Towards Design Rule Extraction from Large Computational Datasets by Causal Correlation Analysis

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Intuitive interpretation of the results from multi- objective numerical optimization of magnetically non-linear electrical machines is very challenging. The resulting designs are typically used "as they are" or tuned by trial and error, due to lack of deeper understanding needed for the tuning in the multi-objective Optimum Design Space (ODS). The results consisting of large sets of generic and optimum designs contain invaluable information on the emerging design rules. We recommend causal correlation analysis for design rule extraction.

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I Motivation for Causal Optimization and AI

Multi-objective optimization – such as genetic optimization or machine learning – for design work typically results in a black box type solution including large sets of optimum and not so optimum design data. While such results can be utilized directly by the designers, sometimes there rises the need to explain them deeper and to provide a more straightforward interpretation and wiser utilization. This can be seen as an attempt to discover the design rules inside the optimum design space (ODS), an approach commonly used in engineering.

Prior work published by the authors demonstrated the powerful capabilities of causal correlation fingerprinting which can provide insight into large datasets in a straightforward manner.[1] In this paper we introduce some approaches how design rules for electrical machines – a nonlinear magnetic problem – can be extracted by causal correlation analysis of the large sets of data coming from multi- objective optimization.

The example here is the design and optimization of magnet shapes with multi-objective goals, where part of the goals is the reduction of load torque harmonics, similarly as described in an ABB patent.[2] The methods proposed in this paper point toward an automated extraction of the relevant design rules in an optimized design space, for nonlinear magnetic problems by utilizing causal correlation analysis.

The causal correlations in the computed datasets are investigated by two approaches. One involves statistical causal analysis [2] and the other has been based on observation of the statistical correlations between variables. Our goal is to extract design rules how to reduce torque harmonics (TTHD) while remaining in the multi-objective design space. (ODS) For this analysis we separated the datasets into all computed designs and another including optimum designs in the pareto optimal front only.

The computations for the multi-objective optimization have been performed by 2D FEM analysis of the electrical machine designs considering nonlinear electromagnetics.

II Demonstration Case: Design Optimization of Permanent Magnet Generators

An industrially relevant case of electrical machine design optimization is the shaping of the permanent magnets in a rotor to reduce cogging torque and load torque harmonics. An ABB patent available publicly describes a magnet shape for such purpose and how design parameters affect these harmonics [2]. Such conclusions have been reached by the engineers going through the computed data and looking for correlations between design parameters and their effects on the performance. Fig 1 shows a picture form the patent describing the four design variables: B1 and H1 describing the total width and height of the magnet block respectively while B2 and H2 are associated with the width and height of the trapezoidal upper part of the magnet.

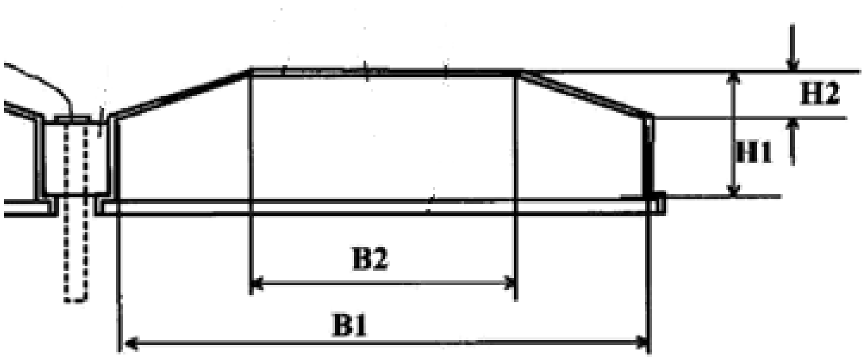


Figure 1: Shaped permanent magnet design with four design parameters.

Fig. 2 shows the dependence of cogging torque and load torque harmonics on the design parameters H2. Similar figures for the other design parameters are also described in the patent.

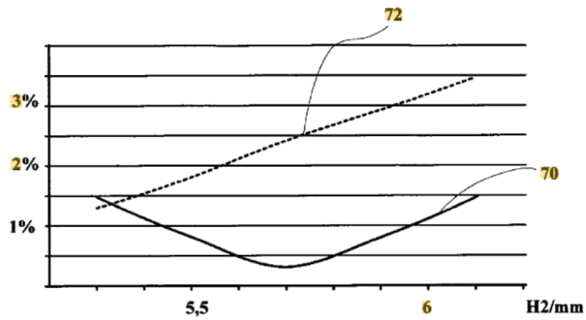


Figure 2: The effect of H2 vs cogging torque (70) and load torque harmonics (72) as described in the patent.

The challenge grows when multi-objective optimization is required. G.O. provides a set of designs for multi-objective goals but by default does not provide the clues to make new optimum designs, just offers to pick some from the pareto optimal front. Hence tuning the designs on the pareto optimal front and to find traditional design rule type correlations still requires time consuming, complex analysis of large amounts of data. The method proposed next provides support to assist and automate that creative work.

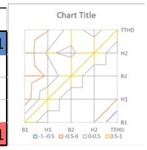
III Design Rule Extraction by Causal Correlation Analysis

Genetic optimization (GO) results not only in the pareto optimal front for recommended designs but also a large set of design variations in several generations of the optimization. These designs evolve according during genetic optimization, and we can observe how design parameters behave compared to performance parameters and in relation to each other. The relationship between design parameters can be seen as design rules and can be extracted by causal correlation analysis.

The correlation matrices between design parameters and TTHD for all designs in the optimization and for designs only existing in the ODS and their difference are shown in Fig.3.

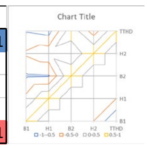
All designs in optimization:

	B1	H1	B2	H2	TTHD
B1	1				-1
H1	-0.35131	1			
B2	-0.43703	0.071128	1		
H2	-0.37122	0.563094	0.38699	1	
TTHD	-0.4294	-0.03804	0.735515	0.27558	1



Optimized Design Space (ODS):

	B1	H1	B2	H2	TTHD
B1	1				-1
H1	0.147472	1			
B2	-0.58066	-0.54735	1		
H2	0.081175	0.342762	0.031959	1	
TTHD	-0.54935	-0.71011	0.864227	-0.27034	1



Difference:

	B1	H1	B2	H2	TTHD
B1	0	0	0	1	-1
H1	0.498778	0	0	0	0
B2	-0.14363	-0.61848	0	0	0
H2	0.452392	-0.22033	-0.35503	0	0
TTHD	-0.11995	-0.67207	0.128712	-0.54592	0

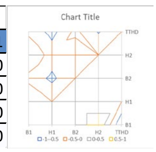


Fig. 3. The effect of the four design parameters on TTHD and on each other. Results from all designs are on the top and optimum designs on the pareto optimal front are in the middle, and their difference is in the bottom.

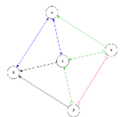
The causal analysis of the same datasets evolving from all designs to the ODS shown in Table I. Relevant causal correlations disappearing from all designs towards ODS are indicated in bold on the left and relevant correlations for the design rules in the ODS are indicated with bold on the right.

From these two approaches we can conclude that the highest causal correlations are between TTHD and design parameters B2 and H1 in the ODS and it is different for the "All designs".

From the signs of the correlations one can extract a basic design rule to increase H1 and reduce B2 to reduce TTHD while remaining in the design space because H1 and B2 are also negatively causally correlated to each other in the ODS.

The correlation between H1 and B1 dropped to statistically insignificant levels in the ODS. Correlation between H1 and H2 is slightly positive so increasing H1 and slightly increasing H2 can be a design alternative as correlation between H2 and TTHD is also negative in the ODS. Another alternative could be to increase B1 also independently or with reducing B2 based on similar logic.

Table 1: Causal Correlation Analysis of All designs and the Optima

All designs:	**Designs on Pareto front:**
Causal Correlations:  Might be causal correlation: TTHD o--> B1 B2 o--> H1 H2 o--> H1 **B2 o--> B1** **H2 o--> B1** TTHD o--> H1 Seen as the Same phenomenon **B1 o--o H1** B2 o--o TTHD B2 o--o H1	Causal Correlations:  **H1 ---> H2** Might be causal correlation: TTHD o--> B1 **TTHD o--> H1** **B2 o--> H1** Seen as the Same phenomenon: **B2 o--o TTHD**

We can also study the causal correlations between actual values of the design variables and the performance parameters. In Fig. 4 we show how some of the concrete design parameter values correlate with low toque harmonic content within the ODS. This confirms the design rule on H1 above also. This approach will be explored further in the extended paper.

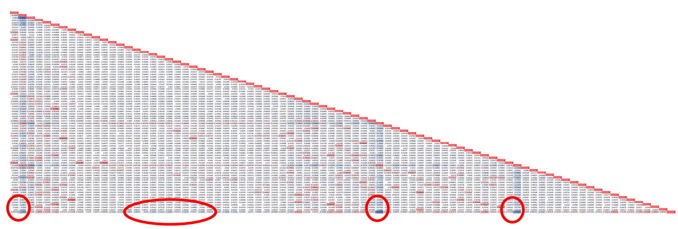


Figure 4: The correlation of the four design parameters values with TTHD and each other in the ODS. The circled areas of the optimum values show strong negative correlation with TTHD in the bottom row. B1, B2, H2 have sharp optimum ranges while H1 is more spread out.

Utilizing causal correlation analysis between design values and performance variables opens new opportunities. We can also study and identify the causal correlations between values ranges of the design variables and establish design rules easier.

IV Conclusions

The above example demonstrates the powerful potential of causal correlation analysis for design rule extraction from large electromagnetic computational datasets. The extended paper will elaborate deeper on causal correlation analysis of design parameter value ranges on performance parameters in the ODS.

References

[1] A. Szucs, "Characterizing the Performance of Field Computation and System Analysis by Causal Correlation Fingerprinting for Digital Twins," 2023 24th International Conference on the Computation of Electromagnetic Fields (COMPUMAG), Kyoto, Japan, 2023, pp. 1-4, doi:0.1109/COMPUMAG56388.2023.10411778.

[2] J Mantere, T Ryyppö, A Szucs, Permanent magnet electric machine and permanent magnet with linearly increasing air gap for an electric machine - US Patent 8,421,291, 2013