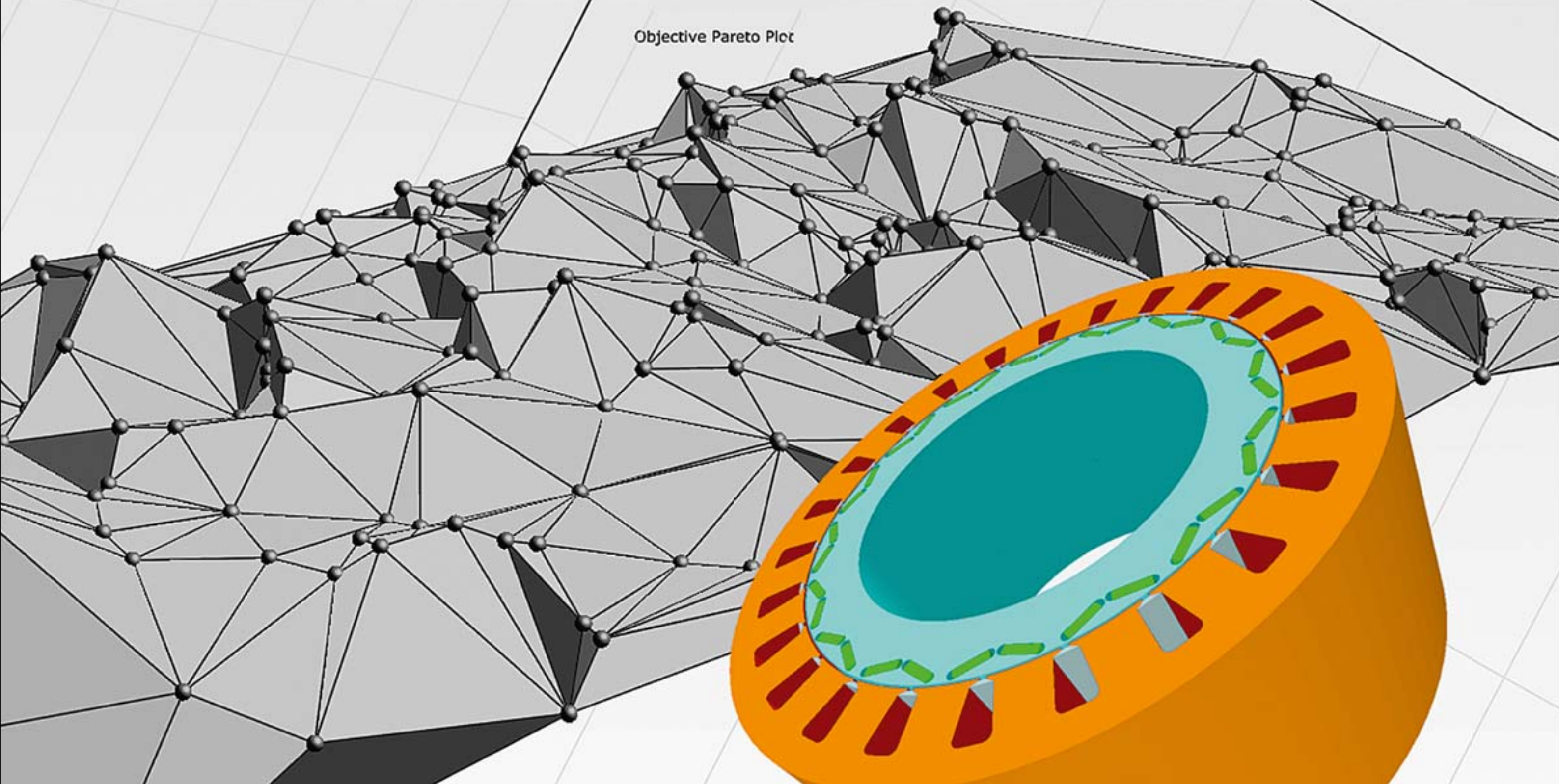

MULTI-CRITERIA ELECTRIC MACHINE DESIGN WITH MOP-BASED PARETO OPTIMIZATION

Experts at Motor Design Ltd demonstrate how the combination of Motor-CAD and optiSLang facilitates a data-driven exploration of the electric machine design space for an EV application utilizing multi-physics simulation.

Introduction

The team of electric machine design experts at Motor Design Ltd. (MDL) in Wrexham, UK, develops the software Motor-CAD consisting of highly efficient motor modeling and simulation tools able to represent besides the electromagnetic facet also the thermal and mechanical properties. The program component Motor-CAD Lab can take in data from all the multi-physical sub-models and based on generating reduced-order models (ROMs) for crucial machine properties (like dissipation through hysteresis in ferromagnetic material and magnetic saturation) entire performance maps can be generated in minutes.

The MDL team around founder Dave Staton and development head James Goss represents decades of experience in academia and industry. It is interesting to reflect how the introduction of optiSLang impacts on the approach to ab initio motor layout. Usually, several basic setup decisions were taken in steps based on simple preliminary calculations, e.g. axial length of the machine, numbers of poles, of slots, of winding turns. Only after fixing that frame, algorithmic optimization was applied further downstream. It is clear that suboptimal decisions taken at the preliminary framing stage can set the entire motor layout procedure on a wrong track. With its automation and sensitivity analysis capabilities, optiSLang brings within reach to greatly systematize and objectivize the entire ab initio machine layout procedure.

This case study outlines the current evolution state of a compressed layout procedure of a permanent magnet synchronous machine intended for use in a plug-in hybrid car, and it shows how automated step-wise model building and MOP-based Pareto optimization are leveraged to ensure a real wide-angle exploration of the available design space, i.e. to avoid premature frame-narrowing.

The machine model

The chosen motor type and topology is a permanent magnet synchronous machine. The embedded magnets in the rotor are ordered in V-shaped pairs to form a pole. This is a well-known design since it was invented by Toyota for the first generation Prius. Figure 1 (see next page) shows the cross section geometry of the 24-slot 16-pole motor. The numbers of slots and poles are indeed kept fixed, but the number of turns of the winding and the axial length of the machine are defined as variables, and they are subject to the overall optimization procedure.

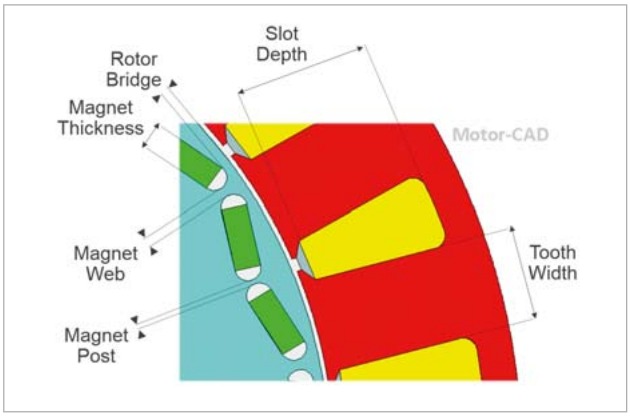

Fig. 1: Motor cross section geometry: Slot Depth Ratio = Slot Depth / (Slot Depth + Stator Back Iron Thickness) | Slot Width Ratio = Avg. Slot Width / (Avg. Slot Widt + Stator Tooth Thickness | Split Ratio = Stator Inner Diameter / Stator Outer Diameter

The introduction of three dimensionless split ratios for (1) slot width, (2) slot depth, and (3) stator-vs-rotor size ensures that (a) there is by principle no infeasible geometry and (b) extremely different setups can be reached by allowing broad ranges for all parameters. All flexible cross section geometry parameters together with the variable active length form a nine-dimensional parameter space.

Actually, no parameters describing electric circuitry or electric driving conditions are subject to variation. The reason is two-fold: on the one hand the main capability properties of the power electronics are considered as given boundary conditions, on the other hand the scripted recipe for single design evaluation together with Motor-CAD-internal routines allows the evaluation procedure to flexibly adjust the winding setup so it optimally conforms to the limits imposed by the power electronics while ensuring a realistic slot fill factor, current density, and cooling properties.

What does the scripted Motor-CAD machine model evaluation look like? Figure 2 shows a schematic of the sequence of analysis steps. Three aspects are particularly noteworthy: (a) the script avoids complete evaluations of motor designs which fail to meet a basic peak torque requirement; (b) scaling for winding turns avoids burdening the analysis with discrete parameters and combinatorial rules or with nested optimization; and (c) in the main part of the script the design evaluation expands the scope beyond selected operating points towards a complete duty cycle. This is made possible by the Lab component of Motor-CAD.

The Lab module utilizes the multi-physics solvers in Motor-CAD. It combines an efficient electromagnetic ROM building method with fast-solving lumped-parameter thermal models and control strategy algorithms. This enables a rapid characterization of the electric machine across the full operating range.

Figures 3 and 4 depict some of the main outcomes of the Lab-based machine analysis exemplarily for one of the optimized designs discussed below. Figure 3 shows the torque-speed envelopes for peak and continuous operation. During peak performance the heat generation in the machine is far

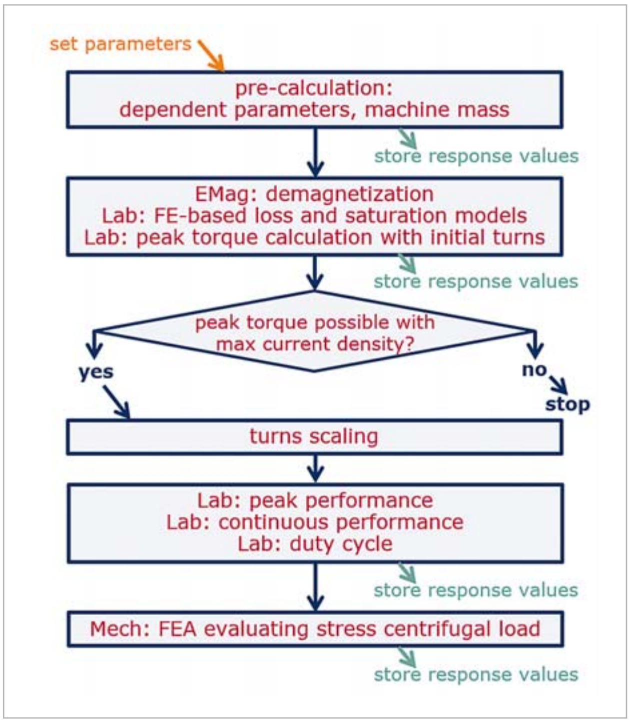

Fig. 2: Schematic of scripted Motor-CAD evaluation of one single design

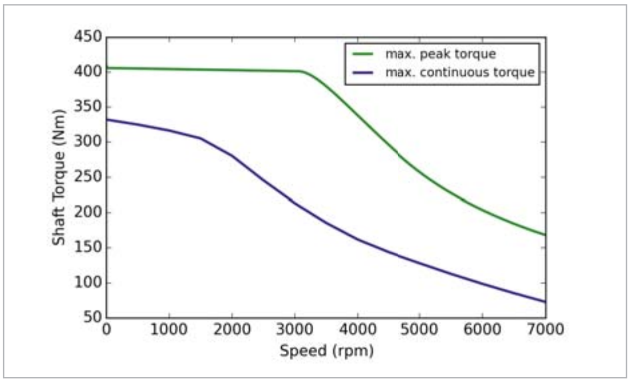

Fig. 3: Short-term and continuous performance envelopes

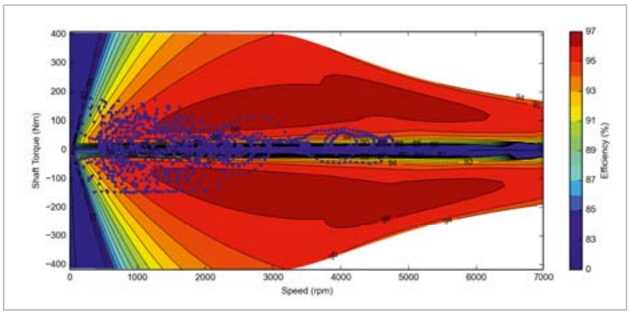

Fig.4: Efficiency map with overlaid WLTP-3 duty cycle

beyond the cooling capacity. The characteristic line of peak performance shows operating points which can be upheld for short time periods, typically up to 30 seconds. The continuous performance curve represents the envelope of all operating points within the machine's thermal limit, i.e. all feasible steady-state operating points where the dissipated

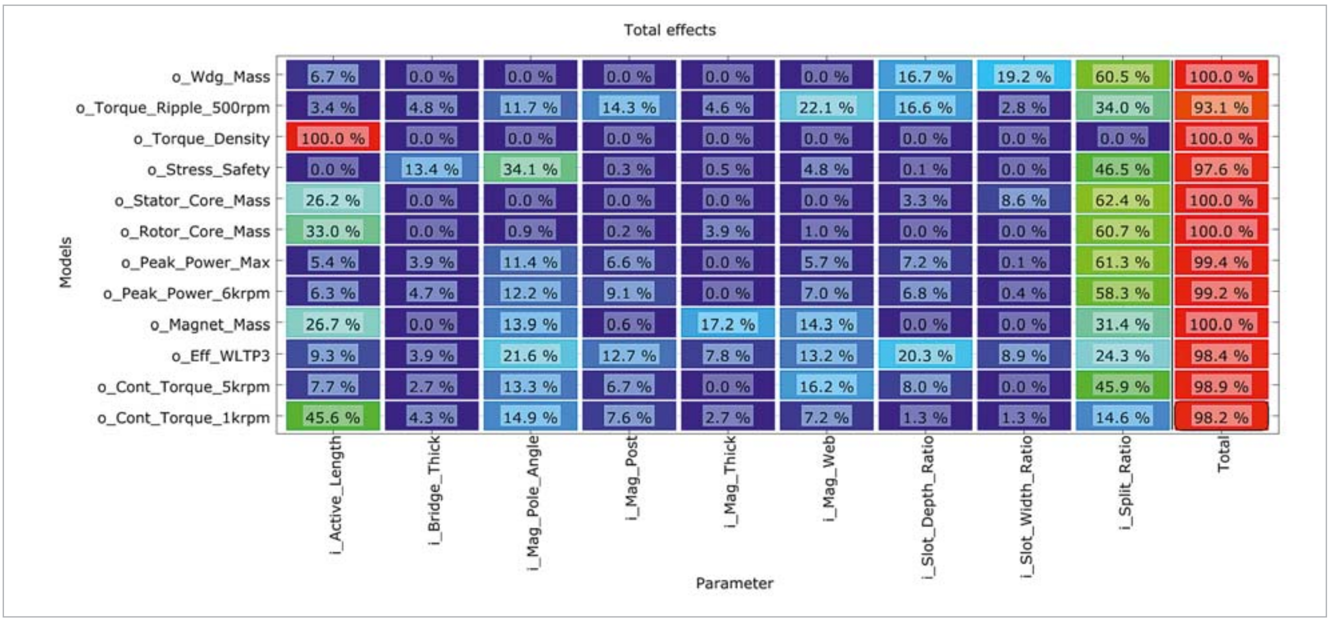

Fig.5: CoP matrix

power does not exceed the capacity of the cooling system.

The performance map in Figure 4 shows motor efficiency in the top half and generator efficiency in the lower. It is based on the "max torque per ampere" strategy of optimal operation point choice. The overlaid set of blue dots symbolizes the WLTP-3 driving cycle. Judging the overall efficiency subject to a realistic drive cycle is very valuable because it does not help to offer few perfectly efficient operating points if they are rarely ever reached and exploited by any vehicle on real-world roads. The overall drive cycle efficiency is calculated by integrating over all phases of motor as well as generator usage.

As a last step of evaluating one machine design, the newest Motor-CAD component is used for conducting a finite element analysis (FEA) of structural mechanics for calculating material stress in the rotor and deducing a safety factor of structural integrity under the centrifugal load at 120% overspeed.

Meta-model-based sensitivity analysis and optimization

With the scripted analysis routine as outlined above, Motor-CAD is used to establish a full machine characterization for every demanded design variation in a few minutes. From each analysis step the characteristic key values are collected in optiSLang for the generation of a comprehensive set of response surfaces, which offers – if good enough by CoP – the potential to conduct the entire design space exploration and optimum search on one single MOP in one run.

After conducting an advanced Latin hypercube sampling (LHS) design variation study of 400 points, 14 designs were sorted out for failing to meet basic torque requirements, leaving 386 useful designs for entering the database for meta-modeling. Figure 5 shows the CoP matrix associated to the MOPs for all optimization-relevant response quantities. On this database, the settings (1) dimension reduction not allowed, (2) anisotropic Kriging included, and (3) CoP tolerances at zero were able to yield for several quantities the best MOP judging not only by the total CoP number, but also comparing point distributions in the residual plots visualizing cross-validation errors. If e.g. a quantity like torque is intended for maximization, then the model fit around the upper data ranges is of course more relevant than towards lowest values. This is how the residual plot may justify a preference even when total CoP values of available MOPs are very similar.

The high total CoP values of generally >97% show that for most responses only a tiny fraction of the variance remains unexplained by their meta-model, which represents ideal preconditions for MOP-based optimization. Only for the quantity characterizing torque ripple the CoP value of 93% is substantially lower. This is not surprising. Torque ripple is due to the tangential component of the magnetic field across the airgap between rotor and stator. The torque effect is created by the integral all around the circumference. Generally, when integral quantities are derived from manifold spatial patterns a high amount of information is lost and the response behavior is hard to relate to the input parameters causing specific pattern expressions.

Exploiting the MOP for finding the optimal motor design

Due to the high CoP values testifying that most of the system behavior was captured, the set of MOPs offers itself for optimization and answering what-if questions in the form of experimenting with different combinations of objectives and constraints. Too sharp constraints make the problem solution impossible, but too weak constraints will allow

Name	Type	Expression	Criterion	Limit	Evaluated expression
constr_Cont_Torque_1krpm	Constraint	o_Cont_Torque_1krpm	≥	315	349.671 ≥ 315
constr_Cont_Torque_5krpm	Constraint	o_Cont_Torque_5krpm	≥	124	158.852 ≥ 124
constr_Peak_Power_Max	Constraint	o_Peak_Power_Max	≥	120	146.288 ≥ 120
constr_Peak_Power_6krpm	Constraint	o_Peak_Power_6krpm	≥	100	136.27 ≥ 100
constr_Stress_Safety	Constraint	o_Stress_Safety	≥	1.5	1.9215 ≥ 1.5
obj_Efficiency_WLTP3	Objective	o_Eff_WLTP3	MAX		-93.4978
obj_Active_Volume	Objective	400/o_Torque_Density	MIN		17.8599
constr_Torque_Ripple_500rpm	Constraint	o_Torque_Ripple_500rpm	≤	10	10.8724 ≤ 10
obj_Material_Cost	Objective	8*o_Wdg_Mass+80*o_Magnet_Mass +1.04*(o_Stator_Core_Mass+o_Rotor_Core_Mass)	MIN		298.728

Fig. 6: Optimization criteria

the algorithms to finish with not quite competitive designs. As no simulations are necessary, these valuable what-if tests for the purpose of orientation in the design space are generally quick to conduct. In this case study, after going through a few setup alternatives, the set of criteria with three objective functions depicted in figure 6 was found to be challenging while at the same time yielding the well-interpretable Pareto front of highly competitive designs shown in figure 7.

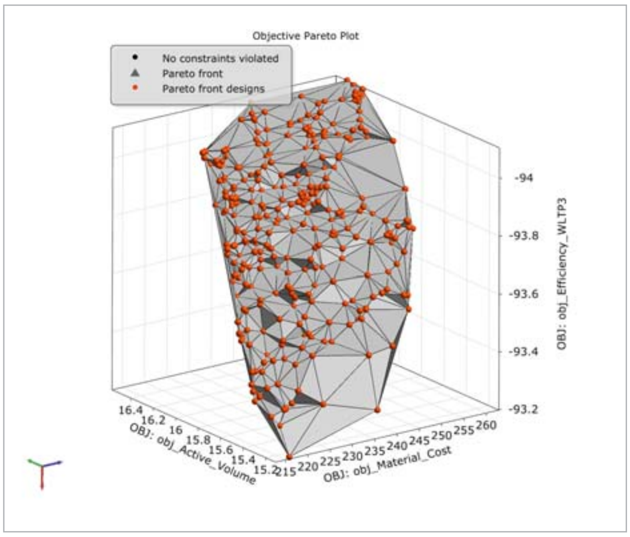

Fig. 7: Pareto front as result of running an evolutionary algorithm (EA) on the MOP

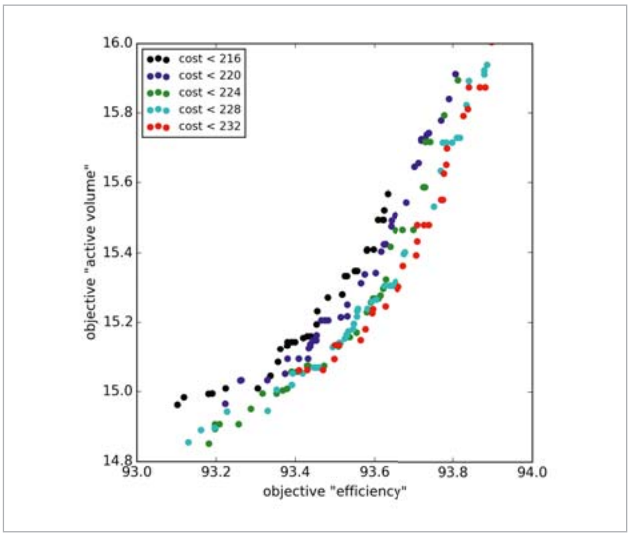

Fig. 8: Set of several two-objective Pareto fronts

While the trade-off between the motor efficiency and its volume is directly revealed by the Pareto surface in the 3D space, the dependency on the material cost (volumes times price of steel, copper & magnet) seems little and the surface appears almost flat in that direction. By taking the cost parameter as constraint instead of objective, it is possible to generate linear Pareto front structures in a 2D objective space. A plot compiling five such Pareto fronts from independent evolutionary algorithm (EA) runs is depicted in figure 8, and this finally reveals the well-known engineering goal conflict for permanent magnet motors, that extremely high torque and efficiency performance in combination with small motor size can only be reached by increasing the cost-driving content, the rare-earth magnets.

The Pareto fronts in figure 8 contain between 34 and 51 designs, each front being the result of an EA run consuming around 10^4 MOP function calls. It is clear that continued evolutionary optimization will be able to resolve the Pareto fronts more and more finely and push the structures forward by a few more increments. Based on a MOP solver the exercise does not have to be computationally burdensome. However, as the tendency caused by the cost limit has already become apparent, and as a small and well-defined set of characteristic designs is most of the time preferable over a large set of stochastic designs, this case study concludes by presenting a final stage of single-objective optimization (SOO) runs: Just as the cost parameter was transformed from objective into limit to get from figure 7 to 8, the transformation of the motor volume from

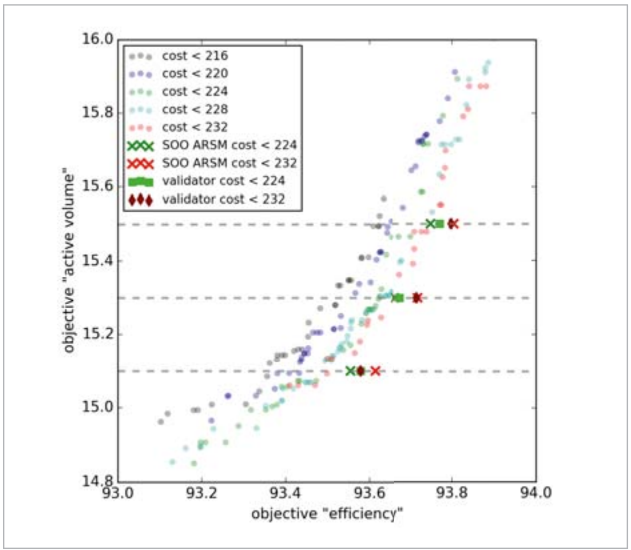

Fig. 9: Validator designs added to the Pareto front plot

objective into constraint yields a single-objective criteria set allowing the use of efficient deterministic optimizers and allows to achieve the series of optima added into the objectives plot of figure 9. Based on two selected steps of the cost limit and three steps of the volume limit (dashed grey lines), and feeding it with a constraint-fulfilling Pareto-efficient start design, optiSLang's ARSM algorithm was run six times and yielded six converged solutions. These six quintessential parameter combinations were finally validated by conducting additional full Motor-CAD evaluation of the designs. The simulation outcomes in terms of the two Pareto objectives "efficiency" and "volume" are appearing as "validator" points in figure 9. Analog to being right on the limit in terms of "volume" (visible) the points were pushed right onto the "cost" limit (not depicted) by the optimizer. In terms of "efficiency" there is a visible small offset between the MOP-based ARSM optima and the validator points which reminds that any MOP is only an approximating model. In terms of "cost" and "volume" the validator offsets were found to be quite infinitesimal which can be attributed to the little complexity of the quantities going into these objectives. From these six designs the one with cost < 224 and volume < 15.3 is furnishing the plots in figures 3 and 4.

Summary

The case study presents a parametrized permanent magnet motor model and outlines its script-driven electromagnetic, thermal, and performance map evaluation in Motor-CAD. This machine simulation setup allows a full optimal layout procedure based on one step of sensitivity analysis and one step of MOP generation. Insight-seeking exploration of a very broad design space and (more or less) constrained optimization can all be conducted on Metamodels of Optimal Prognosis. Conscious steps of constraint sharpening, Pareto front generation, and deliberate trade-off solution choice are outlined. The intention is to show how benefiting from efficient Motor-CAD modeling techniques in combination with optiSLang algorithms and automation features enables to progress the best practice for ab initio electric machine layout towards fewer decision points and greater objectivity.

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