Optimizing Alternator Performance: Harnessing the Power of Design for Six Sigma (DFSS) Applied on Electrical Generation.

Pedro Martins de Oliveira and Ricardo Felipe Junckes

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Pedro Martins de Oliveira[1] and Ricardo Felipe Junckes[1]

[1] WEG Equipamentos Elétricos, Av. Prefeito Waldemar Grubba 3300, Jaraguá do Sul-SC, Bra-zil

Abstract. This work aims to demonstrate the practical application of Design for Six Sigma (DFSS) in enhancing alternator performance. DFSS, a design approach leveraging various methodologies, proves particularly effective for making incremental improvements during the redesign phase, with a focus on Critical to Quality parameters (CTQs). The paper concentrates on implementing DFSS concepts and methodologies to elevate the quality and performance of alternators. Computer Fluid Dynamics (CFD) is employed to evaluate temperature and mechanical performance, both crucial CTQs for alternators. The initial step involves identifying the key components contributing to the analyzed parameters. Subsequently, the variables of each component are categorized as critical or non-critical for further examination through a design for experiment approach. Numerical experiments are conducted to attain the optimal solution for the CTQs. The application of this methodology successfully reduces the temperature from the initial design to an optimized one, with a notable decrease of 16 Kelvin in the average temperature of the rotor, while maintaining mechanical losses within an acceptable range. In conclusion, the application of DFSS proves instrumental in improving product quality incrementally, without requiring substantial investments, in a systematic manner.

Keywords: DFSS, CFD, Alternator, Critical to quality.

1 Introduction

Alternators primarily produce heat due to electrical losses in the copper, stator, and rotor cores. Consequently, the design of these electrical machines is constrained by the need to limit these losses or managing the temperature rise. The amount of copper and the fan design are restricted to manage these losses [1]. To remain competitive, the design of electrical machines must focus on maintaining reliably low temperatures. Additionally, sustaining good performance involves minimizing mechanical losses to ensure high efficiency. While there are various approaches to addressing this design challenge, the Design for Six Sigma (DFSS) methodology becomes particularly appealing when optimization is the goal [2].

The Six Sigma methodology is rooted in the PDCA cycle (Plan, Do, Check, Act), a basic approach for process improvement. It evolved into DMAIC (Define, Measure, Analyze, Improve, Control), forming the foundation for Six Sigma analysis [2]. In summary, the Define phase identifies critical quality characteristics. The Measure phase involves experiments to gauge the impact of these attributes. Analysis pinpoints gaps between performance and the actual product or process. Improvements are made to close these gaps, and Control ensures the sustained implementation of enhancements, maintaining control over the process and measurements.

The tools and approaches changes, some works uses Quality Function Deployment to identify the Critical to quality parameters [3]. And the implementation when it comes to product development most of the time is deterministic. Using a modeling technique as shown Below [4]:

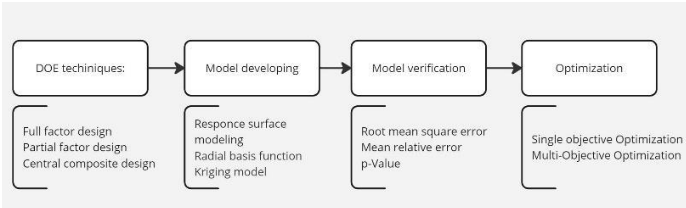


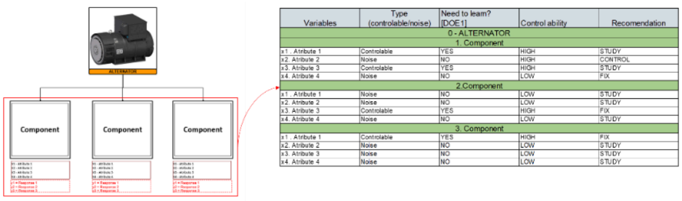
Fig. 1. Surrogate model and optimization [4].

Optimization in this context requires a preliminary design analysis, which may include electromagnetic, thermal, or structural aspects. To validate these designs, theories like electromagnetic theory for electromagnetic design, thermal network theory, or Computational Fluid Dynamics (CFD) analysis for thermal analysis are commonly employed.

This paper aims to assess the benefits of employing Design for Six Sigma (DFSS) tools in optimizing an alternator. The evaluation involved a thermal design approach utilizing CFD for performance assessment and a statistical tool for model construction and statistical analysis.

2 Methodology

For the investigation of the component chain, a product map was developed as the define phase of DMAIC. This is a graphical representation of the product and its related components, serving to assist in the accuracy of selecting attributes that should be manipulated to reproduce events determining the product's thermal-mechanical performance. As shown, this map essentially consists of: the objective or response of the components (Ys), product components affecting the final objective (components), and variables influencing the function of each component (Xs). The product map and decision matrix will be simplified.



Variables	Type (controlable/noise)	Need to learn? [DOE1]	Control ability	Recomendation
0 - ALTERNATOR				
1. Component				
x1 . Atribute 1	Controlable	YES	HIGH	STUDY
x2. Atribute 2	Noise	NO	HIGH	CONTROL
x3. Atribute 3	Controlable	YES	HIGH	STUDY
x4. Atribute 4	Noise	NO	LOW	FIX
2.Component				
x1 . Atribute 1	Noise	NO	LOW	STUDY
x2. Atribute 2	Noise	NO	LOW	STUDY
x3. Atribute 3	Controlable	YES	HIGH	FIX
x4. Atribute 4	Noise	NO	LOW	STUDY
3. Component				
x1 . Atribute 1	Controlable	YES	HIGH	FIX
x2. Atribute 2	Noise	NO	LOW	STUDY
x3. Atribute 3	Noise	NO	LOW	STUDY
x4. Atribute 4	Noise	NO	LOW	STUDY

Fig. 2. Product Map and decision matrix.

Upon finishing the product map, a decision matrix was established, comprising attributes, with the objective of ranking them by criticality. The purpose was to examine variables that could be controlled or studied and identify those that might introduce noise affecting the measurement.

To select the attributes, the following characteristics are necessary: The attribute is controllable, and there is an initial hypothesis that it directly impacts the product's main outcome (y). Attributes considered as noise or with low controllability are either fixed or monitored. Therefore, initially, four attributes were selected for evaluating whether the initial hypotheses were correct.

Than to the measure phase the examination occurred in the conceptual phase of the product, primarily in a virtual setting. Utilizing a finite volume software within this virtual environment, we manipulated variables to simulate events under controlled conditions, creating scenarios capable of replicating failure occurrences.

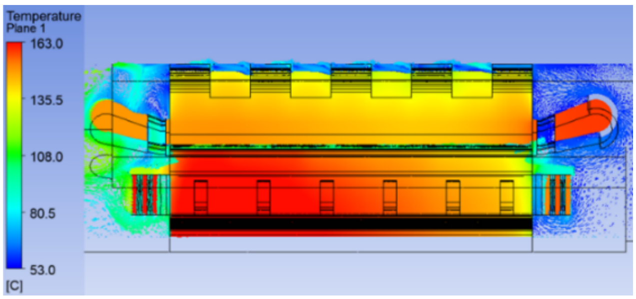


Fig. 3. Simulated failure.

An experimental design was implemented for virtual simulations and subsequent data analysis. Two Design of Experiments (DOEs) were executed. The first, a full factorial with 4 parameters, generated 16 experiments focusing on two responses: temperature increase in the stator and temperature increase in the rotor. The second, a fractional factorial with 6 parameters, resulted in 32 experiments addressing three responses: temperature increase in the rotor, temperature increase in the stator, and mechanical losses. The addition of mechanical losses aimed to evaluate the advantages of using curved-blade fans. Figure 3 illustrates an example of the sampling tree for the second DOE. The decision to conduct two DOEs sequentially was driven by the goal of optimizing mechanical losses.

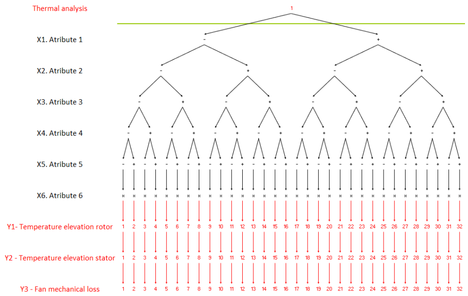


Fig. 4. Sample tree for the second DOE.

To better understand these parameters, some design characteristic is needed, the stator core has axial holes that can guide air through it, and the rotor core has a axial holes with fins, that we can adjust to increase the heat exchange area of the rotor.

These attributes can be categorized as follows: restrictions on air flow to guide it as needed to the rotor or stator, and dimensions and characteristics of the fan and heat exchange area of the rotor.

Using the sampling tree, we gathered data from numerical simulations with modifications. Next, we analyzed the data using a statistical software. During this phase, we conducted a graphical analysis to evaluate the data's consistency. The goal was to identify any special causes that might distort the statistical quality of the analysis or to validate if the parameters generated the necessary variations. Essentially, we aimed to confirm whether the chosen factors were suitable for assessing the response. An illustrative example is provided with the graphical analysis conducted in DOE 2 for the three responses.

The computational effort to reproduce this experiment required an average of 21 hours and 30 minutes of simulation time for each case. In total, all 32 experiments took 1,720 hours of computer time.

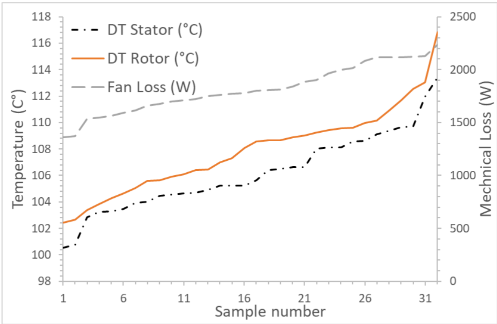


Fig. 5. Graphical analysis

Following the graphical analysis, we conducted a statistical evaluation of the chosen attributes. The attributes considered relevant were those with a p-Value below 0.2. Table 1 displays the results specifically for the rotor temperature increase. It's important to note that this evaluation process was replicated for all response variables.

Table 1. Statistical analysis of second DOE for DT of rotor.

DOE 1		
Term	Estimate	p-Value
X 4	-1.2	0.0021
X 2	2.32	0.0052
X 2 × X3	-0.048	0.1132
X3	-0.042	0.1410

DOE 2		
Term	Estimate	p-Value
X 4	-1.9375	<.0001
X 2	-1.5	<.0001
X 1	1.4375	<.0001
X 2 × X 4	0.6875	0.0236
X 1 × X 2 × X 6	-0.625	00376
X 2 × X 6	-0.5625	0.0588
X 5	-0.5	0.0902
X 1 × X 4	-0.5	0.1350
X 6	-0.435	0.1969
X 1 × X 3	0.375	0.1969

Than a response surface model was used to build the model from the most relevant statistical attribute. For evaluating the model, was used the R square, and mean square root error. For both DOE's the evaluation done gave good results having one Degree of expected error, and 50 Watt of mechanical loss error, corresponding to less than 1% of relative error on temperature and 5% of mechanical loss relative error.

Table 2. Summary of fit of DOEs.

DOE 1		
Response	R-square	Root Mean Square error
DT rotor	0.92	1.4°C
DT stator	0.93	1.2°C

DOE 2		
Response	R-square	Root Mean Square error
DT rotor	0.95	1.0°C
DT stator	0.96	0.9°C

Fan loss	0.98	49.21 W

After that an optimization was done, in this case the stator on average had a higher clearance on temperature, so it was not set as an objective, so only temperature on rotor, and mechanical losses of the fan was minimized. The statistical software uses constrained Newton's method for continuous factors and that is the case [5].

3 Results

In this section, we present the results of the applied optimization validated on a finite volume software and discuss the associated gains. Following the initial methodology, a re-simulation was conducted to assess the optimization results.

After the first Design of Experiments (DOE), the temperature elevation was reduced to 126 K on the rotor and 90 K on the stator, a notable improvement compared to the initial values of 150 K on the rotor and 110 K on the stator before optimization. Since the first DOE did not achieve the set goal, a second one was performed, starting with 116 K on the rotor and 110 K on the stator. Mechanical losses were incorporated into the response, and the fan geometry was optimized to minimize these losses. After optimization, the rotor temperature dropped to 105 K, while the stator temperature remained at 110 K. This temperature was maintained by adjusting parameters to restrict airflow through the stator, increasing airflow through the rotor and air gap, and reduce airflow through the axial holes of the stator. the optimization prioritized the rotor, resulting in the desired temperature improvement, improving the fan geometry the mechanical losses started at 2.3 KW decreased to 1.7 KW.

After the optimization we re-designed the project to maintain 10 K of separation margin for the temperature, this improved 0.3% of efficiency.

4 Conclusion

This paper aims to show the application of a DFSS methodology applied on an alternator. It was successful on generating the response surface model, with good statistical results, and the optimization done achieved a good improvement compared to the original design.

The application of DFSS tools, particularly finite volume software on a conceptual phase, for simulation and optimization, has yielded substantial gains in the performance of the analyzed system. Notably, the optimization process resulted in a significant reduction of 16 K in temperature elevation and a decrease of 600 Watts in power consumption. These gains not only underscore the potential of DFSS in enhancing system efficiency but also highlight its practical applicability in achieving tangible and impactful improvements.

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