Multi-physics, Multi-objective Optimisation of Electric Machines

WHITE PAPER | 2021 | Motor Design Limited

1. Introduction

The electric machine design industry has developed rapidly in recent years, in a move largely driven by the electrification of transportation in response to environmental and natural resource concerns. For electric motor designers this translates into a new set of challenges. Motors need to be more efficient and more compact, with sufficient output power and torque density levels. They should also be designed for mass production, especially for aerospace or automotive applications. On top of that, motor designs need to be developed in a short timeframe and as part of a wider complex system, such as powertrains in electrical vehicles. At a motor performance level, motor designers need to account for different physical domains that interact with each other throughout the design process. To meet these challenges many motor designers utilise a systematic design optimisation strategy to find optimal design solutions to a given set of specified requirements.

2. Design Optimisation Strategy

A systematic design procedure of electric motors is illustrated in Figure 1. The design process starts with an in-depth analysis of a given set of requirements with the goal of finding a concept design. This initial design is then optimised for specific constraints and objectives to determine an optimal solution in line with the specification. During this stage, multi-objective algorithms are required to trade off any conflicting performance criteria and make the decision-making process easier.

For an efficient design optimisation workflow we need multi-physics analysis that explores the electromagnetic, thermal and mechanical aspects of the motor design and for the machine's performance to be evaluated across the full speed range. We also need the ability to explore and leverage a large design space, rapidly trade off the machine performance, evaluate the impact of any change of specification requirement and keep track of design decisions.

These challenges can be perfectly addressed by integrating Ansys Motor-CAD and Ansys optiSLang programs together into a unique surrogate model-based optimisation workflow, as depicted in Figure 2.

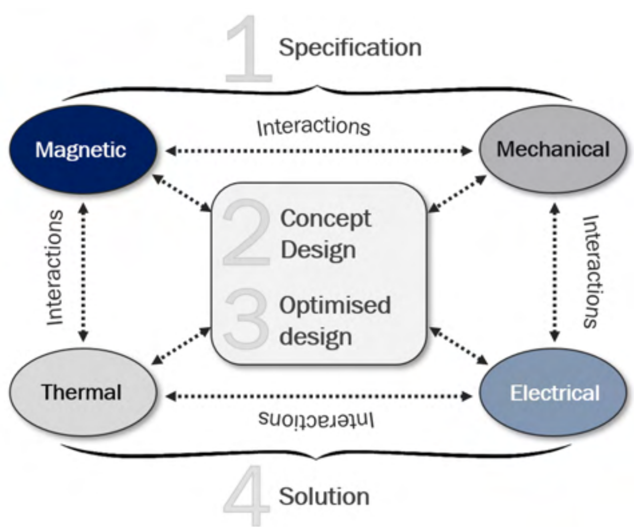

Figure 1: Systematic design procedure of electric motors

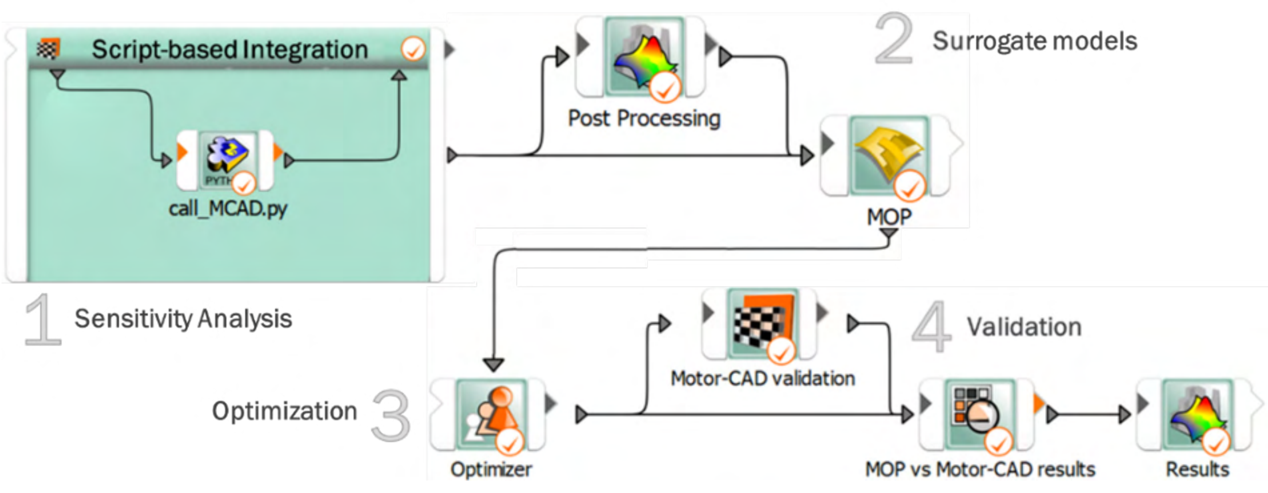

Figure 2: Surrogate model-based optimisation workflow

2.1 Surrogate model-based optimsation

Surrogate model-based optimisation strategies typically break down into four stages:

1. Sensitivity analysis: We begin with a design of experiment that scans the design space in place to extract performance data sets. Extracted data are then analysed to evaluate the sensitivity of every output parameter to input variable changes.
2. Surrogate models: Data from the sensitivity analysis are used to build surrogate models that map the relationship between design parameters and machine performance. For every output parameter the optimal subspace is determined along with the impact of the main influencers.
3. Optimisation: An optimiser is applied directly to the surrogate models with given goals and constraints. If the optimisation is multi-objective then the best results can be interpreted using a Pareto front that shows how the objectives may conflict with each other within the solution space.
4. Validation: The surrogate model-based optimisation results are validated against final FE-based Motor-CAD runs.

In the optiSLang workflow shown in Figure 2, Motor-CAD is used for the sensitivity analysis and the validation. Motor-CAD is automated through a Python script to set a number of input parameters and to run multi-physics calculations. After the calculations are completed, relevant output parameters are extracted and collected in optiSLang for further analysis. The Motor-CAD integration process is summarised in Figure 3.

An example of how this workflow can be used for the design optimisation of an electric motor — in this case, a 24-slot 16-pole IPM traction motor — will now be presented and discussed.

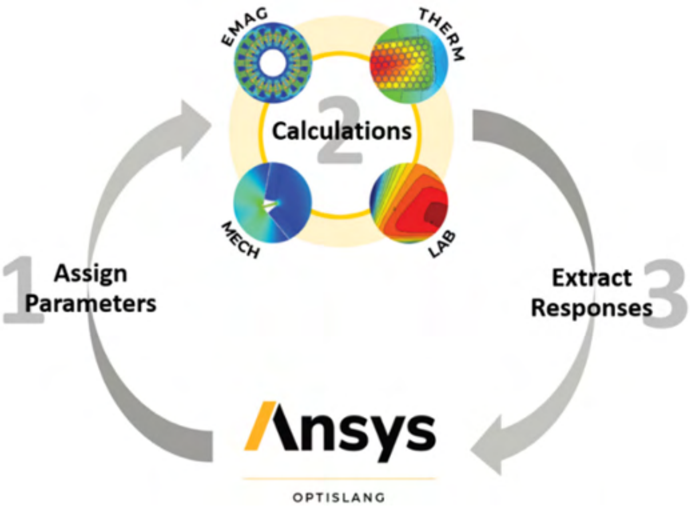

Figure 3: Motor-CAD integration process

3. Preparing for the optimisation

To begin with, this white paper will focus on steps 1 and 2 of the design flowchart given in Figure 1. Specification requirements are first reported and are used both to define a concept design and a consistent optimisation scenario. This concept design is then parameterised in order to cover a sufficiently large design space.

3.1 Specification

For this white paper we use a typical IPM traction motor as an example. The requirements of this example motor can be seen in Table 1. The peak and continuous performance demands across the full operating range, the cooling system characteristics, the electrical boundary conditions along with the maximum packaging envelope are given. The system is cooled with a typical housing water jacket (WJ) using a mixture of Ethylene Glycol and Water (EGW) as a coolant.

Table 1: Motor requirements

Requirement	Value	Unit
Peak torque	400	Nm
Peak power @ 3krpm	120	kW
Peak power @ 6krpm	100	kW
Cont. torque @ 1krpm	300	Nm
Cont. torque @ 5krpm	124	Nm
Maximum speed	7000	rpm
Cooling system	WJ	
Coolant flow rate	≤ 6.5	l/min
Coolant fluid type	EGW	
Coolant inlet temperature	65	°C
Line current	≤ 500	A_{rms}
DC bus voltage	350	V
Machine diameter	330	mm
Machine length	≤ 220	mm

3.2 Concept design

A preliminary design analysis in Motor-CAD was carried out to establish a number of key parameters like the slot pole combination, the stator winding pattern or the geometry of the housing cooling channels—the results of which can be seen in Figure 4.

Our concept design is a 24-slot 16-pole machine with one layer of magnets embedded into the rotor in a v-shaped manner. Typical materials associated with traction applications are used: rare-earth based material for the magnets (N38UH) and silicon iron based material for the magnetic cores (M235-35A). The winding is concentrated with two phases per slot and six branches in parallel per phase. Finally, the stator diameter and mechanical airgap length were fixed to 300mm and 1mm respectively.

3.3 Defining the optimisation scenario

Now that a concept design has been established, the optimisation scenario can be defined. The problem is multi-objective as both the energy consumption through the WLTP-3 drive cycle and the active machine envelope have to be minimised. Figure 5 shows the drive cycle in terms of speed vs. time and torque vs. time.

The problem is also subjected to multiple constraints, as shown in Table 2. These constraints are used to capture the specified requirements, detailed in Table 1, as well as a limitation on the maximum stress allowed in the rotor at high speed to avoid mechanical failure.

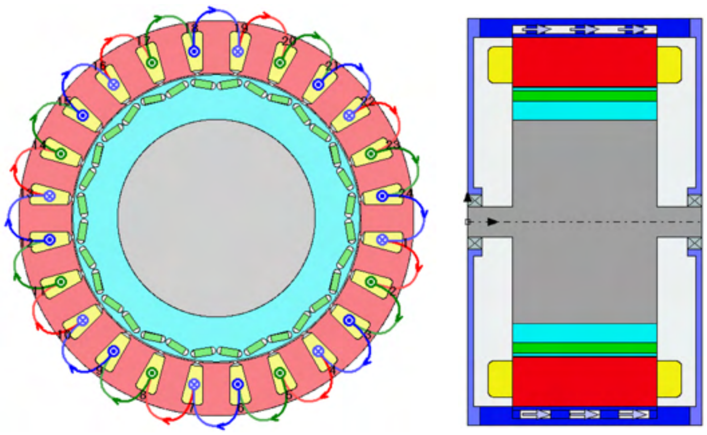

Figure 4: Radial machine cross section with winding pattern (left), axial machine cross section with housing WJ (right)

Table 2: Optimisation constraints

Constraint	Value
Continuous torque (Nm) @ 1krpm	≥ 300
Continuous torque (Nm) @ 5krpm	≥ 124
Peak power (kW) @ 3krpm	≥ 120
Peak power (kW) @ 6krpm	≥ 100
Torque ripples (%) @ 1krpm	≤ 10
Von-Mises stress (MPa) @ 8.4krpm	≤ 300

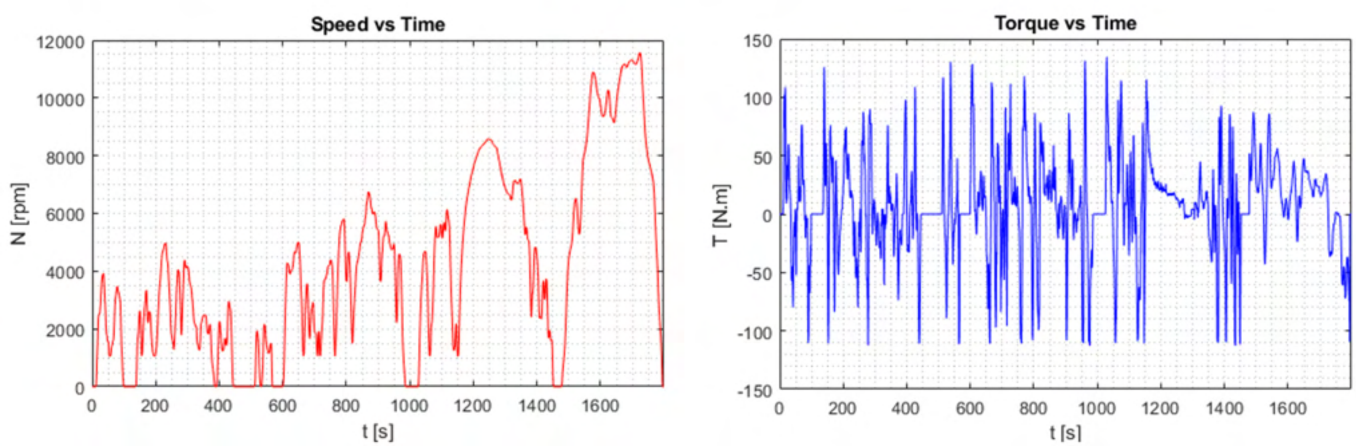

Figure 5: WLTP-3 drive cycle – Torque and speed profiles

Table 3 lists the optimisation variables along with their range of variation. In Motor-CAD, the parameterisation of the machine can be carried out efficiently using a combination of absolute parameters, such as magnet thickness, and geometric ratios such as split ratio (Figure 6). This sort of parameterisation greatly helps both to avoid invalid geometries that may result from overlapping regions and explore a large design space.

Let us say, for example, that we want to explore a significantly large sampling of motor configurations with wide ranges of stator ID and stator OD values. One should expect a high number of invalid geometries as a result, where the stator ID exceeds the stator OD. These scenarios are avoided when using relevant values of the split ratio.

Table 3: Optimisation variables and design space

Parameter	Range	Unit
Active Length	[90; 130]	mm
Bridge Thickness	[0.4; 1.5]	mm
Magnet Post	[0.4; 1.5]	mm
Magnet Thickness	[6; 8.5]	mm
Pole Arc Ratio	[0.8; 1]	
Pole V Angle	[90; 120]	°
Slot Depth Ratio[1]	[0.6; 0.75]	
Slot Opening Ratio[2]	[0.2; 0.4]	
Tooth Width Ratio[3]	[0.55; 0.675]	
Split Ratio[4]	[0.65; 0.75]	

[1] Slot Depth / (Slot Depth + Stator Back Iron Thickness)
[2] Slot Opening Width / Slot Pitch
[3] Tooth Width / (Slot Width + Stator Tooth Width)
[4] Stator inner diameter (ID) / Stator outer diameter (OD)

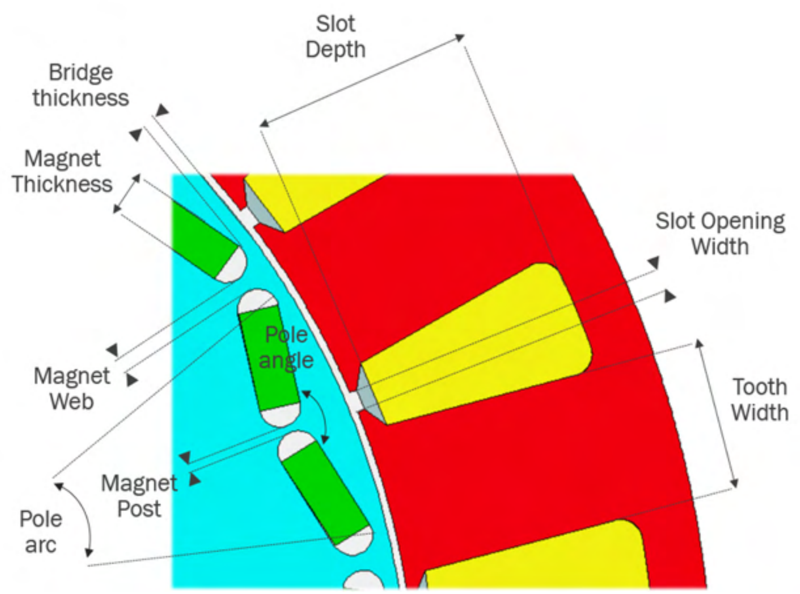

Figure 6: Motor-CAD absolute parameters

4. Applying a surrogate model-based optimisation strategy to our example motor

Now, the surrogate model-based optimisation strategy described previously can be applied to the IPM traction motor parameterised during the preliminary design phase. A stepwise description of the design optimisation process is given.

4.1 Sensitivity Analysis

The optimisation workflow starts with the sensitivity analysis. At this stage the sampling method and the number of samples are the only parameters to be set. In this example, the Advanced Latin Hypercube Sampling (ALHS) method along with 400 samples have been used. This stochastic sampling scheme is well suited to high dimensional problems with continuous variables and will distribute design variants across the design space in an effective way.

The sensitivity analysis was completed within 2 days using a 2-core machine and running 3 instances of Motor-CAD in parallel (note that the simulation time can be reduced further by utilising more computing resources and further parallelisation of the analysis). Performance data sets were collected throughout the variation study and post processed automatically to characterise the sensitivity of every output parameter to the input variables.

The active radial cross section of four design candidates can be visualised in Figure 7. As can be seen there is a deep exploration of the design space, with the shape of the slots and rotor varying significantly from one design to another. Performance data sets can be visualised in Ansys optiSLang within a single interface, as presented in Table 4, making it simple to quickly understand what the most constraining parameters are with respect to the optimisation criteria.

Indeed, from the colour scheme in the results table it is possible to see which constraints are fulfilled (highlighted in green) and which constraints are violated (highlighted in red). In this case, the torque ripples at low speed and the continuous torque at low speed that are the most constraining parameters.

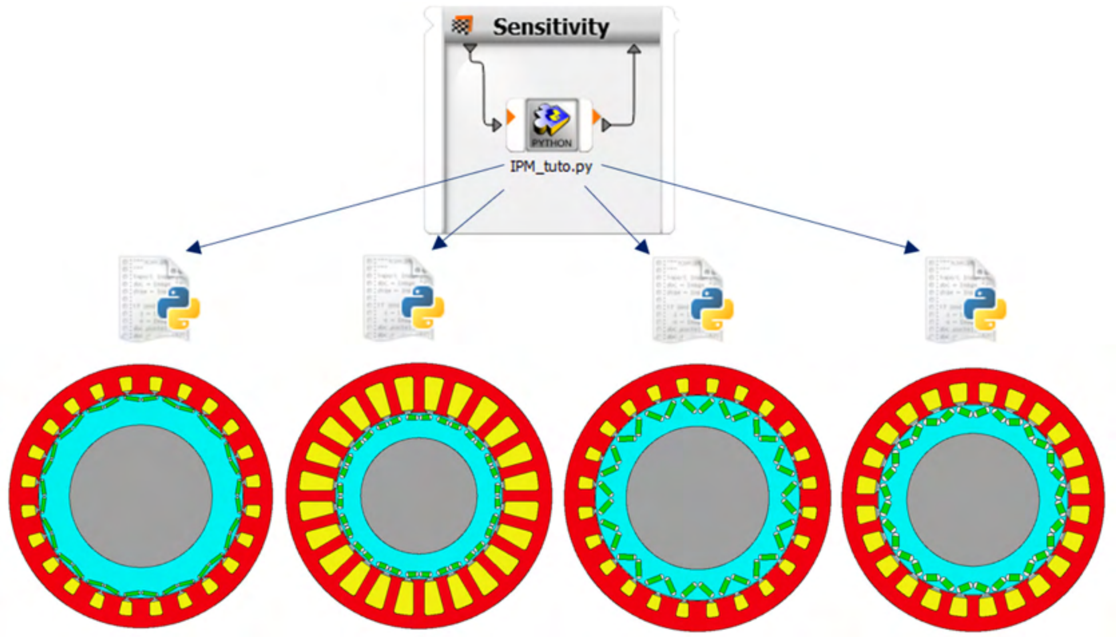

Figure 7: Results from the variation study - radial cross section from four designs generated out of 400 designs

Table 4: Output data collected in the optiSLang results page

Sensitivity

Parameter | Start designs | Criteria | Dynamic sampling | Other | Result designs

	Id	Feasible	Duplicates	Status	constr_Cont_Torque_1krpm	constr_Cont_Torque_5krpm	constr_Peak_Power_3krpm	constr_Peak_Power_6rpm	constr_Peak_Torque_500rpm	constr_Stress_Safety	constr_Torque_Ripples
1	0.1	false		Succeeded	145.134 ≥ 300	97.7991 ≥ 124	94.8983 ≥ 120	141.158 ≥ 100	303.884 ≥ 400	2.2853 ≥ 1.2	26.9902 ≤ 10
2	0.2	false		Succeeded	119.182 ≥ 300	61.9252 ≥ 124	80.4366 ≥ 120	116.02 ≥ 100	258.83 ≥ 400	3.12235 ≥ 1.2	25.5962 ≤ 10
3	0.3	false		Succeeded	71.462 ≥ 300	34.9312 ≥ 124	25.7492 ≥ 120	50.8456 ≥ 100	82.8289 ≥ 400	4.77163 ≥ 1.2	62.6245 ≤ 10
4	0.4	false		Succeeded	144.264 ≥ 300	63.2146 ≥ 124	51.0251 ≥ 120	51.4392 ≥ 100	163.915 ≥ 400	4.02924 ≥ 1.2	86.3683 ≤ 10
5	0.5	false		Succeeded	167.644 ≥ 300	89.2041 ≥ 124	83.5764 ≥ 120	142.642 ≥ 100	268.614 ≥ 400	2.16017 ≥ 1.2	35.0522 ≤ 10
6	0.6	false		Succeeded	108.056 ≥ 300	52.8711 ≥ 124	40.1128 ≥ 120	62.4612 ≥ 100	128.848 ≥ 400	3.77809 ≥ 1.2	68.5876 ≤ 10
7	0.7	false		Succeeded	247.791 ≥ 300	83.8814 ≥ 124	73.1164 ≥ 120	57.9335 ≥ 100	322.862 ≥ 400	4.2153 ≥ 1.2	40.669 ≤ 10
8	0.8	false		Succeeded	180.405 ≥ 300	74.485 ≥ 124	77.7034 ≥ 120	137.762 ≥ 100	249.011 ≥ 400	2.87305 ≥ 1.2	25.0009 ≤ 10
9	0.9	false		Succeeded	222.742 ≥ 300	72.6047 ≥ 124	85.7224 ≥ 120	70.5938 ≥ 100	275.067 ≥ 400	4.32142 ≥ 1.2	59.002 ≤ 10

4.2 Generation of surrogate models

In the next step, a surrogate model for every output parameter is automatically generated. Using the Metamodel of Optimal Prognosis (MOP) approach, highly accurate models are generated with respect to the FE-based sensitivity results. On top of accurately capturing the multi-physics behaviour of the machine, the MOP provides the optimal subspace for each output parameter along with sensitivity measures to the most important variables within this subspace. This way the parameters that have the highest influence on the machine performance can be extracted.

Since the stress safety factor emerged as a very constraining parameter from the sensitivity analysis results, it is used as an example. Figure 8 shows this factor plotted against the two most important parameters of its optimal subspace, namely the split ratio and the pole v angle. From that surrogate model we learn that the stress will be higher if we increase the pole v angle or increase the rotor size. Modelling this behaviour is important both to understand the physics of the machine and to confirm that the results we are seeing are as expected from a design perspective.

The full model coefficient of prognosis (CoP) is used as a forecast quality measure for a given model. For the example shown in Figure 8, the CoP has been calculated to be 99%, indicating we can move to the optimisation stage with high confidence. This value is also given in Figure 9, where the impact of the bridge thickness, pole v angle and split ratio is characterised through single CoP values. From this plot, it is clear that the split ratio has the largest impact on the stress safety factor, followed by the pole v angle and bridge thickness.

From a design point of view, we would be tempted to choose thick rotor bridges to ensure sufficient mechanical integrity. However, electromagnetically, it is well known that the performance can drop out significantly if these bridges are not thin enough and fully saturated. This result can be easily retrieved with a back-to-back comparison of the MOPs of the peak torque and stress safety factor.

Ansys optiSLang gives the CoPs for all output parameters, as shown in Figure 10. This matrix allows us to see the influence of different input parameters with respect to the outputs, and it is clear that the split ratio and the active length have the most important impact on the machine performance. Not only the total CoP for the stress safety factor but all CoP values approach 1, bringing even higher confidence for the upcoming optimisation.

If many motor design trade-offs can be established at this stage, the best compromise between all these conflicting performance criteria will only be found from an efficient multi-objective algorithm.

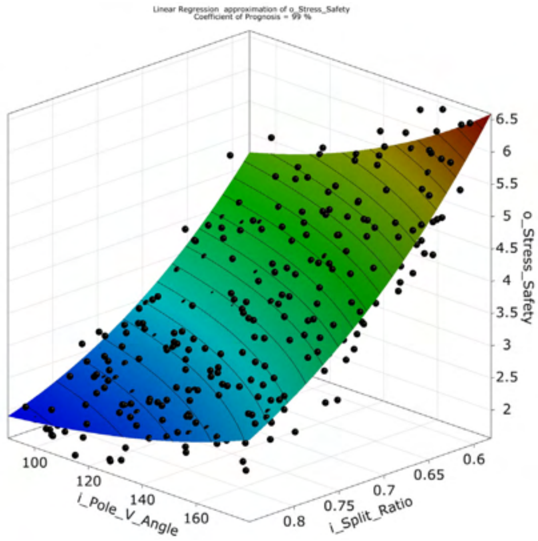

Figure 8: MOP for the stress safety factor

Figure 9: Single CoPs for the stress safety factor

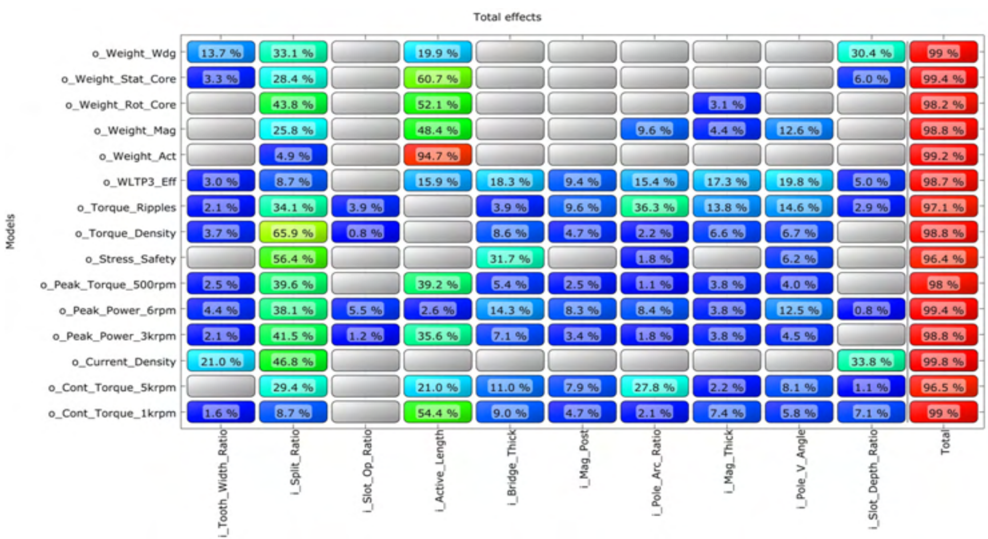

Figure 10: CoP matrix

4.3 Optimisation algorithm and validation

A genetic algorithm was then applied directly to the surrogate models in order to get solutions to the multi-objective, multi-constraint optimisation problem. This results in a two-dimensional pareto front, highlighted in red in Figure 11. This shows the non-dominating solutions with respect to the drive cycle efficient and active volume criteria. In Figure 11, designs that fulfill the constraints are highlighted in black whereas the designs which violate the constraints are shown in light grey. Figure 11 also shows some of the metamodel based optimal solutions validated with Motor-CAD.

The constraints have to be validated as well, as shown in Figure 12 for the specific design n° 9785 which has been taken as an example. Moving along the Pareto front we can see how well the surrogate model-based optimisation results match the validated results with Motor-CAD. This not only allows us to find the solution to a complex motor design problem but also to validate the effectiveness of the developed optimisation strategy.

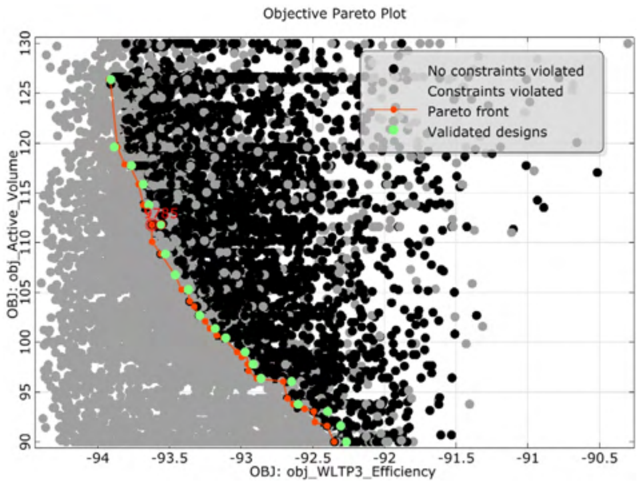

Figure 11: MOP based and validated Pareto front

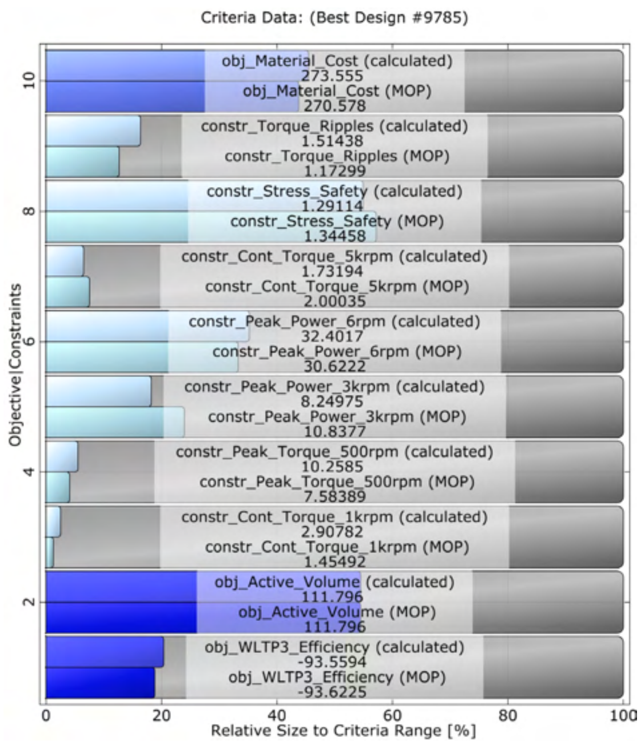

Figure 12: MOP based vs validated designs constraints for design n° 9785

5. Conclusion

A novel surrogate model-based optimisation workflow using Ansys optiSLang and Ansys Motor-CAD has been presented and used for the design optimisation of a 24-slot 16-pole IPM traction motor. The selected motor topology was optimised to provide maximum efficiency over the WLTP-3 drive cycle and within the minimum space envelope, while achieving specific requirements in terms of electromagnetic, thermal and mechanical performance. This cutting edge approach is a significant improvement over previous direct optimisation strategies and is unprecedented in both academic literature on electric machine optimisation and industrial best practice. Besides providing optimised solutions to complex multi-physics, multi-criteria design problems in a computationally efficient way and without massive HPC capabilities, this optimisation strategy also enables motor designers to efficiently trade-off conflicting performance across a large design space and keep track of these trade-offs to significantly reduce the cost of change throughout the development process.

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About Motor-CAD & optiSLang

Ansys Motor-CAD is a leading electric motor design tool combining analytical and finite element analysis (FEA) methods for fast and accurate performance prediction of electric motors. It enables multi-physics simulation across the full operating range. Motor-CAD combined with Ansys optiSLang presents an opportunity for unprecedented optimisation strategy, enables system level trade-offs and allows electric motor designers to quickly experiment with changes to specification with respect to the design space.