



Turbine Blade Optimization Using Response Surface Optimization Method With Multi-Objective Genetic Algorithm In Ansys Designxplorer

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Abstract: In the context of steam turbines, creep becomes a critical concern for components operating under high temperatures and stress. The turbine blades operate in challenging conditions, enduring high temperatures, mechanical stresses, and repetitive loads. The main goal is to decrease the static and thermal stresses of reaction turbine blades, achieved by reducing important factors such as total deformation, equivalent stress, and total heat flux. Static and thermal analyses are conducted on three distinct materials: chrome steel, Hastelloy, and Inconel 600. Response surface optimization, combining Kriging as a response surface model and a multi-objective genetic algorithm (MOGA), efficiently explores the design space. Kriging provides a smooth approximation of complex system behavior, while MOGA identifies Pareto-optimal solutions for multiple objectives. The findings reveal significant improvements in optimized parameters, indicating a decrease of 22.15% in the maximum value of total deformation, 16.88% in the maximum value of equivalent stress, and 5.87% in the total heat flux when compared to the original values. Notably, Inconel 600 emerges as the material that has less stress and heat flux compared to chrome steel and Hastelloy.

Index Terms - Steam turbine blade, Optimization, Response surface, Genetic Algorithm, Chrome steel, Hastelloy, Inconel 600.

1 INTRODUCTION

The design of steam turbine blades is essential to the turbine's performance. The enhanced blade design increases the blade's safety and lessens stress and strain [1, 2]. Heidari et al. [1] additionally identified that the blade bases experience a higher level of stress and strain in contrast to the blade tips. It is preferable to use thicker, shorter blades to lessen strain and stress [1]. The efficiency of the steam turbine power plant system can be increased by optimizing the design parameters of the final stage low-pressure turbine blade. To increase efficiency, more investigation into the low-pressure turbine blade's material qualities is required [3].

The combination of response surface optimization and the Mult Objective Genetic Algorithm (MOGA) represents the most efficacious approach for achieving optimal design solutions while simultaneously minimizing mass and maximum stress [4]. As reported by Jian Zhang et al. [4], they successfully established a response surface model using the MOGA optimization algorithm, resulting in a reduction of 9.43% in mass and a decrease of 5.3% in maximum stress. Koji Shimoyama et al. [5] also concur that the utilization of the Kriging response surface model in conjunction with the Genetic Algorithm (GA) offers the most effective means for global and efficient optimization. The study conducted by Koji Shimoyama et al. [5] involved a thorough optimization process that aimed to optimize the design of a steam turbine stator blade. As a result, they were able to collect a multitude of blade design alternatives that exhibit reduced pressure loss. The

authors of the study specifically concentrated on the selection of blade curves as design variables for the optimization of the steam turbine stator blade design. Furthermore, a separate investigation carried out by Chan et al. [6] delved into the utilization of blade arc as a design parameter, resulting in a significant improvement (up to 33%) in the average power coefficient over time. In their study on thermal analysis of steam turbine blades, Pramod Kale et al. [7] indicate that the minimal fluctuations in heat flux and convection could potentially lead to the degradation of blade longevity over an extended duration. Certain turbine blade portions experience damage due to elevated stress-strain and temperature, which increases the likelihood of failure in such places. In the end, these malfunctions shorten the blade's toughness and longevity [8].

2 METHODOLOGY

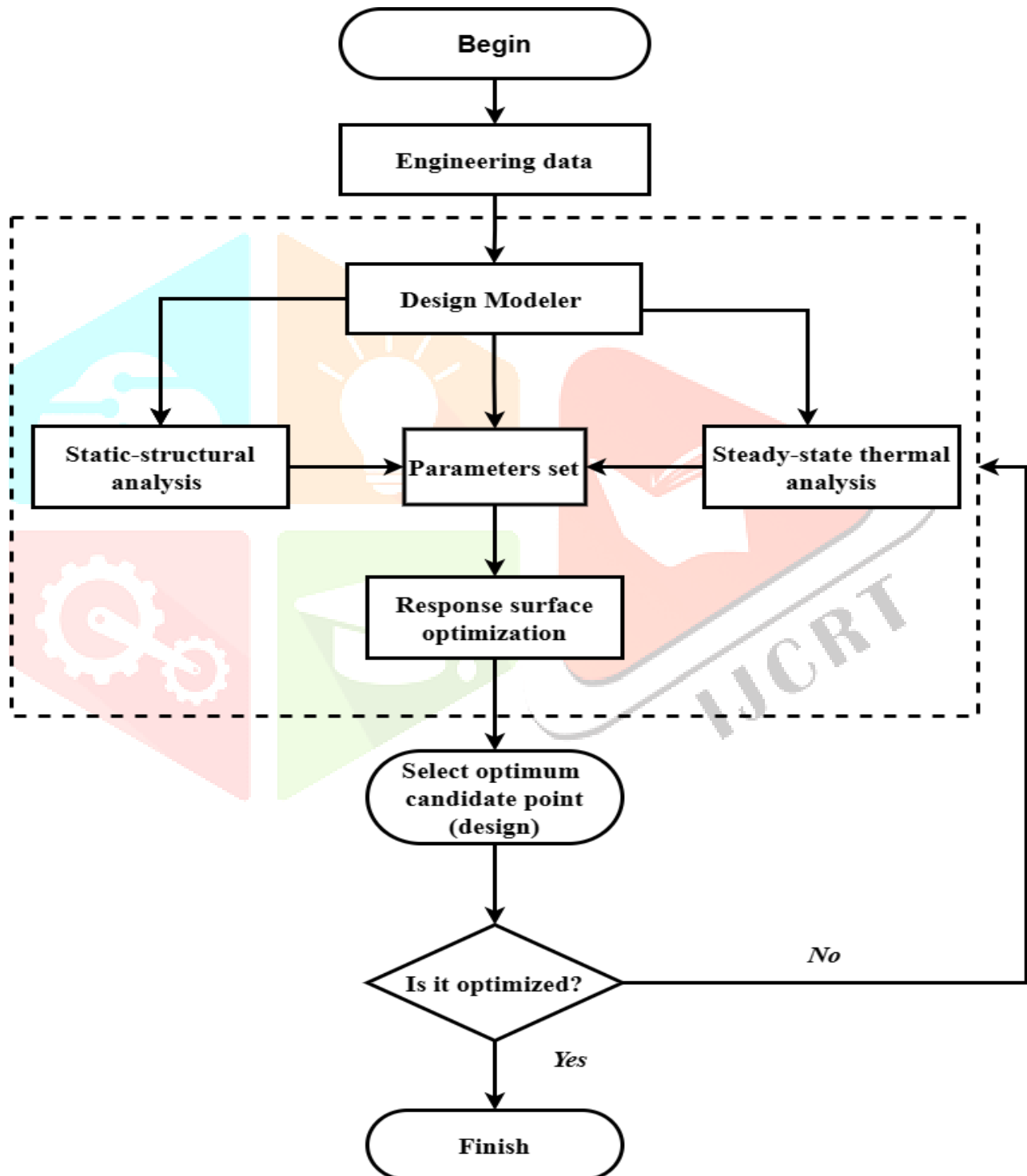


Figure 1: Workflow in ANSYS Workbench

2.3 Steady-state Thermal analysis using FEM

A thermal analysis in a steady state involves the examination of the distribution of temperature within a structure under constant thermal conditions. This analysis is crucial for comprehending how a system attains and sustains thermal equilibrium. By applying steady-state conditions, wherein temperatures no longer vary with time, engineers can assess the thermal behaviour of a component or system in a stable state. The utilization of steady-state thermal analysis empowers engineers to make well-informed decisions concerning the selection of materials, design of heat sinks, and overall strategies for thermal management [11]. The boundary conditions for this study were obtained from the reference[9].

B: Hestelloy
Convection
Time: 1, s
25-02-2024 16:44

A: Blade Temperature: 220, °C
B: Convection: 22, °C, 2.5e-003 W/(mm²·°C)

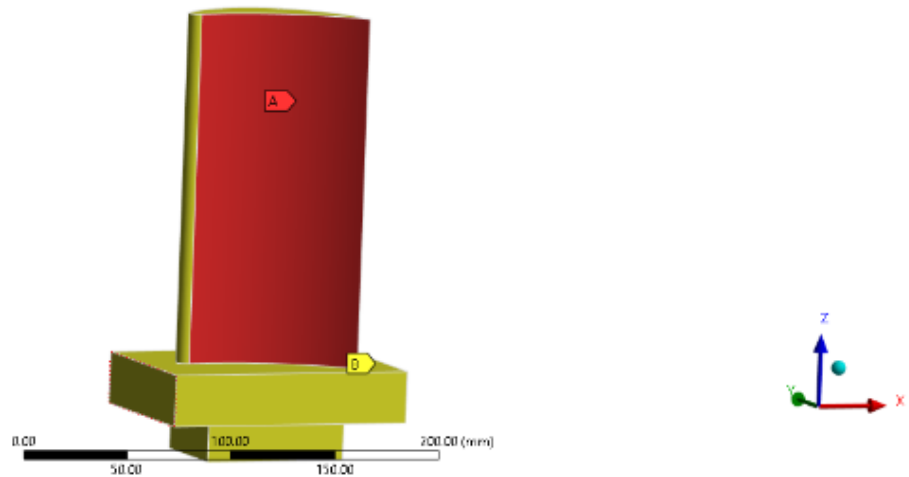


Figure 4: Boundary conditions in Steady-state Thermal analysis

2.4 Response Surface Optimization

The performance of a design is heavily impacted by its shape and size. Designers can employ parametric optimization to assist in achieving the most efficient shape and dimensions for a given structure [12, 13]. Within the realm of parametric optimization, there exist independent variables, referred to as design variables, which can be adjusted in order to enhance the design [12]. For the purposes of this particular investigation, the design variables utilized are the pressure surface circular arc radius, suction surface circular arc radius, and leading-edge radius, all of which are depicted in the accompanying Figure 5. Selecting the blade surface curves (pressure and suction surfaces) as design parameters to achieve an uninterrupted, seamless curve that results in a uniform dispersion of pressure and velocity across the surface of the blade [14].

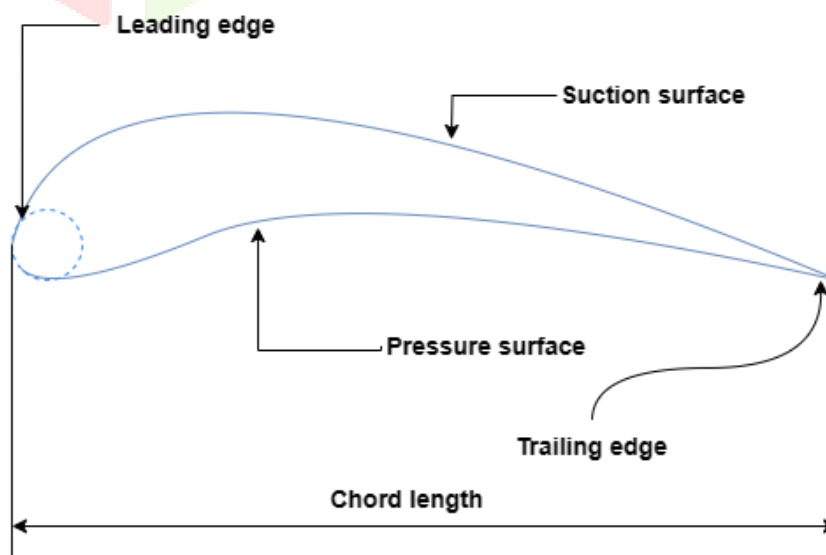


Figure 5: Nomenclature of the Turbine blade cross-section

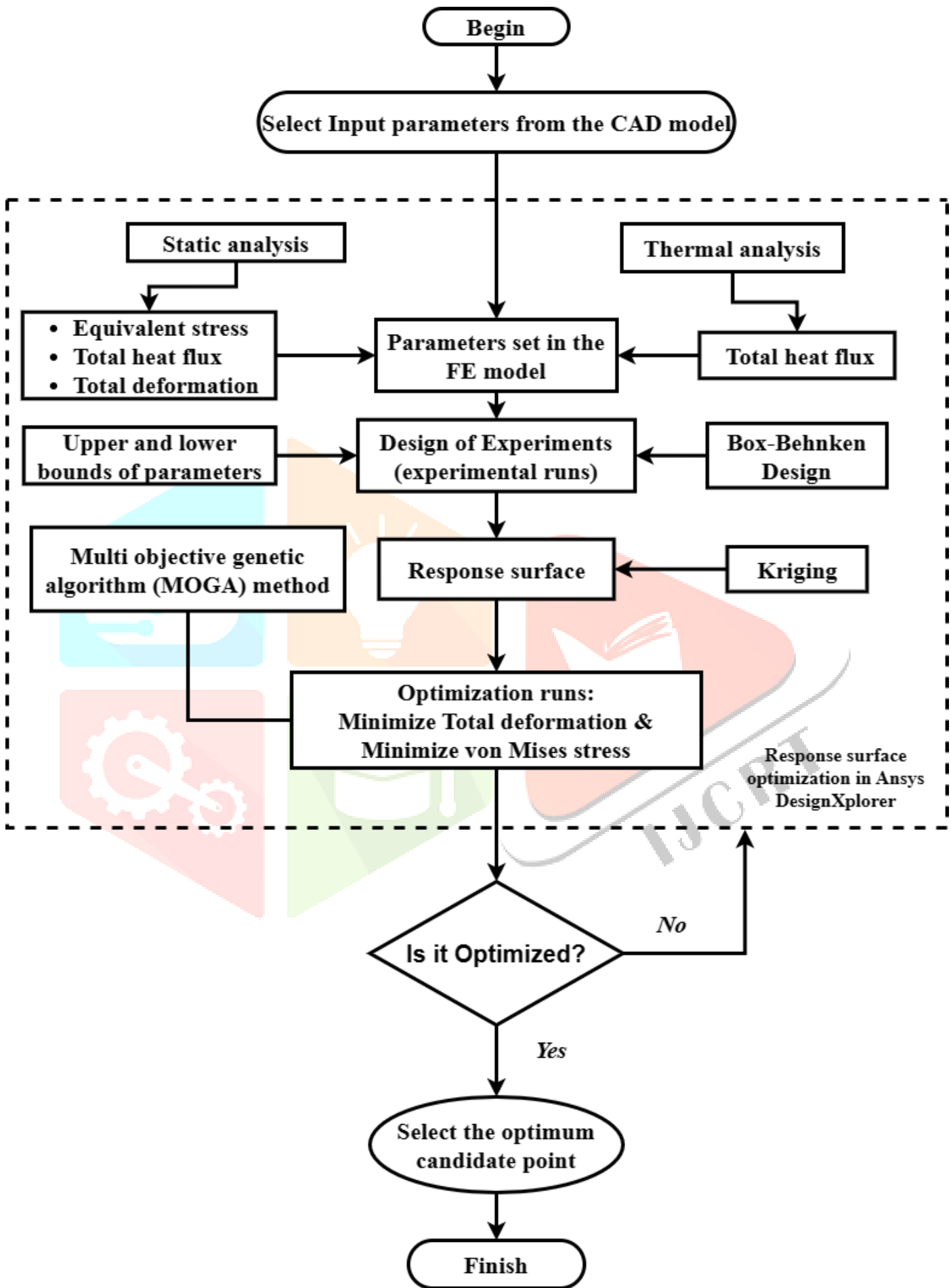


Figure 6: Response surface optimization method in ANSYS DesignXplorer

The technique of response surface optimization is employed to conduct parametric optimization by evaluating the impact of design variables on the objective function [15]. In order to minimize the overall deformation, Equivalent stress, and total heat flux, response surface optimization (RSO) procedures were implemented, as demonstrated in Figure 6. Firstly, the input parameters were chosen to be the pressure surface, suction surface, and leading-edge radiuses, while the output parameters were determined to be the total deformation, equivalent stress, and total heat flux. Subsequently, Ansys DesignXplorer employs the Design of experiments (DOE) with Box-Behnken design which generated twenty-five (25) design points for experimental runs. The upper and lower bounds for input parameters were taken from the research projects [5, 16]. The DOE is a methodology utilized to adjust the simulated response data to align with the experimental data or mathematical equations in the context of design optimization [12, 17].

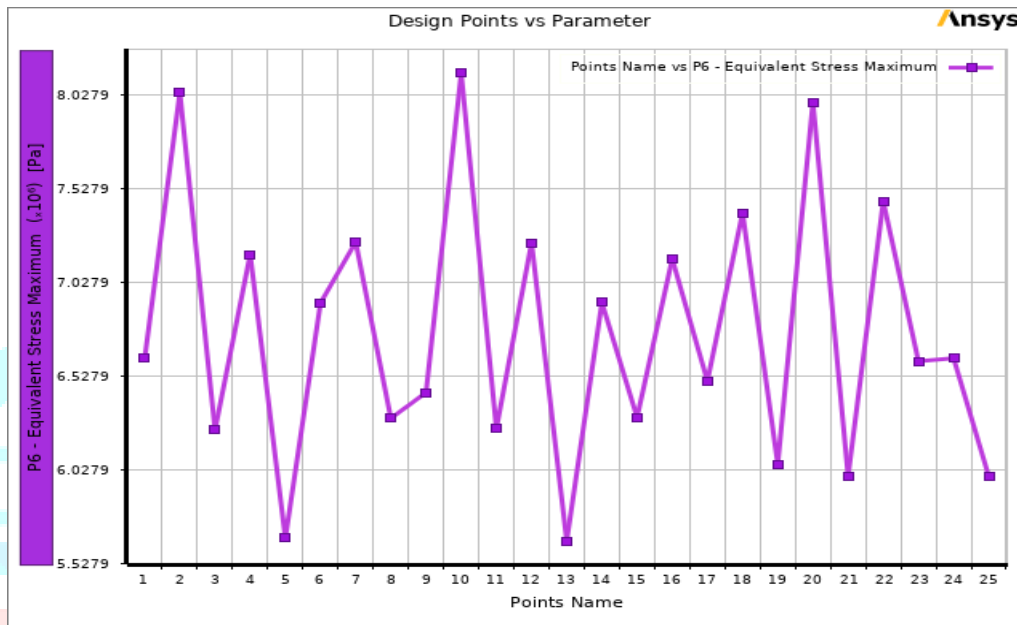


Figure 7: Equivalent stress (maximum) at each design point

In the present investigation, the Kriging technique employed for constructing a response surface model, which is purported to diminish the quantity of simulations necessary for a satisfactory estimation and, thereby, economize computational resources [18]. The validation of the response surface (RS) model can be accomplished by evaluating its fitting performance at specific design points [19]. The ANSYS statistical metrics employ various indicators, including the coefficient of determination (R²), root mean square error (RMSE), relative maximum absolute error (RMAE), and relative average absolute error (RAAE), to assess the quality of the model's fit [20].

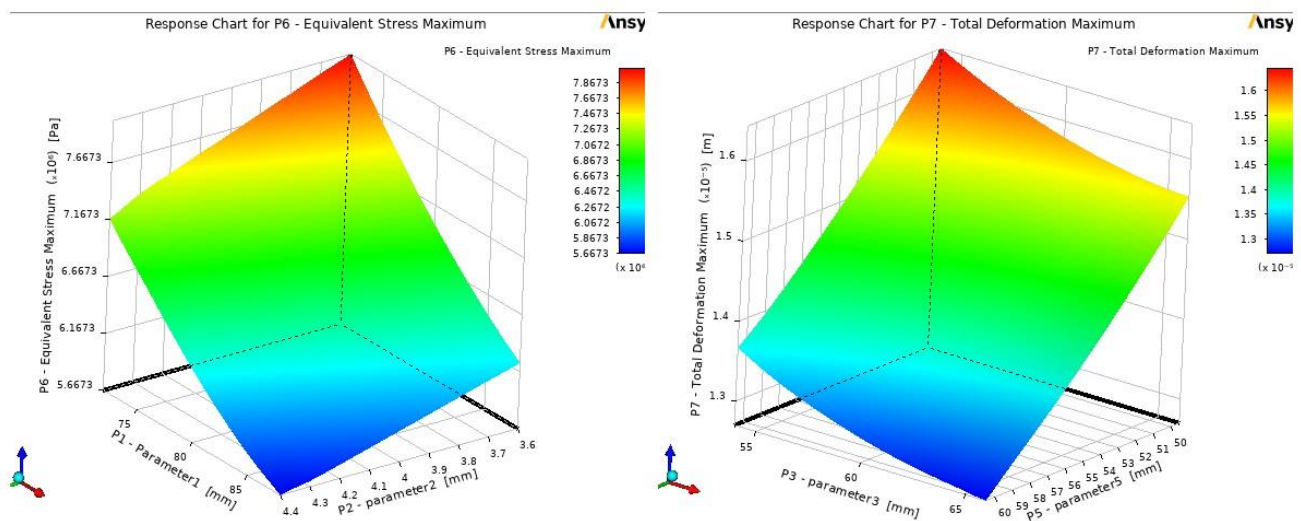


Figure 8: Representation of the 3D response surface for four input parameters.

The objective function for the MOGA in ANSYS Workbench is provided by the response surface optimization (RSO) method. To achieve a comprehensive optimum finding, the multi-objective genetic algorithm (MOGA) utilizes a genetic algorithm that can accommodate multiple objectives and constraints. In addition, MOGA efficiently optimizes numerous design variables by utilizing NSGA-II (Nondominated Sorting Genetic Algorithm II). The interactive approach incorporates a constraint approach with two functions (objective and constraint) in order to identify a single best compromise solution. The genetic algorithm (GA) is widely utilized in structural optimization due to its simplicity and ability to provide accurate optimal solutions with fast convergence speed. Based on the design points and response surface curves, it can be observed that the maximum equivalent stress values are consistently below 6.0228×10^6 Pa, and the total heat flux values are consistently below $0.70002 \text{ W mm}^{-2}$. Therefore, it is determined that the constraints for stress and heat flux should be set at or below 6.0228×10^6 Pa and $0.70002 \text{ W mm}^{-2}$, respectively. In this particular section, the design objective and constraints are established using the multi-objective genetic algorithm (MOGA) in response surface optimization. These objectives and constraints are as follows:

- i. Minimization of Equivalent stress: Minimize P6; $P6 \leq 6.0228 \times 10^6$ Pa
- ii. Minimization of Total heat flux: Minimize P8; $P8 \leq 0.70002 \text{ W mm}^{-2}$

The optimization task initially generates 100 samples and assigns 100 samples per iteration for a total of 20 iterations to obtain three candidate points. The optimization process ultimately converges after 1098 evaluations.

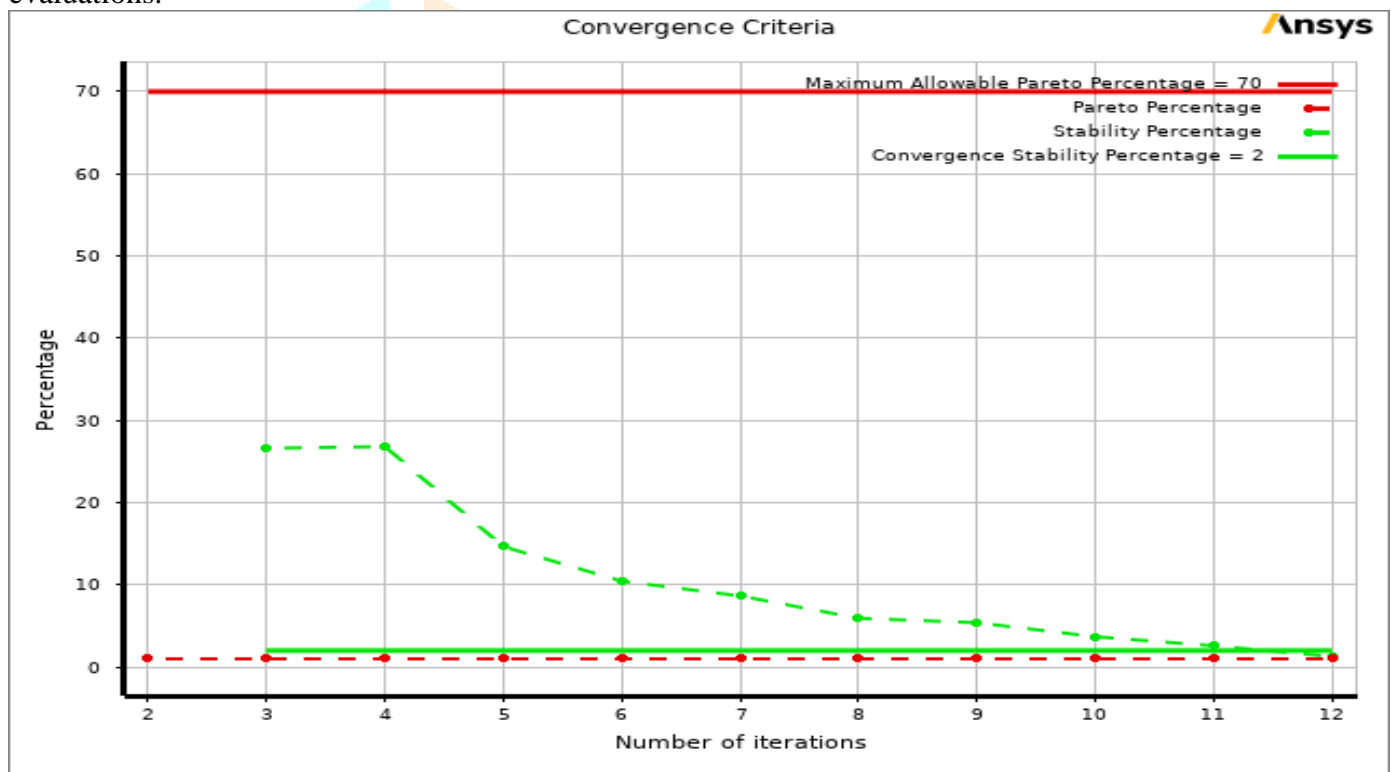


Figure 9: Representation of Convergence of solution after 1098 evaluations

Table 1: Material properties used for ANSYS engineering data

Name	Density	Young's modulus	Poisson ratio	Tensile ultimate strength	Tensile yield strength	Melting point	Thermal conductivity
Chrome steel	7.31 g/cc	200 GPa	0.3	485 MPa	275 MPa	1365 ⁰ C	14.0 W/m K
Hastelloy	8.89 g/cc	205 GPa	0.33	601.2 MPa	275 MPa	1400 ⁰ C	15.0 W/m K
Inconel 600	8.36 g/cc	210 GPa	0.35	570 MPa	340 MPa	1370 ⁰ C	13.6 W/m K

The Engineering Data in ANSYS Workbench serves as a crucial repository for material properties. It allows engineers and analysts to define and manage essential characteristics of materials used in simulations. By

specifying properties like density, Young's modulus, thermal conductivity, and more, it ensures accurate and realistic modelling. Ultimately, this information enables precise simulations, aiding in the design, analysis, and optimization of engineering structures and components.

3 RESULTS AND DISCUSSION

After completing the optimization runs, the three design candidates are determined, as presented in Table 2. Additionally, Table 2 illustrates the optimal output parameters (stress, deformation, and heat flux) of four design variables obtained through the RSO method with the MOGA technique. Consequently, the candidates exhibit a lower stress value along with a reduced heat flux for the four selected parts compared to the original design value. However, the optimal design candidate was meticulously selected in order to simultaneously meet the desired values for stress and heat flux reduction. The maximum total heat flux value of candidate 1 and 2 is higher than the original value. Therefore, candidate point 1 is chosen as the optimal candidate design.

Table 2: Candidate points obtained from response surface optimization

Name	P1 - Parameter 1 (mm)	P2 - parameter 2 (mm)	P3 - parameter 3 (mm)	P5 - parameter 5 (mm)	P6 - Equivalent Stress Maximum (Pa)	P7 - Total Deformation Maximum (m)	P8 - Total Heat Flux Maximum (W mm ⁻²)
Candidate Point 1	87.82	4.39	65.69	60.33	5468780.693	1.11E-05	0.811456114
Candidate Point 2	87.82	4.39	65.74	60.29	5429872.447	1.11E-05	0.811442589
Candidate Point 3	87.82	4.39	65.38	60.30	5502575.366	1.12E-05	0.708805756

3.1 Validation of the design

The findings obtained are in line with the results reported by [9], thereby reinforcing the consistency of our findings with the established research in the field. While our findings deviate from the anticipated outcomes outlined in [9], it is imperative to acknowledge potential factors such as lack of root dimension data and disparities in mesh elements that may contribute to these variations. The comparison between the reference values and our research values are presented in the Table 3.

Table 3: Comparison between experimental values and reference values

Name	Material	Reference values	Experimental values
Shear stress (MPa)	Chrome steel	0.59	0.57
	Hastelloy	0.55	0.55
	Inconel 600	0.53	0.534
Total heat flux (W/mm ²)	Chrome steel	0.74	0.755
	Hastelloy	0.772	0.790
	Inconel 600	0.73	0.731

3.2 Optimized design variables

In our investigation, we conducted optimization on the cross-section of the turbine blade utilizing three distinct materials. The original design values, as presented in Table 4, were compared with the optimized design values. The findings of our analysis demonstrate the intended decrease in the output parameters. The distribution of stress and deformation on the blade can be observed through the Figure 10. Additionally, the **Error! Reference source not found.** allow for the observation of the equivalent stress and heat flux values of the three different materials, aiding in the selection of a suitable material that ensures enhanced durability and lifespan.

Table 4: Comparison between original design values and optimized design values

	Total deformation maximum (m)		Equivalent stress maximum (MPa)		Total heat flux (W/mm ²)	
	Original design values	Optimized design values	Original design values	Optimized design values	Original design values	Optimized design values
Chrome steel	1.4268e-05	1.1114E-05	6.623	5.502	0.755	0.708
Hastelloy	1.3816e-05	1.0744e-05	6.402	5.275	0.771	0.725
Inconel 600	1.3384e-05	1.042e-05	6.202	5.155	0.732	0.689

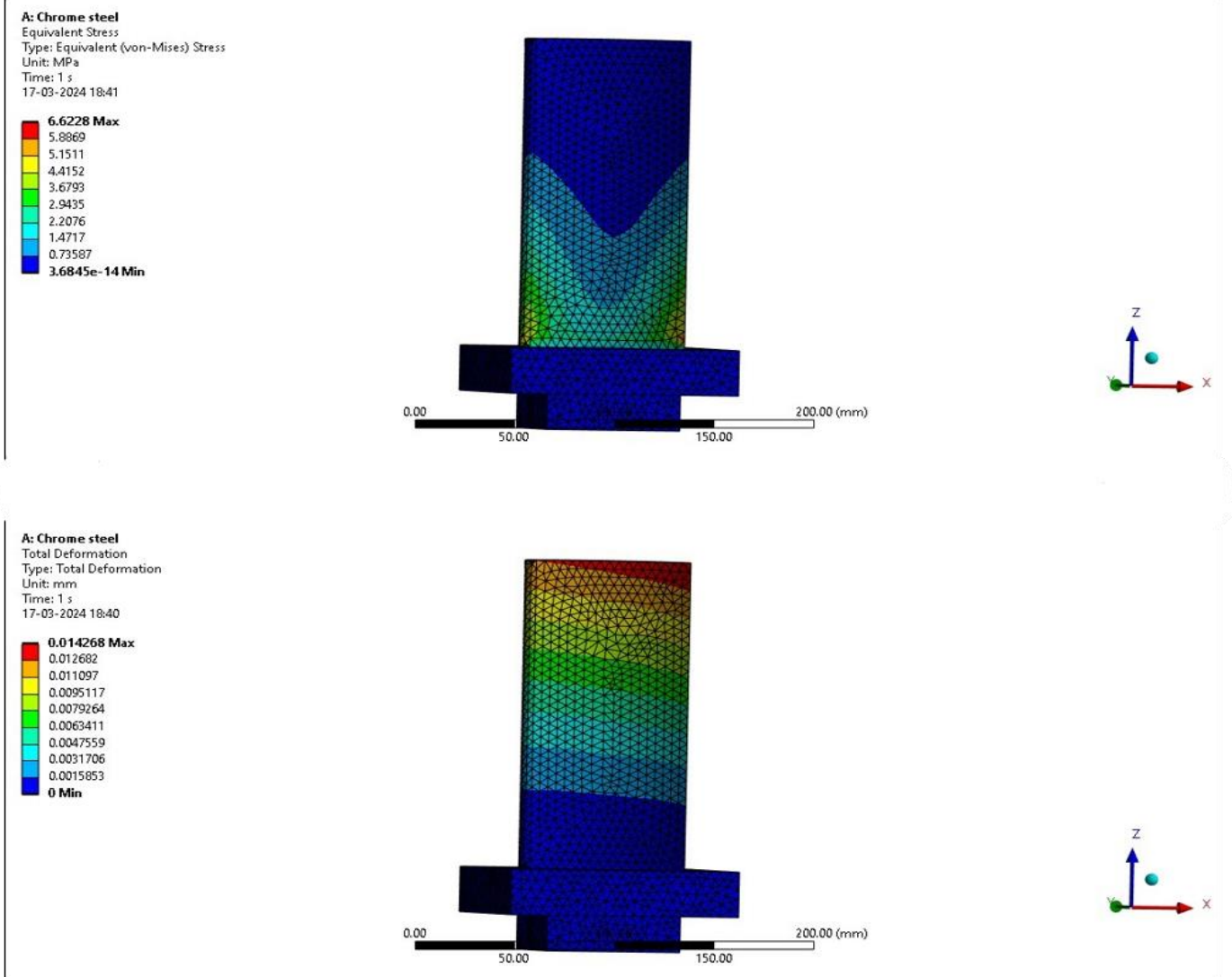


Figure 10: Distribution Equivalent stress maximum and Total deformation maximum on Turbine blade

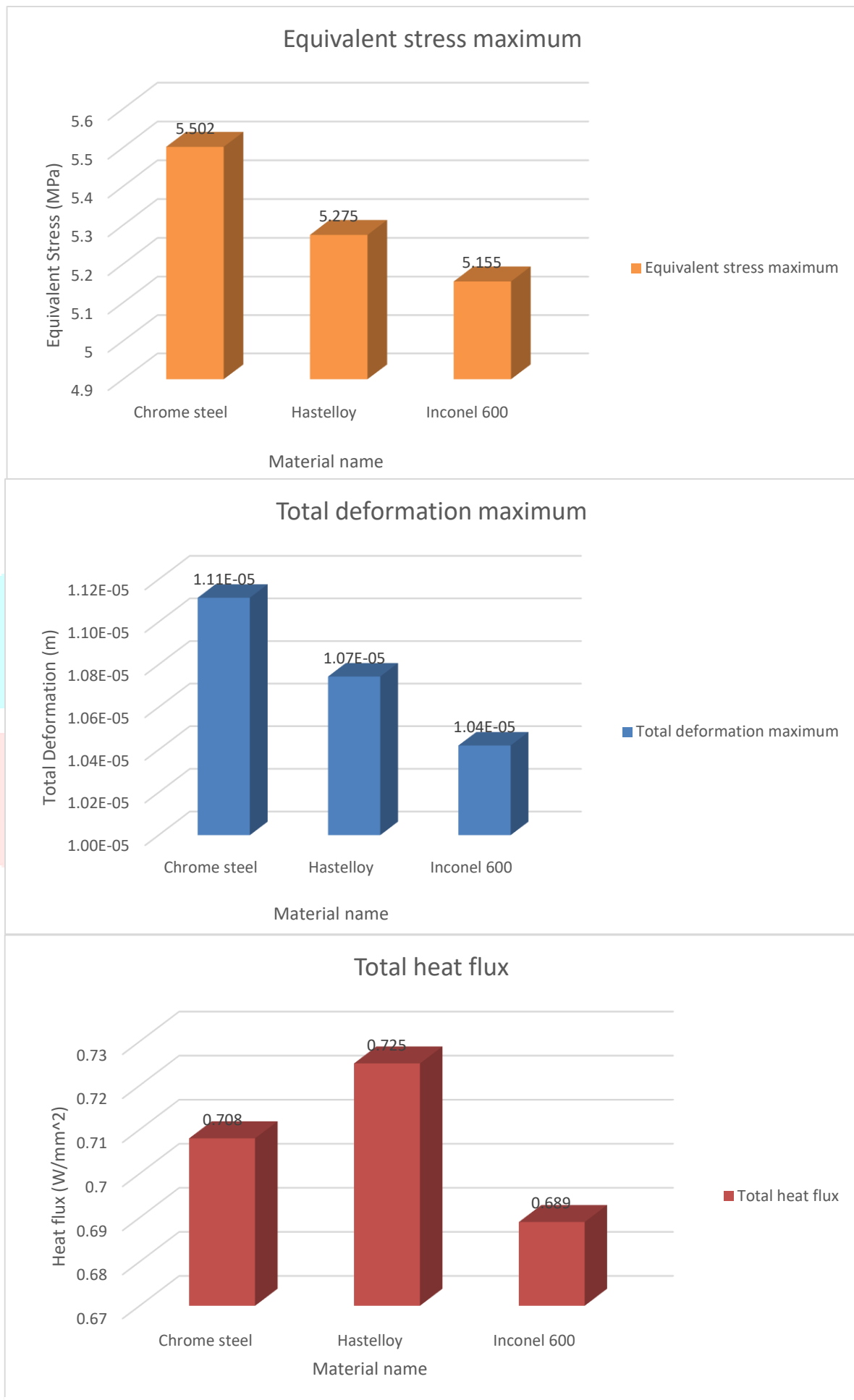


Figure 11: Representation of static and thermal stresses on the three materials

4 CONCLUSION

This investigation enables the examination of a steam turbine blade's static and thermal properties using numerical techniques. Additionally, this study also establishes an enhanced design for the blade through the application of response surface optimization (RSO) method. Furthermore, the analysis and optimization were conducted on three distinct materials in order to gain insights into the more advantageous selection of a material for the steam turbine blade. Therefore, the results obtained from the analysis of the static properties, thermal properties, and optimization can be concisely summarized as follows:

- i. In the original design, the total deformation maximum occurred at the trailing edge of the blade. Moreover, the Equivalent stress maximum was closer to the root, at the leading and trailing edges of the blade.
- ii. After optimization of the blade shape, the total deformation maximum and the equivalent stress maximum are reduced, which facilitates the durability and longevity of the turbine blade.
- iii. The final findings provided insight regarding how the material behaved under both static and thermal conditions. Among the three materials that we analysed; Inconel 600 performed the best overall.

Overall, it can be concluded that the response surface optimization can minimize static and thermal stresses. Additionally, we determined that Inconel 600, with its low stress and heat flux, is the most ideal material for longevity and durability when compared to Hastelloy and Chrome steel.

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