An artificial intelligence pipeline for critical equipment thermal conditioning system design

Raik Orbay, Athanasios Tzanakis, Inko Marcaide, Jonas Löfgren,
Torbjörn Thiringer, Thomas Bernichon
raik.orbay@volvocars.com
Volvo Car Corporation,
405 31 Göteborg, Sweden
https://www.volvocars.com

Keywords

≪Battery Electric Vehicles≫, ≪inverters≫, ≪ machine learning≫, ≪topology optimization≫, ≪genetic algorithms≫, ≪SVM≫, ≪CFD≫, ≪FEM≫

Abstract

Efficient electric machinery often needs to be accurately thermally conditioned. Heat sinks and heating surfaces frequently used to allow for precise temperature control of the critical equipment. To tackle the thermal challenges in the art, different design methodologies, such as the parametric or the topology optimization are introduced. Compared to parametric optimization, topology optimization allows for more tailored cooling solutions on elaborate geometries related to propulsion. Being based on gradient descent algorithm from the machine learning toolbox, topology optimization may suffer from local minima. In this report, the setup is designed to alleviate the risk for local minima and instead aim for a more global optimization. Accordingly, an artificial intelligence pipeline is scripted to run several gradient-descent based topology optimization assessments under a genetic algorithm optimization loop. The resulting geometry is shown to substantially improve the cooling ability in the given packaging volume in a light duty battery electric vehicle with quantified reduction in CO_2 emissions.

Introduction

Main requirements of power electronics for propulsion are high energy efficiency, further downsizing, cradle-to-grave environmental performance and minimum costs. Accordingly, equipment like inverters for motor drive, have reached high switching speeds [1] to decrease losses [2, 3]. Despite this, finite

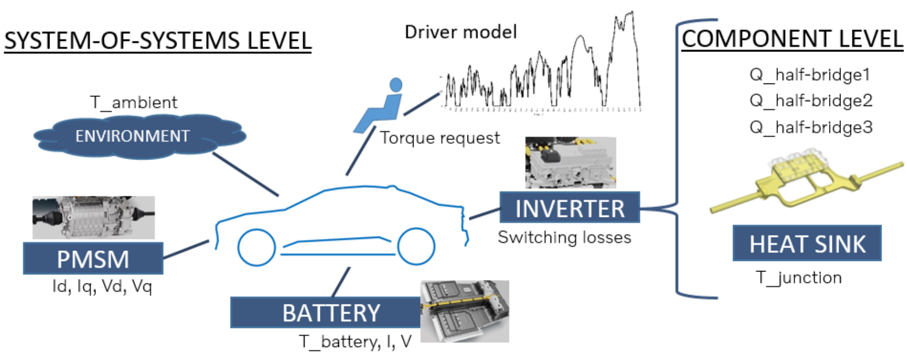


Fig. 1: A system-of-systems level tool is used to quantify inverter losses.

switching speeds fail to eliminate losses completely [4]. Efficient power electronics for propulsion often need to be accurately thermally conditioned to minimize temperature swings [5]. The critical equipment, thus, is connected to a heat sink / source via thermal bridges and kept at the design temperature regardless of the environmental conditions [6]. The coolant is conducted onto the heat exchange surface using piping systems to dissipate heat [7]. The state-of-the art for the heat sink design is by means of using automated parametric optimization [8], where a parametrized geometric entity from the solution domain for the heat sink is taken as a starting point. Several sizes of this geometric entity are populated and then quantified in their heat transfer ability in a computer aided engineering (CAE) loop to reach an optimum in the chosen objective; e.g. pressure drop, flow split, surface shear stress etc. However, as the parametric optimization locks the solution domain to one particular type of the CAD geometry as prescribed by the parametrization, it may come short of all the possible concept candidates. Differing to this in topology optimization, the parameter space is not limited to the parametrized geometric entity, but instead the whole packaging space (computation domain mesh size) is taken as the parameter set. Accordingly, given the extend of the optimization space that the topology optimization is acting in, it has substantial advantage over parametric optimization to reach the optimum. Despite this, as the topology optimization softwares generally use gradient descent algorithm to reach the optimum for the objective function, it is a well-documented behavior that the gradient-descent based approaches are prone to be captured by local optima instead of global optima. Additionally, for cooling of sensitive equipment like inverters, focusing the available cooling power to the exact position of the hot spot is crucial [7]. Usual practice of sensitive equipment cooling is achieved by serial cooling due to its packaging efficiency, compared to the parallel cooling. In this study, each of the switches are cooled in parallel by their dedicated cooling channel to minimize temperature difference among half-bridges. In a sub-optimized application, the heat dissipated by the first and second inverter switches may affect the third inverter switch junction temperatures negatively as this switch is in the downstream of the two initial switches. It is therefore crucial to balance the available cooling power among the switches. To remedy the shortcomings, a

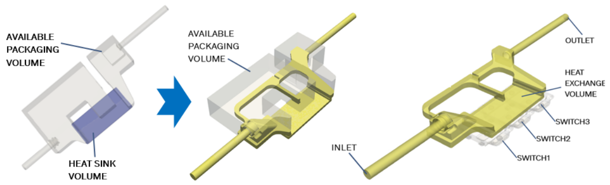


Fig. 2: Available packaging space in grey. A manually designed thermal conditioning topology is shown in yellow. The switch positions are also provided in the rightmost inset. Casing not shown.

critical part of the inverter cooling system is tuned using genetic algorithms in this report. Consequently, an artificial intelligence controlled topology optimization loop for cooling system design is shown to reach to a better optimum than which is allowed by one-step topology optimization. To reduce human intervention even further, the output of the automated topology optimization loop is fed into a machine learning algorithm to analyze concept candidate behavior and pinpoint outliers. The concept candidates populated in this study will be compared to a base cooling system concept designed by human-intense manual optimization loops, as shown in Fig 2.

Computational approach

System of systems level modeling

The initial work to quantify the boundary conditions for the inverter cooling is done using a system-of-systems tool [9] based on lumped parameter models of all the vehicle systems and components. A battery electric vehicle (BEV) is modelled in time domain using a certification cycle, as shown in Fig.1. Form this study, maximum power loss from the inverter is extracted as a continuous power, which was further fed into a 3D thermal CFD tool [10, 11, 12] for optimization, as shown on Fig.1.

Component level modeling

The topology optimization software tool allows for multiobjective topology optimization, thereupon a case with minimization of pressure drop and volume flow maximization or shear stress maximization on heat transfer surfaces was prescribed for this report. The topology optimizer comes with a new geometry with optimized key performance indices, ie., objectives, by computing volumetric sensitivities of chosen objective for changes in mesh element porosities. Two cases of topology optimization approaches are launched to compare the gains in cooling ability and decrease in pressure drop to the base case. Topology optimization of coolant path is done in a predetermined packaging volume shown in the first inset of the Fig. 2. This volume is the remaining inner region when all the geometric constraints (crash surfaces, adjacent component solidity volumes, heat protection distances, cable and plumbing routing, etc.) are united. In the first topology optimization approach, a constant packaging volume is taken as an input to the topology optimizer, as shown in Fig. 3. In a second topology optimization approach, an improvement

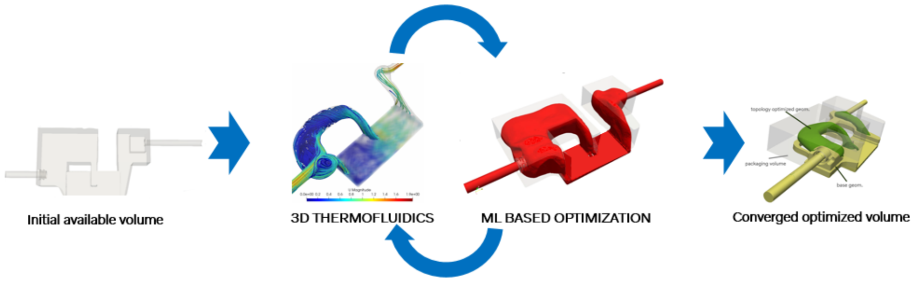


Fig. 3: Pure ML based topology optimization schematics.

in objectives are achieved by means of a pipeline using GA from the artificial intelligence toolbox, as shown in Fig. 4. In this approach, the GA will run several parallel topology optimization cases using alternative packaging limits while updating the overall dimensions of the available packaging volume at a critical region between inverter switch two and inverter switch three, as shown in Fig. 5. For the

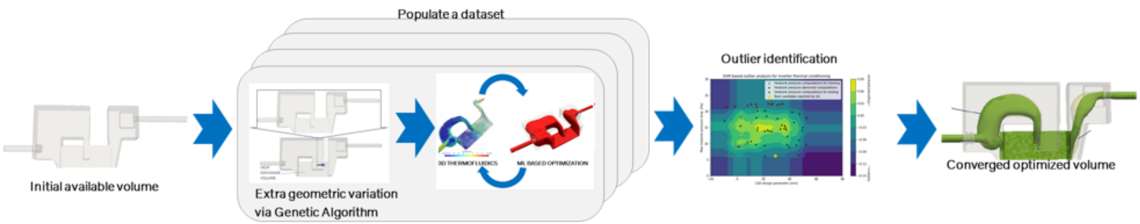


Fig. 4: Prescribed pipeline for GA to run topology optimization schematics.

purpose, the automatized pipeline shown in Fig. 4 is scripted to update the packaging volume dimensions in order to distribute the coolant power to cool the third inverter switch adequately. Another advantage of this approach is that, the topology optimization is run under a GA framework with reduced risk for local optima.

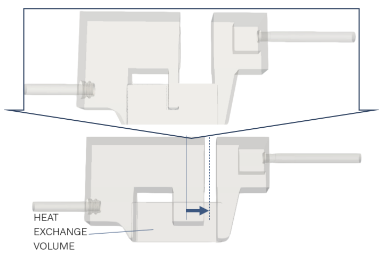


Fig. 5: Available packaging space in grey is morphed to allow for fine tuning of cooling power distribution.

Adjoint-FEM for 3D topology optimization

In this section, finite volume method (FVM), which belongs to the family Finite Element Method (FEM), computations using an adjoint-based solver Helyx [11], which is an OpenFOAM fork [10, 12] will be reported. In the adjoint-state based approaches, an initial CFD run is used as a database to evaluate sensitivities of the objectives, ie., the derivatives of the objectve functions like pressure drop, uniformity, mass flow etc. to changes in flow variables like pressure, velocity, turbulence magnitudes etc. An optimum geometry is created after regions, where the objective function(s) are negatively affected, are blocked by high porosity cells. In the whole computational domain, coupling changes in flow conditions to changes in objective functions is a prohibite task from the computational point of view. But by the introduction of Lagrangian multipliers, the costs of these computations are reduced substantially [13, 14] so that the sensitivity of objective functions to changes in computational domain are analyzed in each and every cell of the computational mesh in a duration comparable to a CFD / Conjugate Heat Transfer (CHT) run. For the current project, a multi-objective approach is chosen. The pressure loss objective is set between inlet and outlet of the heatsink tubes and minimized, as shown in Fig. 6. The second objective, the volume flow maximization objective, is prescribed in the volume in the vicinity of the heat exchange surface, shown also in Fig. 6 as the blue region. In mathematical formalism, an adjoint operation on an

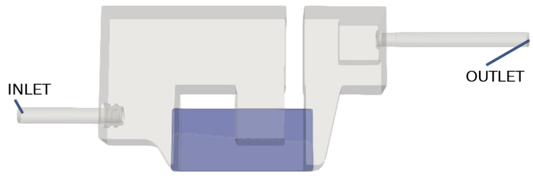


Fig. 6: Prescribed topology optimization objective functions are pressure drop between inlet and outlet and volume flow maximization in the heat exchange volume, as shown in blue in the above.

equation is conducted to be able to write its Lagrange multipliers. Modifying the approach from [13] and taking the first variation of an objective function J, which is a function of flow variables and design variables such as $J(w,\alpha)$, yields

$$\delta J = \frac{\partial J}{\partial w}\delta w + \frac{\partial J}{\partial \alpha}\delta \alpha \tag{1}$$

The set of Navier-Stokes equations can be written in residual form as $N(w,\alpha) = 0$, then the first variation of Navier-Stokes equations can be expressed similarly as

$$\delta N = \frac{\partial N}{\partial w}\delta w + \frac{\partial N}{\partial \alpha}\delta \alpha = 0 \tag{2}$$

Introducing a Lagrange multiplier, λ

$$\lambda^T \delta N = \lambda^T \frac{\partial N}{\partial w}\delta w + \lambda^T \frac{\partial N}{\partial \alpha}\delta \alpha = 0 \tag{3}$$

Following addition of (3) to (1),

$$\delta L \equiv \delta J = \left[\frac{\partial J}{\partial w} + \lambda^T \frac{\partial N}{\partial w}\right]\delta \alpha + \left[\frac{\partial J}{\partial \alpha} + \lambda^T \frac{\partial N}{\partial \alpha}\right]\delta \alpha \tag{4}$$

where, by choosing the suitable λ, variations with respect to flow variables will vanish and it will be possible to define

$$\lambda^T \frac{\partial N}{\partial w}\delta w = \frac{\partial J}{\partial w}\delta w \tag{5}$$

Finally by means of integrating by parts the left hand side of (5), a system of adjoint equations will be obtained, which will reduce the task of gradient calculations comparable to a flow field computation [14]. Subsequently, the topology engine of the adjoint solver will move the surfaces of the initial geometry to reach a final geometric solution in the allowed packaging volume.

Genetic algorithm controlled packaging volume tuning

In Darwin's theory on evolution, the individuals with the best gene pool will survive the natural selection, transmitting their genetic string. The theory comprises analogues for four biological processes in nature: reproduction, mutation, recombination, and selection. The mathematical model starts with a randomly selected population of concept designs on the parameter space (the first generation), where each of the unique design parameters form a genetic string [15]. Through an iterative process discarding the least fit concept solutions to ensure survival of the fittest, the algorithm reaches to a design point in the solution domain that minimizes the objectives of the optimization. For the reported research a two-point crossover technique to exchange genetic string values between the members of the population during the GA breeding process is chosen. The result of the breeding process is a population comprised of the 10 best parent design points (aka. the elitist strategy) plus 40 new child design points. The GA optimization process will be terminated after either certain number of iterations (generations of the GA) where changes in objectives are less than a tolerance or after a finite number of function evaluations. Total number of concept candidates for the study is about 300.

FEM for 3D thermal CFD analysis

When a topology optimization loop is finished, the best candidate was further verified using a steady-state solver for buoyant, turbulent flow of incompressible fluids [12]. For the creation of computational meshes, the hexahedral volume mesher from OpenFOAM is used. To ensure the quality of the fluid mechanical model, emphasis is put on the mesh parameters. A uniform mesh size distribution is preferred for the topology optimization, while Y^+ is acounted for. On the critical heat transfer surface average Y^+ reaches to 10.35 although its mean vaue is 1. Although this is on the higher side of the usual practice, the resulting computational mesh had minimum errors and results were verified to be conform with computations with other CFD software. Both the meshing and computations are parallelized on about 64 CPUs. Turbulence is modelled using the $k-\omega$ SST model [16], which provides a good balance between quality of results and computational time compared to simpler one-/ two-equation models. For the stability of the computations, appropriate settings as relaxation values for the solvers are chosen following tests.

Support vector machine based outlier analysis

Finally, the populated concept candidate pool is further investigated to discern interesting thermal conditioning solutions. For this purpose, a Support Vector Machine (SVM) classifier is used [17]. SVMs aim to construct a hyper-plane in a high dimensional space, to enable classification and regression using the data at hand. SVM is a supervised learning method and here it is used as an outlier detection algorithm. SVMs aim to maximize margin among classes and a good separation is achieved by the hyper-plane that has the largest distance to the nearest training data points of any class, since in general the larger the margin the lower the generalization error of the classifier [17].

Results

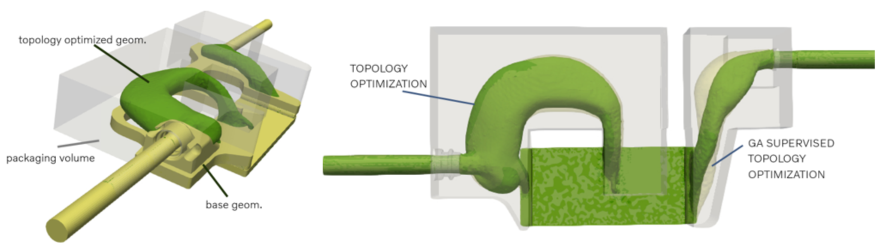


Fig. 7: The manually designed cooling system is in yellow color and the topology optimized geometry is in green in the left inset. On the right inset, the topology optimized geometry is shown in green and the GA supervised topology optimized geometry shown in beige.

In the left inset of the Fig. 7, the geometry from one-step topology optimization result is shown in green, embedded on manually optimized cooling system shown in the same inset as yellow. In the same figure right side, the minute differences among two topology optimization approaches are visualized by comparing the one-step topology optimization geometry in green with GA supervised topology optimization geometry in beige color. The morphology changes imposed by the GA supervised design are especially discernable at the outlet from the heat transfer volume. The manually designed coolant path reaches a 3942.85 W/m^2K. To optimize for a uniform cooling power distribution among all the swithces, the topology optimization runs had volume flow maximization in the heat exchange volume, as shown in blue in Fig. 6, additional to the pressure drop minimization objective. This process effectively distributes the cooling power in whole heat sink. In Fig.8 detail of the flow field is depicted. This case is topology optimization in the initial packaging volume. It is interesting to note that the flow is distributed into

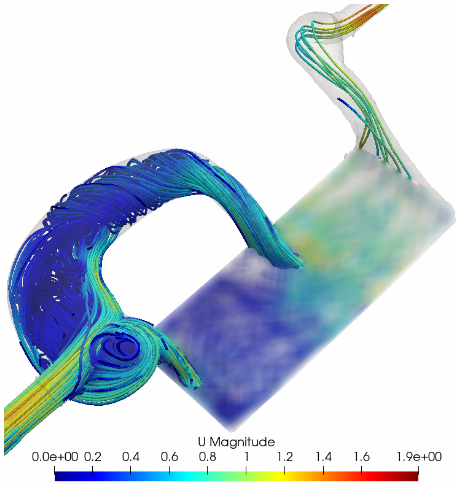
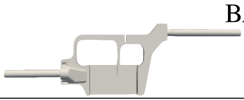
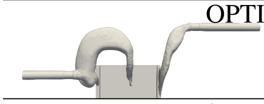
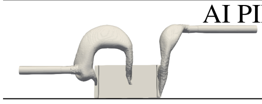


Fig. 8: Illustration of the streamlines in a gradient-descent based multiobjective topology optimization created coolant path.

two coherent structures, one entering the first switch heat exchange region and the other one to a region between the second and the third switches. This enables a heat transfer coefficient of 3950.15 W/m^2K, about 7 W/m^2K higher than the manually optimized cooling sytem, as tabulated in Table I. The topology optimization run under GA supervision reaches to 3983.75 W/m^2K, about 40.90 W/m^2K higher than the cooling system design from the human-intense manual optimization loops, with a substantially lower pressure drop. The same trend is valid for the thermal resistance of the heat sink, as the artificial intelligence supervised topology optimization result shows a decrease in thermal resistance. Additionally, the

Table I: Heat dissipation ability for studied topologies

$T_{Ref} =$ 338.15 [K]	design	$\triangle P$ [Pa]	HTC [W/m^2K]	themal resistance [K/W]	T_{out} [K]
	BASE	4752.42	3942.85	0.00919	346.27
	OPTIMIZED	4325.77	3950.15	0.00917	346.33
	AI PIPELINE	4199.53	3983.75	0.00909	346.38

topology optimized design assures a 0.55 kPa lower pressure drop compared to the manually optimized cooling system, which can be coupled to a 0.228 W decrease in thermal conditioning circuit pumping work. Returning back to the system-of-systems level modelling set-up described in Fig.1, it is simulated that 0.228 W decrease in thermal conditioning circuit pumping power enable a 0.0051 Wh/km reduction in consumption on a WLTP certification cycle for a representative BEV with AWD driveline [9]. For a vehicle with 400000 km / 10 years economic life, these figures can be connected to the reduction in CO_2 emissions [18]. Accordingly, a 0.0051 Wh/km consumption reduction will lead to 27.2 g CO_2 decrease in Sweden and a 470.6 g CO_2 in Europe. Finally, to further help the automation effort, a SVM based outlier analysis is also done on the one of the populated concept pool. For pedagogical reasons, only two-dimensional data is shown. In fact, the complete graph is a six dimensional hyperplane, comprising

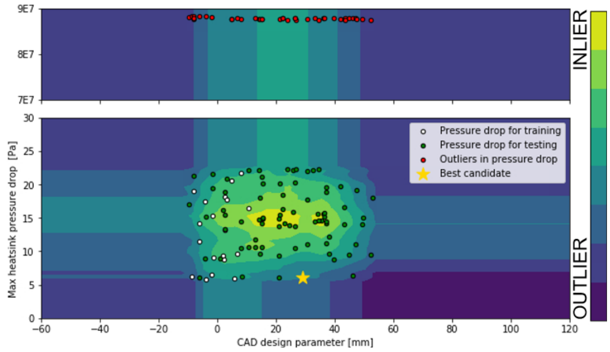


Fig. 9: Concept candidate pool investigated using machine learning. The more the lighter the background canvas color, the likely that the concept candidate is a regular candidate, ie., not an outlier.

four CAD design variables as well as key performance indices, the pressure drop and the uniformity. The candidate number 28 of the concept candidate pool is the optimum according to the GA supervised optimization loop and is well inside the expected region for the concept candidates, as depicted in Fig. 9. In the same plot, some of the divergent CFD runs are also shown in red. These are the concept candidates where the complete flowfield is occupied with high porosity cells, thus leading to extreme pressures and failed computations. All the failed concept candidates are positioned in dark (outlier) region of the canvas. This is an advantageous step in automatizing the complete pipeline as it will further reduce human interaction. In Fig. 9, two plots are shown as the outliers have exteremely high pressure conditions.

Future work

The topology optimized cooling system is produced using additive manufacturing as shown in Fig. 10. The specimens are designed to be smoother than the layered design from the additive manufacturing process, thus advantageous for surfaces adjacent to fluid flows with or without heat exchange [19]. A

Fig. 10: Additively manufactured cooling system morphologies. On the left side, manually optimized design is shown; on the right side a topology optimized geometry is shown.

future publication is planned to report on findings from the experimental study.

Conclusions

A cooling system design pipeline supervised by genetic algorithm is deployed. A machine learning based outlier analysis is programmed as a filter to further help in workflow automation, which successfully captured diverged flow field computations. Finally, the GA supervised topology optimization is shown to reach to 40.90 W/m^2K higher heat transfer coefficient than the manually designed cooling sytem, with 0.55 kPa lower pressure drop. For a representative AWD BEV, the advantage through reduced pumping work in thermal conditioning circuit reaches to a 470.6 g CO_2 advantage in Europe for the economic life of the vehicle.

Acknowledgment

The authors would like to express their gratitude to the Swedish Energy Agency and Volvo Car Corporation for financing the project.

References

[1] A. Poorfakhraei, M. Narimani and A. Emadi, ”A Review of Multilevel Inverter Topologies in Electric Vehicles: Current Status and Future Trends,” in IEEE Open Journal of Power Electronics, vol. 2.
[2] A. K. Morya et al., ”Wide Bandgap Devices in AC Electric Drives: Opportunities and Challenges,” in IEEE Transactions on Transportation Electrification, vol. 5, no. 1,March 2019.
[3] X. Ding et al., ”Analytical and Experimental Evaluation of SiC-Inverter Nonlinearities for Traction Drives Used in Electric Vehicles,” in IEEE Transactions on Vehicular Technology, vol. 67, Jan. 2018.
[4] S. Jones-Jackson, R. Rodriguez, Y. Yang, L. Lopera and A. Emadi, ”Overview of Current Thermal Management of Automotive Power Electronics for Traction Purposes and Future Directions,” in IEEE Transactions on Transportation Electrification, vol. 8, no. 2, 2022.
[5] J. Wölfle, M. Nitzsche, J. Ruthardt and J. Roth-Stielow, ”Junction Temperature Control System to Increase the Lifetime of IGBT-Power-Modules in Synchronous Motor Drives Without Affecting Torque and Speed,” in IEEE Open Journal of Power Electronics, vol. 1, 2020.
[6] K. Numakura, K. Emori, Y. Yoshino, Y. Hayami and T. Hayashi, ”Direct-cooled power module with a thick Cu heat spreader featuring a stress-suppressed structure for EV/HEV inverters,”IEEE Energy Conversion Congress and Exposition (ECCE), 2016.
[7] Seo, H.S. and Shin, D., “Development of Parallel and Direct Cooling System for EV/FCEV Inverter,” SAE Technical Paper 2018- 01-0454, 2018.
[8] Z. Wang, M. Chinthavali, S. L. Campbell, T. Wu and B. Ozpineci, ”A 50-kW Air-Cooled SiC Inverter With 3-D Printing Enabled Power Module Packaging Structure and Genetic Algorithm Optimized Heatsinks,” in IEEE Transactions on Industry Applications, vol. 55, no. 6, pp. 6256-6265, Nov.-Dec. 2019.
[9] Matlab, Accessed: 2021-Jul-29. Available at https://www.mathworks.com/products/matlab.html
[10] Weller H. G., Tabor G., Jasak H., and Fureby C. A tensorial approach to computational continuum mechanics using object-oriented techniques. Computers in Physics, 12(6):620–631, 1998
[11] Engys ltd. Accessed 18-October-2018. Available at https://engys.com
[12] OpenFOAM. Accessed 2020-01-13. Available at https://openfoam.org/.
[13] Juan J. Alonso. A crash-course on the adjoint method for aerodynamic shape optimization. In 17th International Congress of Mechanical Engineering, Sao Paulo, November 2003.
[14] Eysteinn Helgason. Development of adjoint-based optimization methods for ducted flow in vehicles. Doctoral thesis, Chalmers University of Technology, Gothenburg, Sweden, 2015.
[15] Adams B.M. Bohnhof W.J. Dalbey K.R. Eddy J.P. Eldred M.S. Gay D.M. Haskell K. Hough P.D. Lefantzi S. and Swiler L.P. Dakota, Version 5.1 user's manual, 2010
[16] Florian R Menter. Two-equation eddy-viscosity turbulence models for engineering applications. AIAA journal, 32(8):1598–1605, 1994.
[17] Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011
[18] European Environmental Agency. Accessed: 2021- Oct-15. Available: https://www.eea.europa.eu/data-and-maps/daviz/co2-emission-intensity-5.
[19] inkbit. Accessed 2022-03-07. Available at https://inkbit3d.com/technology/