flows such as free jets, mixing layers, impinging flows, among others [4]. In contrast, LES offers a more precise approach by resolving a significant portion of the turbulent kinetic energy (*TKE*, denoted as *k*), and modeling only the small-scale turbulence. LES is an inherently transient model, leading to longer computation time until an appropriate average solution is achieved, and requiring finer meshes to ensure adequately that a significant amount of the turbulent eddies is resolved [5].

This paper aims to present a procedure for tuning a *Generalized k-* model (GEKO) using an adjoint-based optimization scheme. Adjoint-based approaches can reduce the time to optimize shapes for thermal design substantially, which was demonstrated for cooling pin fins by [6] and [7], for gas turbines [8,9], as well as for a heat exchanger by [10] using parametrized CAD. The strategy is coupled with a Neural Network (NN), which has been used in previous work by [11]. The tuning of the GEKO model can be applied to various complex flow scenarios, successfully enhancing prediction accuracy: Wu [12] employs this method to determine the drag coefficient of the DrivAer generic car model more accurately, by using the difference in drag coefficient as the observable metric. DrivAer is a realistic reference car model, developed by [13,14] to support aerodynamic research on passenger vehicles. Klavaris [15] extended this methodology to the simulation of an isothermal combustion chamber, where the observable accounted for the difference in velocity fields between LES and RANS methods, resulting in improved predictions of flow confinement. Similarly, Fischer et al. [11] utilized temperature field discrepancies between LES and RANS simulations to refine the effectiveness of adiabatic trench film cooling designs of combustors. The tuning methodology provides results similar to those with LES methodology, but at the computational expense of a RANS simulation.

Particularly, the application of modeling and experimentation methods to air-cooled flow configurations with fins has been an extensive focus topic in literature. A study by [16] investigates the optimal geometry of plate fins for air-cooling high-power electronic modules numerically, under variation of the fin thickness and height. It is recommended to tune the fins by increasing their thickness along the airflow (at $x^{0.42}$), and when combined with tapering the height of the fin along the direction of flow, thermal hotspot reduction by 40% and beyond can be achieved [16]. Studies with a novel methodology for electronics air cooling utilize double-elastic, inclined fins under nano-enhanced magneto convection [17], as well as fins with hybrid air-cooling, which are partially filled with a composite phase change material [18,19]. Other work from the recent literature quantifies the impact of convection and radiation within flow fields [20], studies the effect of vortex generation and recirculation zone on the local HTC, both numerically and experimentally [21], as well as proposes the use of a flow-guide to enhance the air-cooling effect, while finding a 30% improvement without increasing pressure drop [22].

In the present work, the GEKO tuning strategy is being applied to the cooling of electrical machines. Building upon previous work [11], this approach is selected due to its suitability to describe external flow problems with strong confinement and wall effects. In particular, the present work details the sensitivity to five machine learning parameters for tuning of the turbulence model. The results provide precise data on how to tune the machine learning functionalities built into *Ansys Fluent* for computational efficiency, which is a highly important metric to industry. Building upon our previous work [11], which optimized the temperature distribution downstream of film cooling holes for gas turbine application, we demonstrate that this RANS tuning approach can be validated for another two typical fin cooling geometries relevant to industry. In this study, the geometry consists of a stator flux barrier, with the objective being an optimization of the ribs for convection cooling. The study describes a validation of the procedure to replicate the experimental results of a ribbed channel flow by Rau et al. [1]. Using the validated model, the stator flux barrier domain is described, which consists of a fractional slot concentrated windings (FSCW) 5-phase permanent magnet synchronous (PMSM) machine. The machine is in pre-development at the University of the Bundeswehr [23 26], with numerical simulation targeted to guide the cooling design. In the following sections, the working principles of the optimization and machine learning algorithms are described, proposed model tuning for this specific case is detailed, and finally, optimized results are presented.

2. Computational methodology

2.1. RANS-GEKO turbulence

The GEKO model is formulated as a two-equation turbulence model, based on the *k-* theory. It includes several adjustable coefficients, allowing for precise tuning to match specific flow scenarios without altering the fundamental calibration of the base model. Similar to *k-* models, the GEKO model includes three primary tuning parameters, and two additional parameters associated with *TKE* and *SDR* (specific dissipation rate), enabling further fine-tuning [4,6].

$$\frac{k}{t} \quad \frac{U_j k}{x_j} \quad P_k - C \quad k \quad \frac{}{x_j}\left[\left(\quad \frac{_t}{_k}\right)\frac{}{x_j}\right] \quad S_k \tag{1}$$

$$\frac{}{t} \quad \frac{U_j}{x_j} \quad C\ _1F_1\frac{}{k}P_k - C\ _2F_2 \quad ^2 \quad F_3CD$$

$$\frac{}{x_j}\left[\left(\quad \frac{_t}{}\right)\frac{}{x_j}\right] \quad S \tag{2}$$

$$S_k \quad C_k \quad k \tag{3}$$

$$S \quad C \quad k \tag{4}$$

In the equations above, represents the density, U_j is the velocity, k denotes the *TKE*, is the *SDR*, represents the molecular dynamic viscosity, and $_t$ denotes the turbulent viscosity. Constants $_k$, , C , $C\ _1$, and $C\ _2$ are the standard coefficients associated with *k-* turbulence models. The term P_k corresponds to the turbulent production term, while *CD* accounts for cross-diffusion effects. Finally, S_k and S are the source terms for k and , respectively.

The GEKO model allows for an adjustment of three primary free parameters, F_1, F_2, F_3, and additional source terms (C_k and C), without affecting the basic tuning of the model [4]. These parameters are designed to influence various flow characteristics. The *Ansys Fluent 2024 R1* GEKO model provides four main parameters for optimization, and two additional source coefficients:

- C_{Sep}: Adjusts flow separation from smooth surfaces.
- C_{Mix}: Adjusts the mixing strength in free shear flows.
- C_{NW}: Adjusts the flow in non-equilibrium near wall regions.
- C_{BF}: Adjusts the blending function to activate/deactivate coefficients close to the boundary layer.
- C_k: Adjusts the turbulence kinetic energy source coefficient.
- C : Adjusts the specific dissipation rate source coefficient.

Tuning the parameters of the GEKO model is a process requiring some empirical knowledge. This iterative process involves selecting and adjusting the coefficients to achieve optimal model performance for the specific flow condition. While in traditional RANS these coefficients are defined uniformly across the entire flow domain, using the ML tuning method allows a local tuning of those, to accurately reflect local flow characteristics. Building upon our previous work [11], the present study details the solution sensitivity to these machine learning parameters for tuning of the turbulence model. By providing a recommendation about which ones to focus on, it allows for an optimal computational efficiency in *Ansys Fluent 2024 R1*.

2.2. Adjoint-based optimizer

The adjoint-based optimization method efficiently computes the linear sensitivities of an objective function with respect to a high-dimensional parameter space. [27]. The main benefit is that it allows for the computation of gradients with low computational cost, making it well suited for problems involving a high number of parameters. The objective function, denoted as J, represents the quantity we aim to maximize or minimize through optimization. This function is dependent on a set of design parameters c, as well as a set of states q, which are a function of the design parameters.

$$J \quad f(q(c), c) \tag{5}$$

In our specific scenario, the design parameters c correspond to the GEKO tuning coefficients, the state parameters to the solution of the flow $q(c)$ and the objective function J focuses on minimizing the difference between the averaged LES solution and the RANS-GEKO prediction.

$$c \quad [C_{Sep}, C_{Mix}, C_{NW}, C_{BF}, C_k, C \ ] \tag{6}$$

$$q(c) \quad [u, v, w, p, T, k, \ \ ] \tag{7}$$

Regarding the objective function, its sensitivity to a change of c can be estimated by making small changes to each design parameter individually. However, this method is computationally expensive, because it requires resolving the flow for every single design parameter. The adjoint-based approach significantly improves its efficiency. With this method, calculating sensitivities of the objective function requires solving flow and the adjoint parameters (Lagrange multipliers) only once per iteration step [28]. In addition to those equations, the problem is also constrained by the flow equations, this is represented by the residuals of the flow equations R:

$$R(q(c), c) \quad 0 \tag{8}$$

In order to define the adjoint problem, an augmented objective function can be defined to include the Lagrange multipliers in order to perform a constrained minimization [27].

$$L(q, c, \ \ ) \quad J(q, c) - {}^{T} R(q, c) \tag{9}$$

The Lagrange multipliers or adjoint variables have a correspondent value with each flow parameter so that $[u^*, v^*, w^*, p^*, T^*, k^*, \ ^*]$. Solution of the adjoint equation is set to ensure the independence of the variability with respect to the augmented objective function (equ. 10):

$$\frac{L}{q} \quad \frac{J}{q} - {}^{T}\frac{R}{q} \tag{10}$$

When solving the adjoint equation, total derivative of the observable can be calculated as a function of the design variables (equ. 11):

$$\frac{dL}{dc} \quad \frac{dJ}{dc} \quad \frac{J}{c} - {}^{T}\frac{R}{c} \tag{11}$$

The optimization concludes by applying the sensitivities to update the design variables, thereby altering the observable. For the purposes of this paper, a simple steepest descent approach [27] is used where a percentage value is defined as the step-change:

$$c \quad - \frac{dJ}{dc} \tag{12}$$

2.3. Machine learning model

The versatility of the GEKO turbulence model and the ability to optimize its coefficients have been discussed thus far. However, this approach has limitations. The optimization process yields a unique set of coefficients for each cell in the computational domain. While this can be practical when no further mesh modifications are required, it becomes less effective when the model is intended for use in subsequent design iterations where geometric changes are necessary.

The GEKO model parameters are typically defined as general coefficients uniformly applied across the entire flow domain. This approach has limitations, as flow characteristics can vary significantly across different regions. Using a single set of coefficients may not adequately capture the localized behaviors of complex flows. Therefore, tuning the model to specific regional conditions can yield better results. To address this, a closure model can link the physical aspects of the flow with GEKO coefficients derived from the adjoint optimizer. *ANSYS Fluent* uses a data-driven, predictive modeling framework known as Field Inversion and Machine Learning (FIML), described by Parish and Duraisamy [29]. The FIML method in *ANSYS Fluent* functions as an online optimization process, training a neural network to associate flow conditions with appropriate GEKO coefficients. This occurs simultaneously with the adjoint optimization. Specifically, the adjoint system determines the sensitivities of design parameters relative to the observable. When these are modified by a small delta, the ML is trained to map flow characteristics to the corresponding coefficients. As flow characteristics evolve during the simulation, the NN adapts, mapping these characteristics to optimal design parameters. Through this integrated process, the optimization results in the simultaneous fine-tuning of both the design parameters and the NN, allowing to predict these parameters effectively for similar future simulations.

The machine learning model used is a feedforward NN [12], denoted as Multi-Layer Perceptron. The network consists of an input layer, three hidden layers with 24, 16 and 8 topology nodes for the first, second, and third layer, respectively, and an output layer. The use of nonlinear activation functions in the hidden layers allows it to represent complex dependencies in the data. This study uses the *Softsign* activation function, since previous research [15] indicates that the choice of activation function has only a minor impact on the final optimization outcome. The output layer consists of the selected coefficients C_i, listed in Section 2.1, to allow for an element-wise tuning of the solution field. For input features, the non-equilibrium parameter, the second, third, fourth, and fifth invariants, and the length ratio are utilized.

2.4. Optimizing and tuning

The optimization process starts with generating an initial flow solution using standard GEKO parameters until convergence. Once the flow converges, the observable value is calculated. Observable evaluation method is defined as instantaneous. From this solution, the input variables are used for the ML algorithm, which maps the GEKO coefficients to the input flow variables for every cell within the domain. The adjoint problem is then solved to convergence, enabling the calculation of sensitivities for each design parameter. Updated design parameters are determined based on these sensitivities, and the NN s weights are updated accordingly (Fig. 1 third box). This iterative cycle comprising flow solution, ML training, and adjoint solution continues until the observable is minimized to the desired level. Throughout the iterations, the neural network is continuously trained as well as the flow converges.

A required aspect of the tuning process involves referencing a more accurate simulation, or alternatively, experimental measurements. In this context, incorporating LES enhances the predictive capability of a RANS model. Since CHT simulation is sensitive on a much lower time scale, conducting CHT simulations while solving the flow field with an LES approach requires significant computational expense. To mitigate this, an initial RANS simulation provides boundary conditions for the subsequent LES model, reducing the computational cost. Temperature boundary conditions are considered for close alignment with CHT simulations (Fig. 1 first box). Following this, an LES uses the boundary conditions derived from CHT simulations, averaging results over multiple flow iterations (Fig. 1 second box). The resulting average from LES data is used for calibration of the GEKO model via the adjoint optimizer and the NN, focusing on differences in heat flow rates at the flux barrier

5. Conclusion

In summary, the adjoint optimizer strategy integrated with machine learning demonstrates strong potential in enhancing HTC estimations of air-cooled fin configurations, such as stator flux barriers. With GEKO tuning, overall turbulence levels are adequately enhanced compared to the standard turbulence model, and secondly, the solution maintains higher turbulence levels in near-fin regions, resulting in enhanced local shear velocity. Consequently, the correlation with LES results and validation test data is substantially improved. Quantitatively, tuned GEKO results improve the correlation to test data for the transversely ribbed channel geometry, reducing deviations to a maximum of 7% along the stream-wise direction and 5% along the span-wise direction. This tuning is primarily achieved through a local enhancement of the ML parameter C_{k}, leading to an increase in turbulent kinetic energy of up to 59% in the regions located immediately upstream and downstream of the rib.

When tuning the GEKO simulation for the specific stator flux barrier geometry, the absolute difference of the heat flow rate within the fins is chosen as the optimizer observable. During re-tuning, ML parameters C_{k} and C become impactful, while the remaining ML parameters could be neglected for future investigations. Quantitatively, a heat flow rate offset of 16% has been reduced to deviations below 0.6% for this tuning application. The tuning passes its checks against potential over-fitting, and improves the HTC prediction from a 32% error to $\pm$7.5% deviation, while the temperature error of the tuned model is within only $\pm$1.5%. Beyond that, the investigation does not indicate any adverse impacts of the tuning on the HTC predictions in other areas of the electric machine.

Lastly, the tuned and validated model is used for a sensitivity study of maximal stator temperature, and of pressure drop in the surrounding airflow. Sensitivities are reported with respect to three design parameters of flux barriers, namely rib separation, rib thickness, and flux barrier gap. It is found that with higher length dimension, pressure drop would decrease for all cases, while maximal temperature along the stator flux barrier would generally increase. Temperature is shown at a high sensitivity to the rib thickness, with a peak value of 118 °C at 1 mm, and 132 °C at 3 mm, respectively. An exception to these trends is determined for the rib separation, for which temperature appears fairly insensitive to its separation gap, with an optimal value of 125 °C at 2.5 mm. In conclusion, the presented ML method demonstrates great potential in accelerating the development of novel designs with complex flow features, by means of locally tuning coefficients of a cost-efficient RANS simulation.

CRediT authorship contribution statement

Lukas Fischer: Writing review & editing, Software, Methodology, Conceptualization. **Andres Felipe Sanchez Porras:** Writing original draft, Methodology, Investigation, Data curation. **Lars Zigan:** Writing review & editing, Supervision, Resources, Project administration, Funding acquisition. **Bernhard Stiehl:** Writing original draft, Visualization, Validation, Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research, part of the ELAPSED project *(Electric Aircraft Propulsion safe, efficient, digitally linked)*, is funded by dtec.bw Digitalization and Technology Research Center of the Bundeswehr, with support from the European Union s NextGenerationEU initiative. Special thanks to Daniel Alban and Lucas Brenner from the University of the Bundeswehr, Chair of Electrical Drives and Actuators, for supplying preliminary design geometry and electromagnetic simulation results.

References

[1] G. Rau, M. Cakan, D. Moeller, T. Arts, The effect of periodic ribs on the local aerodynamic and heat transfer performance of a straight cooling channel, J. Turbomach. 120 (2) (1998) *368 375*, https://doi.org/10.1115/1.2841415.

[2] M. Henke, et al., Challenges and opportunities of very light high-performance electric drives for aviation, Energies 11 (2) (2018), https://doi.org/10.3390/en11020344.

[3] D.D. Dang, X.T. Pham, P. Labbe, F. Torriano, J.F. Morissette, C. Hudon, CFD analysis of turbulent convective heat transfer in a hydro-generator rotor-stator system, Appl. Therm. Eng. 130 (2018) 17 28, https://doi.org/10.1016/j.applthermaleng.2017.11.034.

[4] F. Menter, A. HÜppe, A. Matyushenko, D. Kolmogorov, An overview of hybrid RANS LES models developed for industrial CFD, Appl. Sci. 11 (6) (2021), https://doi.org/10.3390/app11062459.

[5] F.R. Menter, A. Matyushenko, R. Lechner, Development of a generalized K- two-equation turbulence model, N. Results Numer. Exp. Fluid Mech. XII (2020) 101 109, https://doi.org/10.1007/978-3-030-25253-3_10.

[6] N.P. Nguyen, E. Maghsoudi, S.N. Roberts, B. Kwon, Shape optimization of pin fin array in a cooling channel using genetic algorithm and machine learning, Int. J. Heat. Mass Transf. 202 (2023) 123769, https://doi.org/10.1016/j.ijheatmasstransfer.2022.123769.

[7] N.P. Nguyen, E. Maghsoudi, S.N. Roberts, B. Kwon, Designing pin fin heat sinks with restarting adjoint optimization approach, Int. J. Heat. Mass Transf. 242 (2025) 126856, https://doi.org/10.1016/j.ijheatmasstransfer.2025.126856.

[8] C.-S. Lee, T.I.P. Shih, Effects of heat loads on flow and heat transfer in the entrance region of a cooling duct with a staggered array of pin fins, Int. J. Heat. Mass Transf. 175 (2021) 121302, https://doi.org/10.1016/j.ijheatmasstransfer.2021.121302.

[9] J. Chen, Y. Rao, C. Xu, Experimental and numerical study of the turbulent flow and heat transfer in a rectangular channel with detached pin-fin under rotating conditions, /09/15/ 2025, Int. J. Heat. Mass Transf. 248 (2025) 127209, https://doi.org/10.1016/j.ijheatmasstransfer.2025.127209.

[10] P. Pai Raikar, N. Anand, M. Pini, C. De Servi, Concurrent optimization of multiple heat transfer surfaces using adjoint-based optimization with a CAD-based parametrization, Int. J. Heat. Mass Transf. 236 (2025) 126230, https://doi.org/10.1016/j.ijheatmasstransfer.2024.126230.

[11] L. Fischer, D. James, S. Jeyaseelan, M. Pfitzner, Optimizing the trench shaped film cooling design, Int. J. Heat. Mass Transf. 214 (2023), https://doi.org/10.1016/j.ijheatmasstransfer.2023.124399.

[12] H.Z. Haibo Wu, Sichuan Xu, Chao Ren, Qian Chen, Tushar Jadhav, Adjoint-based model tuning and machine learning strategy for turbulence model improvement, SAE Tech. Pap. 2022-01-0899 (2022), https://doi.org/10.4271/2022-01-0899.

[13] A. Heft, T. Indinger, N. Adams, Introduction of a new realistic generic car model for aerodynamic investigations, SAE Tech. Pap. 2012-01-0168 (2012), https://doi.org/10.4271/2012-01-0168.

[14] C. Collin, S. Mack, T. Indinger, J. Mueller, A numerical and experimental evaluation of open jet wind tunnel interferences using the DrivAer reference model, SAE Int. J. Passeng. Cars Mech. Syst. 9 (2) (2016) *657 679*, https://doi.org/10.4271/2016-01-1597.

[15] G. Klavaris, M. Xu, C. Hill, F. Menter, S. Patwardhan, I. Verma, Tuning of generalized K-Omega turbulence model by using adjoint optimization and machine learning for gas turbine combustor Applications, J. Eng. Gas. Turbines Power 146 (8) (2024), https://doi.org/10.1115/1.4064367.

[16] M. Morega, A. Bejan, Plate fins with variable thickness and height for air-cooled electronic modules, Int. J. Heat. Mass Transf. 37 (1994) 433 445, https://doi.org/10.1016/0017-9310(94)90043-4.

[17] F. Selimefendigil, H.F. Öztop, Effects of using double elastic inclined fins on cooling of protruding heated electronic equipment mounted in a bifurcating channel under nano-enhanced magneto forced convection: Computational analysis and optimized configurations, /06/01/ 2025, Int. J. Heat. Mass Transf. 242 (2025) 126805, https://doi.org/10.1016/j.ijheatmasstransfer.2025.126805.

[18] A. Arshad, S.A. Iqrar, S.C. Costa Pereira, M.W. Shahzad, K. Nawaz, W. Worek, Cooling performance of an active-passive hybrid composite phase change material (HcPCM) finned heat sink: Constant operating mode, Int. J. Heat. Mass Transf. 207 (2023) 123973, https://doi.org/10.1016/j.ijheatmasstransfer.2023.123973.

[19] S.H. Kim, C.S. Heu, J.Y. Mok, S.-W. Kang, D.R. Kim, Enhanced thermal performance of phase change material-integrated fin-type heat sinks for high power electronics cooling, Int. J. Heat. Mass Transf. 184 (2022) 122257, https://doi.org/10.1016/j.ijheatmasstransfer.2021.122257.

[20] H. Zhao, et al., Development of conduction optimized heat sinks with enhanced fluid flow path for passive cooling applications, Int. J. Heat. Mass Transf. 244 (2025) 126963, https://doi.org/10.1016/j.ijheatmasstransfer.2025.126963.

[21] B. Kanargi, P.S. Lee, C. Yap, A numerical and experimental investigation of heat transfer and fluid flow characteristics of an air-cooled oblique-finned heat sink, Int. J. Heat. Mass Transf. 116 (2018) 393 416, https://doi.org/10.1016/j.ijheatmasstransfer.2017.09.013.

[22] S. Hyeon, C. Kim, K.-S. Lee, Thermal enhancement of an air-cooled motor with a flow guide, /02/01/ 2022, Int. J. Heat. Mass Transf. 183 (2022) 122228, https://doi.org/10.1016/j.ijheatmasstransfer.2021.122228.

[23] L. Brenner, D. Alban, D. Gerling, Thermal modeling of an air-cooled electrical machine for propeller-driven aircraft, in: 2024 IEEE International Conference on Electrical Systems for Aircraft, Railway, 26 29, Ship Propulsion and Road Vehicles

& International Transportation Electrification Conference (ESARS-ITEC),, Nov. 2024, pp. 1 6, https://doi.org/10.1109/ESARS-ITEC60450.2024.10819815, 2024.
[24] L. Brenner, D. Gerling, Thermal modeling of the slot of an electric machine considering position deviations of individual conductors, 28 Nov. 1 Dec. 2023. 2023 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific), 2023, pp. 1 6, https://doi.org/10.1109/ITECAsia-Pacific59272.2023.10372199, 28 Nov. 1 Dec. 2023.
[25] D. Alban, G. Dajaku, D. Gerling, Evaluation of Flux-barrier Stator in five-phase PMSMs for electric aircraft traction, 25th Int. Conf. Electr. Mach. Syst. (ICEMS) (2022) 1 6, https://doi.org/10.1109/icems56177.2022.9983393.
[26] A.F. Sanchez Porras, D. Alban, L. Zigan, Lumped parameter thermal network model investigations for an electric machine stator with flux barriers, 2023 IEEE Int. Electr. Mach. Drives Conf. (IEMDC) (2023) 1 6, https://doi.org/10.1109/iemdc55163.2023.10238979.
[27] M. Giles, N. Pierce, M. Giles, N. Pierce, Adjoint equations in CFD - Duality, boundary conditions and solution behaviour, 13th Comput. Fluid Dyn. Conf. (1997), https://doi.org/10.2514/6.1997-1850.
[28] A.J. Siva K. Nadarajah, A comparison of the continuous and discrete adjoint approach to automatic aerodynamic optimization, vol. AIAA-2000-0667. 38th Aerospace Sciences Meeting and Exhibit, American Institute of Aeronautics and Astronautics, 2000, https://doi.org/10.2514/6.2000-667.
[29] E.J. Parish, K. Duraisamy, A paradigm for data-driven predictive modeling using field inversion and machine learning, J. Comput. Phys. 305 (2016) 758 774, https://doi.org/10.1016/j.jcp.2015.11.012.