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AI-ENABLED DESIGN AND OPTIMIZATION OF AEROSPACE ELECTRIC MOTORS: A TASK-ORIENTED REVIEW

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Abstract: Artificial intelligence (AI) becomes an effective tool in electric motor design. It can speed up design updates, improve optimization in complex conditions, and support physical modeling. However, most existing review papers discuss AI in motor design in a general way. These studies usually do not focus on the special needs of aerospace systems. This paper presents a task-based review of AI methods for aerospace electric motor design under extreme constraints which mainly covers data-efficient learning, surrogate models, multi-objective optimization, constraint-aware optimization, and physics-informed methods. These methods help designers deal with difficult trade-offs among power density, thermal behavior, mechanical strength, and fault tolerance, even when training data are limited. This paper also discusses the main problems in current studies. For example, many methods still lack validation under real flight conditions. In addition, this paper points out several future directions, such as the use of digital twins and AI workflows that can support certification. This review can provide a clear reference for researchers and engineers who apply AI to next-generation aerospace electric propulsion and actuation systems.
Keywords: Artificial intelligence; Task-oriented review; Motor design; Aerospace electric motors; Extreme constraints

1 INTRODUCTION

Electric motors now play a key role in modern aerospace systems. They are used in flight control actuators, fuel pumps, and many other subsystems. They are also becoming important in the primary propulsion of new electric aircraft. Compared with motors used on the ground, aerospace electric motors face much stricter requirements [1-2]. These motors must provide very high power density and torque density, while keeping weight and size as low as possible [3-4]. For example, earlier aircraft motors could usually reach about 5-10 kW/kg, but future electric propulsion systems may require about 20 kW/kg [5]. At the same time, the working environment is much harsher. Aerospace motors often operate under extreme thermal conditions. High-altitude environments reduce cooling capability. These motors also face strong vibration and high-speed mechanical stress. In addition, they must meet very high reliability and safety standards [6]. Aerospace motors need to work for long periods without maintenance. They also need fault-tolerant capability and must satisfy strict certification rules similar to those used for aero-engines. Therefore, aerospace electric motor design must deal with a set of extreme limits, including thermal limits, mechanical limits, space limits, and reliability demands [7].

Traditional design methods are no longer enough for this kind of complex problem. Aerospace motor design is not a single-field task. It involves electromagnetics, heat transfer, structural mechanics, and control at the same time. When designers try to improve power density, losses and local temperature often rise as well. This problem makes thermal management and motor design strongly coupled [8-9]. In the same way, improving reliability may require redundant phases or fault-tolerant topologies, but these choices may increase weight or reduce efficiency. Because of these conflicts, engineers are using more computational optimization methods in design. High-fidelity finite-element models for electromagnetic and thermal analysis are now often placed inside numerical optimization loops [8].

Recent studies have shown the value of these methods. One study used a coupled electromagnetic-thermal model with adjoint sensitivity analysis to optimize a propulsor motor. That method improved efficiency while still meeting thermal and power limits [9]. NASA has also carried out large design studies for eVTOL motors. The goal of these studies is to greatly improve reliability without causing a large increase in mass. These efforts show an important fact: aerospace motor design needs advanced methods such as multi-physics modeling, multi-objective optimization, and reliability-oriented design.

Nowadays, artificial intelligence and machine learning are providing strong support for aerospace motor design. One major difficulty in design optimization is the high cost of evaluating each candidate design. For example, a single 3D finite-element simulation may take a long time. AI can reduce this burden through surrogate modeling. Researchers can train machine learning models, such as neural networks or Gaussian process models, by using data from high-fidelity simulations or experiments. After training, these models can give fast approximate predictions of motor performance [10]. For example, some studies report that an AI surrogate model can evaluate motor performance in milliseconds, while a traditional physics-based simulation may take several minutes. This speedup can greatly improve global optimization efficiency. Researchers have used machine learning surrogates to optimize many design variables, such as pole shape, winding layout, and material choice. Their goals include higher efficiency and lower torque ripple [11]. A recent review on machine learning in motor drive design showed that neural networks, Bayesian regression, and evolutionary algorithms have all been used successfully in multi-objective motor optimization. These AI-based methods can bring clear performance improvements. For instance, one data-driven method combined support vector regression with particle swarm optimization. That method increased motor torque by nearly 7% and reduced harmonic distortion by about 60%, while efficiency changed very little [9].

AI becomes even more valuable in aerospace because data are usually limited. Aerospace prototypes are expensive, and testing opportunities are rare. Because of this, designers cannot depend on very large datasets. Instead, they often combine simulation data with physical knowledge. Methods such as physics-informed machine learning and Bayesian optimization make it possible to explore design spaces with only a small number of high-fidelity samples [12-13]. For example, one study used physics-informed Bayesian optimization to design a high-performance traction motor. That method reduced optimization time by 45% compared with a traditional genetic algorithm [12]. The method added physical knowledge into the learning process, so it needed less training data while still keeping good accuracy. In another example, researchers combined analytical motor models with neural networks. Their results showed that a physics-assisted neural network could reach the same level of accuracy as a fully data-driven model, but it required far fewer training samples [13]. Some researchers have also built generative models to expand small datasets. These models can create new and reasonable motor designs, which helps train deep learning models when real data are not enough [14-16]. These developments make AI more suitable for small-data conditions, and this is especially important for aerospace motor design.

Although more studies now apply AI to electric machine design, most existing review papers are still broad and not specific enough for aerospace use. Many of these reviews focus on algorithm development or general motor optimization. They often do not fully consider the special limits found in aerospace systems. These constraints mainly come from the need for high power-to-weight ratio, tight thermal and mechanical limits, and limited experimental data. At the same time, many existing studies assume that designers can use large training datasets or carry out repeated prototype tests. This assumption is often not realistic in aerospace engineering. Aerospace development usually faces strict limits in cost, safety, and mission requirements, and these limits greatly reduce the chances for large-scale testing and data collection. Because of this, the actual usefulness of many common AI methods in aerospace motor design is still not fully clear. This is especially true when physical consistency, data efficiency, and long-term reliability under certification requirements are considered.

To address these gaps, this paper gives an engineering-based summary of AI methods for the design and optimization of aerospace electric motors under extreme constraints. Different from reviews that mainly classify methods by algorithm type or discuss general applications, this paper is organized around design tasks and engineering problems. It directly links AI methods to actual needs in aerospace design. These needs include limited data, high reliability demands, multi-physics coupling, and complex working conditions. This paper focuses on physics-informed models, data-efficient optimization methods, and learning strategies that can handle design constraints in aerospace applications. The purpose of this review is not only to summarize current work, but also to build a clearer view of how AI can be used in a practical and safe way in the aerospace motor design process. As shown in Figure 1, the main contributions of this paper are as follows:

1) This paper presents a dedicated review of artificial intelligence methods for aerospace electric motor design and optimization under extreme constraints. Different from existing general reviews on AI in electric machines, this work emphasizes the specific engineering challenges of aerospace applications, such as stringent power-density targets, harsh thermal and mechanical environments, limited cooling conditions, high reliability requirements, and scarce high-quality data.

2) The reviewed literature is structured according to the main technical stages of aerospace motor development, including AI-supported modeling and AI-based optimization. Specifically, the paper covers surrogate modeling, thermal and multi-physics modeling, physics-enhanced and constraint-aware modeling, parameter optimization, topology and structural optimization, multi-objective optimization, and sample-efficient design strategies. This organization provides a clearer connection between AI methods and actual aerospace motor design tasks.

3) Beyond summarizing current methods, this paper critically examines their engineering readiness for aerospace applications. It identifies major limitations in current studies, such as heavy dependence on simulation data, simplified treatment of physical and reliability constraints, insufficient validation under extreme conditions, and limited attention to uncertainty quantification and certification compatibility. On this basis, the paper discusses future directions toward more robust, physics-guided, and trustworthy AI frameworks for next-generation aerospace electric motor design.

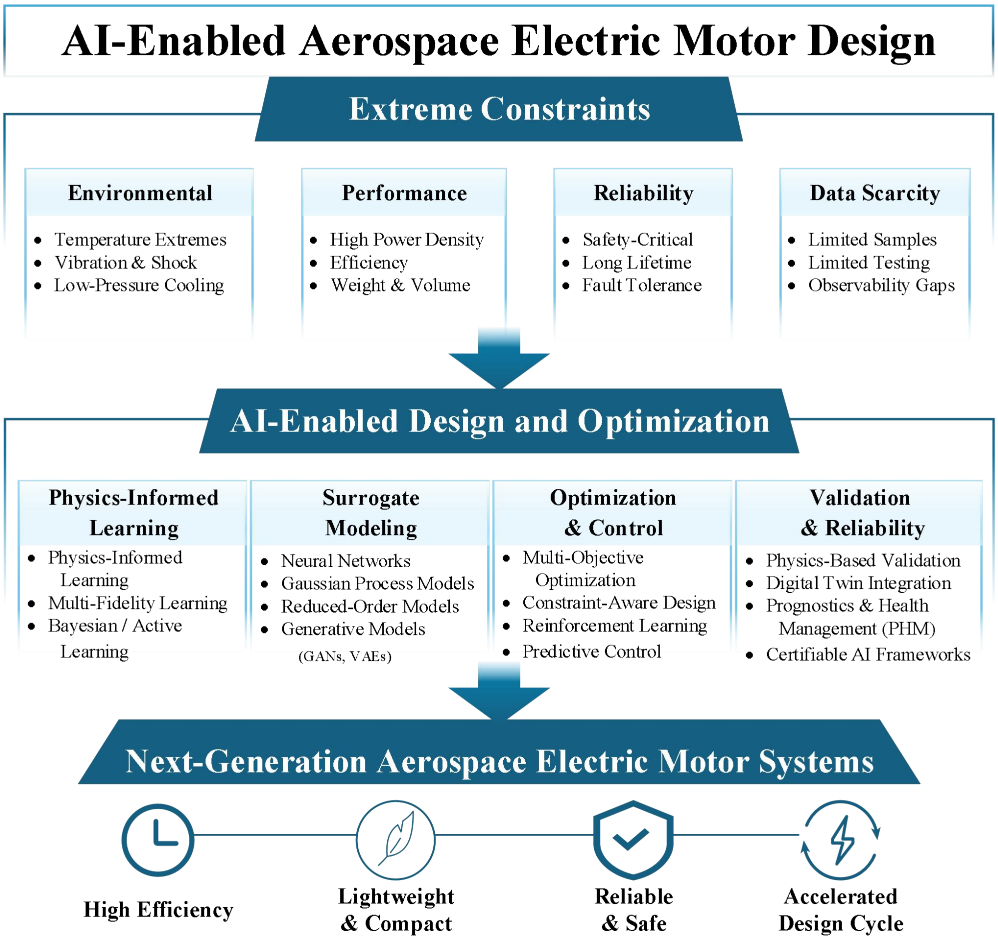

Figure 1 AI Methods in Aerospace Electric Motors under Extreme Constraints

2 EXTREME CONSTRAINTS IN AEROSPACE ELECTRIC MOTOR DESIGN

Modern aerospace electric motor design is subject to many extreme constraints, and these constraints are far beyond those in ordinary industrial applications, as shown in Figure 2. These constraints involve several aspects. They include the environmental conditions that the motor must withstand, the very demanding performance goals, especially in propulsion systems, and the strict requirements for reliability and service life under very limited maintenance conditions. They also include problems caused by limited data and the difficulty of fully observing motor behavior. This part reviews these constraints in detail and explains what they mean and how they affect motor design. Where appropriate, this chapter also gives quantitative indicators and practical examples to show how demanding aerospace requirements can be. In addition, a comparative summary is provided to show the differences between aerospace motors and typical industrial motors, so that the special challenges in aerospace applications can be seen more clearly.

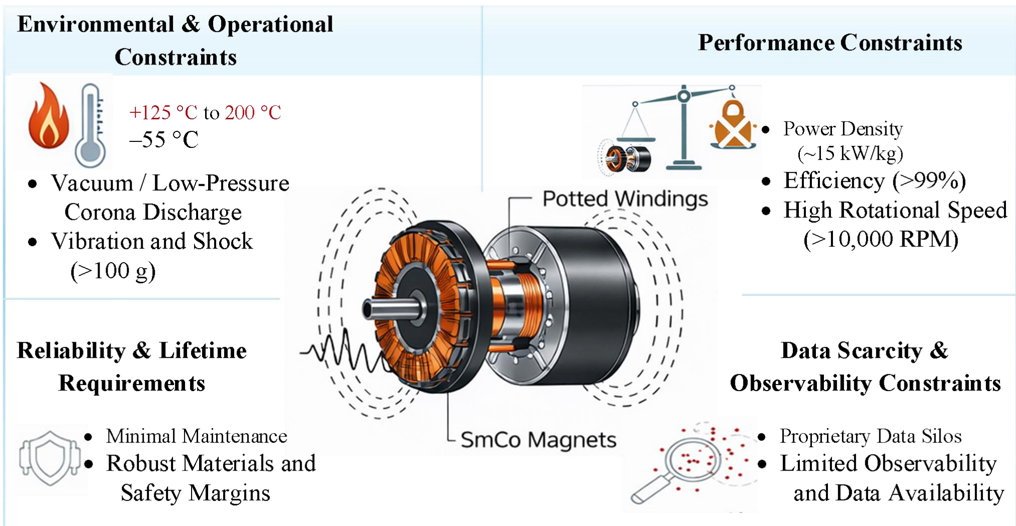

Figure 2 Extreme Constraints Faced by Aerospace Electric Motors

2.1 Environmental And Operational Constraints

Aerospace electric motors work in environments and operating conditions that are much harsher than those of industrial motors. Because of this difference, designers must consider many special factors. Environmental constraints mainly come from outside conditions, such as temperature, pressure, vibration, and shock. Operational constraints mainly come from the way the motor is used, such as repeated take-off tasks or long-duration space missions. These factors place heavy stress on the motor.

a) Temperature extremes

Aerospace motors often face a very wide temperature range during operation. For example, parts outside the cabin of a commercial aircraft may repeatedly experience temperatures from about -55 ℃ at high altitude to +125 ℃ near the engine or during ground operation [17]. These repeated temperature changes can damage the motor over time. They may cause material fatigue, moisture condensation, corrosion, magnet demagnetization, and insulation aging. To deal with these problems, designers usually choose materials that can tolerate high temperatures. For example, rotor magnets may use samarium-cobalt materials. Lubricants and potting materials also need to resist radiation or release very little gas. In spacecraft, the temperature range can be even wider. For instance, bearings and lubricants may need to work from -80 ℃ to +200 ℃ [18].

Industrial motors are usually designed for ambient temperatures of around 40 ℃. Aerospace motors are very different. They need much stronger thermal design. In vacuum or thin air, convection cooling becomes very weak or even disappears. Under this condition, heat must be removed mainly by conduction or radiation. Because of this, designers often add heat sinks, thermal paths, or even active cooling systems. However, these measures may also increase mass and system complexity [19]. To keep the motor working across a wide temperature range, designers often need to reduce output under extreme temperatures and carefully choose materials such as insulation and adhesives, so that these materials can still keep good mechanical and electrical properties.

b) Altitude and pressure

Aircraft motors that work at high altitude must run under low-pressure conditions. Space motors even work in vacuum. Low pressure greatly weakens convective cooling, and this further worsens the thermal problem mentioned above [20]. In addition, when motors are placed in unpressurized areas, low pressure may cause corona discharge or electrical arcing in high-voltage parts if insulation is not sufficient [21]. Vacuum also brings another problem, which is outgassing. Some materials may release gases or vapors in vacuum, and these substances may condense on sensitive instruments. Because of this, aerospace motors must use materials with low outgassing characteristics. For space applications, motors are usually assembled under strict cleanliness requirements, and they are often vacuum-baked before use. Designers also choose wire insulation, potting materials, and lubricants according to low-outgassing standards such as NASA requirements [22]. In addition, space motors usually avoid enclosed cavities that may trap gas, because trapped gas may expand, vent, or even damage the structure in vacuum.

c) Vibration and shock

Aircraft and launch vehicles expose motors to strong vibration and shock. During take-off, turbulent flight, and landing, motors may experience vibration over a wide frequency range. Aerospace qualification standards such as RTCA DO-160G require equipment to withstand these vibration conditions and still work normally. Different applications have different vibration features. For example, a fuel-pump motor in a jet engine may face long-term high-frequency vibration, while a UAV rotor motor may mainly face periodic vibration related to blade passing frequency [23]. To maintain long-term reliability under vibration, designers often strengthen the motor structure. For example, they may pot the windings with resin to prevent movement. They may also use laser welding in the rotor and stator structure to reduce the risk of loosening that may happen with mechanical fasteners. Shock loads are also very important. Aircraft landing or rocket stage separation may produce sudden acceleration. If the structure is not strong enough, these loads may bend the shaft or loosen internal parts.

For example, space stepper motors used in satellite antennas must survive rocket launch conditions. These conditions may include random vibration levels of about 6-10 g RMS for several minutes, as well as discrete shocks of hundreds of g. After that, the motor still needs to complete high-precision positioning in orbit [24-25]. These requirements force designers to use strong structural materials, carry out accurate rotor balancing to reduce self-generated vibration, and in some cases add isolators or dampers to the mounting structure. Table 1 compares several key environmental parameters between industrial motors and aerospace motors.

d) Operational profiles

In addition to environmental conditions, aerospace motors also face demanding operating tasks. Many of these motors work under cyclic or intermittent conditions, and these conditions can lead to fatigue damage. For example, a motor used in an aircraft flight control actuator may need to complete thousands of rapid movements during one flight. At the same time, it must still respond quickly after exposure to very low temperatures [26].

In another case, a propulsion motor in an electric aircraft may run at full power during climb for several minutes and then switch to lower power during cruise. This kind of duty cycle requires the motor to maintain effective cooling under high load and avoid overheating during continuous operation. Industrial motors often run near steady state, but aerospace motors often face rapid changes in speed and load. They may also experience frequent start-stop operation or long idle periods followed by immediate startup. These operating features increase thermal stress and mechanical stress, so designers must control them carefully to avoid fatigue failure [27].

Aerospace motors also face strict power supply limits. On aircraft, electrical power is limited and is usually carefully allocated from generators or batteries. Because of this, motors must maintain high efficiency and avoid large surge currents that could disturb the onboard power bus. This issue is even more important in electric propulsion systems. In such systems, every extra watt of loss becomes wasted battery energy and additional heat that must be removed [28]. Therefore, operational constraints directly affect motor design. Designers often need to choose high-efficiency topologies and advanced control methods so that the motor can maintain good performance under changing operating conditions.

In summary, the extreme environmental and operating conditions in aerospace require electric motors to have stronger adaptability while still maintaining high performance. To meet these demands, designers need to carefully choose materials with good thermal stability and low outgassing properties. They also need to use special enclosures, strengthen the structure, and apply design methods that can reduce thermal stress and vibration stress. These measures help the motor keep stable performance under harsh flight and space conditions. The following sections will further show how these environmental constraints are closely related to performance, reliability, and data-related challenges in aerospace motor design.

Table 1 Comparison of Industrial and Aerospace Electric Motor Constraints in Environmental and Operational Constraints

Constraints	Industrial motors	Aerospace motors
Operating temperature	• ~0 to 40 ℃ ambient (standard factory conditions) • Internal hot spots up to 155 ℃ (Class F insulation) tolerated with cooling	• -55 ℃ to +125 ℃external ambient cycles common • Must survive extreme cold soak and engine-proximity heat • Special materials to handle >200 ℃ in space vacuum
Pressure/cooling	• Normal pressure • Ample convective cooling (fans or ambient air) • No vacuum concerns	• Low pressure at altitude and poor convection • In vacuum, no air cooling and rely on radiation/conduction • Components must be vacuum-rated (low outgassing)
Vibration & shock	• Mild vibration from machines • Typically not design-limiting • Shock rarely significant (perhaps handling drops)	• Severe vibration during flight and launch (e.g. random vib >7 g RMS) and shock >10–100 g • Must meet DO-160G or military vibration tests • Robust structure, potted windings, locking fasteners to withstand lifelong fatigue

2.2 Performance-Oriented Constraints

In aerospace applications, electric motors must reach very high performance, and they often need to do so under strict limits in size, weight, energy, and cooling capacity. Performance-related constraints mainly include high specific power, high torque density, high efficiency at key operating points, fast dynamic response, and limited available power or cooling resources. In simple terms, aerospace motor design aims to obtain higher output and better efficiency, while keeping mass, volume, and energy use as low as possible, as shown in Table 2. These demands lead to a series of quantitative targets that are much higher than those of ordinary industrial motors.

a) Power and torque density

Power density and torque density are among the most important performance requirements in aerospace motor design. Every extra kilogram in an aircraft or spacecraft will reduce payload capacity or overall efficiency. Because of this, the motor must provide as much power as possible with as little weight as possible [29]. For example, NASA has pointed out that fully electric aircraft propulsion may require motor specific power of about 13 kW/kg or even higher. Some advanced designs are pushing this value further. NASA's megawatt-class prototype motor, which partly uses superconducting technology, targets a specific power of about 16 kW/kg and an efficiency close to 99% [30]. Industrial motors are very different. Their specific power is usually around 0.5-2 kW/kg in common designs [31]. This large difference clearly shows how demanding aerospace applications are. To reach such high targets, designers often use lightweight materials, such as aluminum or composite housings, instead of traditional cast iron. They also adopt more aggressive electromagnetic designs, such as higher rotational speed and higher magnetic loading. In some cases, the motor is even integrated with the airframe structure to reduce total weight.

High-pole-count permanent magnet synchronous motors are widely used in this field because they offer both high power density and high efficiency [32]. In particular, permanent magnet synchronous motors are often regarded as a strong choice for propulsion systems, since modern rare-earth magnets help them achieve high torque density. Another common way to increase power density is to raise motor speed. Higher speed can increase output power, but it also brings new problems. Very high speed increases mechanical stress and often requires reduction gears for propeller systems, so the design cannot increase speed without limit. Even so, aerospace motors in turbo-machinery or other special systems often run at tens of thousands of revolutions per minute, which is much higher than the 1500-3000 RPM range that is common in industrial motors. This high-speed operation helps them deliver the required power in a compact structure.

Table 2 Comparison of Industrial and Aerospace Electric Motor in Performance-Oriented Constraints

Constraints	Industrial motors	Aerospace motors
Weight/Volume	• Not a primary constraint	• Minimized weight and size is critical

	• Heavy cast iron frames acceptable • Volume is limited by equipment space	• High power-to-weight targets (5-15 kW/kg vs ~1 kW/kg industrial) • Often requires high-speed or high-torque-density designs and lightweight materials (aluminum, composites, sometimes Ti) to meet tight space envelopes
Efficiency	• Efficiency is balanced with cost	• Peak efficiency at their typical operating load • Target efficiencies is usually over 95% • New materials and topology

There is always a trade-off when designers try to increase power density. If electromagnetic loading becomes higher and the motor structure becomes more compact, loss and temperature usually rise as well. This problem is closely related to thermal limits. Designers need to balance current, magnetic flux, and cooling capability carefully. Forced-air cooling or liquid cooling can help remove heat when these methods are available. However, in many aerospace cases, the cooling condition is still quite limited. This is especially true for air-cooled propulsion motors in small aircraft, where thin air and short flight time both reduce the cooling effect [33]. As a result, a high-power-density design often has to accept a higher operating temperature. This also means the motor needs materials with better temperature tolerance, such as class H insulation or above and high-temperature magnets. At the same time, improving efficiency is also important, because lower loss helps reduce the thermal burden.

b) Efficiency and limited energy

Efficiency is especially important in aerospace systems because onboard energy is always limited, whether it comes from fuel or batteries. For electric aircraft, even a small increase in motor efficiency can bring a clear benefit. It may extend the flight range, or it may reduce the required battery weight. Because of this, aerospace motors are usually designed to maintain very high efficiency around their main operating points. Large propulsion motors often target efficiencies above 95%, and even small actuator motors still need high efficiency, mainly to reduce heat generation in confined spaces [34]. NASA's Electrified Aircraft Propulsion program has even set efficiency targets of around 98-99% for megawatt-class motors [35]. Reaching such a level is not easy. Designers usually rely on low-loss magnetic materials, high-quality lamination steel, and in some cases newer materials such as cobalt-iron alloys. Winding design also matters, because resistive loss needs to be reduced as much as possible. In some studies, researchers have gone a step further and explored special motor topologies such as superconducting windings, which can largely remove resistive loss. Of course, this kind of solution also brings extra complexity, especially because it depends on cryogenic cooling [36]. Even so, it shows that traditional motor designs based only on copper and iron are getting close to their practical limit in terms of achievable kW/kg.

Limited onboard power and energy affect more than efficiency. They also limit the peak power that a motor can draw. In more-electric aircraft, electrical energy usually comes from engine-driven generators or batteries, and both sources have clear supply limits. This means the motor cannot introduce large inrush currents or strong transients that may disturb the electrical system. For this reason, designers often use power electronic converters and control methods, such as soft-start schemes and torque smoothing strategies, to keep motor demand within the allowable range of the power source [37].

This is also one of the features that makes aerospace motor design different from ordinary industrial design. In aerospace systems, the motor and the aircraft power system are closely linked. A propulsion motor, for example, may need to keep stable operation under bus voltage fluctuations, including those found in modern variable-frequency AC or DC systems. Some designs solve this problem by adding active front-end converters to regulate power flow. This increases system complexity, but it also helps the motor maintain performance under strict electrical constraints.

2.3 Data Scarcity And Limited Observability

A more hidden but very important constraint in aerospace motor design and optimization is the lack of relevant data and the difficulty of fully observing motor behavior during operation. Industrial motors are often produced in large numbers, so researchers and engineers can usually access a large amount of data on performance, failure, and operating conditions. Aerospace motors are different. Many aerospace projects involve one-time designs or very small production batches. In some cases, the available data are also separated across different teams or protected for confidentiality reasons. In other cases, the motor may be designed for a new operating scenario, such as eVTOL propulsion, where very little historical data exist [38]. This lack of data can affect both motor design and later health monitoring during service (Table 3).

Table 3 Comparison of Industrial and Aerospace Electric Motor in Data Scarcity and Limited Observability

Constraints	Industrial motors	Aerospace motors
Data sources	• Large-scale data • Data can be measured and recorded easily	• Few data points under actual flight conditions • Simulation data are more accessible
Data observability	• Data can be obtained through extra sensors	• Fixed structures lead to difficult measurement • It is hard to detect or diagnose motor states
Ownership and rarity	• Can be widely shared • Testing qualification is low	• Cannot be shared • Testing qualification is extremely high

a) Scarce design data and testing opportunities

The development of a new aerospace electric motor usually depends heavily on simulation, because real testing is expensive and the number of tests is limited. Building a prototype and verifying it in flight costs far more time and money than testing an industrial motor on a bench. Because of this, designers usually have only a small amount of data from real flight conditions [39]. Some key questions are therefore difficult to answer directly. For example, designers may not know exactly how a motor will perform after many years of thermal cycling at high altitude, or under rare peak-load events such as emergency climb conditions. In many cases, these issues can only be estimated through extrapolation or handled by using conservative margins.

This lack of test data pushes designers to depend more on high-fidelity models and larger design margins [40]. For instance, when long-term life data are not enough, insulation systems are often designed more conservatively or operated below their nominal limit in order to reduce risk. The same problem appears in design optimization, especially when AI or machine learning is introduced. In aerospace conditions, the datasets needed for performance prediction or failure prediction are often very small, and in some cases they do not exist at all [41]. Engineers usually address this by using simulation data based on physical models, or by borrowing experience from similar systems, such as wind turbine generators or electric vehicles. Still, these replacements are not fully equivalent. As a result, aerospace motor design often remains conservative. Designers tend to leave larger safety margins and avoid pushing components too close to their theoretical limit, simply because the uncertainty stays high when supporting data are limited.

b) Limited observability in operation

After an aerospace motor is put into service, its condition is often difficult to observe in a complete way. This is mainly due to limits in sensor installation, communication bandwidth, and the operating environment itself [42-43]. Many motors are placed in wings, nacelles, or other compact locations where only a few sensors can be installed in practice. These may include temperature sensors, one vibration sensor, or several electrical measurements. In space systems, the situation can be even more restrictive, since telemetry bandwidth is very limited and only the most important signals can be sent back. Because of this, faults or performance degradation may be hard to detect at an early stage [44]. For example, if a motor starts to develop bearing wear during flight, the fault may not be easy to identify. In an industrial setting, engineers could use detailed vibration analysis to detect such a problem early. In an aircraft, however, the vibration background is much more complex and the number of sensors is much smaller. A bearing fault may therefore remain hidden until it becomes serious. NASA has reported a similar problem in prognostic studies of valve actuators, which are similar to motors in several respects [45]. In that case, the available health model could not separate each failure mode clearly and could only reflect their combined effect. Aerospace motors face a similar issue. Engineers may have only phase currents and a few temperature signals, but they still need to infer many health conditions, such as demagnetization, insulation aging, and bearing damage. This kind of inference is under-constrained, and it remains an active research topic in aerospace prognostics and health management.

c) Data ownership and rarity

Another difficulty is that aerospace data are often not openly available. Even when useful data exist, they are usually kept by companies, research institutes, or defense organizations and are not widely shared [46]. This means that each new motor project often starts with very limited data-driven knowledge. The situation is very different from the automotive field. Electric vehicles have already generated a very large amount of motor data through large-scale deployment, and these data can support analysis and model development. Aerospace does not yet have a comparable fleet, especially in electric aircraft.

For this reason, many researchers point out the need for stronger data infrastructure and better sharing mechanisms. Some studies have called for dedicated databases of reliability and performance data for electrified aircraft propulsion systems. Under this background, AI and machine learning methods for aerospace motor design must often work in a small-data setting. They usually rely on surrogate models, physics-informed learning, or transfer learning from other engineering domains [47].

A related issue is that aerospace motors do go through strict qualification testing, but the resulting data are usually generated only once, and the sample size remains very small. Engineers therefore still need to make decisions under limited evidence. A common response is to adopt worst-case assumptions and keep generous safety margins. For example, even if two out of two motors successfully complete a 2000-hour endurance test, engineers may still require the design to meet a much longer life target, such as 4000 hours, before it is considered sufficiently safe [48]. This practice is very different from consumer products, where dozens or even hundreds of units can be tested to build statistical confidence. In aerospace, reliability analysis is often carried out under incomplete data and wide confidence intervals [49]. Because of that, certification authorities usually do not rely on quantitative test data alone. They also look for qualitative support, such as compliance with standards and the use of conservative design methods. This culture helps protect safety, but it can also slow down the use of new AI-based design tools, especially when those tools depend on extrapolation beyond validated data.

Recent studies on aerospace propulsion motors also reflect the fast progress in this field. For example, the University of Nottingham has outlined a clear development trend for direct-drive aircraft propulsion systems. Early designs were at about 5 kW/kg. More recent demonstrators have increased this value to around 10 kW/kg. Future systems are expected to go beyond 20 kW/kg within a similar speed range. One reported example is a 4 MW, 15 krpm generator that achieved a power density of 17.3 kW/kg and an efficiency of 98.3% in experiments. This result shows that megawatt-class electrified propulsion is technically feasible. In another case, a 300 kW aerospace propulsion motor prototype reported a power density of 15-25 kW/kg, depending on insulation temperature limits and cooling strategy [50]. These results show that multi-domain electromagnetic-thermal co-design and advanced cooling technology are becoming central to high-power-density aerospace machines.

Overall, data scarcity and limited observability form a basic constraint in aerospace motor design. They make environmental, performance, and reliability challenges even harder to address. In many cases, aerospace motor engineers work with very weak feedback from both development testing and real operation [51]. A new design, a new material, or a new method may not be fully validated until very late in the development process. Once the motor enters service, the available monitoring information may still be quite limited.

Progress in this area depends on two directions. One is better sensing, so that more useful information can be collected during operation. The other is better use of simulation and AI, so that limited data can be used more effectively. Some researchers have therefore argued for a more data-driven aerospace engineering framework, where simulation data, experimental data, and operational data are integrated more systematically [52]. Before such a framework becomes mature, AI tools used in aerospace motor design must remain robust under uncertainty and must work together with expert knowledge rather than replace it. Even so, the field is moving forward. For example, researchers such as Daigle have already demonstrated real-time prognostics for actuator motors by using compact lumped-parameter models, and new electric aircraft projects are beginning to accumulate flight data that may support the next generation of design methods [53].

3 AI-SUPPORTED MODELING UNDER EXTREME CONSTRAINTS

As discussed in Section 2, aerospace electric motors operate under extreme constraints in power density, efficiency, reliability, and coupled electromagnetic–thermal behavior. These requirements render brute-force finite-element-based optimization computationally prohibitive, motivating the use of AI-supported surrogate and reduced-order modeling techniques.

3.1 Surrogate Modeling for Electromagnetic Performance

Evaluating the electromagnetic performance of a motor, such as torque, loss, and efficiency, usually depends on detailed finite element analysis or relatively complex analytical models. Under extreme design requirements, such as high speed, compact geometry, or the use of new materials, the simulation process often becomes highly nonlinear and computationally expensive [54]. In many cases, designers need to run a large number of iterations before they can explore the design space clearly. For aerospace motors, this problem becomes more prominent, because the cost of each design iteration is high and the number of iterations should be kept as low as possible. A key issue, therefore, is how to obtain fast and reliable predictions of motor performance over different operating conditions and structural parameters.

Data-driven surrogate models provide a useful way to address this problem. These models learn the relationship between inputs and outputs from a limited number of high-fidelity simulations or experiments. After training, a surrogate model can predict electromagnetic performance much faster than direct finite element analysis. For example, Gao et al. reported that an ANN-based surrogate model could evaluate a motor-drive design in 0.044 s, whereas the corresponding physics-based simulation required 90 s [55]. This kind of speed improvement makes broad design space exploration and optimization much more practical.

Table 4 summarizes several representative surrogate modeling methods used in electric machine design, including support vector machines, random forests, and neural networks [56-57]. In aerospace motor design, surrogate-assisted optimization can greatly reduce the need for repeated FEA while still maintaining acceptable prediction accuracy for engineering use. By placing surrogate models inside the optimization process, designers are able to search high-dimensional parameter spaces more efficiently. This also helps them balance torque density, efficiency, thermal limits, and mass requirements in a more practical way.

Table 4 Surrogate Modeling for Electromagnetic Performance

Constraints	Key Features	Strengths	Limitations
Polynomial response surface	• Uses low-order polynomials to fit simulation data	• Simple, fast to train • Interpretable	• Limited for nonlinear or high-dimensional problems
Gaussian process regression	• Probabilistic model with uncertainty estimates	• Excellent interpolation • Handle noise well	• Computationally expensive for large datasets or dimensions
Machine learning	• Flexible nonlinear models; universal approximators	• Fast evaluation after training • Capture nonlinear effects	• Needs hyperparameter tuning; black-box behavior

3.2 Thermal And Multi-Physics Modeling With AI Assistance

Aerospace motors usually work under very severe thermal and mechanical stress. High current density and concentrated loss can produce a large amount of heat. If this heat is not removed in time, the motor may suffer from magnet demagnetization or insulation failure. For this reason, thermal behavior cannot be studied alone. It usually needs to be analyzed together with electromagnetic effects, and in some cases also with structural vibration or acoustic behavior, as shown in Figure 3. This makes the problem a typical multi-physics task. High-fidelity methods, such as coupled electromagnetic-thermal FEA or CFD, can be used for this purpose, but it is not practical to run these models for every design case or every operating condition [58]. The real difficulty is how to predict temperature, stress, and other physics-related indicators with sufficient accuracy, while still meeting the speed requirements of design optimization or real-time health monitoring.

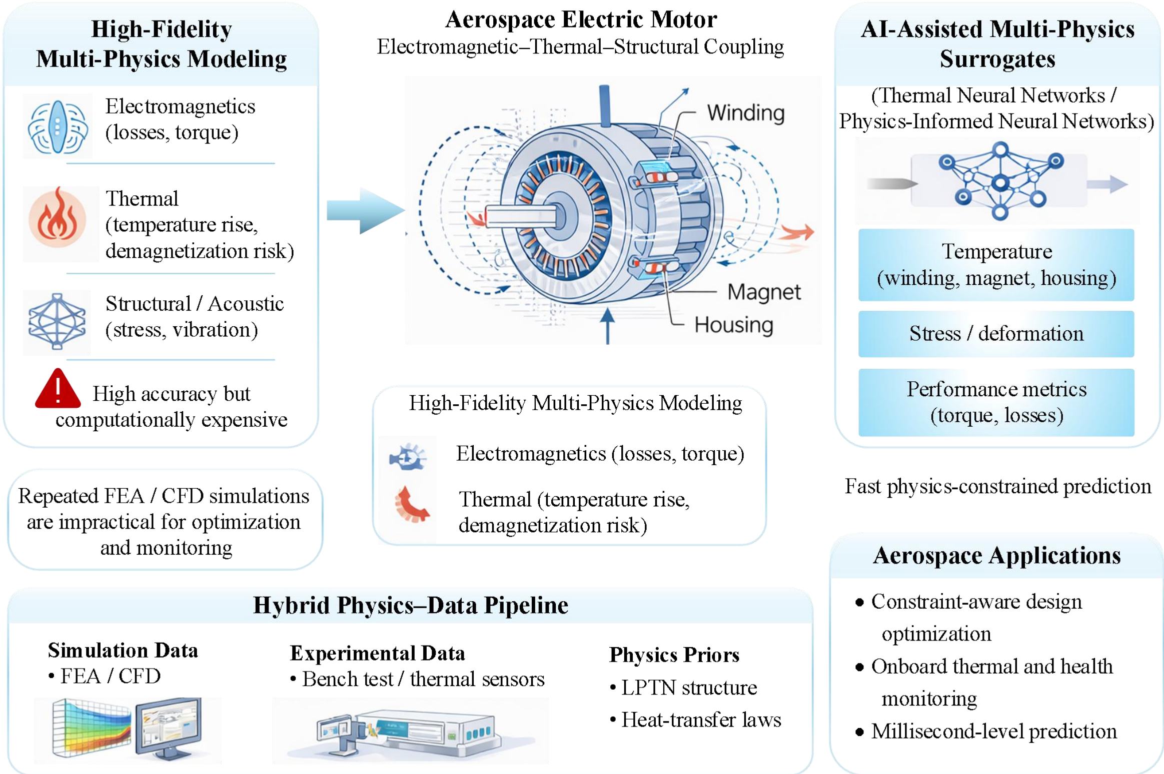

Figure 3 Hybrid Physics–Data Framework for Thermal and Multi-Physics Modeling of Aerospace Electric Motors

Hybrid reduced-order methods provide a more practical solution. Among them, lumped-parameter thermal networks are widely used because they are easier to implement and much faster to compute. The Thermal Neural Network proposed by Kirchgässner et al. combines the structure of an LPTN with a neural network framework, so it keeps physical meaning while also gaining the flexibility of data-driven modeling [59–61]. Experimental results show that this method can improve temperature prediction accuracy with only 64 tunable parameters, which also reflects the efficiency of physics-informed model design.

This type of reduced-order thermal modeling has also been validated in aerospace actuator systems, not only in general industrial cases. For example, fault-tolerant PMSMs developed for aerospace use have been studied with carefully tuned LPTN models, and the predicted temperatures were compared with both FEA results and experimental data under normal and fault conditions [62]. The reported results showed good agreement between predicted and measured winding temperatures in different cases. These cases included normal operation as well as typical aerospace actuator faults such as single-phase open-circuit and short-circuit conditions. These results suggest that structured thermal models can provide engineering-level accuracy while still keeping the computational cost low enough for iterative design and mission-profile analysis.

Overall, AI-assisted modeling offers a practical way to deal with coupled multi-physics problems in aerospace electric motors, while still keeping the computation manageable under extreme operating conditions.

3.3 Physics-Enhanced and Constraint-Aware Modeling

Pure data-driven models can be very effective, but they still have clear limits. In some cases, they may produce results that do not follow physical laws. In other cases, their performance drops quickly once the input moves beyond the training range. To reduce these problems, researchers have started to develop physics-enhanced and constraint-aware AI models. These methods add physical knowledge or design constraints directly into the learning process. The main idea is to combine the strengths of both sides. Physics-based methods offer prior knowledge and clearer interpretation, while data-driven methods offer stronger flexibility, as shown in Table 5.

Physics-informed neural networks are a typical example. These models introduce Maxwell equations or thermal governing equations into the loss function, so the predicted results are pushed toward physically reasonable solutions [63-64]. This kind of method is especially useful in aerospace propulsion applications. In such cases, experimental data are often limited, and the model usually has to work beyond normal operating conditions. Under this background, physics-informed methods can provide better support for prediction and analysis.

Table 5 Comparison of Physics-Enhanced and Constraint-Aware Modeling Approaches

Approaches	Key Features	Strengths	Limitations

Physics-informed neural networks	•Embed PDEs (Maxwell's equations) in loss function	•Ensure outputs satisfy physical laws •Work well with sparse data	•Requires careful formulation of equations and training •Limited to known physics
Physics-assisted neural networks	•Use physics model output as input or residual target	•Combine analytical structure with ML flexibility •Fast convergence	•Relies on availability and accuracy of a physics baseline
Constraint-aware modeling	•Adds design/physical limits to loss function	•Prevent unphysical predictions •Help avoid unsafe regions	•Hard constraints may limit flexibility •Tuning penalties can be nontrivial

Another common idea is to use physics-assisted neural networks or other hybrid model structures. In this kind of method, the network does not learn only from direct input-output pairs. Instead, it also uses an intermediate result given by a physical model. This extra information can guide the learning process. Sakamoto et al. used this idea in motor design optimization by combining a subdomain analytical model with a neural network [65]. The analytical model first gives an approximate estimate of air-gap flux distribution and torque based on the motor geometry. The neural network then learns the remaining error between this estimate and the high-fidelity result. Their results showed a clear advantage. The physics-assisted neural network reached the same accuracy as a purely data-driven model, but it needed much less training data. It also performed better than the physical model used alone. In torque ripple prediction, the hybrid model gave lower error and smaller variance than a comparable black-box model, especially when the available data were limited [66].

AI models can also include design and operating constraints more directly, not only physical equations. For example, the loss function can be modified to penalize predictions that break known limits, such as efficiency above 100% or negative inductance [67]. Some methods can also enforce monotonic relationships during training [68]. In this way, the learned model follows important constraints from the beginning. This is especially useful under extreme operating conditions, because it reduces the chance that the model will output physically impossible or unsafe results. In aerospace applications, this kind of property can improve confidence in the model.

Overall, physics-enhanced AI models can improve both generalization ability and physical consistency. For this reason, they are considered to be promising for digital twin development and for aerospace motor applications that place strong emphasis on validation and certification.

3.4 Model Fidelity, Data Generation, and Validation

The fidelity of an AI-supported model describes how well it can reflect the actual behavior of the motor. In general, higher fidelity depends on better training data, and in many cases it also depends on suitable multi-fidelity modeling strategies. In practical design problems, engineers often face an uneven data structure. They may only have a small amount of high-fidelity data, such as 3D FEA results or experimental measurements, while a larger amount of lower-fidelity data, such as 2D simulations or simplified analytical results, is easier to obtain. Instead of building separate surrogate models for different data sources, multi-fidelity methods try to combine them in a more efficient way [69]. The purpose is to improve prediction accuracy without relying too much on expensive high-fidelity data. One study compared three advanced surrogate modeling methods on a PMSM design problem and reported clear improvements in both accuracy and computational efficiency [70].

No surrogate model or hybrid model should be used directly, especially in safety-critical aerospace systems, without careful validation. This usually requires comparison with reserved high-fidelity data and, when possible, with real experimental measurements [71]. Common evaluation factors include prediction error, possible failure cases, and the valid operating range of the model. Sakamoto et al. gave a typical example. After using a physics-assisted neural network surrogate to optimize motor designs, they rechecked the final solutions with FEA and found that the Pareto-optimal points predicted by the surrogate still remained close to the optimal results from FEA [72]. They also showed that the physics-assisted model had much smaller validation error in torque ripple prediction than a purely data-driven model [73]. Results like these help increase confidence in the model under expected operating conditions. In aerospace applications, validation may also include stress cases, such as cold start at high altitude or emergency overload, so that the model can be examined beyond normal operating conditions [74].

An AI-supported model is also not necessarily fixed once it is built. During later testing or operation, new data can be added back into the model, as shown in Figure 4. For example, when an aerospace motor goes through more test stages, the measured data can be used to update or fine-tune the surrogate model through online learning or periodic retraining. In this way, the model can gradually become closer to the real system over the full life cycle. This idea is closely related to the concept of a digital twin, where the model continues to evolve so that it can better match the physical motor.

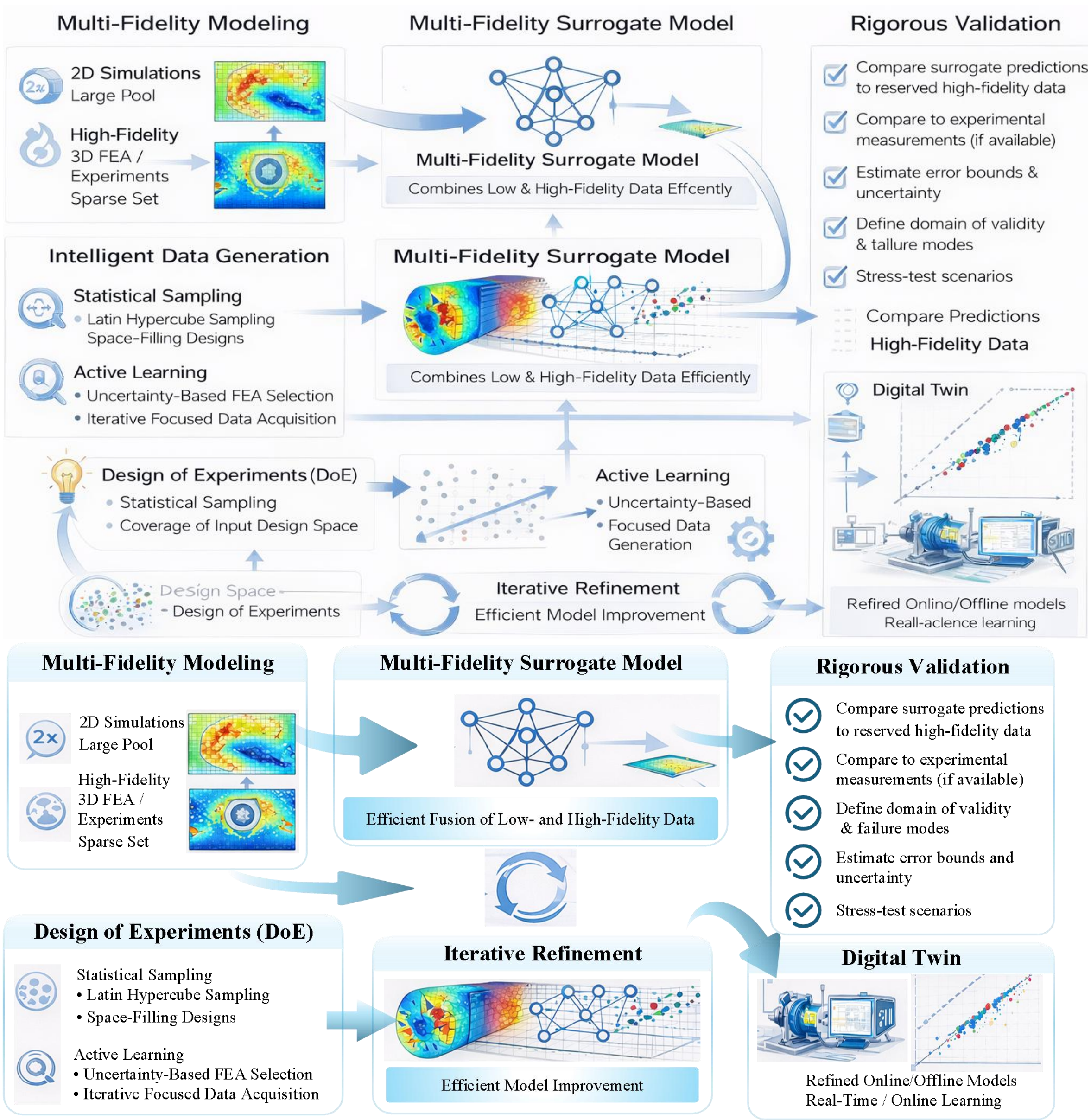

Figure 4 Model Fidelity, Data Generation, and Validation Workflow in AI-Assisted Motor Design

4 AI-BASED DESIGN AND OPTIMIZATION UNDER EXTREME CONSTRAINTS

4.1 Parameter-Level Design Optimization

Aerospace electric motors are required to deliver very high performance under strict weight and size limits. This requirement forces designers to optimize many parameters at the same time, such as magnet size, slot and tooth geometry, and winding arrangement. These parameters together form a continuous and high-dimensional design space. In this kind of problem, brute-force search is usually too expensive, and conventional gradient-based methods are often difficult to apply because motor behavior is strongly nonlinear. To deal with this issue, many studies use AI methods to build surrogate models, so that expensive finite element analysis does not need to be called repeatedly in the optimization loop [75-76]. Artificial neural networks and Gaussian process regression are two common examples. Both have been used to build mappings from design parameters to performance indices with good accuracy, which makes design space exploration much more efficient [77].

A typical strategy is to combine an ANN-based surrogate with an evolutionary optimization algorithm. Shoaei et al., for example, developed a Bayesian-optimized ANN to predict torque, torque ripple, and weight in a reluctance magnetic gear design problem [78]. On this basis, they used a multi-objective genetic algorithm to search for Pareto-optimal parameters. The final results showed clear benefits. The optimized design reduced torque ripple by 47%, lowered total weight, and improved torque output. At the same time, the required computation time was much lower than that of direct FEA-based optimization.

Similar ideas have also been explored in other forms. Gu et al. trained deep neural-network surrogates to evaluate motor designs either from a vector of geometric parameters or directly from cross-sectional images [79]. Their results showed that a convolutional neural network using image input could predict outputs such as cogging torque more accurately than models based only on geometric parameters. This result suggests that high-dimensional representations may capture subtle geometric effects more effectively. Gaussian-process-based surrogates have also shown good performance in parameter optimization. For instance, Son et al. used an adaptive-sampling Kriging model to optimize magnet placement in a synchronous reluctance motor. Their method was able to narrow the search region for the optimal design while using far fewer FEA evaluations. Overall, the key value of AI surrogates lies in their ability to connect high-dimensional design variables with multiple performance targets in a fast way. This capability provides an important basis for motor optimization under very tight design margins [80]. Representative AI-based optimization methods and their engineering effects are summarized in Table 6.

Overall, surrogate-assisted parameter optimization enables efficient exploration of high-dimensional design spaces under extreme aerospace constraints, allowing designers to balance torque density, efficiency, ripple suppression, and mass targets within feasible computational budgets.

Table 6 Parameter-Level Design Optimization

AI approaches	Optimized parameters	Strengths	Benefits
ANN	• Torque & ripples	• Nonlinear modeling	• Fast surrogate evaluation
GPR	• Flux linkage & losses	• Uncertainty quantification	• Adaptive sampling
CNN	• Cogging torque	• Geometry input handling	• Captures subtle geometric effects
Bayesian-optimized ANN	• Torque & ripples & weight	• Multi-objective capability	• Reduces computation time

4.2 Topology And Structural Optimization Under Practical Constraints

Beyond the optimization of continuous parameters, AI is also being used in the topology design of motor components. This is important because topology optimization can produce designs that do not follow traditional intuition but still achieve better performance than conventional structures. Traditional topology optimization methods, such as density-based methods or genetic-algorithm-based shape evolution, usually require high computational cost. The burden becomes even heavier when manufacturing limits and structural constraints also need to be considered [81].

To improve this process, some studies have introduced deep generative models for faster topology exploration. For example, Shimizu et al. combined a generative adversarial network with a vision transformer in an automated design framework for interior permanent magnet motors [82]. In their method, the generative model could produce new rotor topologies that satisfied torque requirements, while the total optimization time was reduced by one to two orders of magnitude compared with more traditional methods.

Another common idea is to use AI as a fast evaluator during topology search. Sasaki and Igarashi showed that a CNN trained on rotor images could be used as a substitute for FEA in the topology optimization of an interior permanent magnet motor based on a genetic algorithm [83]. In their method, the CNN quickly predicted the performance of each new rotor shape, and only the more promising candidates were checked again by FEA. This reduced the number of expensive FEA evaluations by about 90% without reducing the quality of the final optimization result. Because of this, the design space could be explored much more broadly within a practical time range, including changes such as adding or removing material features in the rotor. In a related study, Khan et al. trained a reinforcement learning agent to modify the rotor shape of a synchronous reluctance motor step by step, with the goal of increasing torque output (Table 7) [84].

Table 7 Topology and Structural Optimization

Method	Use Case	Constraints Handled	Impact
GAN + ViT	• Rotor topology	• Torque	• Non-intuitive topologies
CNN surrogate + GA	• Rotor topology	• Structural limits	• 90% fewer FEA runs
Reinforcement Learning	• Rotor shape evolution	• Stress, geometry	• 70-90% compute savings
Generative Cooling Design	• Thermal channel design	• Thermal, manufacturability	• Integrated lightweight cooling

When topology optimization is applied to aerospace motors, designers cannot focus only on electromagnetic performance. They also need to consider thermal and structural requirements at the same time. Some recent AI-assisted methods have started to include these factors in the optimization process [85-86]. For example, internal cooling channels or lightweight support structures can also be designed through topology optimization. In this case, generative design algorithms can be used to propose new cooling path layouts that improve heat dissipation under strict weight and space limits. With the support of thermal FEA, and in some cases transfer learning, these methods can generate motor housings or cooling jackets that perform better than conventional designs while still remaining manufacturable. In many cases, the resulting structures are smoother and more practical, such as curved channels instead of sharp cavities [87].

AI-based optimization can also take stress and deformation limits into account. These limits may be added directly into the objective function, or they may be used later as a screening condition. In this way, the final topology is not only efficient but also strong enough for high-speed operation. For example, the algorithm may introduce reinforced ribs or fillet-like features so that the rotor can better withstand mechanical load. In practice, some new design frameworks are already combining multi-physics simulation with generative AI to produce motor structures that are lighter and more compact, while still maintaining structural reliability and reducing dependence on trial-and-error design [88-90].

4.3 Multi-Objective And Constraint-Aware Optimization

Aerospace electric motor design involves several strongly coupled trade-offs. Designers usually need to balance torque density, efficiency, torque ripple, thermal behavior, and mass at the same time, while still satisfying structural and reliability requirements, as shown in Table 8. Under this kind of condition, AI-assisted multi-objective optimization provides a more practical solution. It can approximate the constrained Pareto front more efficiently and reduce the need for exhaustive parameter sweeps [91].

For example, Li et al. combined random-forest-based variable screening with a neural-network surrogate to carry out multi-objective optimization of an IPMSM [92]. Their optimization considered torque, efficiency, and torque ripple at the same time. Based on the surrogate model, they then used a multi-objective particle swarm algorithm to search for Pareto-optimal solutions. The final results showed clear improvements over the baseline design. Average torque increased by 4.6%, efficiency improved slightly, and torque ripple decreased by more than 10% [93]. These results show that AI-based methods can improve several performance targets at the same time. This is especially important in aerospace motor design, where improving one aspect at the cost of seriously weakening another is usually not acceptable.

Table 8 Multi-Objective and Constraint-Aware Optimization

Approaches	Objectives	Constraints	Outcome
Random Forest + NN + PSO	• Torque, efficiency, ripple	• Embedded via surrogate	• Balanced Pareto front
CatBoost for NVH	• Noise, torque, cost	• Hard constraints in model	• NVH improved without cost
GAN with constraint filtering	• Efficiency vs torque	• Minimum torque enforced	• Valid Pareto-optimal designs
Constrained BO	• Feasibility + torque	• Feasibility probability	• Reduced samples, feasible outputs

AI tools are also becoming more aware of design constraints. This means they can deal with hard constraints, such as minimum torque or stress limits, directly during optimization, instead of checking them only after the optimization is finished. A common way to do this is to add penalty terms or constraint checks into the objective evaluation process. For example, Noh et al. proposed an AI-based optimization method for EV motors that focused on reducing noise and vibration while still meeting torque and cost requirements [94]. In their work, a CatBoost regression model was trained to predict acoustic noise and torque from design parameters with good accuracy. Based on this model, optimization algorithms were then used to reduce motor noise. At the same time, torque and material cost constraints are enforced during the search process. In this case, the final design achieved lower noise without reducing required performance or exceeding the cost limit. The optimized motor also showed better NVH behavior while still satisfying the main functional requirements. In a similar way, the previously mentioned GAN-based IPM motor design method directly removed candidate solutions that failed to meet the minimum torque requirement, so that the search remained focused on the feasible region of the Pareto front [95].

To make learning models more constraint-aware, researchers have also started to introduce physical knowledge and failure criteria into machine learning models. One common idea is to use constraint-augmented loss functions, where extra terms are added to penalize constraint violations during training. Another idea is to use feasibility classification networks, so that the model can better distinguish between feasible and infeasible design regions [96]. For example, Bayesian multi-objective optimization methods can include the probability of feasibility in the acquisition function, so that new samples are more likely to come from regions that satisfy all key constraints [97]. Loka et al. demonstrated this idea in a constrained multi-objective Bayesian optimization framework for motor design. Their method first used an active learning stage to identify the boundary between feasible and infeasible designs, and then carried out optimization only within the feasible region. The final results showed that this method could find high-performance motor designs more quickly and without violating critical constraints, and its performance was better than that of a traditional unconstrained Bayesian optimization method. Besides physical limits, AI methods can also handle manufacturability requirements [98–100]. In recent generative design frameworks, egineers can consider the following goals: reducing part count, matching standard material sizes, or avoiding overhang structures in 3D printing. In this way, the optimized motor or component is not only better in performance, but also easier to manufacture with available processes..

4.4 Sample-Efficient and Sequential Optimization Strategies

When high-fidelity simulations are too expensive to run repeatedly, sample efficiency becomes a very practical issue in aerospace motor design, as shown in Table 9 [101]. In this case, the point is no longer to sample the whole design space as evenly as possible. What matters more is whether each new evaluation is worth doing. This is why sequential optimization methods have attracted attention. With the help of AI, they can decide which design points are more informative and should be tested first.

Bayesian optimization and adaptive sampling are typical examples. In constrained motor design problems, these methods have shown that good solutions can be found with much fewer high-fidelity simulations than those required by conventional evolutionary search [102]. A similar idea appears in multi-fidelity optimization. Instead of relying only on expensive simulations, it combines simplified analytical models with a small number of high-fidelity evaluations [103-104]. In this way, the computational burden can be reduced without causing a clear loss in prediction quality.

The practical value of these methods is quite direct. They can shorten the design cycle and allow designers to examine more feasible motor configurations even when the simulation budget is limited. Table 9 gives several representative examples and their engineering impact.

Table 9 Sample-Efficient and Sequential Optimization

Method	Sampling Strategy	Benefit	Application Example
Bayesian Optimization	• Uncertainty-based acquisition	• Fewer high-cost samples	• Torque/ripple optimization
Active Learning	• Refine high-error areas	• Targeted sampling	• Ripple minimization
Multi-Fidelity Models	• Low-to-high fidelity training	• Accuracy with less data	• PMSM design
Reinforcement Learning	• Knowledge transfer across tasks	• Reduced training time	• Topology reuse

4.5 Design Cycle Acceleration And Engineering Impact

AI-assisted optimization does more than improve motor performance. It also makes the engineering process much faster, as shown in Table 10 [105]. In traditional development, designers often need to run a very large number of high-fidelity simulations before they can gradually narrow down the design. After surrogate models are introduced, this process changes a lot. The number of required high-fidelity simulations can drop from thousands to only hundreds, but the optimization can still move quickly toward feasible high-performance solutions. This effect has already been reported in several studies. For example, in the design of interior permanent magnet motors, some generative design frameworks greatly reduced the time needed to build efficiency maps when compared with conventional FEA-based evaluation [106]. Similar results have also been reported in surrogate-assisted multi-objective optimization studies, where the computational cost was clearly reduced while the final solution quality remained at a comparable level.

The benefit is quite direct. When the optimization process becomes faster, designers can check more candidate schemes within the same project schedule. This is especially useful when propulsion requirements are still changing, because the design can be adjusted more quickly. Some studies have reported that AI-assisted workflows can shorten the development cycle by roughly 30% to 50%, although the exact improvement still depends on the problem itself and on how many constraints must be considered. Table 10 lists several representative examples of this kind of acceleration and the corresponding performance gains. For aerospace motor development, this matters not only because the design targets are demanding, but also because validation is expensive and time-consuming. In that setting, reducing the computational burden can make the whole design process more practical and can also help lower development risk.

Table 10 Design Cycle Acceleration and Engineering Impact

Use Case	Cycle Time Reduction	Performance Gains	Industrial Relevance
GAN-based motor design	• <1/3000 simulation time	• Efficient Pareto front	• EV traction motors
Surrogate-assisted optimization	• ~90% fewer iterations	• Ripple drops by 47%	• Magnetic gear
RL for design reuse	• 70-90% savings	• High generalizability	• Synchronous reluctance motor
AI platform (Monumo)	• 30–50% overall cycle reduction	• Torque ripple drops by 50%	• Switched reluctance motor

4.6 Structured Case Study: Literature-Based AI-Driven Propulsion Motor Optimization Workflow

To make the technical basis of this review more solid, this section gives a structured case study based on representative published work. The purpose here is not to add new experimental results. Instead, this section brings together results from existing studies and organizes them into a relatively complete workflow for AI-assisted propulsion motor design under aerospace requirements.

Step 1: Defining the problem under aerospace propulsion requirements

For hybrid-electric aircraft, propulsion motor design is not a single-objective task. It usually has to balance several goals at the same time [107]. In most cases, designers hope to improve torque density and efficiency, while still controlling mass and torque ripple. The difficulty is that these goals must be achieved under strict constraints, especially thermal limits in low-pressure cooling conditions, high-speed mechanical stress, and the reliability demands of safety-critical systems.

Reported studies on electric aircraft suggest that propulsion motors are often expected to reach around 10 kW/kg or more in specific power, while efficiency is usually required to stay above 95% [108]. Of course, the exact target still depends on the mission and the overall system architecture. Once these requirements are brought together, motor design is no longer just a matter of parameter selection. The electromagnetic and thermal parts become closely linked, and the whole problem becomes much harder to handle.

Step 2: Generating data with different fidelity levels

In aerospace programs, experimental data are usually limited, so high-fidelity FEA is still the main source of design data. A common approach is to evaluate dozens or sometimes hundreds of candidate designs by using structured sampling methods. This gives an initial dataset for later model training and optimization.

But relying only on high-fidelity simulation is costly. Because of that, many studies use multi-fidelity strategies. The usual idea is to first use simplified analytical models to capture rough trends, and then bring in high-fidelity FEA for correction and refinement [109]. This kind of setup helps reduce the simulation burden while still keeping the main physical trends.

Step 3: Building surrogate models

With the dataset in place, the next task is usually surrogate modeling. Studies in this area often use ANN, Kriging, SVR, or physics-assisted neural networks. The purpose is to estimate several key motor outputs, including torque, loss, efficiency, ripple, and sometimes mass.

The advantage of this step is fairly direct. Once the surrogate is accurate enough, the optimization no longer needs to call FEA every time. Some surrogate-assisted studies have reported about 93% reduction in total computation time when compared with workflows based entirely on FEA [110]. More broadly, the literature suggests that surrogate models can reduce the number of expensive simulations by roughly 70% to 90%, although the exact number still depends on the stopping rule and optimization setting.

Step 4: Multi-objective optimization with explicit constraints

Once the surrogate model has been established, methods such as NSGA-II or PSO can be used to search for Pareto-optimal solutions within the feasible region [111]. The purpose at this stage is not simply to push one performance index as high as possible. What really matters is whether several coupled objectives can be balanced in a way that is meaningful for engineering design.

Reported results are quite representative. In many studies, torque density improves by around 4% to 10% compared with the baseline design. Torque ripple is often reduced by more than 30%, and in some cases the reduction approaches 40% to 50%. At the same time, the overall optimization time is often more than 80% lower than that of brute-force simulation-based search [110]. For propulsion motors, this kind of improvement matters a lot, because power density and thermal feasibility are usually linked very tightly.

Step 5: Thermal and multi-physics validation

Even after optimization, the final design cannot be used directly. It still needs to be checked carefully. In most cases, this step relies on coupled electromagnetic-thermal simulation, although some studies also use physics-informed neural-network models [111]. The point of this step is to make sure that the optimized motor still meets the required thermal and reliability limits under propulsion operating conditions (Table 11).

Table 11 Quantitative Outcomes Reported in AI-Assisted Propulsion Motor Design Studies

Design Stage	Representative AI Approach	Reported Quantitative Outcome
Surrogate modeling	• ANN / GPR / PANN	•70–90% reduction in FEA calls
Multi-objective optimization	• NSGA-II / PSO	• 4–10% torque density improvement
Ripple mitigation	• Surrogate-assisted optimization	• >30% ripple reduction (up to ~40–50%)
Computational efficiency	• Surrogate-assisted workflow	• ~93% time reduction; >80% runtime savings
Thermal modeling	•Physics-informed NN	•Improved constraint-consistent prediction

5 DISCUSSION ABOUT CHALLENGES AND FUTURE DIRECTIONS

Current AI-based design methods for aerospace electric motors still face several clear limitations. The first problem is data scarcity. High-fidelity motor design data, whether from simulation or experiment, are expensive to obtain and usually very limited. As a result, machine learning models often have to be trained on very small datasets, while the number of design variables remains large. Under this condition, methods that depend heavily on large datasets, especially deep learning models, are very likely to overfit. In practice, this means a surrogate model may fit the available samples well, but once it is used on a new design, its prediction may no longer be reliable.

A second problem is that purely data-driven models usually do not contain enough physical constraints. Because of this, they may produce results that look reasonable from a statistical point of view but do not make sense physically. For example, a generic Gaussian process surrogate may violate basic physical rules if no constraint is added during modeling. The same issue appears in many conventional generative models. These models often behave like black boxes, so there is no clear guarantee that their outputs are physically consistent. In extreme cases, a model may even predict impossible quantities, such as negative loss or behavior that breaks energy conservation. This is clearly unacceptable in engineering design.

Another important limitation is poor generalization under unseen or extreme conditions. Aerospace motors do not work in a narrow and stable range. They may face high temperature, high speed, varying loads, and other conditions that are not fully covered by the training data. A model trained only on limited cases may perform well inside the known range, but once it is asked to extrapolate, the error can increase sharply. This problem comes partly from the lack of data, and partly from bias in the model itself. In other words, small datasets not only make overfitting more likely, but also leave the model unable to describe operating regions that have never been observed. This makes robust design under rare or extreme conditions much harder.

The next difficulty comes from the multi-physics nature of aerospace motor design. In practice, motor performance is never determined by electromagnetic behavior alone. Thermal limits, mechanical stress, vibration, and reliability requirements all matter at the same time. For example, even if an electromagnetic design looks very good, rotor stress or temperature rise may still prevent it from being used at high speed or high power. However, many current AI-based design methods still focus on a single physical domain, usually electromagnetic performance, and pay too little attention to coupling with other fields. Recent studies have made it clear that electromagnetic, thermal, and structural interactions cannot be ignored, even at an early design stage. Once these coupled constraints are considered together, the optimization problem becomes much harder. A purely data-driven method often struggles to handle this kind of strongly coupled and sometimes conflicting design requirement.

Uncertainty is another weak point in current research. Most neural networks and surrogate models only provide a single predicted value, but they do not tell the designer how reliable that value is. In aerospace applications, this is a serious problem. Designers need not only a prediction, but also some measure of confidence. Without uncertainty quantification, the model cannot warn the user when the input is far from the training range or when the result is likely to be unreliable. At the same time, many recent studies still lack thorough validation against high-fidelity simulation or experimental data. Because of this, it is often difficult to judge how trustworthy the model really is, especially in operating conditions that were not included during training.

Taken together, current AI methods in aerospace motor design are still limited by small datasets, weak physical consistency, poor extrapolation ability, difficulty in handling coupled constraints, and the lack of built-in uncertainty estimation. On top of that, there are also certification and regulatory barriers. These issues show that future research should not only pursue higher prediction accuracy, but also pay more attention to reliability, interpretability, and engineering credibility. Several research directions appear especially important.

One important direction is physics-guided and constraint-aware learning. If physical laws can be introduced directly into the model, the learning process becomes more stable and the final result is more likely to remain feasible. This can be done in different ways. Some methods add conservation laws, governing equations, or monotonic relationships into the loss function. Others modify the model structure itself so that unphysical outputs are ruled out by design. A reported example showed that a physics-guided regression model could still achieve very high accuracy and narrow uncertainty bounds even under limited data, because hydraulic conservation relations were enforced during learning. In general, this type of method is promising because it combines the flexibility of machine learning with the reliability of physical constraints.

Another important direction is multi-fidelity modeling together with active learning. Since high-fidelity data are limited, it is not realistic to depend on them alone. A more practical approach is to combine information from several sources. For example, coarse simulations or simplified analytical models can first be used to capture the main trend, and then a smaller amount of high-fidelity FEM or CFD data can be used for correction. Active learning can further improve this process by selecting the most informative new samples for simulation or testing. Instead of adding data blindly, the method focuses on regions where uncertainty is high or where the design response changes quickly. In this way, limited simulation and testing resources can be used more efficiently.

Uncertainty-aware design frameworks are also needed. Future optimization should not rely only on point estimates. Probabilistic machine learning models, such as Bayesian neural networks, Gaussian process models, or ensemble methods, can provide confidence intervals together with performance predictions. This makes robust optimization possible. Designers can then consider not only expected performance, but also reliability margin and failure risk. In addition, input uncertainty, such as manufacturing error or material variation, can be propagated through the surrogate model, so that the final design is evaluated in a more realistic way. Compared with current point-based optimization, this kind of framework is much more suitable for safety-critical aerospace systems.

Digital twins and online model updating also offer a valuable path forward. A digital twin can combine physical models with sensor data collected during operation, such as temperature or vibration signals, and use them to keep updating the design model. In this way, the model does not remain fixed after the initial development stage. Instead, it gradually becomes closer to the real motor as more data become available. This idea is useful not only for design refinement, but also for fault diagnosis, predictive maintenance, and long-term health management. More importantly, it helps reduce the gap between offline design assumptions and real in-service behavior.

A further issue is certification and explainability. In aerospace applications, even a highly accurate model may still be difficult to use if its reasoning process cannot be understood or verified. For this reason, explainable AI methods are becoming increasingly relevant. These methods can help engineers understand why a model prefers a certain design or which features are driving its predictions. At the same time, more rigorous engineering workflows are also needed, including traceable model development, version control, testing procedures, and validation pipelines. Some recent studies suggest that MLOps tools and explainable AI methods may help support future certification efforts. But this area is still at an early stage. The aerospace community will likely need dedicated standards, benchmarks, and regulatory guidance before AI-designed motor components can be accepted with the same level of confidence as conventionally designed systems.

In the end, solving these problems will require progress from several directions at once. Better machine learning alone is not enough. The field also needs stronger physical modeling, better use of limited data, more complete uncertainty treatment, and methods that can meet aerospace validation and certification requirements. If these aspects can be developed together, AI will have a much better chance of becoming a practical and trustworthy tool for aerospace electric motor design under extreme constraints. These directions also provide a clearer path for future research in this area.

6 CONCLUSIONS

Artificial intelligence has shown great potential in electric motor design and optimization. This advantage is more obvious in problems with many design variables, strong nonlinear behavior, and costly multi-physics simulations. Aerospace electric motors especially need such methods. These motors often work under very strict limits. These limits include power density, efficiency, thermal management, structural strength, reliability, and limited data. In this setting, traditional design methods mainly depend on repeated high-fidelity simulations and manual adjustment. As design demands keep rising, these methods are becoming harder to maintain.

This review has presented a task-based summary of AI methods for aerospace electric motor design and optimization. The paper does not simply sort previous studies by algorithm category. Instead, it discusses the literature based on practical engineering tasks. These tasks include electromagnetic surrogate modeling, thermal and multi-physics modeling, parameter optimization, topology and structural design, multi-objective optimization, and sample-efficient sequential search. This view helps show the role of AI in a clearer way. AI can do more than shorten design cycles. It can also help designers deal with coupled constraints and find feasible high-performance solutions in a more organized and effective manner.

At the same time, this review also shows that current AI-based methods still have clear limitations before they can be used reliably in aerospace engineering practice. First, high-quality data are still scarce. Second, purely data-driven models often lack enough physical consistency. Third, many models still have weak generalization ability under extreme operating conditions. In addition, existing studies do not fully address multi-physics coupling. Many methods also lack uncertainty evaluation, sufficient validation, and workflows that meet certification needs. In safety-critical aerospace applications, these issues are not minor details. They are key requirements. They directly affect whether AI tools can be trusted in real engineering design.

Overall, the most promising path is not to replace physics-based design with purely data-driven methods. A better direction is to build AI frameworks that are guided by physics, aware of constraints, able to describe uncertainty, and suitable for the full lifecycle of engineering design. Future progress will likely rely on closer integration of multi-fidelity modeling, active learning, digital twins, explainable AI, and validation processes that match aerospace engineering standards. As these areas continue to improve, AI is likely to become a more practical and reliable tool for next-generation aerospace electric motor design under extreme constraints.

COMPETING INTERESTS

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