A Review of Research Methods for Stator Temperature Monitoring in PMSM

Songze Zhao, Puqi Ning, *Senior Member*, *IEEE*, Tao Fan, *Senior Member*, *IEEE*, Xiaoshuang Hui, and Qibiao Shi

***Abstract*—High-density permanent magnet synchronous motors (PMSMs) are widely used in electric drive systems. However, they are susceptible to temperature influences under complex operating conditions, and prolonged operation at high temperatures can first damage the stator winding insulation, which in turn will damage the windings themselves and cause faults. Therefore, stator temperature monitoring is of crucial importance. This paper summarizes the existing temperature monitoring technologies for stator windings of permanent magnet motors, compares the advantages and disadvantages of various methods to help researchers understand this technology, and analyzes its opportunities and challenges, followed by an outlook.**

***Index Terms*—Permanent magnet synchronous motors (PMSMs), Stator winding, Temperature monitoring and estimation.**

I. Introduction

Electric motors serve as the core component for electromechanical energy conversion and play a pivotal role in achieving the “dual-carbon” (carbon peaking and carbon neutrality) goals. Among various motor types, permanent magnet synchronous motors (PMSMs) hold particular significance in the electric vehicle (EV) sector [1]-[2], primarily attributed to their inherent advantages of high dynamic response, excellent reliability, high torque density, and superior efficiency [3]-[4]. Driven by the advancement of high-performance rare-earth permanent magnet materials and advanced motor control technologies, the installed capacity ratio of permanent magnet motors in the EV drive system reached 94.4% in 2021 [5]-[6]. Nevertheless, China’s new energy vehicle (NEV) industry still confronts prominent challenges, such as the insufficient innovation capability in core technologies and the urgent need to optimize quality assurance systems [7]. As one of the three core components of NEVs (alongside power batteries and electronic control systems), the operational reliability of drive motors has garnered extensive attention from the academic community [8]-[9]. In practical vehicle operation, PMSMs, as the key driving component, are highly susceptible to external adverse factors (e.g., mechanical vibration, environmental moisture). More critically, they tend to experience overheating issues under complex operating conditions (e.g., high-load acceleration, continuous climbing). Fig. 1 delineates the relationship between motor operating temperature (T) and stator winding insulation life across different insulation classes. Notably, a well-recognized empirical rule in motor engineering indicates that for every 10 °C increase in the operating temperature of the stator winding (beyond its rated insulation temperature), the insulation life of the motor will be reduced by approximately 50% [10]. This phenomenon further emphasizes the urgency of effective thermal management for PMSMs in NEV applications.

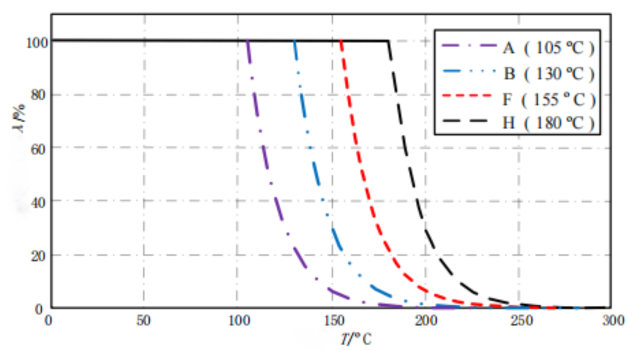

Fig. 1. The influence of temperature on the insulation life of motors [10].

Contemporary research consistently identifies overheatingas a primary contributing factor to permanent magnet motor failures [11], with specific failure mechanisms and correlation patterns illustrated in Fig. 2. Prolonged overheating not only accelerates stator winding insulation degradation (a critical failure precursor) but also triggers adverse consequences including irreversible damage to key components (e.g., permanent magnet demagnetization, bearing wear), reduced service life, and declined drive system reliability [12]. Against this backdrop, accurate temperature estimation and real-time temperature monitoring have emerged as pivotal technologies for ensuring safe and optimal operation of permanent magnet motors, as they enable proactive identification of potential thermal risks and provide essential data support for dynamic adjustment of motor control strategies (e.g., load redistribution, torque limitation),

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thereby mitigating overheating-induced failures and safeguarding motor performance within the optimal operating range.

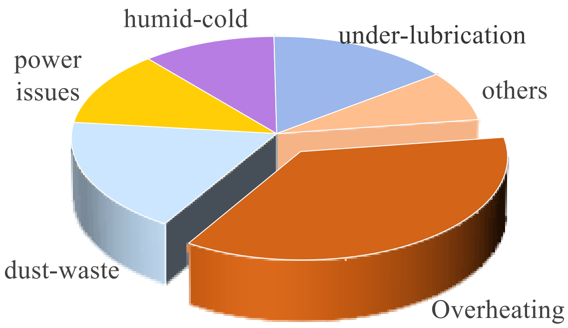


Fig. 2. The main factors causing motor damage [11].

From the implementation perspective, stator temperature monitoring methods are primarily categorized into direct measurement methods and indirect measurement methods. From a technical standpoint, existing motor stator temperature estimation and monitoring technologies can be further classified into four main types, namely sensor-based monitoring, thermal model-based monitoring, electrical model-based monitoring, and data-driven algorithm-based monitoring, with their specific classification system and technical scope illustrated in Fig. 3.

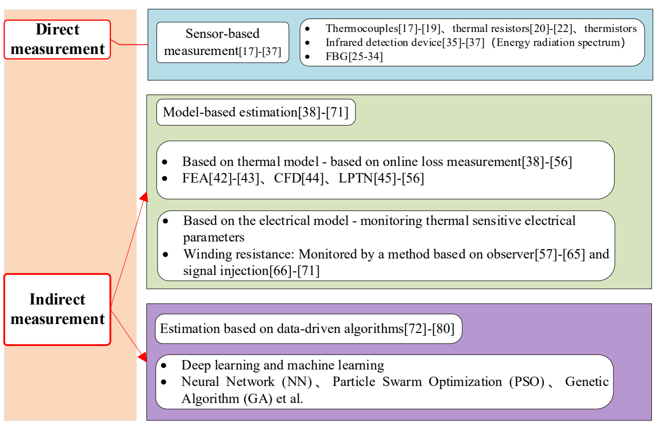


Fig. 3. Classification of stator winding temperature monitoring methods.

Although existing studies encompass both mature and emerging research directions, a systematic overview of motor stator winding temperature monitoring and estimation technologies remains lacking. This paper aims to systematically summarize and classify domestic and international research on these technologies, conduct in-depth discussions, identify the limitations of current studies, and prospect future development trends.

Compared with existing review articles, this paper has two key innovative points and differentiators: First, in terms of classification logic, it not only covers the four mainstream technical categories but also further refines the sub-types under each category (e.g., dividing lumped parameter thermal network (LPTN) in thermal model-based methods into white-box, gray-box, and deep gray-box models based on node division granularity) to form a more hierarchical technical framework. Second, in terms of content coverage, it emphasizes the cross-integration of different technologies (e.g., the combination of data-driven algorithms with LPTN parameter identification, the coupling of finite element analysis (FEA) and computational fluid dynamics (CFD) in thermal simulation) and supplements the latest research progress (2022-2024) in fields such as data-driven algorithms for temperature estimation, which fills the gap of insufficient coverage of cutting-edge technologies in existing reviews.

The structure of this paper is organized as follows: Section II analyzes sensor-based monitoring technologies; Section III summarizes temperature estimation technologies based on thermal models (including FEA, CFD, and LPTN technologies) along with their application prospects; Section IV focuses on temperature estimation technologies based on electrical models, with an emphasis on introducing the thermally sensitive electrical parameter method and its development prospects; Section V summarizes temperature estimation technologies based on data-driven algorithms; and Section VI outlines the development trends and key challenges of related technologies.

II. Sensor-based Stator Winding Temperature Monitoring Method

The sensor-based stator winding temperature monitoring technology is mature, functioning as a direct and straightforward method while also being widely used for experimental verification. This technology measures temperature directly via thermosensitive devices and can be categorized into two types: contact-type and non-contact-type temperature measurement. Contact-type temperature measurement mainly depends on electronic sensors, which are deployed through surface-mounted devices [13]-[15] (e.g., thermocouples, thermal resistors, fiber Bragg grating (FBG) sensors [16], etc.), whereas non-contact-type temperature measurement typically relies primarily on infrared sensors. Benefiting from advantages such as high accuracy, high sensitivity, a broad temperature measurement range, and low cost, this type of method is frequently employed as the reference for actual temperature in experimental comparison and verification. Nevertheless, it is constrained by the number and installation positions of sensors and is vulnerable to electromagnetic interference inside the motor, factors that ultimately lead to a decrease in temperature measurement accuracy.

A. Contact Sensor-based Temperature Measurement

Commonly used electronic sensors mainly include thermocouples [17]-[19], thermal resistors, and thermistors. In one research study, [20] installed 37 PT100 temperature sensors at key stator positions (including slot windings, end windings, stator teeth, yokes, and casings) of a 10 kW PMSM-with the sensor layout shown in Fig. 4 and arranged uniformly. These sensors were used to provide true value verification for the three-dimensional thermal network model; however, this method has drawbacks such as complex hardware configuration and large wiring volume.

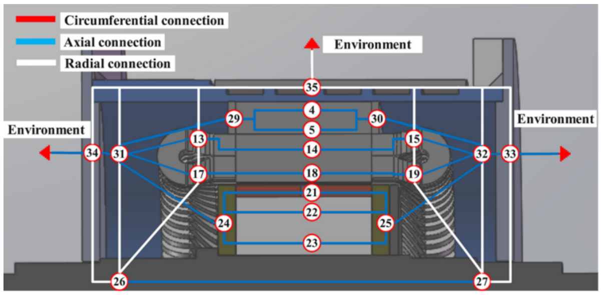


Fig. 4. Overall sensor layout distribution map [22].

In [21], 10 PT100 sensors were arranged on an interior permanent magnet synchronous motor (IPMSM), and infrared probes were additionally installed. By combining contact and non-contact temperature measurement methods, the study obtained true temperature values for verifying the LPTN method, achieving a relatively small measurement error. Reference [22] also utilized PT100 sensors to monitor the temperature of key components (including slot windings and end windings) of the prototype motor, with the measured data serving as the true value for verifying the 3D finite element model. Reference [23] symmetrically embedded 6 K-type thermocouples at the tooth tips of the end part of a 12-slot 10-pole prototype motor to monitor temperature, which was used to validate the estimation results of the discrete loss thermal network model. Reference [24] pre-embedded PT100 sensors in the stator windings of an ultra-high-speed motor to monitor the actual operating temperature, and the collected data were applied to verify the simulation results.

As early as 2002 [25], a study proposed FBG as a novel contact-type temperature measurement method. Its working principle is as follows: When broadband light is incident on an FBG, the grating reflects light that satisfies the Bragg wavelength condition while transmitting light of other wavelengths; since the Bragg wavelength can be modulated by external temperature and strain, temperature sensing is thereby realized (Fig. 5). This method has been applied in various fields such as biomedical sensing, respiratory monitoring, and structural health monitoring. In the power industry, compared with sensors like thermal resistors, FBG sensors are not affected by electromagnetic interference and feature a small size [26]-[29]. However, they suffer from drawbacks, including complex installation and maintenance processes as well as high costs.

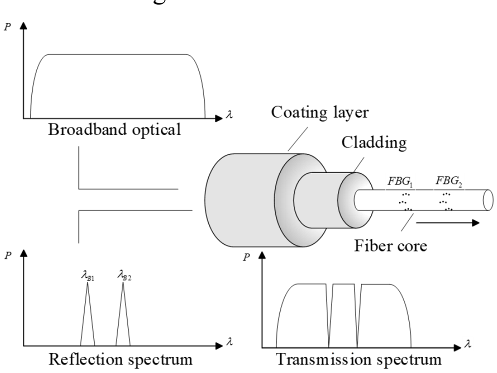


Fig. 5. The sensing principle of FBGs.

In the early stage of partial discharge in motor windings, a phenomenon of sharp temperature rise will occur; therefore, the winding temperature can be used as a basis for detecting the degree of insulation degradation. Many researchers have applied FBG sensing technology to the temperature monitoring of motor stators. The sensor designed in [30] (Fig. 6) is encapsulated with a capillary steel tube and filled with modified acrylate. This design increases the temperature sensitivity by 2.7 times, with an operating temperature range of −30-120 °C, a measurement accuracy of ±0.5 °C, and a resolution of 0.1 °C.

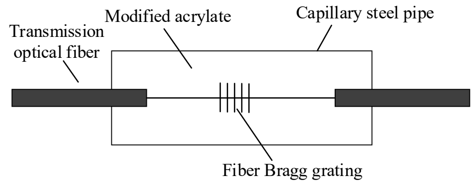
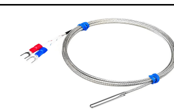
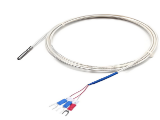


Fig. 6. Capillary steel tube-encapsulated FBG stator temperature sensor [30].

In-situ FBG sensors were employed in [31] to monitor the thermal characteristics of windings for inter-turn short-circuit detection, verifying their capability to detect single-turn and multi-turn short-circuits. Reference [32] developed an FBG-based multi-parameter system, which can realize real-time temperature measurement and visualize hotspots by combining with 3D modeling. Comparative verification in [33] shows that the temperature measurement response time of FBGs is shorter than that of platinum resistors, and they are superior in monitoring local hotspots. Reference [34] estimated the remaining life of windings based on the temperature values measured by in-situ FBG sensors, providing a basis for motor control, waste prevention, and accident prevention. Table I presents a comparison of current mainstream electronic sensors.

TABLE I
COMPARISON OF MAINSTREAM SENSORS

Sensor types	Advantages	Disadvantages	Images
Thermocouple	Fast response, high-temperature, wide range	Needs calibration, EMI-susceptible installation, may damage structure	
Thermal resistance	High precision, stable, wide range	Slow response, high cost, complex installation	
Thermistor	High sensitivity, low cost, fast response	Limited temperature range, poor long-term stability	
Infrared imaging (radiation)	High sensitivity, low cost, and fast	Limited temperature range and poor long-term stability	
Fiber optic temperature sensor	Anti-EMI, high-voltage applicable, and high precision	Complex installation, high cost, and cross-sensitivity to solve	

B. *Non-contact Sensor-based Temperature Measurement*

Non-contact temperature measurement primarily relies on the infrared method, which employs infrared thermal imagers and radiation sensors (Fig. 7). The measurement process involves focusing the infrared radiation emitted by a target object through a lens; after the detector converts and processes the radiation signal, the surface temperature is calculated by integrating emissivity parameters and relevant algorithms. This method is commonly used for temperature measurement of motor rotors or casings, featuring low requirements on the structure of the measured object and no adverse impact on system balance, along with the advantages of high resolution, high accuracy, and fast response. However, it is highly susceptible to environmental interference (e.g., ambient temperature fluctuations, dust). Infrared thermal imagers can directly display thermal distribution images and have been applied in temperature measurement of motor windings and permanent magnets [35]-[36].

In [35], an industrial infrared thermometer was aligned with the rotating field winding, and the pole face temperature was obtained through error correction and signal conversion. After calibration, the dynamic monitoring error was approximately ±2 °C, providing reliable temperature data for constructing the generator's active power–reactive power (*P*-*Q*) diagram. Nevertheless, this method only captures the average surface temperature; significant measurement errors may occur when there is a large temperature difference between poles or when the measurement angle is improperly set. Reference [37] employs infrared thermography to detect the motor's surface temperature and uses a heat transfer model to estimate the stator current, while analyzing the impact of measurement errors on current estimation.

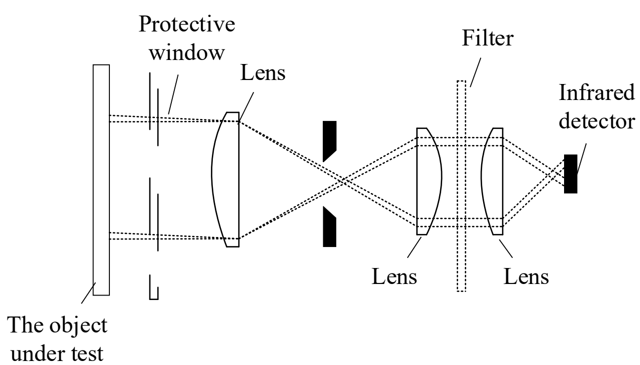


Fig. 7. The temperature measurement principle of infrared method.

C. *Summary*

In summary, sensor-based stator temperature monitoring methods have achieved mature development, with their precision and accuracy widely recognized in the field of electrical engineering. These methods are frequently adopted as the reference for true temperature values in experimental comparison and verification; meanwhile, the experimental data obtained can also be used to assess the rationality of other temperature estimation or monitoring approaches. Then its applicable scenarios and limitations are very clear.

Applicable scenarios: Contact-type methods (thermocouples, PT100, FBG) are suitable for laboratory verification, motor development and testing, and scenarios requiring high measurement accuracy (e.g., calibration of thermal models or electrical models); non-contact infrared methods are applicable to on-site maintenance of industrial motors, dynamic monitoring of rotating components (e.g., rotor surface), and scenarios where sensor installation is not feasible (e.g., motors with ultra-compact structures).

Limitations: These limitations include the requirement for motor structural modification during sensor installation, complicated on-site deployment procedures, difficulty in repairing or replacing faulty sensors, high susceptibility to interference from harsh operating conditions (e.g., electromagnetic noise, mechanical vibration), and constraints related to cost control and spatial layout inside the motor.

III. Stator Winding Temperature Estimation Method based on Thermal Model

Based on the thermal model approach, an LPTN thermal network model is usually constructed first in accordance with the motor's physical geometric model and initial parameters. Subsequently, combined with the electrical parameters under operating conditions, thermal parameters are identified through algorithms to ensure estimation accuracy. This method relies on reasonable measurement protocols and specifications, and achieves temperature estimation by solving the processes of heat generation and heat conduction. It is mainly categorized into two types: parametric thermal networks (with LPTN as a typical representative) and modeling and simulation (with FEA and CFD methods as typical representatives).

A. *Thermal Modeling and Simulation based on FEA and CFD*

FEA and CFD are maturely applied in the thermal modeling and analysis of PMSMs; they couple and solve the electromagnetic field and temperature field through two-dimensional (2D) and three-dimensional (3D) models, respectively, with the numerical solution of partial differential equations as the core, enabling accurate acquisition of the transient temperature rise of permanent magnets and complete 3D temperature distribution. This technology plays a critical role in the design of motor bodies and cooling water channels, designers can optimize the internal structure based on temperature rise analysis to improve motor efficiency and extend its service life [38]. The core of thermal analysis is thermal conduction paths and heat transfer mechanisms, so it is necessary to master the processes of heat generation, heat transfer, heat absorption, and heat dissipation inside the motor to establish a reliable thermal model. Fig. 8 illustrates the internal heat transfer process of the motor (red arrows (Cond) represent conductive heat flux, green arrows (Conv) represent convective heat flux, purple arrows (Rad) represent radiative heat flux), and Fig. 9 presents the combined application framework of FEA and CFD.

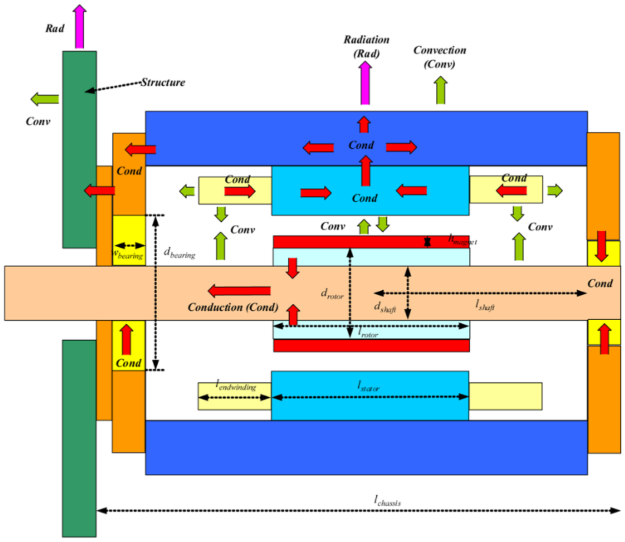


Fig. 8. The heat transfer process inside the motor [39].

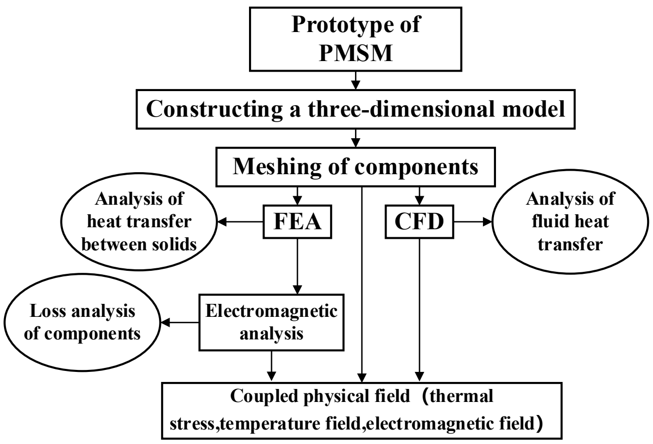


Fig. 9. Estimation based on FEA and CFD.

FEA subdivides the geometric domain of a target object into discrete meshes, on which numerical solutions for partial differential equations (governing heat transfer) are obtained [40]. Its calculation accuracy is influenced by the equation discretization method, mesh generation quality, and mesh quantity; thus, careful design of domain discretization is essential to ensure the credibility of simulation results [41]. Mesh generation should be carried out in accordance with the actual motor geometric model: Denser meshes help improve calculation accuracy, but excessively high mesh density will significantly increase computational time and complexity.

In motor thermal analysis, FEA enables efficient modeling of heat transfer processes between solid components (e.g., stator core, windings, rotor), with the key advantage of accurately solving heat conduction problems in structures with complex geometries. Notably, the refinement degree of the simulated temperature field depends on both mesh discretization quality and the rationality of applied boundary conditions (e.g., convective heat transfer coefficients, ambient temperature). In [42], a 3D FEA model of a PMSM was established; after setting appropriate boundary conditions and simulating heat source input (e.g., copper loss in windings, iron loss in cores), the overall temperature distribution map of the motor was obtained (Fig. 10). This map enables clear visualization of the temperature distribution across all motor components, with the stator winding temperature displayed with particular clarity.

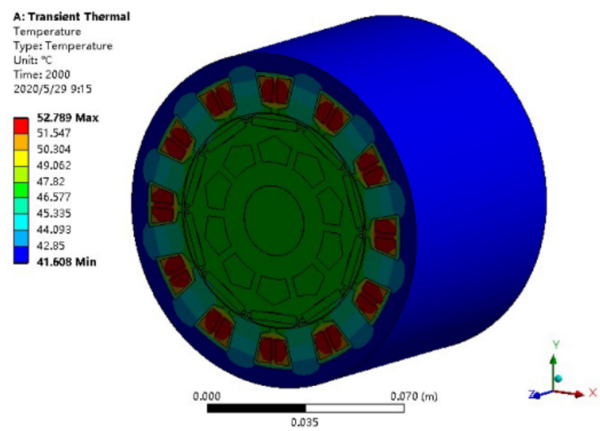


Fig. 10. Temperature distribution of PMSM based on FEA [42].

In conjugate heat transfer (CHT) analysis, the surface heat transfer coefficient of the motor exhibits an axial variation [43]. Since CHT involves coupled heat transfer between solid and fluid (or among multiple fluids), a process influenced by temperature differences and fluid thermophysical properties, and exerts a significant impact on the accuracy of FEA results through the heat transfer coefficient, it must be coupled with CFD for comprehensive simulation.

For fluid-related problems in motor thermal analysis, CFD is the preferred approach, as its governing equations (e.g., Navier-Stokes equations) can more accurately characterize changes in fluid flow states (e.g., laminar, turbulent). Considering the indispensable role of fluid in motor cooling systems, CFD serves as a key technique for electromechanical thermal analysis and cooling system design: It incorporates key convective heat transfer factors, couples with solid heat conduction to solve for wall temperatures at solid-fluid interfaces, predicts heat transfer coefficients under turbulent flow conditions, and offers greater convenience than FEA in handling CHT problems. CFD was adopted in [44] to conduct a temperature field simulation of a PMSM, and the resulting temperature distribution is presented in Fig. 11.

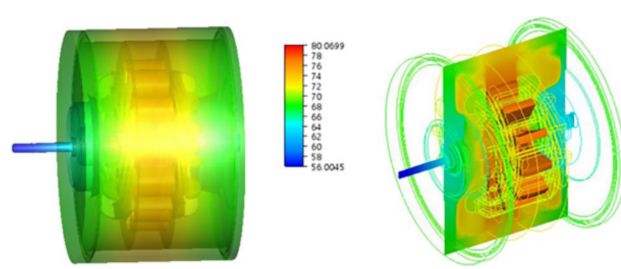


Fig. 11. Temperature distribution of PMSM based on CFD [44].

The optimal approach for motor thermal field simulation is the coupling of FEA and CFD: Specifically, CFD is used to capture the spatial variation characteristics of convective heat transfer coefficients in the motor cooling system, while FEA is employed to calculate the internal loss distribution (e.g., copper loss, iron loss) of the motor and the subsequent temperature field distribution. The overall simulation accuracy of this coupled method depends on two key factors: the calculation precision of motor internal losses and the reliability of turbulence models adopted in CFD.

This FEA-CFD coupling method offers several distinct advantages, including clear visualization of temperature distribution for individual motor components, high precision in multi-physics (electromagnetic-thermal-fluid) coupling simulation, favorable cost-effectiveness, and widespread application in commercial motor thermal design. However, the CFD and FEA coupling method encounters real-time bottlenecks mainly due to its high computational complexity and time consumption. Both CFD, which simulates fluid flow and heat transfer by solving complex partial differential equations, and FEA, which deals with numerous finite element equations, are computationally intensive. When coupled, their combined computational load increases significantly. Moreover, the data interaction between CFD and FEA is intricate. The coupling process requires multiple iterations for convergence, and the use of different software tools for CFD and FEA can lead to data transfer delays and conversion issues.

Striking a balance between model accuracy and computational efficiency is challenging yet crucial. While model simplification can enhance computational speed, it may compromise accuracy. Achieving high precision inevitably raises computational demands and time consumption. In dynamic systems like EVs and in applications requiring online monitoring and real-time control, the CFD and FEA coupling method struggles to meet the stringent real-time requirements due to its lengthy computation and iterative processes. This restricts its broad application in scenarios demanding rapid responses.

B. Temperature Estimation based on LPTN

In the field of stator winding temperature estimation based on thermal models, the LPTN stands as the mainstream method. Serving as a temperature estimation and online monitoring solution that balances accuracy and computational efficiency, the LPTN "clusters" motor components with similar temperature characteristics into discrete thermal nodes, this simplification reduces the network scale and lowers computational load effectively.

This model adopts the assumption that the internal temperature of each thermal node is uniform; by dividing the motor (the research object) into such nodes, the temperature of each node can be obtained by solving the node-specific heat balance equation [39]. The overall modeling process of the LPTN and its associated calculation methods is illustrated in Fig. 12. Based on differences in node division granularity, LPTN networks are categorized into three types: highly discretized white-box models (typically with more than 15 nodes), medium-scale gray-box models (with 5 to 15 nodes), and the most simplified deep gray-box models (with no more than 5 nodes).

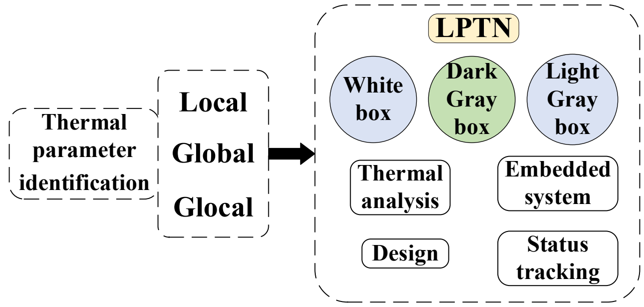


Fig. 12. Estimation and monitoring based on LPTN.

1) White Box

White-box LPTN has excessive node division, which increases computational complexity and time, making it unsuitable for online temperature monitoring [45]. Nevertheless, its fine node division boosts reliance on motor material properties and geometric data. Due to low computational resource consumption, it is often used in motor development and design [46]; however, its complex structure and prior data requirement usually limit it to design-aid tools rather than real-time monitoring models [47]. Reference [48] bidirectionally coupled white-box LPTN with the electromagnetic field, which not only accurately acquired the motor's temperature distribution, electromagnetic performance and thermal characteristics but also significantly reduced traditional FEA computational time (a typical model in Fig. 13). Reference [49] built a 38-node thermal network, whose high accuracy was verified by comparison with FEA results and temperature rise test data.

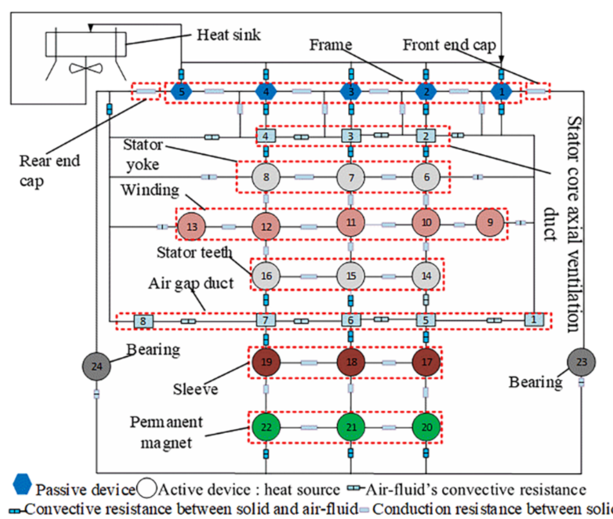


Fig. 13. Model of white-box LPTN [49].

2) Gray-box Model

Gray-box thermal network models typically map thermal nodes to key motor components (e.g., rotor, stator windings) and are classified into shallow and deep types. The classification depends on the granularity of node division: Shallow gray-box models are often employed as embedded online monitoring tools, while deep gray-box models integrate both temperature estimation and monitoring functions. This type of model omits detailed structures such as cooling channels, resulting in a lightweight architecture that facilitates embedding into motor controllers. However, thermal parameters, including thermal conduction resistance and convective heat transfer coefficient, which are difficult to calculate directly due to the complex structure of motor components, are mostly identified through experimental data [50]-[51]. In current research, thermal network models with 2 to 6 nodes are considered most suitable for online temperature monitoring of motors.

Reference [51] proposed a second-order gray-box thermal network model that accounts for the thermal effects of end windings. While this model can predict the average temperature of stator windings, its low order limits it from reflecting the overall temperature distribution of the motor. Reference [52] simplified a 7-node thermal network model to 3 nodes and developed a low-dimensional lumped capacitance (LCC) model, which reduces implementation costs while maintaining acceptable temperature estimation accuracy. Reference [53] constructed a 2-node LPTN model, with stator core temperature data (collected by sensors) as input; thermal resistance and thermal capacitance parameters of the model were identified using thermocouple-measured data, and subsequent verification confirmed the model's accuracy and robustness. Reference [54] proposed a 5-node LPTN model that considers both radial and axial heat transfer in the motor: model parameters were identified via multiple linear regression, motor loss data required for temperature calculation were obtained using K-type thermocouples, and the majority of temperature estimation errors were within ±5 °C. Reference [55] established low-order LPTN models with 3 to 6 nodes (Fig. 14) and adopted the weighted model iteration-square root extended Kalman filter (WMI-STEKF) algorithm for temperature estimation. The model achieved high accuracy with an error of ≤ 3 °C, but the lack of cross-condition data comparison restricted its applicability in varied operating scenarios. Reference [56] proposed a 5-node LPTN model and used the improved particle swarm optimization (IPSO) algorithm for parameter identification under different operating conditions, demonstrating high convergence speed and estimation accuracy. However, this model failed to calculate the temperature of other hotspots in the motor beyond the targeted monitoring nodes.

The LPTN is a mature and widely applied temperature calculation technology in motor thermal analysis: white-box LPTN models are suitable for motor thermal compensation design due to their high discretization and detailed temperature characterization, while gray-box LPTN models are well-suited for motor embedded systems, as they can provide high temperature monitoring accuracy with a lightweight structure. For stator winding temperature estimation based on LPTN, this method offers distinct advantages, including strong applicability to different motor types, relatively easy model construction, and fast computational speed. However, it also has inherent drawbacks: it imposes high requirements on the professional knowledge of researchers (e.g., in motor thermal dynamics and node division), and it is challenging to achieve real-time and accurate identification of thermal parameters when motor operating conditions change (e.g., load fluctuations, speed variations).

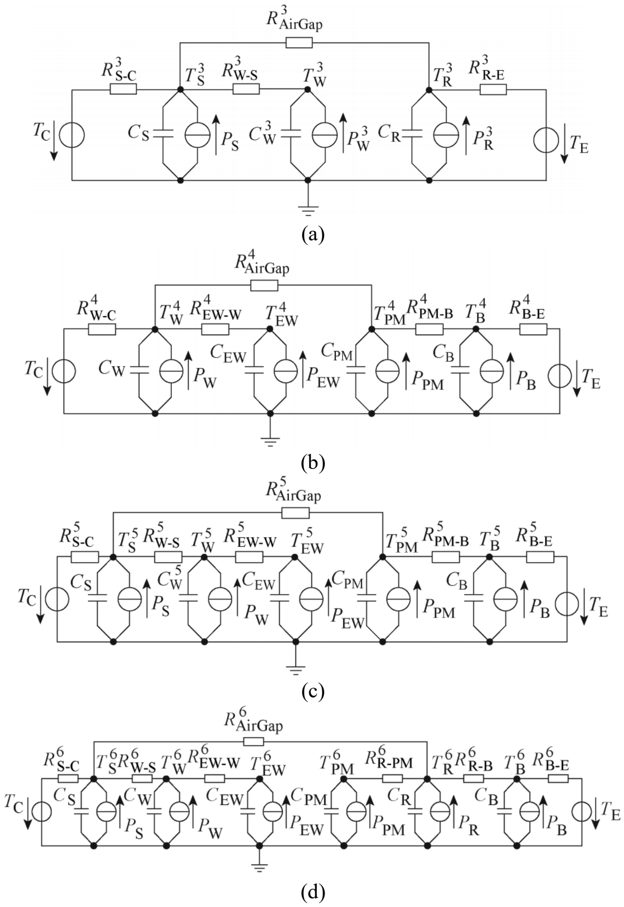


Fig. 14. LPTN of different nodes [56]. (a) 3-node model. (b) 4-node model. (c) 5-node model. (d) 6-node model.

The key to improving the accuracy of LPTN-based temperature estimation lies in the precise identification of thermal network parameters (e.g., thermal resistance, thermal capacitance); the rationality of these identified parameters requires repeated verification through experiments and simulations. Notably, the accurate identification of thermal parameters under complex and variable operating conditions remains an unresolved issue that requires further research. In the future, two directions are expected to become mainstream in LPTN-related research: first, expanding traditional 1D LPTN models to 2D or 3D thermal network models to achieve more comprehensive acquisition of motor internal temperature fields (including local hotspots); second, deeply coupling motor control models with LPTN models, which can reduce the overall computational load of the system while maintaining temperature estimation accuracy, thereby facilitating the integration of LPTN into real-time motor control systems.

C. Summary

In summary, the primary thermal model-based methods for stator winding temperature estimation are FEA/CFD coupling simulation and LPTN. These two methods have distinct applicable scenarios, and each comes with its own set of limitations. The detailed breakdown of their applicable contexts and limitations is provided in the following.

Applicable scenarios: FEA/CFD coupling is suitable for motor design optimization (e.g., cooling channel layout, material selection), offline thermal performance verification, and scenarios requiring high-precision temperature field visualization (e.g., analyzing local hotspots in stator slots); LPTN (especially gray-box models) is applicable to online real-time monitoring (e.g., automotive PMSM controllers), embedded systems with limited computational resources (e.g., microcontroller unit (MCU)-based control units), and scenarios requiring fast temperature response (e.g., transient load conditions).

Limitations: FEA/CFD has extremely high computational costs and cannot meet the real-time requirements of online monitoring due to its complex calculations and large resource consumption. LPTN relies on accurate thermal parameter identification (e.g., thermal resistance, thermal capacitance), and its estimation accuracy decreases under variable operating conditions (e.g., load mutations) as it struggles to adapt to sudden changes. Also, low-order models (2-3 nodes) in LPTN cannot capture local hotspot temperatures in the stator.

Table II presents a summary of the comparison of thermal-model-based stator temperature monitoring methods mentioned in the surveyed literature.

TABLE II
COMPARISON OF DIFFERENT METHODS BASED ON THERMAL MODEL

Estimation method	Sub-type	Accurary/°C	Computation burden	Hardware cost	Reference
FEA-based	3D full-model	±1–3	High	High	[42]
FEA-based	2D axisymmetric model	±3–5	Medium	Medium	[41]
CFD-based	Turbulent model	±2–4	High	High	[44]
CFD-based	Laminar model	±3–6	Medium	Medium	[43]
FEA-CFD coupling	3D coupled model	±1–2	Very high	Very high	[38]
LPTN	White-box model	±1–2	Medium	Low	[49]
LPTN	Gray-box model (5-node)	±3–5	Low	Low	[54]
LPTN	Gray-box model (2-node)	±5–8	Very Low	Low	[53]

IV. TEMPERATURE ESTIMATION METHOD BASED ON ELECTRICAL MODELS

The electrical model of PMSMs plays a crucial role in multiple fields, serving as the theoretical foundation for research areas such as motor control, parameter identification, signal injection, and optimal control strategies [57]-[58]. Its temperature monitoring principle relies on tracking temperature-sensitive electrical parameters, which necessitates parameter estimation during normal operation while minimizing adverse impacts on operational stability. However, the electrical mathematical model of PMSMs, characterized by four variable parameters, strong nonlinearity, and inherent rank deficiency, imposes limitations on the estimation accuracy of fundamental frequency model parameters.

Since PMSM stator windings are predominantly made of copper (whose resistance exhibits a linear relationship with temperature), stator winding temperature estimation primarily depends on accurate winding resistance estimation. Currently, winding resistance estimation methods can be categorized into two main types: non-intrusive observer-based methods and intrusive signal injection-based methods.

A. Method based on Non-intrusive Observers

In motor control systems, accurate monitoring of stator resistance is critical for the implementation of high-performance field-oriented control (FOC); however, online measurement of stator resistance remains challenging under complex operating conditions (e.g., variable load, fluctuating speed). To address this issue, researchers have proposed non-intrusive estimation methods, including full-order state observers [59] and adaptive observers [60]. These methods construct observers based on the PMSM mathematical model to estimate stator winding resistance, and then derive the stator winding temperature from the estimated resistance by utilizing the linear temperature-resistance characteristic of copper. Nevertheless, the robustness performance of such observer-based methods is affected by several key factors, and the technical details can be reflected through the research findings of relevant literatures.

Model uncertainty is the primary factor affecting observer robustness. Since observer design relies on an accurate PMSM model, parameter deviations (e.g., permanent magnet flux linkage decay due to high temperature, inductance variation from magnetic saturation) significantly increase estimation errors. For example, [61] proposed a nonlinear interconnected observer that can simultaneously estimate multiple PMSM electrical parameters (including stator resistance) to support temperature calculation. However, when the permanent magnet flux linkage deviates by 10% from the nominal value, the stator resistance estimation error rises from 2% to 8%.

External disturbances and operating condition adaptability are also critical. Load torque fluctuations and measurement noise from current/voltage sensors interfere with estimation accuracy. Reference [62] applied the model reference adaptive system (MRAS) to estimate stator resistance and convert it to winding temperature via the resistance-temperature coefficient. However, this method has limited adaptability: It performs well under rated speed and load but degrades sharply at low speeds (near zero speed). This is because the extremely small back electromotive force (EMF) at low speeds makes it hard to distinguish the voltage drop caused by stator resistance from other components (e.g., inverter nonlinearity). When speed is below 5% of the rated value, the resistance estimation error exceeds 10%. Reference [63] directly demonstrates the impact of external disturbances. It employed a Kalman filter combined with a thermal model, using real-time measured electrical and mechanical data (e.g., phase current, rotational speed) to simultaneously estimate stator winding and permanent magnet temperatures. Experimental results show that under 50% load torque step change, the transient error of this Kalman filter-based observer reaches 15%, and it takes 0.5-1 s to recover to a steady-state error (< 3%).

Besides observer-based methods, the recursive least squares (RLS) algorithm is also applied in stator resistance estimation. Reference [64] simplified the PMSM electrical model via Park transformation and adopted a fast-slow dual RLS algorithm to identify stator resistance, improving estimation efficiency. Reference [65] utilized a pre-established offline PMSM model and online RLS for resistance estimation, compensating for temperature-induced degradation in motor control performance.

B. Method based on Invasive Signal Injection

Intrusive signal injection-based methods for stator winding resistance (and thus temperature) estimation typically utilize direct current (DC) signals. Compared with high-frequency signal injection, DC signal injection avoids the skin effect in stator windings (an issue that distorts resistance measurement in high-frequency scenarios) and concurrently reduces additional hysteresis losses and eddy current losses induced by alternating signals in the stator core. Fig. 15 presents the flow chart of this DC injection-based stator winding temperature estimation method, where the key operational step lies in accurately extracting the DC component of the stator current (or voltage) after signal injection; this DC component serves as the critical input for subsequent winding resistance calculation and temperature derivation.

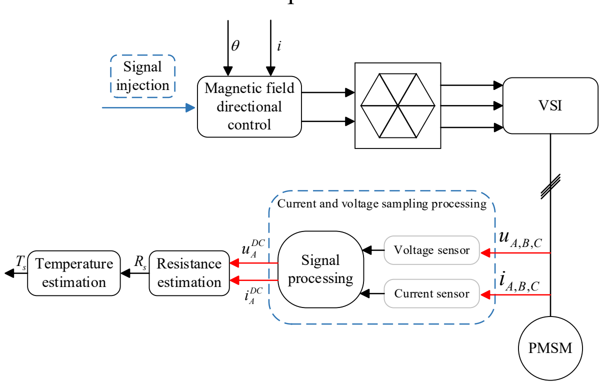


Fig. 15. Flow of signal injection methods.

Reference [66] established a steady-state voltage model for dual three-phase PMSMs that accounts for voltage source inverter (VSI) nonlinearity, and realized stator winding temperature estimation by tracking the voltage difference derived from this model. Reference [67] proposed a winding temperature tracking technique based on dual DC current injection; this method is not affected by VSI nonlinearity, but the dual-phase current injection tends to increase additional copper loss in the stator windings, which in turn impairs the accuracy of temperature estimation.

Reference [68] injected high-frequency voltage into the d-axis of the IPMSM rotor reference frame model to measure the high-frequency stator resistance, derived the quantitative relationship between resistance and temperature using negative temperature coefficient (NTC) sensor data, and further constructed an online temperature estimator with good estimation accuracy. Reference [69] optimized the DC injection parameters and adjusted the current ratio to improve temperature estimation accuracy, while also taking into account the influences of magnetic saturation and signal injection effects on resistance measurement. Reference [70] estimated stator winding temperature by combining an adaptive fuzzy algorithm with an improved DC injection method; this approach enhanced estimation accuracy through data fusion, but the dual-operation mechanism (algorithm calculation + signal injection) complicates the tuning of model parameters. Reference [71] injected DC voltage into the α-axis of the stationary reference frame to calculate stator winding resistance for temperature estimation; however, sliding mode chattering in the control system and filtering delay in the signal processing loop limit the dynamic response speed of resistance estimation.

C. Summary

Stator winding temperature monitoring based on electrical models essentially relies on tracking stator resistance, a temperature-sensitive electrical parameter, with the core challenge lying in the accurate calculation of this resistance. The methods are divided into observer-based and signal injection-based types, with clear applicable scenarios and limitations.

Applicable scenarios: Observer-based methods are suitable for closed-loop control systems (e.g., FOC) that require non-intrusive monitoring (no additional signal injection), and scenarios with stable operating conditions (rated speed/load, no severe load mutation); signal injection-based methods are applicable to low-speed or zero-speed conditions (where observer-based methods fail due to weak back EMF), and scenarios that allow minor interference to motor operation (e.g., EV idle mode, industrial motor start-up phase).

Limitation: Its limitations are that estimation accuracy is constrained by multiple factors (e.g., VSI nonlinearity, magnetic saturation) and that intrusive signal injection may have adverse impacts on motor operational performance (e.g., increased losses, torque ripple). Future research work in this field should focus on reducing the reliance on external auxiliary equipment, avoiding signal interference in resistance measurement, and further improving estimation accuracy; in particular, combining electrical model-based methods with other temperature monitoring technologies to enhance overall monitoring accuracy deserves in-depth exploration.

Table III presents a summary of the comparison of electrical-model-based stator temperature monitoring methods mentioned in the surveyed literature.

TABLE III
COMPARISON OF DIFFERENT METHODS BASED ON ELECTRICAL MODEL

Estimation method	Sub-type	Accurary/°C	Computation burden	Hardware cost	Reference
Observer-based method	Nonlinear interconnected observer	±2–4	Medium	Low	[61]
Observer-based method	MRAS observer	±3–5	Low	Low	[62]
Observer-based method	Kalman filter + thermal model	±1–3	High	Medium	[65]
Observer-based method	Fast-slow dual RLS	±2–4	Medium	Low	[63]
Signal injection-based method	Dual DC current injection	±2–5	Low	Low	[67]
Signal injection-based method	High-frequency d-axis voltage injection	±3–6	Medium	Low	[68]
Signal injection-based method	DC voltage injection (α-axis)	±3–5	Low	Low	[71]
Signal injection-based method	Adaptive fuzzy + DC injection	±1–4	High	Medium	[70]

V. TEMPERATURE ESTIMATION METHOD BASED ON DATA-DRIVEN ALGORITHMS

Data-driven algorithm-based methods rely on large sets of initial and target parameters, with measured variables covering electrical, mechanical, and thermal-related parameters. After sufficient training, they can derive non-directly measurable parameters from updated measurements. For motor temperature estimation and monitoring, effective data-driven algorithms include machine learning and deep learning. With the development of big data, historical datasets with high-speed computing capabilities have driven the rapid advancement of data-driven methods; the overall flow of their temperature estimation and monitoring is shown in Fig. 16.

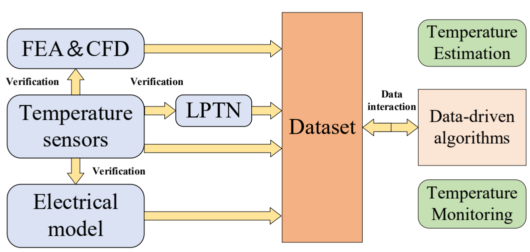


Fig. 16. Estimation and monitoring based on data-driven algorithms.

For drive modeling, [72] discusses in detail the prediction accuracy comparison of various drive models, with the the mean square errors (MSE) of the training sets of different methods are shown in Fig. 17. Results indicate that algorithms with better performance (e.g., ordinary least squares (OLS), multi-layer perceptron (MLP), extremely randomized trees (ET)) exhibit superior performance when the training set size is small. Machine learning methods have been proven effective in estimating and monitoring PMSM temperatures, and data-driven algorithms demonstrate robustness under various operating conditions [73].

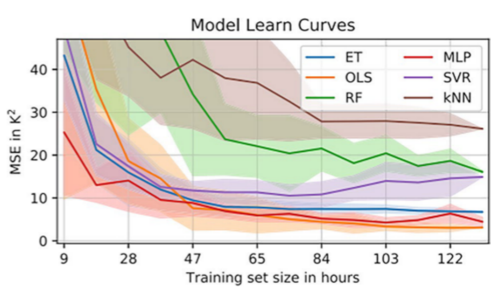


Fig. 17. MSE for fixed test set and growing training set [72].

For temperature monitoring of PMSMs, data-driven algorithm-based methods have gained attention in recent years. Reference [74] combined geometric models, finite element method (FEM) simulations, and back propagation (BP) neural networks, inputting stator parameters to predict winding temperature with a goodness of fit exceeding 0.99991. Reference [75] utilized existing controller signals and predicted temperature via a dual-channel multi-scale convolutional neural network (MCNN) model. Reference [76] integrated an LPTN model with a data-driven method to construct a TNN, achieving high prediction accuracy. Reference [77] proposes a soft sensor method integrating principal component analysis (PCA) and extreme learning machine (ELM) to achieve high-precision and low-complexity prediction of stator winding temperature for PMSMs.Reference [78] adopted a deep residual machine learning method, enhancing prediction capability through feature enhancement and residual connections; it identified coolant temperature as critical for stator temperature estimation but required repeated training, leading to high time costs. The advantages and disadvantages of the mainstream data-driven algorithms are shown in Table IV.

TABLE IV
PROS AND CONS OF MAINSTREAM DATA-DRIVEN ALGORITHMS

Data-driven algorithms	Advantage	Disadvantage
ET	Fast, anti-overfitting, feature importance	Weak interpretability, lower extreme accuracy
OLS	Simple, efficient, sound parameter theory	Linear-only, outlier-sensitive
RF (random forest)	Strong generalization, handles high dimensions	High computation, weak interpretability
MLP	Strong nonlinear, adapts to diverse data	Needs massive data, slow
SVR (support vector regression)	Good small-sample generalization	Large-data complex, Kernel parameter-sensitive
KNN (*k*-nearest neighbors)	Simple, no training, handles nonlinearity	High computation, K-sensitive

Data-driven algorithms can be applied to thermal parameter identification of LPTN thermal networks; typical examples include particle swarm optimization (PSO), which reduces knowledge requirements and the randomness of empirical settings. Reference [51] used multiple linear regression to identify LPTN thermal parameters, but its linear assumption made it difficult to capture the strong nonlinearity of thermal resistance, leading to deteriorated residuals after aging; Reference [55] adopted PSO for parameter identification.

Data-driven algorithms are also integrated into electrical model parameter identification, offering greater flexibility in handling complexity and nonlinearity. However, they suffer from large computational load, along with issues like particle local optimization and slow convergence, problems that can be alleviated via algorithm optimization. Reference [79] used an adaptive PSO algorithm based on the logistic function for online identification of PMSM parameters, achieving faster and more accurate convergence. Reference [80] constructed a state estimator using a Lyapunov-optimized radial basis function (RBF) neural network, identifying parameter changes solely based on system states.

Data-driven algorithms provide novel and efficient methods for parameter identification of motor thermal and electrical models, with great potential in temperature estimation, especially new insights for algorithm application and integration with other methods. Their advantages include reduced knowledge dependency, strong anti-interference ability, excellent generalization, distinct targeting, and visualization benefits. Nevertheless, they face challenges such as insufficient operating condition coverage in training sets, increased model errors over time, high power consumption, low accuracy in multi-output scenarios, and constraints on data/model updates with complex corrections. Research on complete data-driven models is worthwhile: Training data should cover normal and abnormal operating conditions, while the "selective training" of samples remains unvalidated. A key issue is whether the model can adaptively adjust parameters to handle transient conditions. Future exploration of online learning mechanisms and development of models with real-time training updates and low power consumption hold broad prospects. As for the above-mentioned literature content, Table V summarizes and analyzes the data-driven algorithms in the literature in terms of data requirements, training costs, generalization abilities, interpretability, and application scenarios.

TABLE V
COMPARISON OF VARIOUS DATA-DRIVEN ALGORITHMS

Data-driven algorithm	Data requirements (input variables)	Training cost	Generalization capability	Interpretability	Key application scenario	Reference
ET	Electrical (current, voltage), mechanical (speed, torque), and thermal (coolant temperature), total 5–8 variables	Low	Low	Medium	Online monitoring with limited computational resources	[72]
RF	Electrical (3-phase current, voltage), mechanical (speed, load torque), thermal (coolant, ambient temperature), total 8–12 variables	Medium	Medium	Medium	Multi-condition temperature estimation (e.g., variable speed/load)	[73]
MLP	Electrical (current, voltage, frequency), mechanical (speed, acceleration), thermal (coolant flow rate, temperature), total 10–15 variables	High	Medium	Low	Nonlinear temperature prediction (e.g., transient load, start-stop cycles)	[74]
BP neural network	Electrical (current, voltage, power), mechanical (speed, torque), thermal (coolant temperature, stator core temperature), total 7–10 variables	Medium	Low	Low	Laboratory calibration, offline temperature prediction	[77]
Deep residual learning	Electrical (current, voltage, harmonic components), mechanical (speed, torque, vibration), thermal (coolant temperature, flow rate, ambient temperature), total 15–20 variables	Very high	High	Low	Cross-motor generalization, high-precision prediction	[78]
TNN (LPTN + data-driven)	Electrical (loss data), mechanical (speed), thermal (network parameters, coolant temperature), total 6–9 variables	Medium	Medium	Medium	Integration with thermal models (improves LPTN accuracy)	[76]
Dual-channel MCNN	Electrical (current/voltage time series), mechanical (speed sequence), total 12–16 variables	High	Medium	Low	Dynamic condition monitoring (e.g., EV acceleration, deceleration)	[75]

VI. CONCLUSION

A. Limitations of Current Research

1) Sensor-based temperature monitoring remains the optimal method for verifying the accuracy of other estimation and monitoring models in the future, and will increasingly serve as a calibration tool. However, considerations are still needed regarding complex circuit design, electro-magnetic interference (EMI) resistance, integration into electric drive systems, and proper control of manufacturing costs.

2) For temperature estimation and monitoring based on thermal models, FEA and CFD remain important tools for motor design in both research and commercial applications. Nevertheless, time and computational costs must be considered to obtain more comprehensive and realistic motor temperature responses; low-order, single thermal network models in the LPTN method prioritize fast computation while neglecting the analysis of local hotspots and overall motor temperatures.

3) In terms of stator winding calculation based on electrical models, issues such as model accuracy and interference caused by signal injection methods to the motor affect temperature estimation accuracy, which remain to be addressed.

4) Current methods for stator winding temperature monitoring mainly focus on average temperature, and relying

solely on a single method for monitoring results in less-than-ideal performance in terms of stability, accuracy, and other aspects.

5) For data-driven algorithms, the training set cannot cover all operating conditions, resulting in poor generalization in unknown scenarios. The long-term operation causes the model to "age", increasing estimation errors. Also, the high computational cost makes it difficult to embed these algorithms in controllers.

B. Future Perspectives

1) To mitigate the limitations inherent in sensor-based stator winding temperature monitoring, future research should prioritize the adoption of high-precision sensors, the integration of contact and non-contact measurement methodologies, and the implementation of multi-sensor collaborative monitoring systems. Concurrently, the design of high-precision monitoring circuits and the optimization of their spatial layout represent directions worthy of in-depth investigation, as they are critical to enhancing monitoring reliability.

2) Regarding thermal modeling, the future development of 2D and 3D thermal network models demonstrates substantial research value and promising application prospects. Specifically, the longitudinal deployment of multi-node configurations at key motor components to characterize hotspot temperatures, coupled with the integration of FEA and CFD techniques for optimizing node planning, will facilitate the acquisition of comprehensive and accurate motor temperature distributions.

3) For stator winding resistance calculation, the optimization of signal injection strategies, including parameters such as injection magnitude, timing, and interval, holds significant potential for reducing adverse interference to the motor operation and improving resistance calculation accuracy. This direction is expected to provide robust technical support for high-precision temperature estimation.

4) Aiming to address the constraints of single temperature monitoring methods, the future adoption of multi-method synergy, which leverages data fusion techniques to generate more comprehensive and wide-coverage temperature datasets, exhibits considerable prospects. This approach can effectively compensate for the inherent shortcomings of individual methods and enhance the overall performance of temperature monitoring systems.

5) In terms of data-driven algorithms, the future lies in devising online updating mechanisms, enabling models to adapt to varying operating conditions. Additionally, exploring lightweight models to cut computational costs also shows great promise.

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