Combined Machine Learning and Differential Evolution for Optimal Design of Electric Aircraft Propulsion Motors

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***Abstract*—Electric aircraft propulsion requires highly efficient and power-dense fault-tolerant electric motors optimized for specific flight profile operation. State-of-the-art design of electric motors involves substantial computational resources and combines electromagnetic finite element analysis (FEA) and optimization techniques. This paper proposes a new approach using a physics-based machine learning (ML) multi-input univariate meta-model trained on FEA and differential evolution (DE) optimization results to predict electromagnetic torque output. Hundreds of individual designs, generated through multiple generations of a DE algorithm, are analyzed by 3D FEA to create a database, which is then employed for the training and satisfactory validation of the ML model. The coreless axial flux permanent magnet (CAFPM) machine topology considered for an example study typically necessitates intensive 3D FEA simulation due to its specific geometry, although it does not experience the non-linear saturation associated with ferromagnetic core materials. The hybrid ML-DE model is satisfactorily validated with an R^2 value of 0.97 and normalized root mean squared error (NRMSE) of less than 0.05. The relative merits of the newly proposed combined ML-DE optimization are discussed, especially in terms of low error and the potential for overall computational time minimization.**

***Index Terms*—Meta-Modeling, artificial neural network, deep learning, electric aircraft, axial flux, coreless stator, Halbach PM array.**

I. Introduction

The transportation industry has consistently remained a significant contributor to global carbon emissions [1]. If worldwide emission reduction goals, such as those outlined in [2], are to be met, it will be through the widescale deployment of electric transportation systems. Electric propulsion systems are being researched and developed to reduce emissions in the aviation sector. The electric machines employed by these systems are required to satisfy a conflicting set of performance criteria across different operating conditions with key requirements including ultra compact design with minimal weight, fault tolerance, and high efficiency over the flight profile [3, 4].

Permanent magnet (PM) machines are considered a leading candidate for aviation propulsion systems due to their superior specific power and higher efficiency when compared to alternatives [5]. Coreless axial flux PM (CAFPM) machines offer a significant advantage in weight-sensitive applications, such as electric aircraft, due to their ability to achieve high power densities in a more compact volume [6]. Further enhancements to torque density, when compared to conventional surface-mounted PM rotors, may be made by integrating a Halbach array PM configuration into the rotor of these machines [7]. A critical challenge inherent to high-performance PM machines is their susceptibility to demagnetization, especially at elevated temperatures, impeding fault tolerance, an essential requirement of aircraft propulsion systems.

To address this issue, researchers have been investigating hybrid designs that combine the distinct benefits of different electric motor topologies. One such approach, proposed by the authors in [4], involves coupling a CAFPM machine, e.g. [8] with a hybrid stator DC-excited synchronous (SDCES) motor unit with a reluctance rotor, e.g. [9, 10]. This innovative dual-stage machine, illustrated in Fig. 1, utilizes a selective operation system, allowing the aircraft to simultaneously activate and switch between motor units based on flight conditions, thus enhancing fault tolerance. The example dual-stage machine is intended for distributed propulsion across a blended wing aircraft, like that proposed in [11] and shown at the top of Fig. 1, taking advantage of the unique power requirements corresponding to the flight profile.

To ensure these machines are optimally designed, time and computationally extensive FEA simulations are employed. Optimization methods based on differential evolution (DE) algorithms are among the most effective for predicting the Pareto front for problems with multiple conflicting objectives [12]. A key challenge with evolutionary algorithms lies in their need for a large number of candidate solutions to accurately determine the Pareto front, making the process time-consuming and computationally demanding, especially when using 3D finite element analysis (FEA).

Recent studies have proposed the application of meta-modeling techniques, such as artificial neural networks (ANN), to estimate behavior, even for complex nonlinear systems, which typically require computationally extensive simulations [13, 14]. The ANN-driven meta-models may be suitable as they can learn and determine patterns from large datasets by estimating the key relationships in the data [15]. Previous

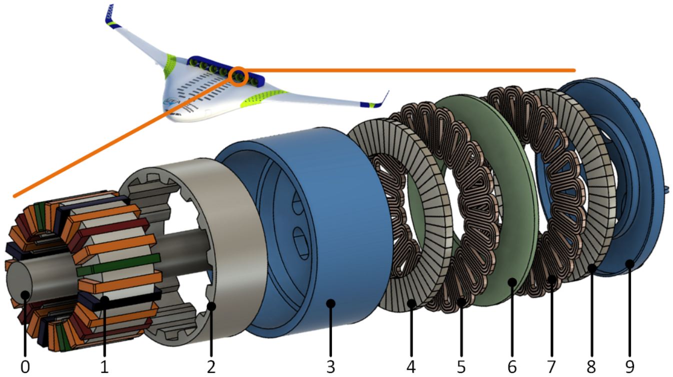


Fig. 1. Overview of an example dual-stage electric machine concept for aircraft propulsion. (0) Shaft, (1) SDCES stator ferromagnetic core and windings, (2) SDCES rotor ferromagnetic core, (3) SDCES and CAFPM composite material rotor holder, (4 and 8) CAFPM rotor Halbach PM array, (5 and 7) CAFPM stator 3-phase winding module, (6) CAFPM cooling plate – heat exchanger, (9) CAFPM composite material rotor holder.

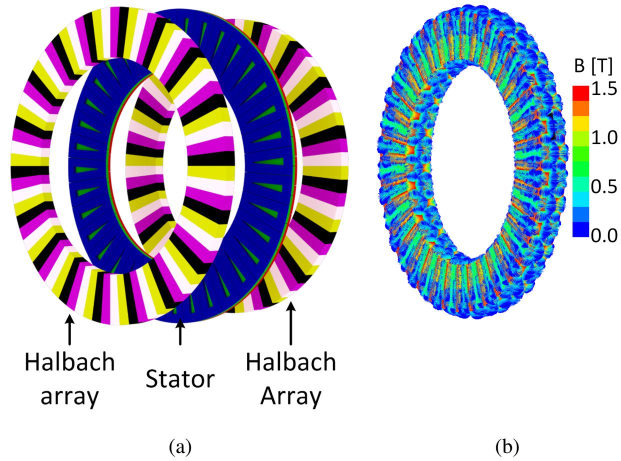


Fig. 2. Exploded view of the studied CAFPM machine (a) and the FEA no-load magnetic flux distribution for an example design (b).

research has suggested the viability of creating ANN meta-models that offer rapid results with reasonable accuracy that match FEA simulations as validation [16–18].

This paper proposes a multi-input univariate ANN for the design, analysis, and optimization process of CAFPM motors with Halbach array rotors, such as those previously introduced by the same research group [7]. The structure of the remaining paper is organized as follows. Section II briefly reviews previously employed machine learning (ML) techniques for electric machine design. Section III details the topology and optimization process of the CAFPM motor. Lastly, Section IV presents a case study demonstrating the use of an ANN as a surrogate model in the optimization process of the CAFPM machine.

II. Overview of Machine Learning Applications in Electric Machine Design

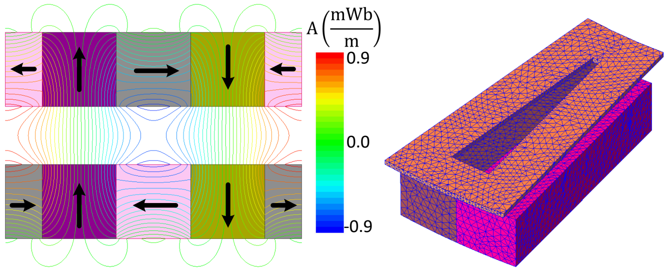
The application of AI and ML techniques to electric machine design is growing in popularity, as indicated by recent publications on a variety of previous example studies. Meta-models of electric machines may produce, in principle, satisfactorily accurate results based on collections of previously obtained simulation and experimental data, reducing the need to re-run computationally expensive FEA simulations. This section provides a brief review of recent applications of ML based performance prediction and design optimization for electric machines.

In such cases, inputs for the algorithms typically consist of geometric variables and material characteristics, while outputs are referred to as Key Performance Indicators (KPIs) that typically include output torque, efficiency, power losses, magnetic flux density, cost, etc. An automated deep learning based methodology, proposed by Poudel *et al.* [19], was employed for the design and optimization of a complex machine structure with hybrid PMs, utilizing a total of 10,000 data sets with 7,000 for training and 3,000 set aside for cross validation.

Another ML-based algorithm, proposed by Tucci *et al.* [20], employs cross sectional images as inputs, utilizing bitmap representation to assign specific locations within the machine to individual pixels. The study also indicated that this methodology produces high-dimensional input data, which can present challenges for traditional optimization algorithms, as they encounter difficulties when exploring large design spaces. From that same study a variational auto encoder (VAE) is proposed as a solution to these issues. This VAE compresses the high-dimensional input data into a lower-dimensional latent space that can be more easily processed by the optimization algorithm. Another study from Parekh *et al.* [21] compares both parameter and image based learning techniques for KPI prediction, concluding that image based techniques perform closely to scalar-parameter based models if the pixel resolution of the training data is sufficient.

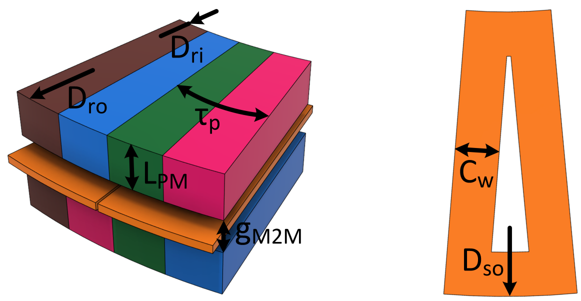
According to Doi *et al.* [22], convolutional neural networks (CNNs) are potentially much better suited for high dimensional data than ANNs as they can better process the high number of degrees of freedom (DoFs) found within each pixel. Two different approaches for training a CNN with cross-sectional images were proposed for the optimization of an interior PM (IPM) motor. The first focusing on fast evaluation of feasible designs, and the second focusing on torque performance prediction for designs constrained by a predefined iron loss threshold. The proposed methods reduced the total FEA simulations required by 50% and 30%, respectively, illustrating the CNN effectiveness in accelerating the computational process.

In multi-stage machines, distinct topologies may be coupled together to maximize the respective benefits of each machine, which significantly increases the total computational time required by the optimization algorithm. One potential solution, presented by Parekh *et al.* [23], involves the use of a VAE to simultaneously optimize two distinct machine topologies, specifically a synchronous machine and a PM synchronous machine. Numerical results suggest that, compared to a direct deep neural network (DNN) based approach, the VAE is



(a) (b)

Fig. 3. Magnetic flux line distribution in a linear unrolled view with each Halbach magnet color indicating a 90° shift in magnetization direction (a), and the sectioned parametric 3D FEA model with its mesh plot (b).



(a) (b)

Fig. 4. Sectional view of one pole pair of the CAFPM machine with dual Halbach array rotors (a) and the macro coil representation for one coil of the stator with labeled geometric design parameters (b).

capable of generating more valid and meaningful designs with very little expected increased computational effort for multiple machine types.

III. Coreless Axial Flux PM Machine Topology and Differential Evolution Optimization

The machine under study in this paper is of the CAFPM type with double-sided Halbach array rotors, as shown in Fig. 2. The stator winding is modeled as a macro coil representing a collection of many strands of conductors to minimize eddy current losses with previous studies indicating satisfactory approximation with a turn by turn very complex model. The stator is constructed with no ferromagnetic core, minimizing associated eddy current losses. Alongside increased efficiency, the absence of the core may decrease the total active mass of the machine, making it more suitable for electric aircraft propulsion applications.

The case study was conducted for a laboratory-scale model of the CAFPM machine with ratings and dimensions similar to the prototypes previously developed by the research group [24, 25]. The studied design topology employs dual Halbach array PM rotors consisting of 36 poles each, with four magnets per wavelength, as depicted in Fig. 3a. The Halbach array configuration results in up to a 30% increase in flux density compared to conventional surface-mounted PM configurations within the same rotor envelope. This unique arrangement of PMs yields in an increase in specific power density, to the same degree as flux density, a crucial metric in applications where overall mass is of major concern.

Table I
Independent Variables and Corresponding Limits for the CAFPM Machine under study.

Var.	Description	Min.	Max.
K_{dr}	Rotor diameter ratio = $\frac{D_{ro}-D_{ri}}{D_{ro}}$	0.15	0.35
K_{PM}	PM axial length ratio = $\frac{L_{PM}}{\tau_p}$	0.15	0.50
K_g	Magnet-to-magnet gap ratio = $\frac{g_{M2M}}{\tau_p}$	0.14	0.75
K_{cw}	Coil side width ratio = $\frac{4C_w}{\tau_p D_{ri}}$	0.77	1.00
K_{oh}	Overhang ratio = $\frac{D_{so}-D_{ro}}{2C_w}$	0.00	1.00

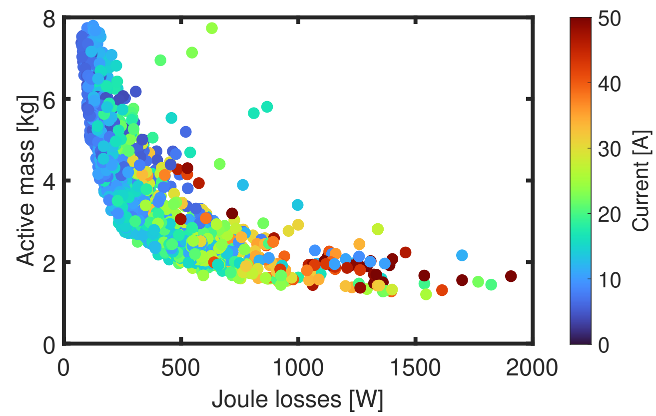


Fig. 5. Results of a differential optimization (DE) study for CAFPM machines obtained thorugh 3D FEA. The candidate designs are employed for the development of the proposed ML meta-model.

In this CAFPM machine topology, losses include components due to the Joule effect in the windings, and due to the eddy currents in the stator conducts and PMs, which are typically mitigated through the use of the Litz wire and magnet segmentation. Furthermore, it should be noted that due to the very low armature reaction, PM eddy current losses are minimal in CAFPM machines. Electric aircraft propulsion systems require minimizing component mass while maximizing efficiency. To achieve these conflicting optimization goals, efforts focus on reducing total electromagnetic mass and losses, minimizing the combined mass of the dual Halbach PM rotors and the three-layer stator. Joule loss is the primary loss component considered in this optimization.

For the 3D geometry specific to axial flux designs, a parametric electromagnetic FEA model was developed using the Ansys Electronic Desktop software [26]. To reduce the computational effort, a matching boundary condition was applied tangentially over one rotor pole pitch, and a symmetry boundary condition was used axially. The final parametric model and an example mesh are shown in Fig. 3b. For further improvements, a computationally efficient FEA (CE-FEA) technique, introduced in [27] and requiring only two rotor positions in order to calculate torque with satisfactory

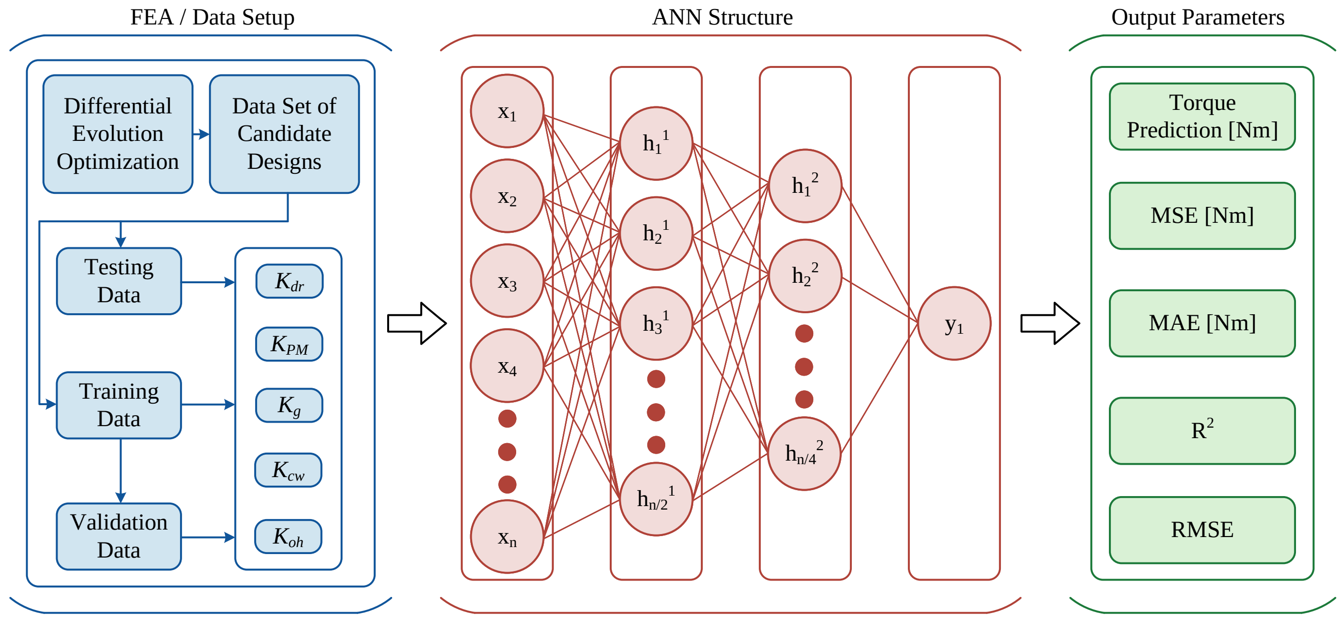


Fig. 6. Overview of the surrogate model framework used in the optimization process of the CAFPM machine. Only the training set was used to update the model weights, ensuring the validation set served as an independent check on the overall performance of the model.

accuracy, was employed.

The design variables include five geometric parameters, primarily normalized based on the pole pitch, which depends on the rotor's PM length in the radial direction provided that the pole count and the outer diameter are held constant. These geometric variables and their respective limits are listed in Table I. Note that coil thickness is defined through the magnet-to-magnet (M2M) gap; larger M2M gaps allow for greater coil thickness, while the clearance airgap between the stator and rotor remained fixed at 1 mm for the design case study.

To ensure all candidate designs produce the same power, the current density was scaled after each candidate was analyzed with a preset current density. Consequently, Joule losses and cost function values are updated based on the adjusted current density. Since the CAFPM under study operates without magnetic saturation, torque scales linearly with current density, eliminating the need for multiple FEA solutions per candidate to achieve the specifed torque.

The optimization results for over 1,500 candidates with two conflicting objectives, active mass and power loss, are presented in Fig. 5. The color of each scatter point represents the phase current value. Designs with higher current values typically have lower mass but higher Joule losses, indicative of high current loading and low magnetic loading. The optimal candidate may be chosen based on the trade offs between the objectives of minimum loss and mass, ideally near the knee region of the Pareto front.

IV. Machine Learning Case Study for Coreless AFPM Machines

An ANN meta-model was developed using TensorFlow [28] and implemented using the 3D FEA results of DE to predict the torque output for multiple designs of CAFPM machines. The ANN model comprised a one input layer with 128 neurons, two hidden layers with 64 and 32 neurons, respectively, and one output layer with 1 neuron and was integrated directly, as shown in Fig. 6. Utilizing feasible designs from the DE optimization to train the meta-model may allow for the very fast generation of further designs within the optimal range at varying output torque. In this case, the meta-model may replace computational extensive electromagnetic 3D FEA and serve as a surrogate model instead, for example, the kriging-based model proposed in [29].

The ANN model was trained on a dataset of 1,500 candidate designs generated through 3D FEA-based DE optimization

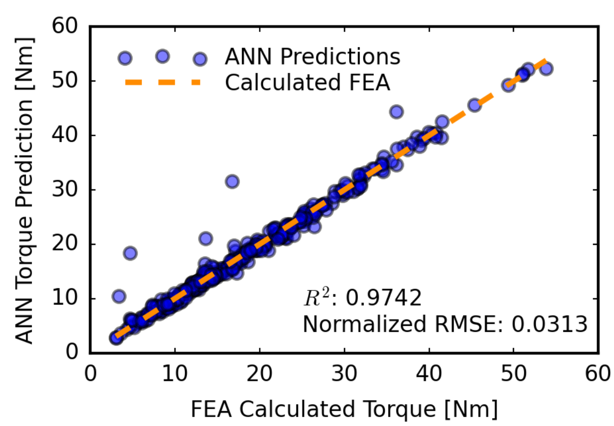


Fig. 7. Regression curve between ANN predicted and 3D FEA calculated torque in the test dataset. The resulting R^2 and normalized root mean squared error indicates high accuracy.

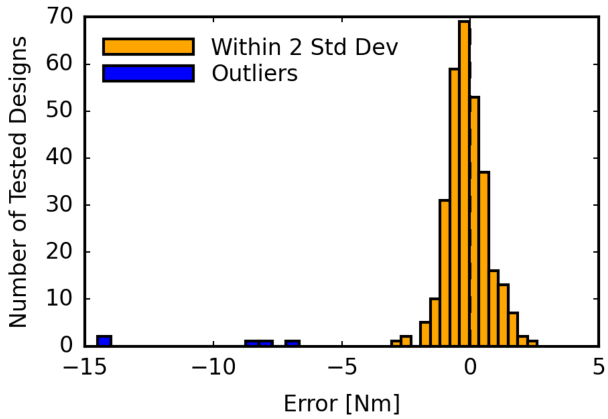


Fig. 8. Residuals plot showcasing the error between the torque predictions made by the ANN and the FEA calculated torque, indicating high correlation between calculated torque from the FEA and ANN.

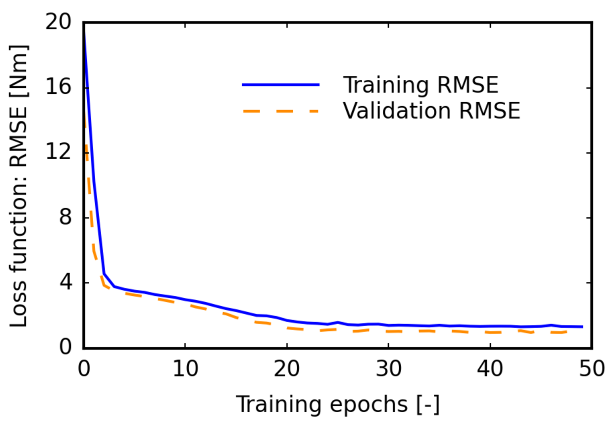


Fig. 9. Progression of the RMSE for the training and validation sets over all 50 epochs. The RMSE first rapidly declines during the first 10 epochs, then stabilizes, indicating effective learning.

(Fig. 5). This dataset, consisting of geometric input parameters K_{dr}, K_{PM}, K_g, K_{cw}, K_{oh}, with ranges provided in Table I, is fed into the ANN for torque prediction without adjusting current to reach the same torque. From the candidate designs, 64% were employed for training, 20% for testing, and the remaining 16% reserved for validation of the ANN meta-model.

The ANN's feasibility as a surrogate model was evaluated based on the R-squared (R^2) and root mean square error (RMSE) metrics, depicted in the regression curve from Fig. 7. The R^2 value of 0.9742 indicates a strong correlation between the ANN predictions and the FEA results. The low normalized RMSE of 3.13% further supports this claim, indicating that the majority of the model's predictions align closely with calculated values. The distribution of error across all tested designs, shown in Fig. 8, illustrates that 80% of all torque predictions made by the ANN only differ from the FEA calculated values by ±1 [Nm].

In order to evaluate the generalization capabilities of the ANN, the RMSE values for both the training and validation datasets were examined across all 50 epochs, as depicted in Fig. 9. The close alignment between the two curves across all epochs suggests that the model generalizes well and is not over-fitting. The RMSE value decreases rapidly within the first 10 epochs, indicating that the model is capable of quickly learning the underlying patterns present in the data. After the steep decline, both the training and validation RMSE stabilize at loss of approximately 1.3Nm, with the model reaching its optimal performance at around 30 epochs.

V. Conclusion

Recent developments, which have been briefly reviewed in this paper, recommend AI and ML for developing techniques of automated analysis and design optimization for electrical machines. The newly proposed method combines nature-inspired computational intelligence algorithms, i.e. differential evolution (DE), for providing a data base of designs analyzed with electromagnetic 3D FEA, with an artificial neural network (ANN) algorithm for producing a meta-model.

The new meta-model was exemplified for a coreless axial flux permanent magnet (CAFPM) machine topology, which is suitable for electric aircraft propulsion. The model developed based on a large-scale database with more than 1,500 designs has been satisfactorily validated with an R^2 value of 0.97 and normalized root mean squared error (NRMSE) of less than 0.05. The model is considered suitable to replace computational extensive 3D FEA and support ultra-fast optimization design. Ongoing research aims to establish the minimum number of DE generations and individual designs that are required for a satisfactorily accurate meta-model, so further saving of computational efforts are enabled.

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