attribute statistics of a single sign to diagnose the demagnetization faults. Because the attribute records of a single sign are too simple, it is challenging to comprehensively represent the fault attribute information, which makes the accuracy of the demagnetization fault diagnosis low and susceptible to misdiagnosis. The DT models provide a virtual representation for real PMSMs, in which the various operating parameters and states can be monitored and recorded online. The information can thus be transformed to the above-mentioned methods to realize the fast, accurate and comprehensive diagnosis of demagnetization faults in PMSMs.

4.2. Design Optimization of HSPMM

The design optimization of HSPMMs is a high-dimensional and high-nonlinear issue, coupled with the characteristics of being multi-objective and multi-disciplinary. Through the significant efforts of researchers, the design optimization of electrical machines (including HSPMMs) has been developing very fast. The most important parts in the design optimization process include (a) design methods with analysis models, and (b) optimization methods with algorithms. The first stage aims to provide enough information including motor parameters and performance evaluations to the development of optimization models, while the second stage can be utilized to improve motor performance via optimization methods or strategies [75–96].

4.2.1. Optimization Models

(i) Multi-physics optimization model

In the design optimization process of HSPMM, due to the super-high rotation speed and sometimes special operating requirements, severe uncertainties appear in different physical fields including the electromagnetic, thermal and mechanical force fields. Coupled with intense interaction and confliction among these physics, it is necessary to establish optimization models of HSPMMs with multi-physics analysis [43,75].

Figure 6 shows the design framework of modern HSPMMs regarding the multi-physics analysis, which can also be used by other types of electrical machines. As shown, the first step is to define the motor specifications, mainly including the cost, output power, working efficiency, temperature rise, and resonance frequency. Then, the key designs/selections process, related to the motor topology, dimension, material and manufacturing method, need to be investigated based on the defined constraints. After that, multi-physics analysis models, composed of electromagnetic models with an advanced core loss model, thermal model, and mechanical model with vibration and noise analysis, can be developed. Finally, the performance of the designed motor needs to be evaluated and then utilized for the next optimization [43,75,76].

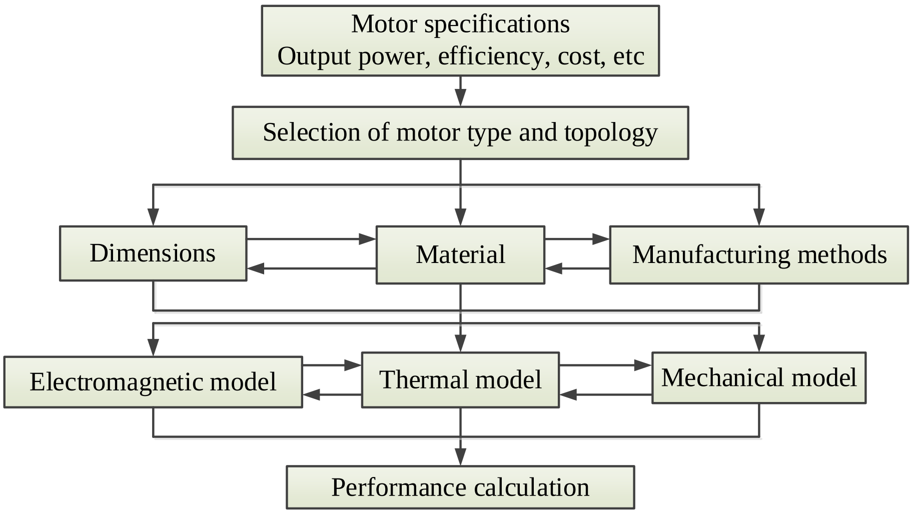


Figure 6. Design framework of HSPMMs and other electrical machines with multi-physics analysis.

In view of a single-objective optimization problem with N constraints, the multi-physics design optimization model of HSPMM can be shown as follows [76].

$$\begin{aligned} &\min : f(\boldsymbol{X}) \\ &\text{s.t.} \quad g_i(\boldsymbol{X}) \le 0, \quad i = 1, 2, \cdots N \\ &\qquad \boldsymbol{X}_l \le \boldsymbol{X} \le \boldsymbol{X}_u \end{aligned} \tag{3}$$

where $\boldsymbol{X}$ is the design parameter vector, $\boldsymbol{X}_u$ and $\boldsymbol{X}_l$ are respectively the upper and lower boundaries of $\boldsymbol{X}$, N is the number of constraints, and f and g are respectively the objective function and constraints.

In (3), different multi-physics constraints should be defined via (4) [75,76].

$$\text{Constraints:} \begin{cases} g_1(B_{ry}) \le 0, \quad g_1'(B_{st}) \le 0, \quad g_2(P_c) \le 0 \\ g_3(\Delta T_w) \le 0, \quad g_3'(\Delta T_{st}) \le 0, \quad g_3''(\Delta T_{sy}) \le 0 \\ g_4(\rho_p) \le 0, \quad g_5(\eta) \le 0, \quad g_6(P_{out}) \le 0 \\ g_7(T_{lm}) \le 0, \quad g_8(\delta_t^d) \le 0, \quad g_8'(\delta_{VM}^d) \le 0 \end{cases} \tag{4}$$

As shown, eight key constraints are commonly used in multi-physics optimization. These are respectively related to (a) the flux density at the rotor yoke (B_{ry}) and stator tooth (B_{st}), (b) the residual contact pressure between magnets and rotor iron (P_c), (c) the maximum temperature rise of the winding (ΔT_w), stator tooth (ΔT_{st}) and yoke (ΔT_{sy}), (d) the power density (ρ_p), (e) the efficiency (η), output power (P_{out}), (f) the maximum torque per loss per mass (T_{lm}), (g) the total rotating tangential stress (δ_t^d), and (h) the equivalent Von Mises stress (δ_{VM}^d).

(ii) Multi-objective optimization model

Considering the design optimization process of HSPMM, there are many design parameters, objectives and constraints. For example, maximizing the average torque or torque density and motor efficiency as well as minimizing the cost, loss and volume, weight and torque ripple can all be selected as direct optimization objectives. At the same time, some other parameters are also closely related to the performance of motors, such as magnetic flux density, air gap, back-EMF, and sleeve thickness. These parameters are often selected as indirect optimization objectives for motors [43,75]. Therefore, the design optimization of HSPMM is normally a multi-objective optimization problem. The multi-objective optimization model with p objectives and N_d constraints can be established as (5).

$$\begin{aligned} &\min : \left\{ f_{d1}(\boldsymbol{X}_d), f_{d2}(\boldsymbol{X}_d), \cdots f_{dp}(\boldsymbol{X}_d) \right\} \\ &\text{s.t.} \quad g_{di}(\boldsymbol{X}_d) \le 0, \quad i = 1, 2, \cdots N_d \\ &\qquad \boldsymbol{X}_{dl} \le \boldsymbol{X}_d \le \boldsymbol{X}_{du} \end{aligned} \tag{5}$$

where $\boldsymbol{X}_d$ is the design parameter vector, $\boldsymbol{X}_{du}$ and $\boldsymbol{X}_{dl}$ are the upper and lower boundaries of $\boldsymbol{X}_d$, f_d and g_d are the objective functions and constraints, respectively.

Theoretically, the multi-objective optimization solutions are a compromise among different objectives. That is, to obtain the optimum for each of these objectives is always impossible. In this case, one can only acquire the non-inferior solutions that can be called as Pareto optimal solutions by the way of getting the objectives as close as possible to their optimums [43,75]. However, different from the solutions of single-objective optimization, the Pareto solutions may have a very large or even infinite number, which should be passed around as evenly as possible at the front of Pareto solutions. The detailed definition of the Pareto front can be found in [75]. A specific case of Pareto optimal front with two objective functions is shown in Figure 7. We can see that points 'B' and 'C' are located at the Pareto frontier. Then, the results solved from 'B' and 'C' are the Pareto optimal solutions. Moreover, based on the definitions, we can say that the solutions of points 'B' and 'C' dominate the solutions of point 'A'. So far, plenty of algorithms such as MOGA, NSGA and the improved NSGA II and MPSO methods can all be utilized for completing the design and optimization of various multi-objective problems [77].

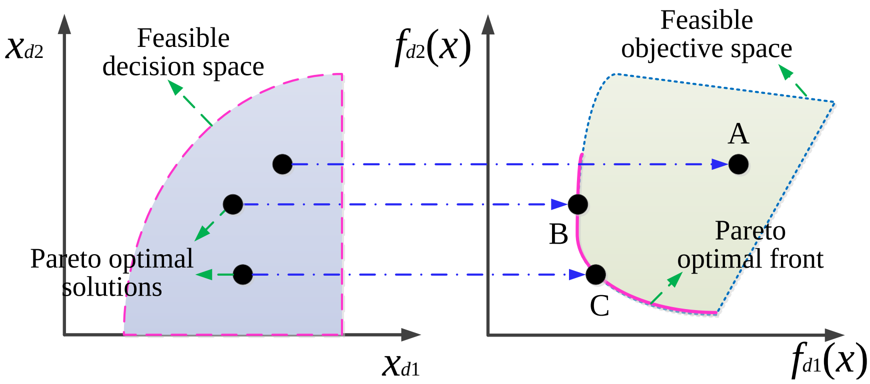


Figure 7. A specific case of the Pareto optimal solution.

(iii) System-level optimization model

With the purpose of further improving the operating performance of HSPMM, the steady-state performance such as torque, average output power, and efficiency, as well as the dynamic responses including settling time, speed overshoot and torque ripple should be considered comprehensively. Generally, during the design optimization, multi-physics analysis of the motor is always required to estimate these steady-state performances, while simulation analysis for the control systems of the machines needs to be conducted to evaluate the dynamic responses. Moreover, electrical drive systems have become a popular part of future applications, which aims to integrate electrical machines and control systems together. Therefore, the system-level design optimization of the whole electric drive system is very meaningful in the future to ensure the best optimal system performance, instead of assembling the motor, inverter and other individual optimized components into a drive system [43,75,78,79].

Figure 8 illustrates a succinct system-level design optimization framework of electrical drive systems with particular HSPMM and its control system. As shown, there are five key steps: (a) determine system requirements and specifications for input, (b) select motor type, drive and controller units according to the system specifications, (c) joint design of the motor and controller, (d) construct design optimization models for the whole system including both the motor and controller, and (e) evaluation of the system performance [43,75,78,79].

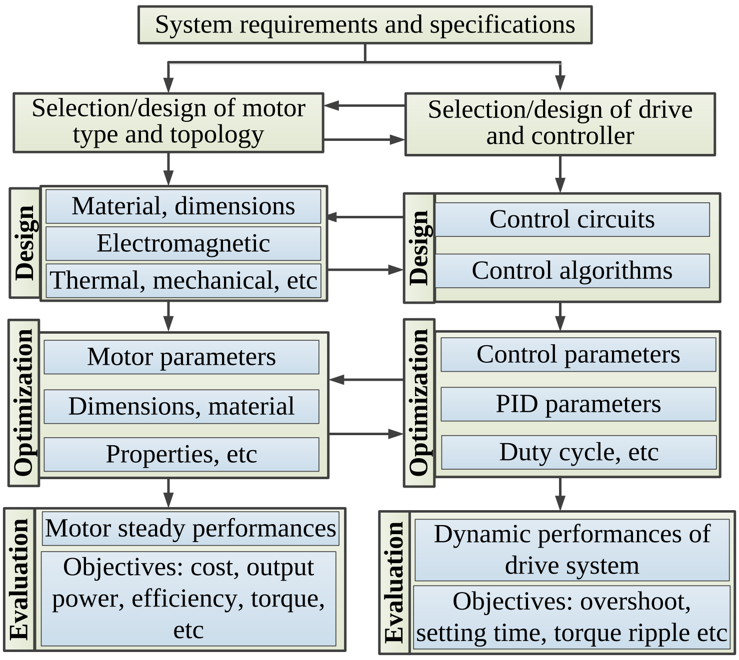


Figure 8. System-level design optimization framework for an electrical drive system with specific HSPMM and control system.

(iv) System-level optimization model

With the higher application requirements and standards for HSPMMs, industrial design and manufacturing factors should be considered during the motor design optimization due to inevitable manufacturing uncertainties and variations in the practical electrical machines' production process. Generally, for a permanent magnet motor, manufacturing tolerances, material diversities and assembling inaccuracy are the key issues to affect the final performance like back EMF and cogging torque, which indicates that the deterministic optimization models might sometimes be not appropriate for improving motor performance and manufacturing quality [43,75,78–80].

As a result, robust approaches have been investigated for the multi-disciplinary optimization of electrical machines with single- or multi-objective conditions [80–83]. Figure 8 shows a robust design optimization framework for an electrical drive system. As shown, compared to the framework shown in Figure 9, the practical process design and manufacturing quality are considered. Moreover, to solve the robust models, design for six-sigma (DFSS) [43,81], Taguchi parameter design [82], and worst-case design [83] methods can be used. The DFSS method, developed from quality engineering, focuses on different specific objectives for probabilistic analysis and/or optimization, and has attracted much attention recently. In this method, assuming all parameters in deterministic models as variables follow the normal distributions with different means and standard deviations. In this case, all constraints and objectives can be formulated as functions of mean and standard deviations [43,81]. Meanwhile, different examples have been investigated to illustrate the advantages of the robust optimization method, by which the improvements in motor performances and reliabilities were verified [43,75,80–85].

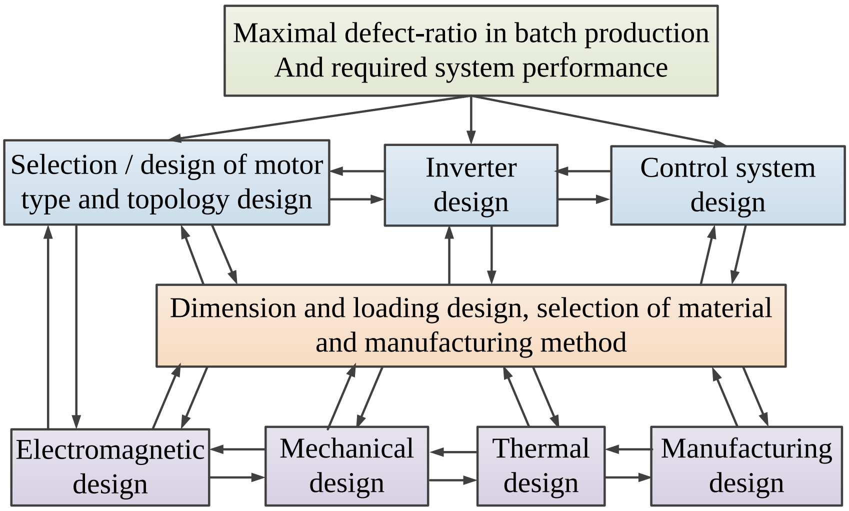


Figure 9. Robust design optimization framework of an electrical drive system.

4.2.2. Optimization Methods/Strategies

After developing the optimization models of HSPMMs, the optimization solutions can be obtained by using an appropriate optimization method/strategy.

(i) Conventional optimization method

The conventional one is simple in implementation that can be used to evaluate objectives and constraints by optimizing the physical models (such as analytical, magnetic circuit, FEM and thermal network models). For example, taking advantages of electromagnetic analysis's analytical models, the conjugate gradient and sequential quadratic programming algorithms have been successfully used to realize the design optimization of several kinds of motors. Additionally, intelligent algorithms and FEM can also be coupled (GA&FEM, DEA&FEM and MOGA&FEM) in conventional optimization methods [75,86].

Generally, the conventional direct optimization method can present good optimal design schemes for electrical machines by using an optimization algorithm such as GA. Although the classical optimization methods are relatively simple to implement, the optimization accuracy cannot always be guaranteed, especially for the high-dimensional design and optimization of HSPMM. The main reason lies in that the number of limited samples is insufficient for approximate models to replace FEM with satisfactory accuracy for high-dimensional problems. These challenges by using classical or traditional direct optimization methods based on both FEMs and the approximation models have contributed to the investigation of new optimization strategies.

(ii) Multi-level optimization method

The design optimization of HSPMM is generally a non-linear multi-physics and multi-objective problem. In this process, a number of design parameters should be concerned and may have different sensitivities related to different design objectives. Additionally, more attention should also be paid to reduce the huge computation cost required by conventional methods when high dimensional optimization problems exist. To address these challenges and better optimize the sensitive parameters, a kind of new multi-level optimization method is recently investigated, by which the initial big and high-dimensional design parameter space can be refined into two or three low dimensional subspaces by using sensitivity analysis methods for all the covered parameters [87–89]. The key flowchart for multi-level optimization method with three subspaces is given as Figure 10.

As shown, compared to conventional methods, with the multi-level optimization method, the initial high and big dimensional design space is divided into three subspaces (**X1**, **X2** and **X3**). The first subspace (**X1**) includes all the highly significant factors, and all the significant factors are in the second subspace (**X2**), while all the non-significant factors fill the third subspace (**X3**). The design optimization of subspaces **X1**, **X2** and **X3** can be realized one by one, and the optimization results in the up-level can be used in the next level. It is seen that for each subspace, the dimensions are much smaller than that in the initial space. As a result, the general optimization approximate models can be utilized in all sublevels and the calculation complexity can be reduced.

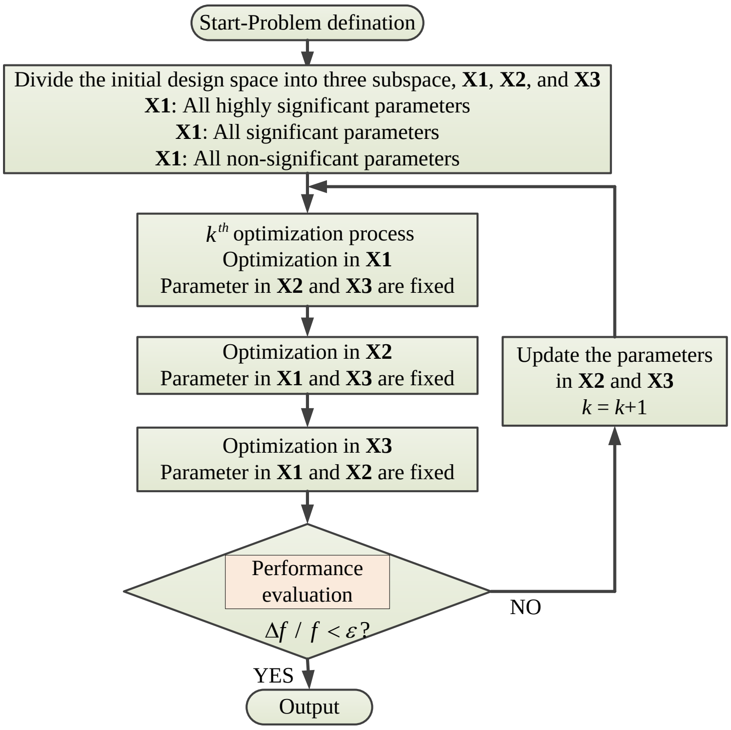


Figure 10. Flowchart for the multi-level optimization method.

Taking advantages of multi-level optimization method, in [87], Putek et al. synthesized a multi-level set method with the incorporation of a topological gradient to optimize the topology of a permanent magnet machine. In [88], the optimization of all sensitive parameters of permanent magnet synchronous generators was realized through both dual-level response surface methodology and Booth's algorithm by Asef et al. Then, a multi-level design optimization method for double-stator permanent magnet synchronous motor was also proposed, by which the rotor weight and mechanical stress distribution in the rotor core are effectively reduced [89]. In [90], a multi-level optimization design method for the flux-concentrating permanent-magnet brushless machine was proposed with considerations of permanent-magnet demagnetization limitation. Results showed that the optimized motor's output torque was increased while the torque ripple was greatly decreased. In our previous works [91–93], the multi-level optimization method with sensitivity analysis was employed for various types of electrical machines.

The above-mentioned achievements published on the same topic have showed the significant advantages of multi-level method in improving the optimization performance and calculation efficiency, which have contributed a lot to the research and development of the design optimization for electrical machines. However, the following critical issues still need to be solved: (a) The sensitivities of the design parameters are usually calculated separately, which means that the correlations or mutual sensitivities among different design parameters are neglected. Thus, the accuracy of optimization results may be affected. (b) In previous works, researchers fully-considered the correlations between optimization parameters and objectives, without giving concerns about the correlations among different optimization objectives fully. So far, cross-factor variance analysis and Pearson correlation coefficient methods can be utilized to classify the optimization objectives. (c) It is difficult to set multiple objectives for each optimization level since only Pareto solutions can be obtained without specific parameters, and traditional methods cannot be used. Future works about multi-level optimization should be carried out to solve problems in terms of analyzing correlations of design parameters and objectives, as well as selecting the key points from Pareto solutions of each level. Consequently, the multi-objective optimization can be employed at each level and the final optimization accuracy can thus be guaranteed.

(iii) Multi-disciplinary optimization method

Explanations concerning the multi-physics nature of HSPMM indicate that the design optimization processes of electrical machines and drive systems are complex and challenging since multiple disciplines such as structural mechanics, electromagnetics, heat transfer and control, as well as multi-constraints and multi-objectives should be involved. Moreover, the related disciplines are not isolated but normally strongly coupled. In this case, the systematic multi-disciplinary analysis and optimization method can be utilized to achieve the multi-objective optimization of electrical drive systems in wind power generation and electric vehicles, which need challenging specifications [43,75].

Figure 11 shows the basic framework of the systematic multi-disciplinary optimization method. In the disciplinary level, the indirect optimization models (IOMs) for optimization variables, constraints, objectives and models can be obtained by the analysis and modelling of electrical machines in different disciplines based on the methods (such as LPTN model, FEM and CFD methods) introduced in the electromagnetic design part. Then, system level robust optimization variables, constraints, objectives and models can be derived by using collaborative algorithms to finally complete the systematic multi-disciplinary optimization of a specific electrical drive system. In [76,94], the multi-disciplinary design optimization method was utilized for the drive systems based on permanent magnet machines with soft magnetic composite cores. The results showed the satisfactory optimization performance of the multi-disciplinary optimization method in terms of increasing motor reliability, reducing computation cost and improving the manufacturing quality for drive systems.

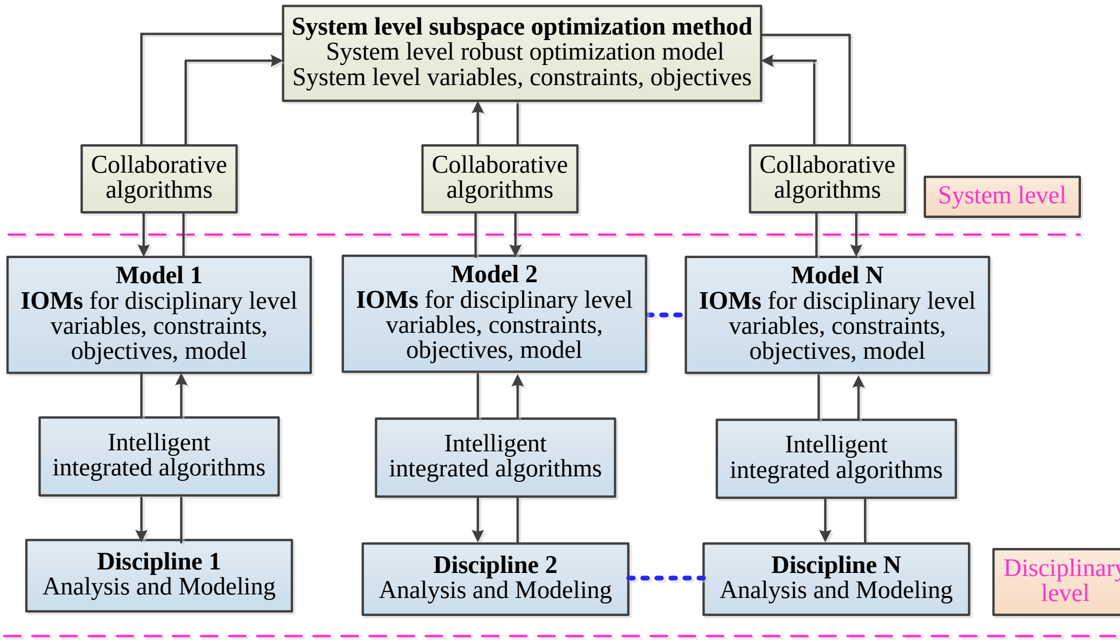


Figure 11. Flowchart for systematic multi-disciplinary optimization method.

(iv) Space reduction sequential optimization method

Apart from the multi-level optimization method, the sequential optimization method is another kind of space reduction strategy for completing the design optimization of electrical machines, especially with the considerations of inevitable uncertainties in manufacturing processes [43,75,95]. In contrast to the multi-level method, the idea of the sequential optimization method is to reduce the unnecessary waste in computation costs that comes from the samples outside the interested subspaces [95,96]. Figure 12 illustrates the flowchart of a multi-objective sequential optimization method for HSPMMs.

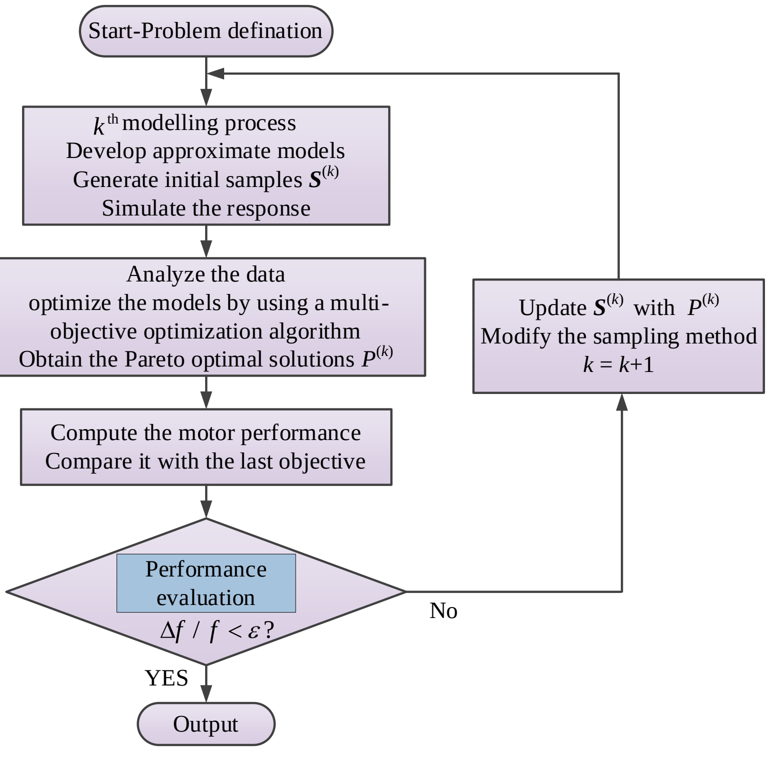


Figure 12. Flowchart for space reduction sequential optimization method.

Generally, the shape of interesting spaces is a critical issue in this method, which requires an advanced space reduction method to guarantee optimization accuracy. Based on the modified central composite design technique, a multi-objective sequential optimization method was presented [96]. In [95], by using a convergence measure consisting of an orthogonal design method and a hyper-volume indicator, the authors proposed a multi-objective sequential optimization method for electrical machines' deterministic and robust design optimization. Case studies verified that, once the proposed method is employed, the motor performance can be enhanced and the computational cost can also be reduced by about 10–40% compared with that of the direct optimization method (like DEA plus FEM).

Although the sequential optimization methods are efficient for the optimization of HSPMM, these strategies are difficult to use for extremely high-dimensional optimization problems due to the high computation cost of FEM. Moreover, since the sequential optimization method is a kind of iterative optimization, the efficiency of the sequential optimization method is not highly dependent on the type of surrogate models.

5. Conclusions and Future Directions

The modeling for electrical drive systems covers multi-disciplinary areas such as magnetic, thermal, mechanical fields, and control circuits. Traditional or single-component modelling methods may not be able to meet the needs of characteristic analysis, optimization design and predictive control of the whole electrical drive system. Targeting Industry 4.0 or smart manufacturing, PMSM drive systems based on DT models have been attracted with the superiorities of embodying multi-scale and full life cycle of entities, integrating typical services at the decision-making level as well as making up for the imbalance and lack of original data categories, and so on. This paper overviews and summarizes the development of DT technology as well as the design requirements and fundamentals of PMSM drive systems. The overall framework and technical route of building DT models for PMSM drive systems have been put forward. In addition, it also expounds the key problems and technologies to be solved in the specific implementation of the two typical stakeholders' application scenarios, including system design optimization and fault diagnosis caused by temperature rise.

Aiming at the application and development of the PMSM drive system–digital twin, there are the following prospects.

(1) With the flourishing of involved areas such as intelligent algorithms, engineering automation tools and simulation methods, in the domain of electrical drive systems, we should leverage our expertise in electrical machines and their drive systems to develop DT models with multiscale and multi-operating modes for realizing system level and multidisciplinary modelling. To ensure the consistent state between the entity and the DT model, effort should be given to the combined modelling of mechanism and data, the special working conditions considered for improving the DT model database and the life prediction of key components.
(2) Based on the PMSM drive system–DT technology, the coordinated control strategy served for system and subregion levels should be put forward. Improving the capability of optimal decision making regarding multiple timescales, multi-objective and multi-constraint will be another issue. Moreover, substantial work should also be done towards promoting the technologies concerning data perception, transmission and real-time processing & sharing.
(3) It is necessary to tap into the potential information from massive data to deal with uncertainty, error, coupling interaction and other disturbances. Therefore, a series of services, such as fault diagnosis and detection, health management, state prediction, system control optimization, etc., will be greatly developed at the decision-making level, which will be beneficial to engineering efficiency, accuracy and practicality.

This review could bring reflections and guidance for the future developing directions for the PMSM drive system towards Industry 4.0. Furthermore, there are types of pressing issues to be addressed by researchers in this decade, in order for the digital twin to be used to its full potential.

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