

Review

Literature Review on LPTN Applied to Radial PMSM: Formulation and Approaches

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Abstract

Permanent magnet synchronous motors (PMSMs) possess high power density and efficiency, which make them suitable for broad applications, including the transportation sector, thus contributing to its decarbonization. As demand for electric vehicles increases, the need for performance improvements on electric motors also rises. An essential requirement is efficient thermal management to prevent and mitigate overheating-related premature motor failure. Among the methods of thermal analysis, the Lumped Parameter Thermal Network (LPTN) model is distinguished by its versatility of applications and its low computational requirements, making it a proper tool for analyzing the temperature distribution within a motor. This paper focuses on radial PMSMs, emphasizing the identification of the primary heat sources and the corresponding heat transfer mechanisms involved. Furthermore, it provides a comprehensive literature review of LPTN models implemented by different authors, analyzing the formulations and highlighting the similarities and differences between the models presented in the existing literature.

Keywords: lumped parameter thermal network; PMSM; copper loss; iron loss; conduction; convection; radiation; heat transfer coefficient; thermal resistance; capacitance

1. Introduction

The transportation sector is one of the main contributors to detrimental exhaust emissions due to its dependence on fossil fuels as the primary energy source. Transitioning to electrified transportation involves shifting from internal combustion engine vehicles to electric vehicles, reducing CO₂ emissions from fossil fuels and greenhouse gas emissions in the automotive sector [1–6].

As demand for electric machines continues to rise, improving their functionality and reliability has become a crucial requirement for advancing industrial development in the transport sector [7–9]. Electric motors employed in EVs (electric vehicles) and HEVs (hybrid electric vehicles) feature high torque and power density, wide speed range and constant-power operating capability, high efficiency, reliability and robustness, low acoustic noise, and reasonable cost [10,11].

Electric motors can be classified according to the type of motor power supply into direct current (DC) and alternating current (AC). Figure 1 illustrates the most common typologies and their classifications.

A recent review from Drexler et al. [12] performed a systematic analysis and categorization of 48 electric traction motors from 31 EVs from 2018 to 2023 in which 62.5% of the motors studied were Permanent Magnet Synchronous Motors (PMSMs), followed by



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18.75% of induction motors and 18.75% of EESMs. Given the current relevance of radial PMSMs, from now on, the article will focus on interior rotor radial PMSMs, both Internal Permanent Magnet Synchronous Motors (IPMSMs) and Surface Permanent Magnet Synchronous Motors (SPMSMs).

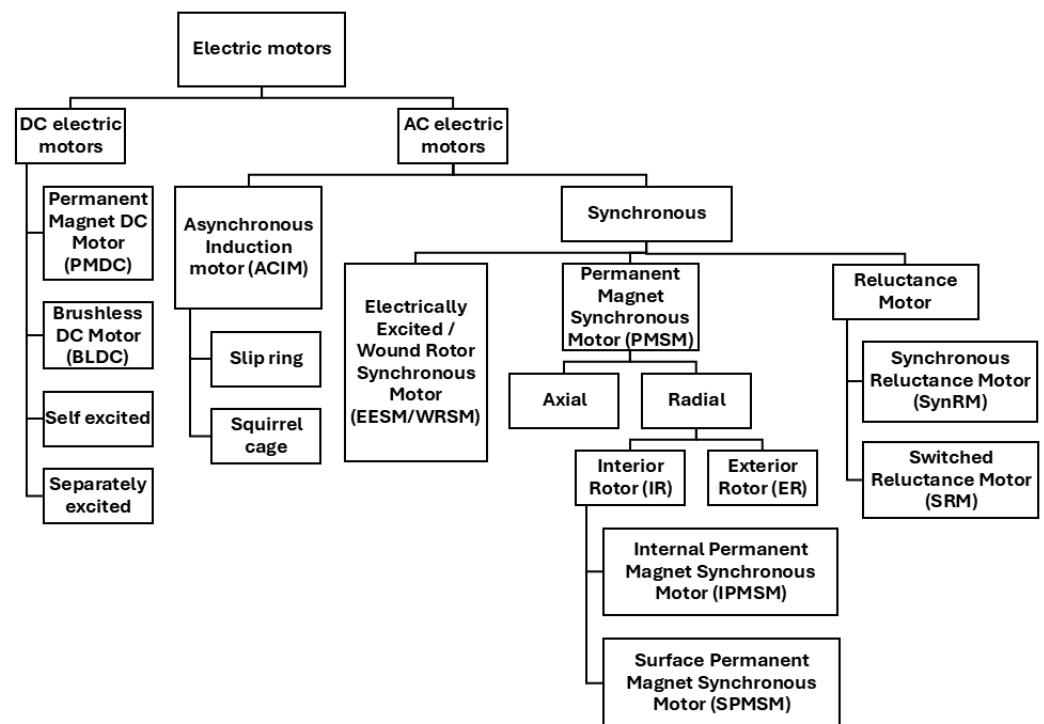


Figure 1. Classification of electric motors.

PMSMs exhibit key performance attributes that are highly desired for EV traction machines and various other applications, such as manufacturing and medical science. These include higher efficiency, reduced mass and volume, lower rotor inertia, precise control, high speeds, and a simplified structure [7,13]. Permanent Magnets (PMs) also provide them with outstanding advantages of high coercivity and high remanence [10]. Moreover, as PM motors do not need a DC source for excitation, this results in low copper loss and high power and torque density [14,15].

Inadequate heat transfer conditions in a PMSM can lead to deterioration and irreversible damage to the motor. The losses originating in the rotor can lead to significant heating and irreversible demagnetization in located sections of the magnets. Moreover, losses generated in the stator and windings can lead to temperature peaks that exceed the thermal limits of the winding and destroy the insulation varnish [16–22]. The increasing power density in contemporary high-performance machines requires the implementation of advanced thermal modeling and management techniques [23]. These strategies are crucial for understanding the different heat sources and heat paths in the PMSMs, ensuring efficient heat dissipation and maintaining optimal operational performance to implement loss-minimizing design and control strategies.

Electric motor thermal analysis can be performed using Computational Fluid Dynamics (CFD), Finite Element Analysis (FEA), or a Lumped Parameter Thermal Network (LPTN) model. FEA and CFD methods are highly accurate and provide reliable predictions of the thermal system behavior during device development. Traditionally, CFD approaches were used to predict fluid flow and conduction and convection heat transfer in complex regions of the motors, whereas FEA was primarily used for conduction heat transfer in solid components and, for convection boundaries, analytical and empirical algorithms

were implemented as in LPTN [24]. Modern multiphysics FEA tools are capable of handling convection through coupled analysis of well-defined boundary conditions, giving high-accuracy results, particularly for convection characterization [25,26]. Both methods, however, require considerable computational resources, which limit their applicability for real-time applications.

LPTN models appear as a less computationally demanding approach for simulating heat transfer; the circuit and variable parameters must be rigorously defined to represent accurately the primary heat transfer pathways [24,27,28].

LPTN models have been extensively studied in numerous scientific articles for their applications in the design and monitoring phases of a wide range of electric motors, as a result of their versatility and low computational requirements.

To the best of the authors' knowledge, no comprehensive reviews specifically addressing LPTN modeling of PMSMs that incorporates circuit definitions and analyzes the heat transfer mechanisms have been published. This should include an examination of the modeled motor components, the identification of primary heat transfer pathways, and the establishment of thermal resistance and capacitance parameters as defined in the existing literature. This paper aims to provide a systematic review of these methodologies, facilitating a clear and precise understanding of LPTN applications in the context of PMSMs.

A previous study from He et al. [26] about methods for temperature estimation of PMSMs covers a wide variety of sensors and methodologies for estimating temperatures in PMSMs; since LPTN models account for only a section of the article, it focuses on classifying the LPTN and analyzes various studies of models ranging only from 2 to 6 nodes, presenting them in a table that also indicates the different parts of the motor studied in these models. In the review made by Khalesidoost et al. [7], LPTN models also represent only a section of the article, the review lacks a detailed review of the formulation employed by the authors, and the recapitulatory table of the literature for LPTN does not include the year published, the parts modeled, the loss modeling, the heat source, and the information regarding capacitances and validation techniques, all of which are considered in the present article.

Gronwald and Kern [18] present a comprehensive study of heat transfer mechanisms in motors, compiling geometry-based formulas for modeling heat transfer phenomena. The article is very detailed in its compilation of these formulations, which are classified according to the elements involved in the process; within each classification, the motor topology used is specified. However, it should be noted that several authors cited used formulas to model convection in PMSM motors that were derived from studies of induction motors; therefore, there was a gap in the review of these implementations and in linking the formulation of heat transfer coefficients to the resistances of the LPTN models in which they were used.

The methodology used to select the scientific articles listed in Table 1 is as follows: The publication dates of the articles to be reviewed were limited to the period between 2010 and 2026. The search focused on LPTN models applied to radial PMSMs, excluding axial motors and considering both surface-mounted and internal magnet motors. An initial search was conducted using Google Scholar, Web of Science, Consensus, and ResearchRabbit. Based on that initial search, the relevant citations from the selected articles were consulted to expand the review. Approximately fifty scientific articles were reviewed, and those that did not provide sufficient information regarding model validation and formulation, such that their contribution to the summary table and the overall picture of trends would be relevant, were excluded.

Table 1. LPTN of the PMSM literature review.

Year	Ref.	Motor Type	Parts Modelled	N.N.	Loss Modeling	Heat Sources	TH. B.	R. Modelling CD CV RD			Capacitances	Verification
2010	[29]	SPMSM	A, CH, SY, R, EW, SW, SFT, BB, IA, MS	10	Analytical loss model (winding losses) and experimental measurements (iron losses)	4 (BB, SY, SW, EW)	T	x	x		7	Experimental
2011	[30]	IPMSM	COO, F, SY, ST, SW, EW, AG, R, SFT	5	Constant losses assumption (not specified the calculation method)	3 (SY, SW, R)	SS	x	x		4 (SY, SW, R, SFT)	Experimental
2012	[31]	IPMSM, 25 kW 12-pole/18-slot	F, SY, EW, SLT, ST, ECA, AG, R, PM, SFT, FB	32	3D transient FEA with temporal and spatial variations of the magnetic flux (core loss and eddy current loss)	5 (SY, EW, SW, ST, PM)	T	x	x		Constant thermal capacitance in every node	Experimental
2014	[17]	IPMSM	SW, EW, PM	2-3	Measurement-based loss model from the ECU	1 (S)	T	x	x		In every node	Experimental
2015	[32]	PMSM, 60 kW	SY, SW, ST, PM, RI, SFT	7	Empirical approach	5 (SY, SW, ST, PM, RI)	T	x	x		5 (SY, SW, ST, PM, RI)	Experimental
2016	[27]	PMSM, 60 kW	SY, SW, ST, PM	4	Empirical approach	4 (SW, ST, PM, ST)	T	x	x		4 (SW, ST, SY, PM)	Experimental
2017	[33]	IPMSM	F, SY, ST, SW, RC, PM, SFT	32	FEA	5 (SY, ST, SW, EW, PM)	T	x	x		Constant thermal capacitance in every node	Loss simulation
2019	[34]	PMSM	A, IA, F, SY, ST, R, SW, PM, SFT	12	Classical copper loss equation + FEA	11 (SFT, PM, SW, SY, ST, R, F, IA)	T	x	x	x	In each node, fixed values	Matlab-Simulink
2019	[35]	PMSM	COO, S, R, EC, F	5	Classical copper loss equation + dynamic equivalent circuit	2 (S, R)	T	x	x		3 (S, R, EC)	Experimental
2021	[36]	PMSIWM	SLT, SW	2	Not specified	1 (SW)	SS	x			-	FEA, CFD, experimental
2021	[37]	PMSM	SLT, SW, ST, AY, AG	*1	FEM	1 (SW)	SS	x	x		-	FEM, experimental
2022	[14]	PMSM, 10 pole, 12 slot	F, SC, RC, SW, EW, ST, SY, RP, RY, PM, SFT, BB, EC, ES	*2	Empirical equations (iron and copper loss), CFD-CHT (windage loss and end spaces), FEA for checks	*1	T	x	x		In every node-connected resistance or conductance	FEA, experimental
2024	[38]	IPMSM, 80 kW	COO, F, ES, SHL, S, SY, ST, SW, EW, AG, IA, R, PM, SFT	154-19	Electromagnetic field simulation software JMAG 21.0 + experimental + empirical formulas	6 (SY, ST, SW, EW, RI, PM)	T	x	x		Fixed values	Experimental
2024	[39]	IPMSM	SFT, BB, R, PM, EC, ER, SY, SW, EW, IA	23	Commercial multiphysics simulation software	13	T	x	x		10	Experimental

Table 1. Cont.

Year	Ref.	Motor Type	Parts Modelled	N.N.	Loss Modeling	Heat Sources	TH. B.	R. Modelling CD CV RD			Capacitances	Verification
2025	[40]	PMSM	AG, ST, SW, SLT	55	Transient electromagnetic FE simulation	Distributed	SS	x	x		-	Experimental and FEM
2025	[41]	IPMSM, 40 kW 8-pole/48-slot	ST, SY, SW, AG, EW, PM, RI	*1	Segmented iron losses model proposed and electromagnetic FEM	Uniformly distributed	T	x	x		Constant thermal capacitance in each node	Experimental
2025	[42]	IPMSM	PM, SY, ST, SW	*1	MLP + SC-SE	Dynamic load adjustment	T	x			Learnable inverse thermal capacitances from MLP	TNN + CNN-RNN baselines+ Ablated versions of OLTEM
2026	[43]	IPMSM, 10-pole/12-slot	COO, F, ES, S, SY, ST, SW, EW, AG, IA, R, PM	*1	Analytical loss model	*1 (SW, R, PM)	SS/T	x	x		Dynamic value for cooling oil and fixed values	Experimental
2026	[44]	IPMSM, 80 kW 8-pole/48-slot	F, SY, SW, ST, R, BB	6	Analytical loss model and bidirectional coupling method	5 (SY, SW, ST, R, BB)	T	x	x		5 (SY, SW, ST, R, BB)	Experimental and FEM
2026	[45]	IPMSM, 4-pole/24-slot	A, ST, SW, PM	4	Analytical loss model + hierarchical physics-aware network	3 (SW, ST, PM)	T	x	x	x	Constant thermal capacitances	Experimental
2026	[46]	IPMSM	COO, ST, SY, PM	4	Temperature adaptative analytical loss model (copper loss) + empirical regression surrogate formula	2 (SW, SY)	T	x	x		Constant thermal capacitances in every active node	OOD stress test

*1: Not specified. *2: Not specified, 24 identical resistances in parallel for the stator yoke.

The rest of this article is organized as follows: Section 2 briefly introduces the various types of losses that occur in a PMSM, whose heat paths are analyzed by the LPTNs. Subsequently, Section 3 discusses the different heat mechanisms present in a PMSM, outlining their definitions and functions in the context of electric motor operation. Section 4 focuses on the pure analysis of the LPTNs, beginning with its classification and continuing with the formulation used by different authors in the literature regarding conduction, convection, radiation, and capacitance resistances. Additionally, a bibliographic table is used to analyze the trends presented in the literature regarding the application of LPTNs to PMSMs. Lastly, Section 5 summarizes the topics covered in this article and the main trends identified.

2. Loss Generation

Loss identification is crucial in implementing proper mechanisms that ensure efficient performance and thermal management, ensuring operation reliably and preventing premature failure or wear. Typically, PMSM losses are classified into copper losses, iron losses, magnet losses, stray losses, and mechanical losses.

Copper losses represent the major source of losses of the motor and refer to the losses caused by the Joule effect on the copper windings of the coils in the motor stator [47]. They are influenced by proximity and skin effects [48].

Conductors that are adjacent and parallel to the conductors of an energized coil show more flux penetration than the conductors that cross over; this increases the losses by the proximity effect at the adjacent coils of the excited conductors [49]. Skin effect results from eddy currents generated by a conductor's own magnetic field [48].

As detailed by Yang et al. [48], both effects cause a non-uniform current distribution in the conductors of the motor, which becomes higher as frequency increases. Copper losses P_{cu} can be calculated from (1) using the winding resistance R_s and the three-phase currents of the stator, i_a , i_b , and i_c . However, in reality, the Joule effect dominates the copper losses at low frequencies, whereas proximity and skin effects start to become more relevant at high frequencies. Moreover, the resistance increases with temperature.

$$P_{cu} = R_s(i_a^2 + i_b^2 + i_c^2), \quad (1)$$

Iron losses, also known as core losses, are distributed through both the stator and the rotor and represent the second major source of losses in a motor, becoming dominant at high operating frequencies. These losses occur when ferromagnetic materials are subject to time-varying excitations, resulting in energy dissipation primarily due to the following [48–52]:

- Hysteresis loss or static loss occurs due to a time-varying magnetic field primarily in major loops. The flux density inside the material suffers from “cumulative lagging behind” when an external varying field is applied. Every time a hysteresis loop is traversed, energy is dissipated; this loss is proportional to the hysteresis loop of a given material and therefore proportional to the amplitude of the excitation.
- Eddy current loss or dynamic loss is primarily caused by electrical currents induced in the core due to skin and proximity effects. These currents are generated within the ferromagnetic materials when subject to time-varying excitations and circulate within the material, dissipating power due to their electrical resistivity. These losses correspond to the classical eddy current losses, whereas the total eddy current losses also take into account the excess losses related to the non-uniform profiles of magnetic flux density, caused by the delayed response to the excitation magnetic field strength as it diffuses into the lamination.

Iron losses can be calculated based on the Steinmetz equation and the Bertotti equation; however, these equations have shortcomings due to their dependence on peak magnetic

flux density, and they do not account for phenomena such as non-sinusoidal flux waveforms caused by inverter pulse-width modulation, or rotational flux distribution, among others [53,54]. FEA simulations and equivalent circuits parameterized from experimental measurements or FEA are also widely employed by researchers; however, their results are generally applicable only to the specific motor studied. In recent years, machine learning approaches have been a new trend in research [53]. There is no consensus in the current literature on the best modeling approach, and it is usually selected based on the available material characterization data, the required physical fidelity, and computational complexity constraints.

Hysteresis loss is higher than eddy current loss under the base frequency, while eddy current loss is higher in the high-frequency region [47]. Excess losses refer to the difference between the combined classical eddy current and hysteresis losses when compared to the measured losses [52]. At higher frequencies, core losses are caused by the harmonic content due to slotting, winding distribution, and non-sinusoidal and pulse-width modulation (PWM) excitations [48,49].

The highest iron losses in AC machines are concentrated in the stator core, especially in its teeth and back iron, with the losses generated in tooth tips, or pole shoes, being low in comparison and negligible for thermal design. The frequency of the magnetic flux density variation is lower in the rotor core compared to the stator, which makes the rotor core loss smaller in comparison to the stator core losses. Additional iron losses are caused by the generated alternating rotor flux harmonics of air gap and current harmonics [48].

In the case of SPMSMs, the rotor core losses are negligible, which is not the case in IPMSMs, in which the magnets are inserted into the rotor and the core directly faces the air gap [49].

Magnet losses are caused by the eddy currents that are induced in them due to rotor flux variation [48]. They represent a small amount of the total losses; magnet over-temperature significantly affects the thermal management of PMSMs [48]. Sustained temperatures above the Curie temperature can cause irreversible demagnetization due to metallurgical changes that counteract magnetic properties, leading to drops in torque and power over the motor lifetime [18,55,56].

Stray losses are due to the energy loss from higher winding space harmonics and slot harmonics in the surface layers of the stator and rotor adjacent to the air gap, as well as in the volume of the teeth [47].

Mechanical losses consist of friction and windage losses [47]. Friction losses in the motor bearings result in heating that can result in the degradation of the lubricant and bearing wear. Windage losses occur at the rotor due to aerodynamic drag and may also be caused by the cooling fan [48].

3. Heat Transfer Mechanisms

The main source of heat generation and thermal stresses is power loss [7]. Losses incurred in electric motors are transformed into thermal energy, causing a temperature increase in various components within the motor where these losses are generated. The resultant heat is subsequently transferred to adjacent components via established heat transfer mechanisms: conduction, convection, and radiation.

This section provides a comprehensive analysis of each mechanism, outlining its definitions and roles within the context of electric motor functionality.

As defined by Khalesidoost et al. and He et al. [7,26], heat transfer refers to the process of thermal energy transferring from a region of higher temperature to a lower-temperature region, driven by the temperature difference. The mechanisms of heat transfer can be classified into the following:

- Conduction or conductive heat transfer involves the transfer of energy within a material without any motion of the material and the transfer of energy between two elements in contact and in close proximity with each other. When a temperature gradient exists in a solid or stationary fluid medium, heat is transferred from one point to another. Conduction is the transfer of thermal energy through the interaction and collision of neighboring molecules; therefore, conductive heat flow follows the direction of decreasing temperature, as the higher temperature corresponds to higher molecular energy and, therefore, more intense molecular motion [29,57].

Thermal conduction is influenced by the thermal conductivity of the material, its cross-sectional area and the temperature drop.

- Convection or convective heat transfer is the thermal energy transfer resulting from the bulk motion of the fluid. It corresponds to those heat transport processes affected by fluid flow; heat is transferred from a solid to a fluid, within a fluid, or between two fluids [57,58].

Boundary conditions are crucial in convection heat transfer, considering two key boundary layers: the velocity boundary layer, present wherever a fluid flows in contact with a solid, and the thermal boundary layer, which arises from a temperature gradient between the solid and the fluid.

There are two types of convection mechanisms: natural convection, caused by pressure gradients from buoyancy forces within the fluid, and forced convection, when an external source is used to move the fluid [29].

Factors that influence thermal convection include: the fluid velocity, the temperature difference, the convection coefficient, the pressure conditions, the area available for convection, the type of fluid involved, and the texture of solid surfaces in contact with the fluid.

- Radiation heat transfer refers to the transfer of energy through electromagnetic waves. This mechanism does not require a material medium and can occur in a vacuum. Factors that influence the thermal radiation energy transfer rate are absorption rate, surface emissivity, reflectivity, transmissivity, and temperature difference.

In general terms, the heat stored that causes a temperature rise in the motor is equal to the heat produced from losses, plus the heat dissipated through cooling processes [7].

Demetriades et al. [29] describe the heat flow within a SPMSM. The rotor shaft conducts heat to the rotor core and the ball bearings. Conduction also occurs between the rotor core and the magnets, along the stator winding, between the stator winding and the external structure, and between the external structure and the ball bearings. Convective heat transfer inside the motor occurs across the air gap involving the winding, end windings, PMs, and the shaft; in the case of an IPMSM, the convection with the air gap does not involve the PM but the rotor. Convective heat transfer mechanisms are also observed at the external casing. The most relevant radiation heat transfer mechanism in the motor occurs at its external casing.

4. Lumped Parameter Thermal Network

LPTN is a thermal modeling technique that groups components with similar temperatures into a common node to avoid complicated thermal networks and high computational cost [7]. LPTN assumes a uniform spatial distribution of temperature within each material or subcomponent [22].

In its most basic form, the heat transfer network can be considered analogous to an electrical network, where the analysis involves the calculation of the conduction, convection, and radiation resistances associated with various components of the motor [24]. In this analogy, electric current represents heat flow, electric potential corresponds to temperature

drop, and electric resistance, capacitance, and voltage sources are assimilated to thermal resistance, thermal capacitance, and thermal energy sources, respectively. Thermal resistances are used to represent the thermal properties of different materials and the thermal connection between different structures. Likewise, thermal capacitances model the thermal energy stored in a structure [29]. Figure 2 serves as an example of a visual representation of the configuration of a LPTN for a PMSM, where heat losses are introduced as heat sources on the stator yoke, winding, and rotor.

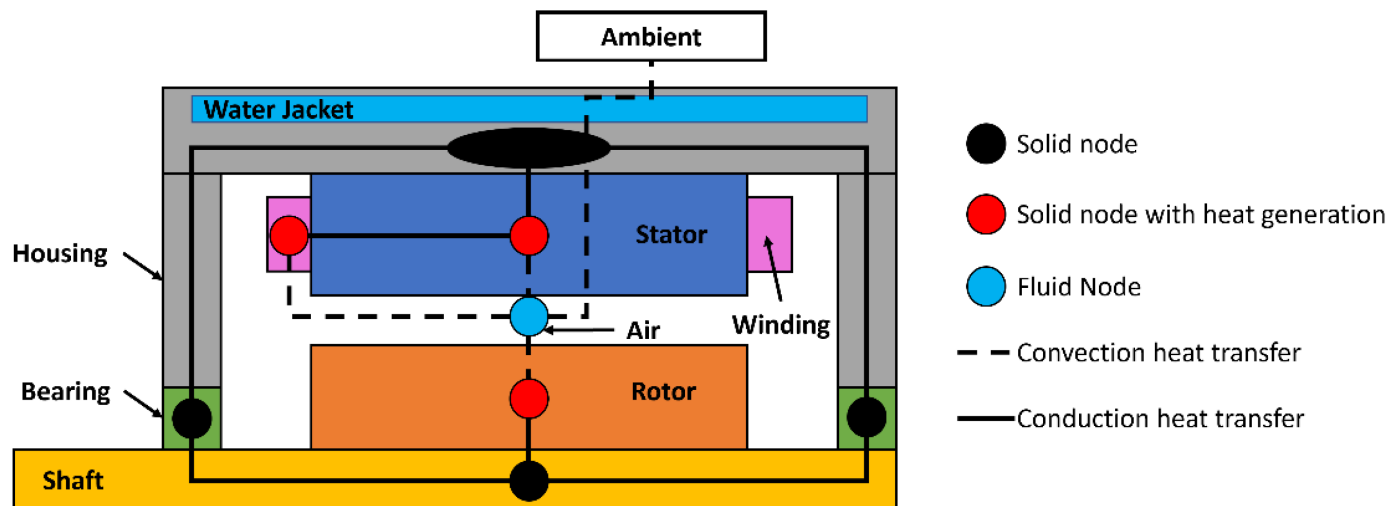


Figure 2. Lumped thermal model of a PMSM from [59].

4.1. Classification

The LPTN can represent two modes of operation in electrical machines: stationary and non-stationary. In the second case, thermal capacitors are included in the model to consider non-stationary conditions, while they are neglected in the first case.

Depending on the number of nodes and prior knowledge of materials and geometric data of the machines, LPTN models can be classified into the following [7,27,32,35,60,61]:

- White-box model or advanced analytical LPTN: This type of model usually contains a high number of nodes; the machine geometry is divided into fine meshes, and the prediction of the temperature of the machine entirely relies on the heat transfer equations and on its material and geometry data. Certain critical motor parts are modeled with high discretization levels, resulting in fine meshes.
- Light-gray-box model or basic analytical LPTN: This type of model employs machine geometrical data and relies on heat transfer equations for temperature prediction. The model can be optimized via empirical measurements. In this kind of model, a medium level of discretization, approximately 5–15 nodes, is employed.
- Dark-gray-box model or abstract LPTN: This type of model focuses on the implementation of nodes on the most dominant heat paths in the motor, limiting the number of nodes to a lower number between 2 and 5. They can be set up without detailed knowledge of heat-exchange processes, material data, or geometric motor structure. Low-order LPTN models are contingent upon this category; they are parameterized through the estimation of model parameters, with subsequent optimization based on empirical measurements. This approach cannot be considered a black-box model, as the principles of a LPTN are rooted in a specific model structure aligned with the fundamental formulations of heat transfer theory.

White-box models are predominantly utilized during the design phases of motors, where temperature predictions are employed for thermal design optimizations; the accuracy

of the thermal analyses depends on the availability of precise load profiles. For real-time monitoring applications, high levels of discretization lead to high-order models that exceed the computational time available for these applications; light-gray-box models and dark-gray-box models are more suitable [61].

For motor operation prediction, dark-gray-box models only guarantee the estimation accuracy within the identification framework of the empirical measurement data. Outside of the defined scope, the reliability of these estimations may be compromised. Light-gray-box models combine the advantages of the white-box and dark-gray-box models, as they integrate the heat transfer principles, material, and geometrical data of the motor with the fitting of the selected model parameters with respect to empirical test data; this approach enhances the overall estimation accuracy and breadth of application [32].

4.2. Formulation

As stated previously, thermal resistances and capacitances are calculated considering analogies with electrical circuits. In addition to the basic formulations, some authors have developed new approaches to facilitate the calculation of heat transfer mechanisms in different parts of the motor.

The motor can be represented as a set of discrete nodes, each characterized by constant isotropic thermal properties and interconnected through independent directional heat transfer mechanisms [14].

Assuming constant thermal capacitance and resistance at each node, a linear differential equation such as (2) can be derived for each node. C_i corresponds to the thermal capacitance of the i -th node, while $R_{th,ji}$ represents the thermal resistance between the i -th node and its adjacent node j . Additionally, heat generation g_i is considered at node i [31,33].

$$C_i \frac{dT_i}{dt} = \frac{1}{R_{th,ji}} (T_j - T_i) + g_i \quad (2)$$

The set of heat balance equations derived from the motor heat flow can also be written in matrix form to allow for an efficient computation [30]. The various methods used by different authors for the determination of thermal resistances and capacitances are discussed in the following sections.

4.2.1. Conduction Thermal Resistance

The conduction resistance is defined in (3), where l is the length of the heat transfer path, λ is the thermal conductivity and A is the effective cross-section area [27,29,44].

$$R_{th,cond} = \frac{l}{\lambda A} \quad (3)$$

Motor geometry can be characterized as a set of fundamental element shapes; their thermal conductivity resistance can be evaluated via basic formulas as follows [14]:

- Rectangular block: Equation (3) allows us to model the conduction thermal resistance for a three-dimensional rectangular prism in which the heat energy is uniformly distributed across one of the faces and exits out of the opposite flat face. This represents the standard linear conduction through a solid wall or block.
- Hollow cylinder: This fundamental element shape consists of a hollow tube, where r_o corresponds to the outer radius, r_i to the inner radius, and l is the height.

- Axial flow: Thermal resistance for axial heat flow in hollow cylinders when the heat flows vertically from one of the flat faces to the opposite is given by (4).

$$R_{th} = \frac{l}{\pi \lambda (r_o^2 - r_i^2)} \quad (4)$$

- Radial flow: Thermal resistance for radial heat flow in hollow cylinders when the heat flows radially from the inner radius surface to the outer radius is given by (5).

$$R_{th} = \frac{\ln\left(\frac{r_o}{r_i}\right)}{2\pi \lambda l} \quad (5)$$

- Cylindrical sector: This fundamental element shape consists of a slice taken out of a hollow cylinder, where r_o corresponds to the outer radius, r_i to the inner radius, l is the height, and θ is the angle of the section.

- Axial flow: Thermal resistance for axial heat flow in cylindrical sectors when the heat flows vertically from one of the flat wedge-shaped faces to the opposite one is given by (6).

$$R_{th} = \frac{2l}{\lambda \theta (r_o^2 - r_i^2)} \quad (6)$$

- Radial flow: Thermal resistance for radial heat flow in cylindrical sectors when the heat flows radially from the inner curved surface to the outer curved surface is given by (7).

$$R_{th} = \frac{\ln\left(\frac{r_o}{r_i}\right)}{\lambda \theta l} \quad (7)$$

Applied examples of the use of these basic formulas can be found in the literature for PMSMs and induction motors, with the resistance formulation transferable to PMSMs. Notably, Liang et al. [38] comprehensively employ the entire set of basic formulas listed below for conduction modeling. Additional authors are referenced along with their specific formulations.

Staton et al. calculate the contact thermal resistances of the shell and the stator adapting (3): the radial conduction thermal resistance of the shell, (8); the axial thermal resistance of the tooth, (9); and the thermal resistance between winding and stator iron core, (10). λ_{air} is the thermal conductivity of the air, D_{sh} the diameter of the shell, t_{ho_air} the thickness of the casing and the stator yoke, A_{air} the area of the surface in contact with the air, l_{si} the length of the iron core, h_{st} the height of the stator tooth, w_{st} the width of the stator teeth, N_{ss} the number of stator slots, $t_{im_air}^{eq}$ the equivalent thickness of the insulating material, A_{i_slot} the internal surface area of a slot, and N_{slots} the number of slots.

$$R_{th,ho_air} = \frac{t_{ho_air}}{\lambda_{air} A_{air}} \quad (8)$$

$$R_{th,ax_st} = \frac{l_{si}}{\lambda_{ax_si} h_{st} w_{st} N_{ss}} \quad (9)$$

$$R_{th,w_st} = \frac{t_{im_air}^{eq}}{\lambda_{im_air} A_{i_slot} N_{slots}} \quad (10)$$

Equation (11) corresponds to (4) adapted for the calculation of the axial conduction thermal resistance of the yoke; here, l_{si} is the length of the stator iron core, λ_{ax_sy} the axial thermal conductivity of the yoke, D_{o_si} the outer diameter of the iron core, and t_{si} the thickness of the iron core [62].

$$R_{th,ax_sy} = \frac{l_{si}}{\pi \lambda_{ax_sy} [Do_{si}^2 - (Do_{si} - t_{si})^2]} \quad (11)$$

Equation (5) can be adapted to calculate the radial conduction thermal resistance of the shell, (12), the radial conduction thermal resistance of the yoke, (13), and the radial conduction thermal resistance of the stator, (14). λ_{sh} is the thermal conductivity of the shell, D_{sh} the diameter of the shell, t_{sh} the thickness of the shell, λ_{ra_si} the radial thermal conductivity of the stator iron core, l_{si} the length of the iron core, Do_{si} the outer diameter of the iron core, t_{sy} the thickness of the stator yoke, r_{ta_ca} the ratio between the stator iron core tooth area and the ring area, Di_{sy} the internal diameter of the stator yoke, and Di_{st} the internal diameter of the stator teeth.

$$R_{th,sh} = \frac{1}{2\pi \lambda_{sh} l} \ln\left(\frac{D_{sh}/2}{D_{sh}/2 - t_{sh}}\right) \quad (12)$$

$$R_{th,ra_sy} = \frac{1}{2\pi \lambda_{ra_si} l_{si}} \ln\left(\frac{Do_{si}}{Do_{si} - \frac{t_{sy}}{2}}\right) \quad (13)$$

$$R_{th,ra_st} = \frac{1}{2\pi \lambda_{ra_si} l_{si} r_{ta_ca}} \ln\left(\frac{Di_{sy}}{Di_{st}}\right) \quad (14)$$

In addition to the basic formulations, various authors have developed formulas to better approximate the heat conduction mechanisms depending on the part of the motor being studied.

The axial thermal resistance of the shaft is studied in [30], where the motor shaft is modeled as a cylinder without heat generation, and its axial heat conduction is divided into three sections as seen in (15). l_{shf} corresponds to the shaft length, λ_s is the thermal conductivity of the shaft, l_s is the axial length of the rotor core, and r_{or} and r_{ir} correspond to the outer and inner radius of the rotor, respectively.

$$R_{th,shf} = \frac{1}{2\pi \lambda_s l_s} \ln\left(\frac{r_{or}}{r_{ir}}\right) + \frac{1}{4} \left(\frac{0.5 l_s}{\pi \lambda_s r_{ir}^2} \right) + \frac{1}{2} \left(\frac{0.5 (l_{shf} - l_s)}{\pi \lambda_s r_{ir}^2} \right) \quad (15)$$

Liang et al. [36] aim to understand the influence of the impregnation material on the thermal behavior within the slot, calculating the thermal conductivity of the total thermal resistance associated with the equivalent insulation between the slot wall and the winding, see (16). It consists of the combination of the impregnation paper thermal resistance, $R_{th,ip}$, insulation varnish thermal resistance, $R_{th,iv}$, and the impregnation material thermal resistance, $R_{th,im}$. l_{IL} is the section length of the equivalent insulation, l_s the stator length, and λ and t are the thermal conductivity and the thickness of each insulation layer, respectively.

$$R_{th,il} = R_{th,ip} + R_{th,im} + R_{th,iv} = \frac{1}{l_{IL} l_s} \left(\frac{t_{ip}}{\lambda_{ip}} + \frac{t_{im}}{\lambda_{im}} + \frac{t_{iv}}{\lambda_{iv}} \right) \quad (16)$$

Liang et al. [38] propose a simplified thermal resistance model to calculate the temperature change near the stator tooth and the slot of the stator yoke for a constant cross-sectional area, see (17). The heat flow path of a hollow cylinder or a hollow cylindrical section is defined as a line along the average radius, and its integral basis can be written as the angle and swept along the perigon of the cylindrical section.

$$R_{th} = \frac{t}{\lambda A} = \int_0^\theta \frac{1}{\lambda l (r_o - r_i)} d\theta \frac{r_o + r_i}{2} = \frac{\theta}{2\lambda l} \frac{r_o + r_i}{r_o - r_i} \quad (17)$$

The same authors propose an equivalent thermal resistance model for the winding. The stator slot is modeled as a rectangular slot, and the insulation material between the air and the winding is divided into two layers at the outer side; the thicknesses of the two layers are t_i and t_a . The total thickness of the two layers is t , and the height and the width of the rectangular slot are H and w , respectively. The total thermal resistance between the slots and the surrounding nodes is expressed as Equation (21), Q_s being the specific volume power in the rectangular slot.

$$R_{th,ix} = \frac{t_i}{\lambda_i H} + \frac{t_a}{\lambda_a H}, \quad R_{th,iy} = \frac{t_i}{\lambda_i w} + \frac{t_a}{\lambda_a w} \quad (18)$$

$$R_{th,x0} = \frac{w}{\lambda_{mix} H}, \quad R_{th,y0} = \frac{H}{\lambda_{mix} w} \quad (19)$$

$$R_{th,x} = 0.5 \left(R_{th,ix} + \frac{R_{th,x0}}{6} \right) \quad (20)$$

$$R_{th,y} = 0.5 \left(R_{th,iy} + \frac{R_{th,y0}}{6} \right)$$

$$R_{th,s} = \frac{R_{th,x} R_{th,y}}{Q_s l (R_{th,x} + R_{th,y})} \left(1 - \frac{R_{th,x0} R_{th,y0}}{720 R_{th,x} R_{th,y}} \right) \quad (21)$$

4.2.2. Convection Thermal Resistance

Similarity implies that the convection mechanism is determined by dimensionless quantities such as the Reynolds (Re), the Nusselt (Nu), the Prandtl (Pr), the Taylor (Ta), and the Grashof (Gr) numbers [14].

Convective heat transfer between the air, whether internal or external, and the exposed surfaces of solid components can be modeled using a single thermal resistance. Focusing on how to determine the convective heat transfer coefficient (HTC), the general formulation of the convection resistance (22) is equal to the inverse of the product of the surface area in contact with the cooling air, A_{air} , and the boundary film coefficient or convective heat transfer coefficient (HTC), h [14,29,31,34,38].

$$R_{th,conv} = \frac{1}{h A_{air}} \quad (22)$$

As described by Lee et al. [31], for the case of heat transfer between the frame and the surrounding air, h is an empirically determined natural convection heat transfer coefficient. Heat transfer between the air gap and the stator or rotor is calculated from Equation (23), where h_{ag} is the forced convection HTC.

$$h_{ag} = \frac{Nu \cdot \lambda_{air}}{l_g} \quad (23)$$

For small air-gap machines, the Nusselt number i.e., the dimensionless HTC can be determined using the Taylor number Ta and the Prandtl number Pr , see (24). These parameters are derived from the air gap dimensions and the fluid properties. The critical value of 41 for the Taylor number indicates the transition from laminar flow, which is normal in small air-gap machines, to turbulent flow.

$$Nu = \begin{cases} 2.2 & Ta \ll 41 \\ 0.23 Ta^{0.63} Pr^{0.27} & 41 < Ta \ll 100 \end{cases} \quad (24)$$

The same authors propose Equation (25) for the heat transfer in the end cap. Here, h_{ec} corresponds to the forced convection heat transfer coefficient that is calculated between the end cap air and the stator iron, rotor, end windings, or endcaps.

$$h_{ec} = 21 \cdot \left(2\pi r_m \cdot \frac{\omega}{60} \right)^{0.67} \quad (25)$$

Liang et al. [38] propose Equation (26) to determine the thermal contraction and expansion of the rotor, where $t_{ag,0}$ is the initial thickness of the air gap and α_r is the thermal expansion coefficient of the rotor material.

$$t_{ag} = t_{ag,0} - \alpha_r r_m \Delta T \quad (26)$$

Demetriades et al. [29] suggest the use of Equation (23) to calculate the heat transfer coefficient of the shaft, using (27) to calculate the Nusselt number for this case.

$$Nu = \left(0.825 + \frac{0.387 Ra_L^{1/6}}{\left[1 + (0.492/Pr)^{9/16} \right]^{8/27}} \right) \quad (27)$$

Kylander [63] proposed equations for determining HTC's associated with the internal air for small cage induction motors. These formulas are presented below and were used by Demetriades et al. [29] for PMSMs.

Equation (28) describes the internal air convection heat transfer coefficient established through experimental methodologies. In this context, u_r denotes the peripheral velocity of the rotor.

$$h_{ia} = 15 + 6.75^{0.65} \cdot u_r^{0.65} \quad (28)$$

Equation (29) represents the thermal convection coefficient of the heat transferred between the end windings and the end shields, taking into account the effect of radiation heat transfer as well.

$$h_{ew} = 6.5 + 5.25 \cdot u_r^{0.6} \quad (29)$$

Equation (30) calculates the amount of heat transferred from the end-face of the rotor to the internal air.

$$h_{rotor} = 16.5 \cdot u_r^{0.65} \quad (30)$$

Yanhua and Chun [30] used Equation (31) as an approach for calculating both conductivity and convection heat transfer processes in the air gap between the stator and the rotor. The thermal resistance of the air gap between the stator and the rotor of an IPMSM is modeled as three processes: convection between the stator and the air gap, conduction through the air gap, and convection between the air gap and the rotor.

$$R_{th,airgap} = R_{th,s-a} + \frac{1}{2\pi \lambda_{air} l_s} \ln\left(\frac{r_{is}}{r_{or}}\right) + R_{th,a-r} \quad (31)$$

R_{s-a} corresponds to the convection resistance between the stator and the air gap, and R_{a-r} to the convection resistance between the air gap and the rotor, see (32). l_{air} is the radial length of the air gap, Nu the Nusselt number, and A_{air} the average area of the air gap along the axial direction.

$$R_{th,s-a,a-r} = \frac{l_{air}}{Nu \lambda_{air} A_{air}} \quad (32)$$

$$Ta = Re \left(\frac{l_{air}}{r_{or}} \right)^{0.5} \quad (33)$$

$$Nu = \begin{cases} 2 & Ta < 41 \\ 0.202 Ta^{0.63} Pr^{0.27} & 41 < Ta < 100 \\ 0.386 Ta^{0.5} Pr^{0.27} & Ta > 100 \end{cases} \quad (34)$$

The same authors also determine the convection resistance between the end winding and the case; see (35). Here, l_{oc} is the external case length, r_{oy} the outer stator yoke radius, l_{sy} the stator yoke height, and α_{red} the reduction coefficient.

$$R_{th,ew} = \frac{1}{2\pi\lambda_{air}(l_{oc} - l_s)} \ln \left(\frac{r_{oy}}{r_{oy} - \alpha_{red} l_{sy}} \right) \quad (35)$$

4.2.3. Radiation Thermal Resistance

In most LPTN models for PMSMs, radiation effects are neglected for simplicity. Radiation effects have only a noticeable impact on heavily used compact traction motors [32].

Boglietti et al. studied radiation in totally enclosed fan-cooled induction motors in a vacuum chamber [64]. It is stated that, at nominal speed, forced convection is the main contributor to motor cooling and thus radiation resistance is neglected. When totally enclosed fan-cooled induction motors are working at low speed, radiation heat transfer can be non-negligible. The results from the experiments performed in this study regarding the housing and wall temperatures showed that it is possible to neglect radiation resistance when forced ventilation is active, but it has to be included in the calculations when the motor fan is missing or when the motor is working at very low temperatures.

When analyzing the radiation thermal exchange in the interior of the motor in deep vacuum, the primary radiation paths detected include the areas between the copper wires inside the slots and the stator laminations, as well as the space between the end winding and the inner surface of the external frame. The results of the radiation heat transfer coefficient for the test performed were 8.5 W/m²K for the heat transfer radiation between the stator copper and the iron, 6.9 W/m²K between the end winding and the external cage, and 5.7 W/m²K between the external cage and the ambient. These motor parts are also found in the PMSM. Natural and forced convection heat transfer coefficients are usually one order of magnitude above the radiation heat transfer coefficient. To compare it in terms of convection resistance values, the results from Boglietti et al. can be compared with the values used by Park [65] to model an IPMSM, where the convection heat transfer coefficient is 64.5 W/m²K for the air gap, 10 W/m²K between the frame cover and the outer air, and 10 W/m²K between the stator and the inner side and the rotor and the inner side. As it can be observed, the heat transfer coefficients for radiation are lower than those for convection.

Kačenka et al. [34] calculate the effect of radiation heat transfer in a PMSM as an analogy to conduction, see (36). The radiation resistance is defined from the radiation heat transfer coefficient, h_{rad} , as follows:

$$R_{th,rad} = \frac{1}{h_{rad} A} \quad (36)$$

Kylander [63] included radiation resistances for small cage induction motors. The net radiation of a surface depends on its area, material characteristics, temperature, and surroundings; heat exchange depends on the radiation angles, emissivity, and temperatures

of the interacting surfaces. In compact bodies, the emissivity and absorptivity are often assumed to be equal, with no transmission occurring. For simplicity, surroundings can be interpreted as a black body, i.e., the absorptivity is 1. Equation (37) calculates the net radiation from a body to the surroundings and (38) the resistance to the surroundings, with T_w being the absolute temperature of the body, T_∞ the absolute temperature of the surroundings, and σ the Stefan–Boltzmann constant and ε the emissivity of the body.

$$q = \sigma \varepsilon (T_w^4 - T_\infty^4) \quad (37)$$

$$R_{th} = \frac{T_w - T_\infty}{\sigma \varepsilon A (T_w^4 - T_\infty^4)} \quad (38)$$

4.2.4. Capacitances

The thermal capacitance of each node C_i is an influencing factor in transient heat conduction; it can be determined using (39) for a component with mass m_i and specific heat capacity c_i . All thermal capacitances are considered in relation to the surrounding environment, assuming a constant temperature input [14,27,43,44].

$$C_{th} = m c = \rho V c \quad (39)$$

The total thermal capacitance of a cylinder (40) depends on its material density, ρ , the specific heat, c_p , the length of the cylinder, l , and the difference between the outer r_o and the inner radius, r_i [31].

$$C_{th} = \rho c_p \pi (r_o^2 - r_i^2) l \quad (40)$$

The thermal capacitance of a motor component in cylindrical coordinates is given by (41), where m is the component mass, V the component volume, $\Delta\theta$ the circumferential radius, and c the specific heat capacity [32]. Finally, c is temperature-dependent for many materials, thus making C_{th} a varying parameter [32,66].

$$C_{th} = m c = \rho V c = \rho \pi (r_i^2 - r_o^2) l \Delta\theta c \quad (41)$$

4.3. Approaches

In Section 4.2, the different approaches used to calculate thermal resistances and capacitances in a LPTN have been reviewed. The additional variations that the different LPTNs show in the literature will be commented on in this section.

Table 1 shows the data for each reference (REF) in terms of the parts modeled, number of nodes (N. N.), loss modeling, heat sources, thermal behavior (TH. B), whether conduction (CD), convection (CV), radiation (RD) resistance (if applicable, they are marked with an x), use of capacitances, and verification method. PMSIWM denotes permanent magnet synchronous in-wheel motor, SS denotes steady, and T denotes transient.

4.3.1. Model Order and Boundary Conditions

In Table 1, it can be observed that usually a greater number of nodes corresponds to a greater number of modeled parts. However, Liang et al. [38] demonstrate that accurate results can be obtained for the same modeled parts with either a 154- or a 19-node model.

Continuing with the number of nodes and modeled parts, it is also noted that when the number of nodes is less than five, the casing or chassis temperature is typically not calculated. These studies focus on simulating specific components of the motor. For instance, Liang et al. [36] examined the heat transfer between the stator slots and the

windings, while Huber et al. [17] evaluated the temperature of the winding, the end of the winding, and the PM using two- and three-node models.

In contrast to the aforementioned approaches, some researchers adopt a high-discretization method to accurately simulate the thermal dynamics of specific motor components. For instance, Hebala et al. [40] use a 55-node LPTN to analyze the passive slot heat paths, covering a broad spectrum of motor and slot design configurations. The model considers only half of the slot, leveraging symmetry boundary conditions to enhance computational efficiency while ensuring an accurate analysis.

From the literature, it can be concluded that low-order models are preferable for applications to temperature monitoring due to their low computational effort, since only the average temperature of the components is required, and when researchers do not have detailed motor specifications; examples of the applications of low-order methods can be found in [17,27,32]. When using low-order models for online monitoring, it is key to apply conservative safety margins to the motor thermal limits if only average temperatures are estimated [27]. In addition, the complexity of a white-box model is only justified in the design and optimization phases of the motor and for the identification of the exact spatial location of hot-spots. White-box models can only be applied when precise information of the motor geometry and material properties is available. Examples of high-order models can be found in [33,38,40]. As seen in the study by Liang et al. [38], it is possible to obtain results very similar to those of a highly complex model using a reduced-order model; therefore, if the goal is not to obtain detailed temperature data for every part of the motor but rather to have a general and accurate picture of the motor thermal behavior, a gray model would be preferable in this case. Starting with a reduced number of nodes and comparing the results with experimental temperature data is recommended, gradually increasing the number of nodes based on the application requirements and the improvement in temperature prediction accuracy, until the desired level of uncertainty is reached.

Most common boundary conditions used in LPTN models are Dirichlet boundary conditions, Neumann boundary conditions, adiabatic symmetry conditions, and time-varying boundaries. Dirichlet boundary conditions are applied in nodes in which the temperature is modeled as a fixed independent temperature source; in the majority of cases, coolant inlet and ambient temperatures are fixed, and examples can be found in [17,32,39,46]. Neumann boundary conditions are applied for convective heat transfer at solid–fluid interfaces, such as the air gap between the rotor and stator or between the end windings and the internal air; convective heat transfer coefficients are derived from simplified empirical equations [29], simplified formulas based on dimensionless numbers [30,31], or from CFD calculations [36]. Adiabatic boundary conditions are applied to model the symmetry conditions of the slot center and tooth center in the work of Hebala et al. [40]. Time-varying boundaries are applied in the work of Fu et al. [43] in which real-time corrections for the thermal conductivity, dynamic viscosity, and density of the cooling oil are introduced.

4.3.2. Loss Inputs, Thermal Behavior of the Model, and Resistance Modeling

The modeling of losses for subsequent introduction into the LPTN model presents two marked trends throughout the literature. The first trend is the use of 2D and 3D FEA and CFD-CHT simulations to calculate electromagnetic losses, such as [14,31]. Kačenka et al. [34] simulate the thermal behavior of the machine using an FE-electromagnetic model in ANSYS/Maxwell to calculate, via a Matlab script, the thermal resistances and capacitances for the LPTN. The second trend is based on obtaining experimental motor losses, either by directly extracting them from experiments or through empirical formulas, such as [17,27,32].

A third approach is found in the work of Zhu et al. [35], where iron loss is calculated via a dynamic equivalent circuit of a PMSM.

The choice of heat sources in thermal networks depends on the focus of the study. Some studies analyze the entire motor, like [38], while others focus solely on specific components, such as the stator and slots, as in [36]. Additionally, regarding rotor characterization, some papers [32,38,43] consider the rotor and the PM as heat sources, certain papers consider only rotor losses as heat sources [30,44], whereas others include only PM losses as a heat source node [27,33].

Regarding conduction and convection resistances, it is commonly noted in the literature that the effects of these two heat transfer mechanisms are typically considered when analyzing the thermal network. As explained in Section 4.2.3, most studies consider radiation to be negligible.

In the literature, both transient and non-transient models are prevalent, with transient models notably predominant in the reviewed articles. Capacitances are used to simulate transient phenomena, typically applied across all the nodes within the system. However, some studies selectively assigned these capacitances to specific components of the motor. Generally, fixed capacitance values are adopted in these modeling approaches. Fu et al. [43] considered a dynamic capacitance in order to model the thermal behavior of the oil cooling structure to improve the accuracy of the thermal model.

4.3.3. Simplifying Assumptions, Limitations, Parameter Uncertainty, and Computational Cost

As previously commented on in Sections 4.1 and 4.2, LPTN models rely on simplifying assumptions to model the motor thermal behavior. The most relevant assumptions repeated in the literature and their limitations are the assumption of uniform nodal temperature, constant material properties, simplified convection coefficient, neglecting mechanical losses, neglecting radiation heat transfer, the non-inclusion of capacitances, symmetrical heat flow, homogenization of the stator slot, and simplifications regarding the calculation of heat sources.

In the assumption of uniform nodal temperature, one nodal component acts as a single isothermal region, assuming that the thermal capacity and heat generation are evenly distributed throughout that component. This limits the model's capacity of predicting critical and localized hot-spots, as only the average temperature of a component is calculated. When applying these assumptions to LPTN models for monitoring and design purposes, highly conservative safety margins must be considered [27].

Researchers usually assume perfect thermal contact between adjacent solid components, modeling the imperfections in the assembly of material when modeling the thermal contact resistance, which leads to parameter uncertainty. As Zhu et al. [35] point out in their study, which neglects contact thermal resistance between solids, this significantly impacts radial heat flow. Contact thermal resistance is considered in the work of Kačenka et al. [34]: the contact heat transfer coefficient due to imperfect contact between the two areas is modeled and strongly depends on the manufacturing process, and it is therefore difficult to predict.

The assumption that the motor materials have constant thermal properties leads to an inaccuracy in the calculation, since these properties are temperature-dependent and affect the thermal capacitances of the LPTN [32]. Moreover, temperature material properties govern loss generation and heat transfer dynamics; traditional modeling approaches that separate electromagnetic and thermal domains do not effectively capture their interdependency and the resulting nonlinear behavior [44]. Song et al. [14] took into account the change in copper loss power, considering the influence of the temperature and the phase current magnitude on the copper resistivity, the variations of thermal conductivity of

the materials with the temperature, and the thermal expansion coefficient for the thermal resistances. To achieve higher accuracy and a better representation of the transient thermal behavior of the motor, it is recommended to integrate iterative coupling mechanisms to continuously update the electrical resistance and loss generation calculations.

Another major concern with LPTN models is the modeling of the convection coefficient. As seen in Section 4.2, there is no consensus among authors on how to model convection, especially in air-gap regions, end windings, and cooling jackets. They mainly rely on approximate constant values, simplified empirical equations, or simplified formulas based on dimensionless numbers, which can lead to inaccuracies. Empirical formulas are sensitive to the exact motor geometry and operating conditions of the motor; turbulence effects on convection are not modeled properly. Moreover, as reviewed, Demetriades et al. [29] employ formulas depending on rotor linear velocity that were initially proposed for induction motors, which can also lead to inaccuracies as the rotor surfaces vary significantly between an induction motor, an IPMSM, and a SPMSM; and the maximum speed modern PMSMs can reach today is higher than the ones induction motors were capable to reach by the time those formulas were proposed.

Mechanical losses are usually neglected as in [32,38,41]. In the study of Li et al. [41], when comparing the predicted operating conditions of the motor with the experiments, the overload measured time was shorter than the predicted value because the models did not account for the mechanical losses. It is recommended to set operation safety margins higher if mechanical losses are neglected in the LPTN. Neglecting radiation heat transfer effects is a common assumption in the reviewed models; more information was provided in Section 4.2.3. Assumptions like the non-inclusion of capacitances, symmetrical heat flow, and homogenization of the stator slot are more dependent on the purpose of the LPTN and the final applications.

Regarding the modeling of losses to introduce in the LPTNs, it was already commented that there are three approaches defined in the literature: FEA modeling, the incorporation of experimental results, and the dynamic equivalent circuit. Each has its advantages and disadvantages, but based on the reviewed literature, no single method is the best in all cases. While FEA modeling is computationally intensive, characterizing losses experimentally is economically costly. Furthermore, while experimentation fails to properly distinguish between the different types of motor losses, FEA and CFD models fail to account for the additional iron harmonic losses caused by the pulse-width modulation switching harmonics from the inverter, the frequency at which current enters the motor. Both of these methods have a limitation: to achieve an accurate simulation with the LPTN, the specific point of interest must always be measured or simulated. Equivalent electrical circuit models allow for the adaptive calculation of these losses but rely on precise motor data and experimentation or FEA simulation if rotor losses are to be calculated accurately. The most accurate approach today would be to combine FEA results with experimental data, generating loss maps for later use in the LPTN. Simulating or experimenting each point needed to calculate with the LPTN would compromise the speed, which is the primary advantage of this kind of modeling.

Simplifications and assumptions often lead to the application of methodologies to improve the accuracy of the LPTN model, as discussed later in this paper. The final parameter uncertainty varies depending on the model implementation, the levels of abstraction used, and the year in which the model was built. Lee et al. [31], in 2012, calculated the heat sources via an electromagnetic FEA and reported a 10% error in the temperature estimation of the housing, coil, and motor flange when comparing their 32-node LPTN model with constant thermal capacitances against the experimental results. Wallscheid and Böcker [27], in 2016, achieved an estimation error of 8 °C for a low-order LPTN with a high

level of abstraction after applying a global identification technique with linear parameter varying. In 2026, Fu et al. [43] proposed a 3D-LPTN where intranode thermal diffusion was neglected. This simplification may introduce transient errors in response to sudden increases in losses; nonetheless, these errors are temporary and do not compromise the accuracy of temperature estimations, which exhibit a maximum deviation of $-5.8\text{ }^{\circ}\text{C}$. The same year, Gao et al. [45] proposed an adaptive digital twin framework with a LPTN model that achieved an RMSE of $0.919\text{ }^{\circ}\text{C}$ for the stator winding and $1.602\text{ }^{\circ}\text{C}$ for the PMs.

In terms of computational cost, it is generally considered low, provided that preliminary calculations involved in estimating losses using FEA or experimental methods are excluded, which increases the overall computational cost. The purpose of most of the models analyzed is to predict the thermal behavior of the motor in real time with high computational efficiency, and most of them use a lightweight architecture [14,27,29,32,35,39,44]. Regarding computational time, García et al. [39] quantify the computational time difference between the 23-node LPTN model they proposed and finite-difference methods. The LPTN model was 15 times faster than the finite differences approach in the simulated benchmark circuit (0.023 s vs. 0.345 s , respectively) and around 27.5 times faster in the simulated motor circuit (0.112 s vs. 3.076 s , respectively). The sixth-order LPTN model by Wang et al. [44] demonstrates its computational efficiency by being able to complete a coupled magneto-thermal iterative process in 0.8 s on a high-performance server and 1.32 s on a Raspberry Pi platform with 8 GB of RAM.

4.3.4. Validation Techniques

In the context of model validation, experimental methodologies predominantly serve to verify the accuracy and reliability of LPTN models.

The test protocols found in the reviewed literature to thermally characterize the motor are as follows: steady-state operation test [43], continuous conditions test in which the motor works at constant torque and velocity until the internal temperatures reach thermal equilibrium (saturate) [31], high dynamic cycles [43], stochastic driving cycle [45], staircase-like driving cycle with pronounced thermal transitions [17], out-of-distribution (OOD) stress test [46], standardized drive cycles like the Worldwide Harmonized Light Vehicles Test Procedure cycle [39] and controlled boundary condition tests, measuring different speed and torque operation conditions to compare the differences between loss generation and temperature distribution [38].

Researchers typically embed a network of temperature sensors to capture the thermal behavior of the motor. The most frequently used sensors include K-type thermocouples [27,32,35] and T-Type thermocouples [40], PT1000 temperature sensors [29,44,45], and thermistors [41]. Sensors are glued or embedded into critical hot-spots in the middle of the stator slots, end windings, and on the stator yoke. Sensors are also placed in the casing and, in order to obtain the rotor and PM temperatures, Wallscheid and Böcker [27] placed the thermocouples closely around PM elements to obtain a representative PM temperature. The experimental validation is typically performed on a dynamometer test bench. For data recording, two trends are observed: for the cases in which only static parts are measured, temperatures are recorded via a data logger like Pico Technology TC-08, as in the case of Hebala et al. [40]. As they are in constant movement when recording the rotor or PM temperatures, specialized equipment is needed, like a wireless transmitting and receiving device, like the one used by Zhu et al. [35], and telemetry devices as used by Wallscheid and Böcker [27].

Apart from the temperature sensors, the test benches usually incorporate a high-precision power analyzer to measure the input electrical power (Yokogawa WT5000 in [32] and Yokogawa WT3000 combined with a Danfysik Ultrastab 867-700I current transducer

in [27]), a torque transducer to measure the output mechanical torque (HBM T40B in [44] and HBM T10F in [27]), a speed sensor, a signal conversion device (Kvaser in [35]), and a data collection device (Vector VX1060 in [35]).

Experimental measuring techniques have drawbacks, as some authors emphasize, such as the fact that temperature sensors are difficult to access and cannot be simply replaced in case of a sensor failure, as the sensor de-tuning effect can occur within the entire device lifespan. Measuring the rotor and PM temperature is difficult due to shaft rotation and, therefore, costly, sensitive, and not feasible in series production and medium and large industrial applications. Redundant temperature information is required [17,27,32]. Moreover, temperature measurements can be affected by the motor interference [35]; if thermal sensors are glued to the surface, there is still a small gap [14] that may affect the results.

The cost of experimental validation and the drawbacks associated with this approach can lead researchers to opt for model-based approaches such as FEA and CFD as supplementary verification techniques, as in [14,36,40,44]. These methods can simulate the comprehensive thermal distribution of each motor part and handle complex geometries. On the contrary, the computational cost of these methods is very high, they rely on accurate motor material boundary conditions and geometry parameters that are not always available, and they are sensitive to mesh quality. The most used software for FEA and CFD modelization found in the literature are ANSYS ([34]), STAR CCM+ ([38]), JMAG ([38]), and COMSOL ([44]).

In the case of Sheng et al. [42], they validated the LPTN and Deep Neural Model by comparing it against the original thermal network (TNN), a hybrid convolutional neural network–recurrent neural network (CNN-RNN), and ablated versions of the proposed model to assess the contribution of the key components.

4.3.5. Parameter Identification, Improvement of Accuracy of the LPTN Model, and Latest Trends

The literature details the strategies used by researchers to enhance the performance of LPTN models through various optimization techniques. The four-node LPTN proposed by Wallscheid and Böcker [27] emerges from an empirical approach to comprehensive experimental training data and a particle swarm optimization (PSO). The model accounts for varying parameters and physically motivated constraints to broaden its applicability beyond the initial training data domain; a global identification technique for linear parameter-varying (LPV) systems was applied to the thermal model of the motor. The model inputs were compared with the training data, using the US Federal Test Procedure 75 driving cycle for an electric subcompact vehicle as the load profile to cross-validate the model. The same authors, in [32], proposed a three-dimensional approach in cylindrical coordinates, a differential-algebraic state-space model with LVP. PSO was also applied to improve the LPTN model estimation accuracy relative to measurement results to overcome the level of abstraction of the model and the uncertainties in the motor material data.

Zhu et al. [35] proposed a five-node LPTN with a parameter identification method based on multiple linear regression and an open-loop estimation scheme based on the state equation and Kalman filter algorithm to predict the motor temperature online. A ± 5 °C error in the rotor temperature estimation and a 2 °C variation in the end cap were reported. Under conditions of steady stator temperature, the temperature estimation error was nearly 0 °C. However, when there were abrupt changes in load conditions, this error increased significantly. Nonetheless, the model was capable of mitigating the error after adaptation.

Veg et al. [37] implemented a hybrid thermal model combining a LPTN with a FE-winding submodel, achieving an error of less than 5% compared to experimental measurements. The FE-winding submodel was able to generate different conductor distributions

and was used to improve the calculation of equivalent thermal conductivities of stator slots for LPTNs.

García et al. [39] presented a methodology and the application for the analytical determination of the sensitivity of LPTN dynamics with respect to its lumped parameters. The methodology followed allowed them to quantify the influence of circuit parameters on the thermal dynamics of the entire system and addressed the computational load limitations of finite-difference approaches.

Li et al. [41] introduced an improved method for evaluating transient temperatures, proposing a segmented iron loss model based on the Jordan model and integrating the calculated losses into the LPTN. This approach incorporates compensation terms for both eddy current and hysteresis losses, tailored to various frequency and magnetic density ranges. The results demonstrated an improvement in computational accuracy when compared to the traditional evaluation method.

Sheng et al. [42] use the public Electric Motor Temperature dataset (Paderborn University/Kaggle) [67] to train and evaluate their model OLTEM: a physics-informed deep learning model that combines LPTN with a thermal neural network (TNN) to improve the performance of the LPTN model in nonlinear behavior under high power density. The goal of this new model was to improve prediction accuracy while maintaining physical meaning by embedding the LPTN into a recurrent state-space formulation and learning the parameter sets for thermal conductance, inverse thermal capacitance, and power loss. In their research, they introduce a novel state-conditioned squeeze-and-excitation (SC-SE) attention mechanism that incorporates the motor current temperatures to generate attention and model the critical temperature dependence of thermal paths and power-loss characteristics. The authors concluded that the results demonstrated an improvement in the estimation of power losses. However, it would be helpful to have more detailed physical information about the motor and to reduce the model computational cost to enable its applicability in industrial environments.

Wang et al. [44], in one of the most recent studies, improved the calculation of motor losses by combining Proper Orthogonal Decomposition and neural networks to create a temperature-adaptive electromagnetic reduced-order model. This approach enables real-time reconstruction of magnetic field distributions across varying operating points and temperature conditions. It serves as the input for the analytical computations of losses, which are the heat sources in a bidirectional coupling method with a LPTN, which dynamically feeds updated temperature calculations back into the EM model. With detailed magnetic field information, losses can be determined with improved accuracy, especially in critical regions.

Gao et al. [45] propose an adaptive digital twin framework design for the thermal safety monitoring of a PMSM with a simplified thermal network and address the challenges associated with parameter drift in physical models and limited generalization in data-driven methods. Authors integrate a dynamic-batch Bayesian calibration algorithm that identifies uncertain thermal parameters from operational data in the model to adapt to the specific conditions of the individual motor. A real-time demagnetization safety margin monitoring and a fidelity enhancement via a hierarchical physics-aware network to provide real-time physical guidance to the neural network are also introduced.

Hossain et al. [46] present a physics-informed hybrid ensemble for robust and high-fidelity temperature forecasting in PMSMs to address the challenge of predicting the motor behavior in out-of-distribution scenarios presented by artificial intelligence models trained via empirical data. A low-order LPTN model is calibrated to generate consistent data augmentations to pre-train a Temporal Convolutional Network.

The data presented in Table 1, along with the detailed case studies, reveal a clear trend towards employing low-order LPTN models to model the main parts of the motor, as opposed to the previous practice of modeling isolated motor components with low-order models. This new trend is also accompanied by the implementation of advanced parameter identification techniques, as well as the integration of digital twins, hybrid thermal models, and data-driven prediction methods. It is relevant to note that the outcomes generated by these innovative approaches are not universally applicable across all motor types, as thermal behavior and heat loss generation vary among them. However, the developed methodologies can be applicable, provided the experimental and technical information regarding the specific motor is available. The lack of technical data, such as material characteristics or experimental test data, remains a major challenge when modeling the thermal behavior of motors. The new methods aim to address this challenge and improve the accuracy of the modeling of the thermal behavior of motors.

5. Conclusions

This review article provides a comprehensive analysis of the application of the LPTN thermal modeling technique, specifically applied to radial PMSMs, given the importance of transportation electrification and the widespread use of this type of motor in traction applications today. LPTN models stand out for predicting the thermal behavior of the motor with lower computational cost and greater speed than other current simulation methods, making them highly suitable for real-time temperature monitoring applications.

The five main sources of losses in a PMSM were identified—copper losses, iron losses, magnet losses, stray losses, and mechanical losses—along with the main challenges involved in modeling them; achieving a good approximation typically requires computationally expensive tools or experiments that go beyond the low computational cost objective pursued by LPTNs. Equivalent circuits minimize the overall computational cost because they allow the motor to be modeled using a set of FEA simulations or experiments and can provide the accuracy required for most applications if calibrated correctly. In short, while there is no consensus in the literature on the best method in terms of computational cost and information required, new methods using MLP stand out for their ability to cover a wider range of applications than only through experimentation and FEA simulations.

Each of these loss mechanisms contributes to the total energy dissipation within the motor, which involves various heat transfer mechanisms that occur in the motor components, including conduction, convection, and radiation. It has been noted that understanding heat transfer processes is essential for optimizing the performance and efficiency of PMSMs, preventing aging and wear or irreversible damage due to insufficient cooling. In the formulation subsection, it is evident that there is a clear consensus on the modeling of thermal conduction resistances, taking into account the specific adaptations made by each author to the objective of the study and the technical data obtained. However, there is no consensus regarding the modeling of convection. Some authors rely on CFD simulations that increase the model overall computational cost, while others rely on formulas based on dimensionless numbers or simplified empirical formulas derived from induction motor tests, which can lead to errors since they do not account for key aspects of the geometry that affect fluid dynamics and cause the convection coefficient to vary. A potential line of research, therefore, remains open in this field.

With regard to validation, most studies use experimental techniques; it is recommended to use these in conjunction with CFD calculations if greater accuracy is required in the temperature distribution across the various motor components.

Total computational time remains an unresolved issue because, although LPTNs themselves have a low computational cost, the preliminary calculations required through FEA

or CFD, or any experimental measurements, increase this cost when viewed from a holistic perspective. The latest advances that implement neural networks also fall short in this regard, as the initial training involves a high computational cost, and the computational cost of hybrid models or digital twins can be high enough to make unfeasible their application in industry.

New methods that optimize parameter identification improve predictions of motor thermal behavior, as does the implementation of neural networks, and these stand out as current and future trends. Depending on the application, it is recommended to first assess the error percentage required for the application, since by applying appropriate safety margins, it may not even be necessary to apply complex parameter optimization methodologies.

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Abbreviations

The following abbreviations are used in this manuscript:

A	Ambient
AC	Alternating Current
AG	Air Gap
BB	Ball Bearings
CD	Conduction
CV	Convection
CFD	Computational Fluid Dynamics
CH	Chassis
CNN-RNN	Convolutional Neural Network–Recurrent Neural Network
COO	Cooling
DC	Direct Current
EC	Endcaps
ECA	Endcap Air
ES	End Spaces
EV	Electric Vehicle
EW	End Winding
F	Frame
FB	Flux Barrier
FE	Finite Element
FEA	Finite Element Analysis
FEM	Finite Element Method
HEV	Hybrid Electric Vehicle
HTC	Heat Transfer Coefficient
IA	Internal Air
IPMSM	Internal Permanent Magnet Synchronous Motor
LPTN	Lumped Parameter Thermal Network
MLP	Multi-Layer Perceptron

MS	Mechanical Structure
N.N	Number of Nodes
OOD	Out-of-Distribution
PM	Permanent Magnet
PMSM	Permanent Magnet Synchronous Motor
PMSIWM	Permanent Magnet Synchronous In-Wheel Motor
PWM	Pulse-Width Modulation
R	Rotor
RC	Rotor Core
RD	Radiation
RI	Rotor Iron
RY	Rotor Yoke
S	Stator
SC	Stator Core
SC-SE	State-Conditioned Squeeze-and-Excitation
SFT	Shaft/Revolution Axis
SHL	Shell
SLT	Slot
SPMSM	Surface Permanent Magnet Synchronous Motor
ST	Stator Teeth
SW	Stator Winding/Winding
SY	Stator Yoke
TH. B	Thermal Behavior
TNN	Thermal Neural Network

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