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# Jant Tasarım Parametrizasyonu ve Parametrizasyonun Optimizasyona Etkisi

# Wheel Rim Design Parametrization and Its Effect on Optimization

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**Abstract**

The wheel rims are an essential part of the car. The wheels carry the load of the car and its passengers. To carry this load and prevent loss of life in a possible accident, it is necessary and crucial for the wheel to be strong. Additionally, a wheel rim should also be aesthetically pleasing for customers. First of all, design specifications of the rim model are determined. A user study is then conducted, in which each participants create a detailed wheel rim model from a given conceptual model and parametrizes it using design parameters such as spoke number/shape and hub thickness. In a generative design step, participants then generate 20 distinct models using design parameters. The finite element method (FEM) under stationary car forces is then established to find the stress and displacement distribution. The models are next ranked according to the aesthetic scores (given by a volunteer having mechanical design experience) and stress/displacement values (obtained from the FEM analysis). After such sorting, distinct and aesthetic models were obtained using a genetic algorithm (GA). The participant(s) then select the best model(s) among the new models obtained from GA. Two different wheel rim models obtained during the user study are utilized in a GA-based optimization process. According to the optimization results, parametrization highly affects the aesthetic and mechanical performance of the obtained designs.

***Keywords:*** *Design Parametrization, Finite Element Method, Genetic Algorithm, Design Optimization*

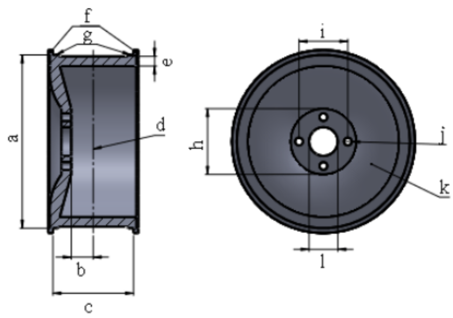
**Öz**

Jantlar arabanın önemli bir parçasıdır ve tekerlekler ile birlikte arabanın ve yolcularının yükünü taşırlar. Bu yükü taşımak ve olası bir kazada can kaybını önlemek için jantın sağlam olması gerekli ve önemlidir. Diğer taraftan estetik açıdan da göze hitap etmelidir. Bu çalışmada öncelikle araba jantının sınır koşulları belirlenmiştir. Bu sınırlar içerisinde farklı jant tasarımları elde edebilmek için bir kullanıcı çalışması gerçekleştirilmiştir. Kullanıcı çalışmasındaki her bir katılımcı bir model tasarlamış ve parametrize etmiştir. Jant telinin sayısı, şekli ve göbek kalınlığı gibi tasarım parametreleri kullanıcı tarafından belirtilmiştir. Sonrasında kullanıcılardan bu parametreler kullanarak jeneratif tasarım yoluyla birbirinden farklı 20 tane jant modeli elde etmeleri istenmiştir. Durağan arabanın etki ettiği kuvvetler altında (parametrik olarak elde edilen) jantlar modellerinin gerilme ve yer değiştirme dağılımını bulmak için sonlu elemanlar yöntemi (FEM) kullanılmıştır. FEM kullanırken, ağ elemanlarının sayısına ve analiz edilen jantın yönüne dikkat edilmiştir. Jantlar tasarım kabiliyetine sahip gönüllü birisinin verdiği estetik puanlara ve FEM testlerinden elde edilen stres ve yer değiştirme değerlerine göre sıralanmıştır. Sıralamanın ardından genetik algoritma (GA) kullanılarak farklı ve estetik modeller elde edilip, kullanıcıya sunulmuş ve seçimi ile en uygun jant tasarım(lar)ı elde edilmiştir. Bu optimizasyon çalışması parametrizasyonu yapılmış iki farklı jant modeli kullanılarak yapılmıştır. Sonuçlar incelendiğinde parametrizasyon optimizasyon sonrası elde edilen modellerin performanslarını etkilemektedir.

***Anahtar Kelimeler:*** *Tasarım Parametrizasyonu, Sonlu Elemanlar Yöntemi, Genetik Algoritma, Tasarım Optimizasyonu*

## 1. Introduction

Technological developments provide a more reliable and comfortable life for people. Developments in automobile industry have also revealed some innovations in terms of the developments people follow. The primary priority of the changes in car industry is safety. Wheels are basic elements that ensure the performance and safety of cars. Wheel rims are one of the components that carry the entire burden of the car, and therefore, they should have good mechanical properties. Although wheel rim models having improved mechanical performance are preferable, they should also have good looking from a customer's point of view. However, it may be hard to obtain a design with both good aesthetic and mechanical performance as they are potentially conflicting each other. In this work, we aim at optimizing both of these criteria. In a design parametrization step (via a user study), a model is developed by a participant and then parametrized by determining its important features (i.e., design parameters). New models can then be obtained by changing values of these parameters. One can obtain plenty amount of designs in this step, however, only some of them will potentially be suitable according to the user-defined criteria. To evaluate the obtained designs, their mechanical performance (computed using finite element method - FEM) and aesthetic scoring (by a volunteer having mechanical design experience) are taken into account.




| | | | |
|---|---|---|---|
| a | Rim diameter | g | Bead seats |
| b | Offset | h | Center hub diameter |
| c | Rim width | i | Pitch circle diameter |
| d | Center line | j | Bolt diameter |
| e | Thickness | k | Spoke |
| f | Flange | l | Center bore diameter |

**Figure 1.** Design parameters for a wheel rim.

In a user study, an outline of a wheel rim design (Figure 1) with its design specifications (Table 1) is given to users, who then conduct detailed design according to those specifications. Note here that different users create different designs starting from the base design in Figure 1. They add details on the given model by drawing rim curves and then determine important dimensions in the model. We call all this process as *design parametrization*. After the user study, we focused only on the two parametrized models to further investigate the effect of the parametrization on the optimized models based on the mechanical and aesthetic performance.

**Table 1.** Wheel rim design specifications.

| Feature | Dimension |
|---|---|
| Diameter | 355 mm |
| Width | 165 mm |
| Offset | 45 mm |
| Thickness | 20 mm |
| Bead seats | 10 mm |
| Center hub diameter | 134.74 mm |
| Center bore diameter | 59 mm |
| Flange height | 10 mm |
| Flange width | 10 mm |
| Bolt diameter | 16 mm |
| Pitch circle diameter | 100 mm |

Abaqus[1] program was used for the FEM analysis. Material selection was chosen in accordance with the literature [1-3]. Recall that the prior objective of the study is to investigate the effect of the design parametrization on the optimized models. The material properties of the wheel rim are also given in Table 2. These properties are taken by 356.0-T6 Permanent Mold cast (SS) aluminum alloy in Solidworks 2017[2] .

Fig. 2 shows the wheel rim optimization pipeline. Wheel rim design specifications are given to participants in a design parametrization study (Figure 2.a). The wheel rim models are parametrized in different ways by the participants. Figure 2.b illustrates models obtained after a design parametrization step. Various loads are applied to the wheels when the cars are in motion and standing.

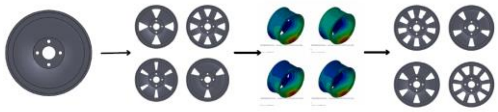
**Table 2.** Material properties for the wheel rim.

| Aluminum 356.0-T6 Permanent Mold cast (SS) Mechanical Properties | |
|---|---|
| Density | 2680 kg/m$^3$ |
| Elastic Modulus | 72400 MPa |
| Poisson's Ratio | 0.33 |
| Yield Strength | 152 MPa |
| Tensile Strength | 228 MPa |

[1] Dassault Systemes SIMULIA Abaqus CAE 2019

[2] Dassault Systemes SOLIDWORKS 2017 SP04

The wheels are highly affected by these forces and should be tested for the mechanical properties of the wheel models. For its applicability, the forces affecting the stationary car are taken as a basis. As a result of the FEM analysis, the stress distribution and displacement of the forces applied by the stationary car can be seen on the rims (Figure 2.c). Accordingly, some wheel models with the lowest stress value and the lowest displacement value are selected as parents for the GA. In addition to these features, a ranking is made with relative aesthetic issues. Here, several wheel models having the highest values have been selected as parent items. The new generation from these parents is subjected to the same GA process (Figure 2.d).



(a) (b) (c) (d)

**Figure 2.** (a) A model with design specifications are given. (b) The model is developed by adding some details to the given model and several variations of the model are obtained. (c) FEM model is obtained and performance of the models are validated. (d) New models are finally obtained using a genetic algorithm while taking mechanical performance and aesthetic criterion into account.

In summary, goals of the present work are listed as follows:

- To perform a user study, in which participants parametrize a given model in their own way.
- Multi-objective optimization via genetic algorithm for the wheel rim models considering both mechanical and aesthetic performance.
- To evaluate the effect of the design parametrization on the optimized wheel rim models.

## 2. Related Works

There are many works in literature about wheel rim design. Here, we only mention a few of them. Generative design techniques are also mentioned. Cosseron et al.[4] made a wheel optimal parametrization study similar to this study. Gondhali et al.[5] used a reverse engineering methodology to determine the size of the current Maruti Eeco automobile rim. While Cosseron was working on a single design, in this study, two different parametrizations were used to increase its accuracy and reliability. Zimmermann et al. [6] designed a wheel rim using topology optimization. They analyzed, simulated, and optimized his design both aesthetically and mechanically in their generative shape design study. Due to the increasing importance of external appearance in today's customer preferences, aesthetics in addition to mechanical properties were also analyzed and optimized in our study. While the analysis was performed both statically and dynamically in the studies of Sureddi et al. [7] and Gondhali et al. [5], only static analysis was performed in this study.

In recent decades, generative design, an algorithm-driven design method that empowers designers to generate acceptable ideas under given design objectives and limitations[8], has grown in popularity and can be used to explore design space. In order to produce desired designs under certain design objectives and restrictions [8,9]. Krish [10] suggested a generative method for providing design options based on an exhaustive search. In [11], the authors developed a tool that generates side silhouettes of sedan automobiles, which were then employed in a generative GD system to forecast drag coefficients of the car silhouette [12]. After uniformly sampling the offsprings, Gunpinar and Khan [13] developed a new offspring selection based on a genetic algorithm. Kazi et al. [14] created a sketching system to aid in the conceptualization of generative design. In [15], a motorcycle or particle tracking algorithm was used to generate unique geometric models based on the authors' explicit design requirements. The Teaching-Learning-Based Optimization approach was used as a sampling method for limited and unconstrained design spaces [16]. Sousa and Xavier [17] proposed a symmetric-based generative system for the digital production of geometric structures (such as rhombicuboctahedrons and triangular prisms). After creating the contour of a given model, Dogan et al. [18] created a tool that made it easier to use primitives and affinities as restrictions. In [19], user perceptions of design uniqueness are incorporated into a generative sampling process. Adam et al. [20] proposed a biologically inspired algorithm for generative leaf venation pattern development. Shea et al. [21] and Turrin et al. [22] also created performance-driven GD systems to achieve lightweight architectural structures. In [23], a design system named "GenYacht" was presented, which created optimal yacht hull designs [24] based on user-specified parameters (s). GD approaches have also been offered by many academics for creating site layouts [25], as well as energy efficient and environmentally friendly building designs [26]. Finally, Tasmektepligil and Gunpinar [27] provided a generative learning method to extract design constraints of a B-spline surface model and demonstrated it using car extroir surfaces. In the literature, generative design efforts (such as [12,15,16,23]) primarily used manually defined design limitations prior to the design exploration process, potentially pruning away the good designs already present in the design space.

Design space contains both feasible and impossible designs. If there is a mathematical form that represents design limitations, this filtering can be done quickly. In a generative design process, these shapes can be integrated into generative design algorithms to explore only viable concepts. By trial and error in a design change stage, Gunpinar & Gunpinar[16] learned design constraints. However, learning design constraints in this manner is a time-consuming and inaccurate process, as there may be complicated (i.e., high-order) relationships between design parameters. In the design space, there may be more impossible designs than plausible ones which are needed to be eliminated [12]. As a result, in this study, a generative designed model is developed by collaborating with participants (i.e., aesthetics sorting and design parameter selection) and Finite Element Analysis (i.e., for Stress, Displacement) to extract design constraints for a CAD model.

The work in this paper does not only involve a wheel rim optimization study (like previous works), but also demonstrates the effect of its parametrization on the wheel rim performance.

## 3. Wheel Rim Parametrization and Optimization Study

### 3.1. Design Parametrization and Generative Design

104 people, who are able to use a Computer-Aided Design (CAD) tool, are participated in a user study. Design specifications (Figure 1 and Table 1) and instructions are given to the participants (Figure 3.a). Participants created their own designs from this base model by drawing curves on the model and specified important dimensions for them, which were considered as *design parameters*. Whole this step is considered as *design parametrization* step. By changing values for the design parameters, new models can be obtained (See Figure 3.b).

(a) (b)

**Figure 3.** (a) Initial model for user study, (b) designs obtained from several participants participating the user study.

The participants of the user study are asked to first add details on the base model as they like. After that, design parameters, which are considered as important features of the model, are specified. They are then requested to create 20 distinct designs by changing values of the design parameters (See Figures 5 and 6). All these steps have been achieved using SOLIDWORKS CAD tool.

At the end of the user study, 104 distinct parametrized wheel rim models have been obtained. Two of them are selected by the authors to proceed for the optimization step, which is conducted by the authors as well.

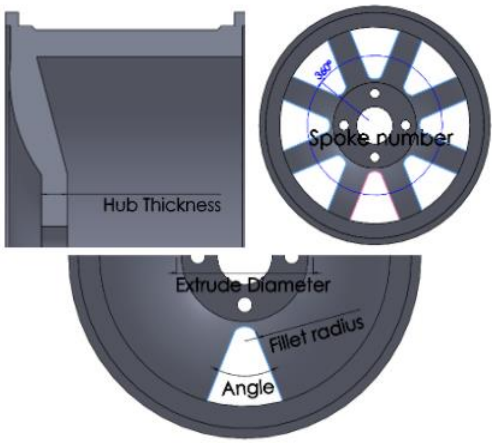



**Figure 4.** Design parameters of P-design 1.

The variables for the first model shown in Figure 1 and Table 1, which are fixed. The first wheel rim (P-design 1) is parametrized as shown in Figure 4 [28]. Design variables/parameters are chosen as hub thickness, extrude diameter, angle, fillet radius and number of spokes. Via a generative design process, the participant generates 20 distinct designs in Figure 5 from the base model in Figure 4.

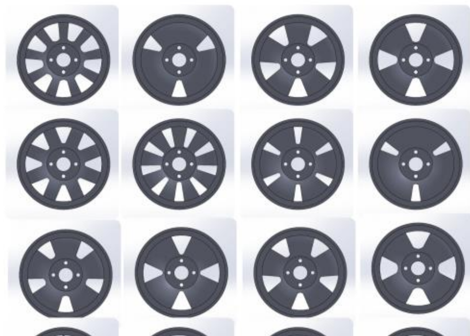


**Figure 5.** 20 new models generated from P-design 1.

Another participant parametrized the wheel rim model as shown in Figure 6 (P-design 2). The design parameters are chosen as spoke top width, spoke bottom width, spoke major radius and minor radius. Figure 7 involves 20 different models obtained from the base model in Figure 6.


**Figure 6.** Design parameters of P-design 2.

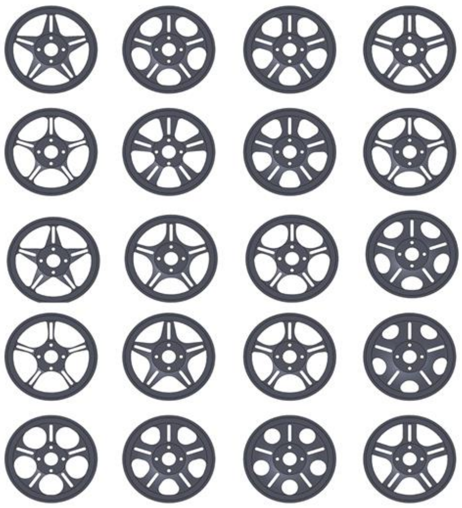


**Figure 7.** 20 new models generated from P-design 2.

### 3.2. Finite Element Method Generation

CAD model is converted to a mesh model as illustrated in Figure 8. Boundary and loading conditions are inspired by a study that examined the pressure and radial load on the wheel by Stearns et al. [1], where the car is assumed to be stationary. The boundary conditions were fixed at the bolt circles. There are three types of load on rim for a stationary car. These are air pressure, the load on the circumference of the rim flange due to air pressure and radial load on tire contact location because of car weight (Figure 9).

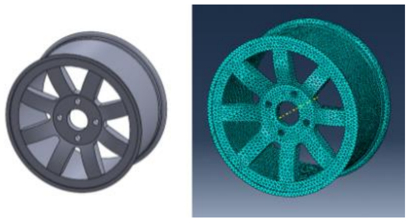
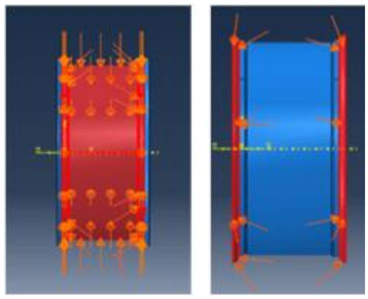
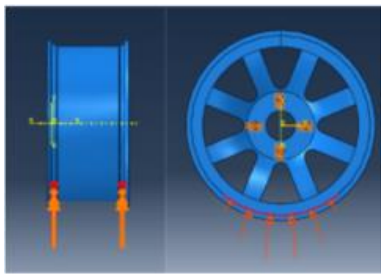


**Figure 8.** Conversion of a CAD model to a tetrahedral mesh model.

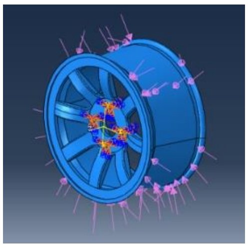
For the air pressure for wheel rim, Dede et. al. [29] stated that the air pressure was 35 psi in their study. Since the rim dimensions are close to the dimensions in this study, same value was used as air pressure in the present work.



(a) (b)



(c)

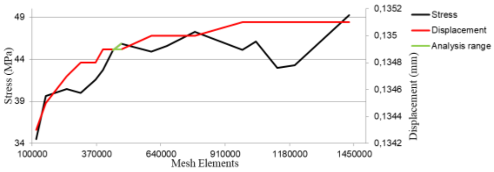


(d)

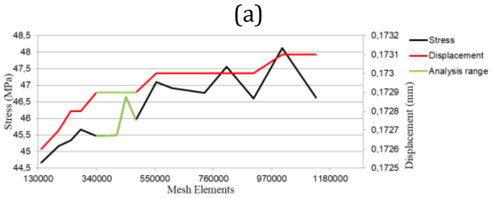
**Figure 9.** Air pressure (a) and the load (b) on the circumference of the rim flange. Radial load on tire contact location (c). Boundary conditions and loads on a wheel rim(d).

The air pressure of the tire is apply load on the center of the rim (Figure 9.a) and bead seats (Figure 9.b) for the flange area. According to Stearns et. al. [1], both the tread of the tire and the flange of the rim support the axial load. The load on the circumference of the rim flange is calculated as 0.495 MPa according to formulation on this work. They stated that the tires transmitted the load to the rim, and the load only affected a limited area of the rim. The distributed loading for an 1175 kg vehicle was maximum 2.009 MPa, and the applied angle was taken at 80 degrees (Figure 9.c). The final stage of the FEM model with boundary conditions and forces before running is shown in Figure 9.d.

In our analyses, the tetrahedral element (C3D10) type was utilized. A mesh independence test was further performed based on the boundary conditions mentioned above to prevent errors caused by the few number of elements. Figure 10.a and b show plots of maximum stress/displacement versus the number of mesh elements for P-models 1 and 2. It can be observed that stress and displacement values change according to the number of elements. Additionally, FEM analysis time is also crucial as many analysis is planned in our own study. After considering all these issues, 439-473k and 340-476k mesh elements were selected for P-model 1 and P-model 2, respectively.




(a)




(b)

**Figure 10.** Mesh independency test for (a) P-model 1, (b) P-model 2.

Spoke orientation is crucial during FEM analysis, and differences in stress distribution and displacement occur when the positions of the spokes are different. Fig. 11 shows FEM analysis results for different spoke orientations. It is easy to observe the changes in results. This difference is due to the radial load on tire contact location. In this case, a fair ranking can be made by placing the blank of two spoke each model symmetrically downwards. Thus, we orient one of the spokes in a way that is exactly at the bottom.

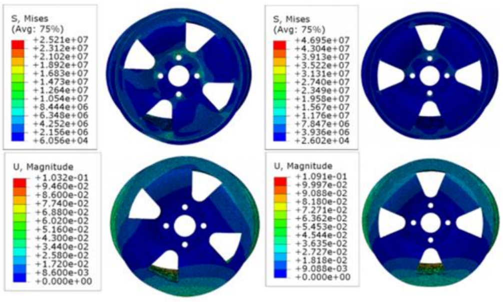



**Figure 11.** FEM results for different spoke orientations.

### 3.3. Design Optimization

In the design optimization process, GA was used to increase model diversity and to obtain more original models. This section includes three stages which are selection, cross-over, and mutation. Parents were selected and then crossed between these parents to produce new offspring. As new generations were created, existing genes are changed by mutation.

Five genes were used in the first wheel rim model (P-model 1). The variables chosen (in GA) were rim width, center hub offset, thickness, extrude diameter and spoke number for the first wheel rim model. Four gens were utilized in the second wheel rim model (P-model 2). Variables for the second wheel rim model were spoke top width, spoke bottom width, spoke major radius and minor radius. According to analysis results, best designs in each field were used as the parent, new generation wheels were obtained by genetic algorithm using the two-point cross-over methodology. In the two-point crossover, the genes were split at two points and gene exchange took place between the two parents. Children were created for each evaluation result, and four children were obtained created using mutation operator. Among the newly generated rim models, the best ones were used as parents. New models were again obtained using cross-over and mutation operators.

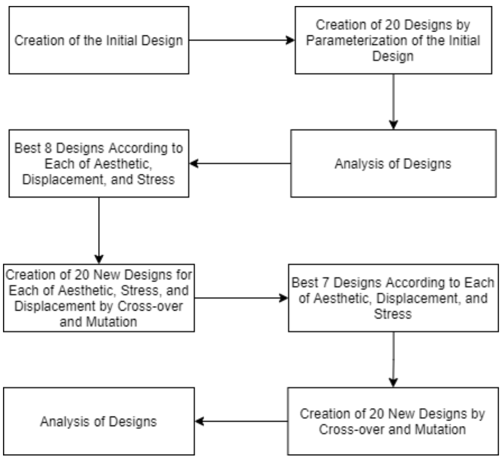



**Figure 12.** Design optimization procedure

Design optimization procedure is summarized in Figure 12. From an initial design, 20 new designs are obtained via a generative design process. After analysis of these designs based on aesthetic and mechanical performance (displacement and stress criteria), 8 designs are separately chosen for each criteria. (1) GA is again utilized, in which 8 designs are considered as parents. 60 new designs are then obtained separately for each criteria. (2) 7 designs are first obtained from the previous 20 designs while taking all three criteria into account (by comparing the performance values of these 20 designs). The 7 designs are utilized as parents in a further GA process so that 20 new designs are generated. As a result, 101 designs exist, which are again analyzed in a last step. Note that the models with the lowest (maximum) stress/displacement values and highest aesthetic values are regarded as the best parents in this design study.

## 4. Results

In an optimization process, parents for the next crossover in GA were selected based on the minimum maximum stress, minimum displacement and maximum aesthetic values. In the first 20 models of P-model 1, the highest aesthetic value was 10, the lowest value was 2. Furthermore, the highest displacement was 0.1950 mm and the lowest was 0.0897 mm. Additionally, the maximum (Von mises) stress value was 62.32 MPa and the lowest value was 22.53 MPa. In the same order, these values for the first 20 models of the P-model 2 were as follows: 4 and 8 for aesthetics, 0.1154 and 0.2962 mm for displacement and 20.73 MPa and 77.78 MPa for the maximum stress. Note that aesthetic values were given by a volunteer, who is interested in cars and has design experience using CAD tools. Scaling was done for the maximum stress, displacement and aesthetic scores as follows using the lowest and highest scores for the criteria for easily evaluate the results:

$$Score = 1 - \frac{X - \text{the lowest value}}{\text{the highest value} - \text{the lowest value}} \quad (1)$$

$$Score = \frac{X - \text{the lowest value}}{\text{the highest value} - \text{the lowest value}} \quad (2)$$

Equation 1 is for the aesthetic criterion, while Equation 2 is for the maximum stress and displacement scores. The scores of P-model 1 and 2 are summarized in Figures 13 and 15, resp. Additionally, the best models for P-model 1 and 2 are given in Figures 14 and 16, resp. Furthermore, Figures 17 and 18 compares the initial and optimized models of the P-model 1 and 2, resp. Note that designs in the group named as 'best' are obtained using GA utilizing 7 designs selected among 20 designs according to all three criteria.

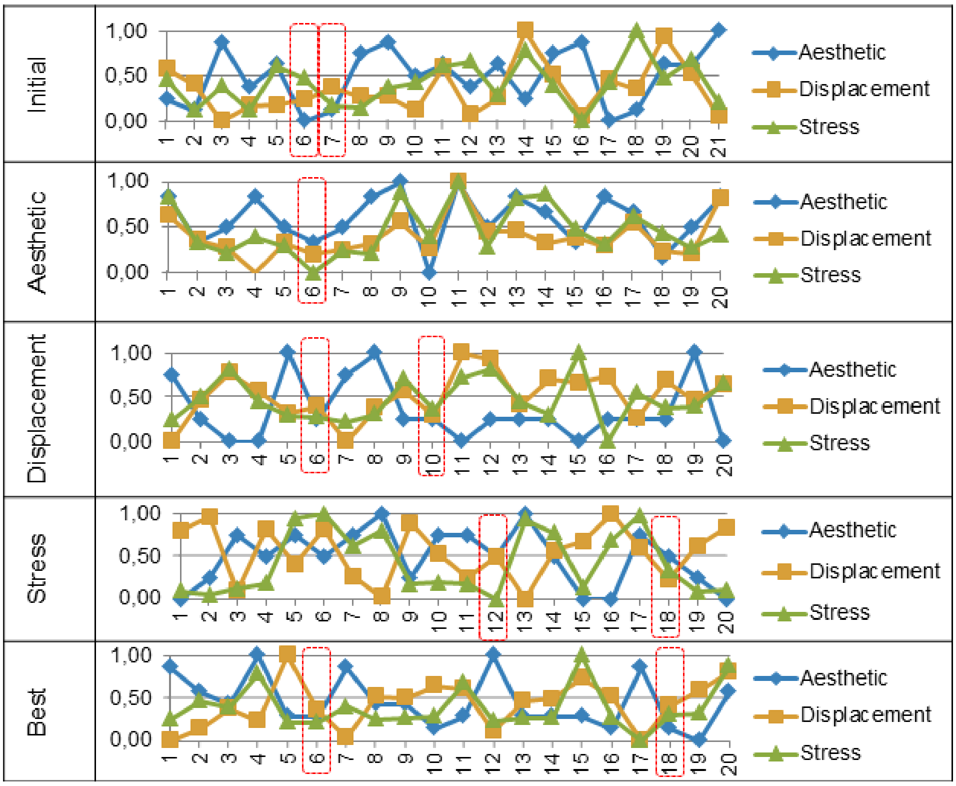



**Figure 13.** Scaled scores of the whole models of P-model 1.

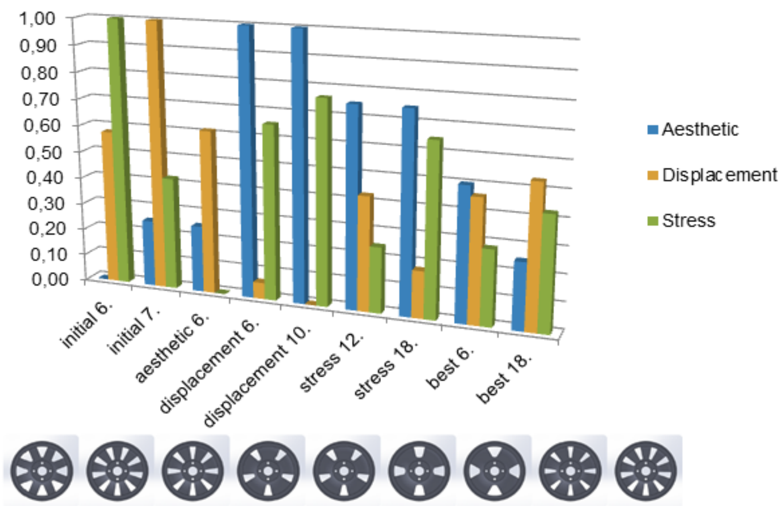



**Figure 14.** The preferable models of P-model 1.

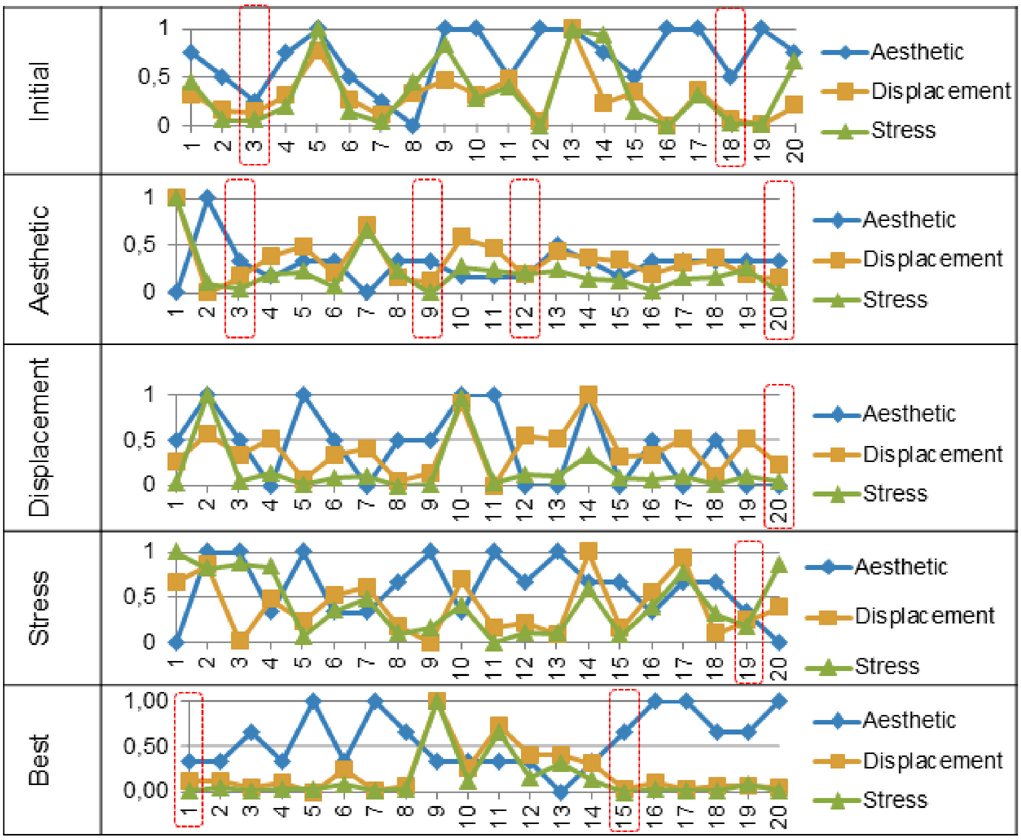



**Figure 15.** Scaled scores of the whole models of P-model 2.

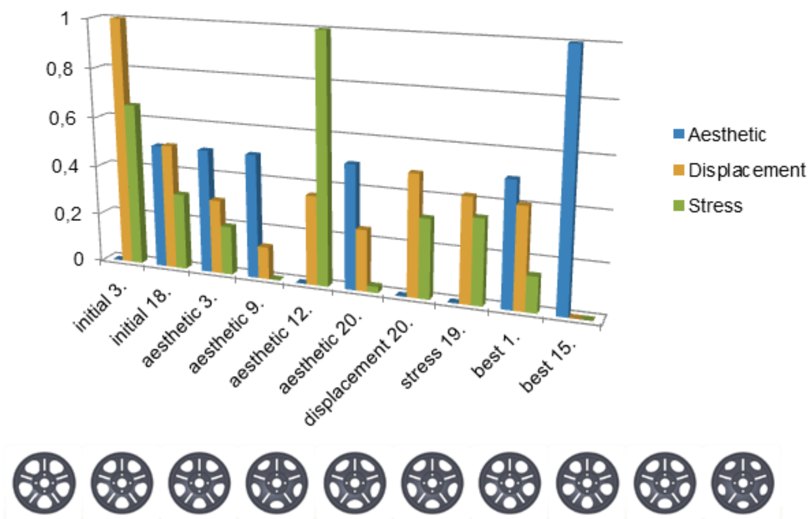



**Figure 16.** The preferable models of P-model 2.

In Figures 13 and 15, some models are marked with the red rectangle, which are potentially preferable models (by the participants) according to the all three criteria. Equations 1 and 2 scales all three criteria between 0 and 1 for better readability of the scores. The scores close to zero is regarded as preferable.

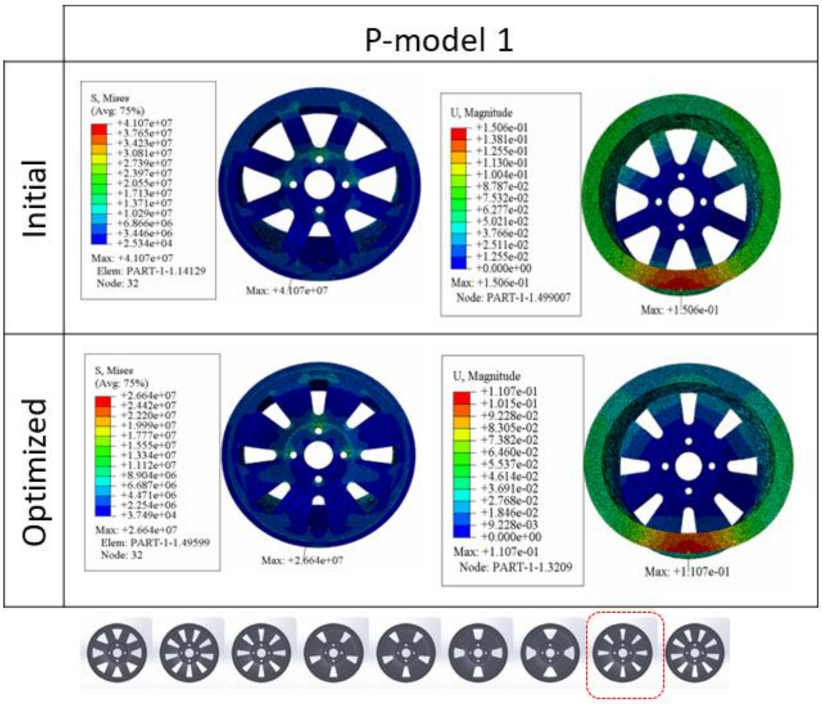



**Figure 17.** Comparison of the initial and optimized models for the P-model 1.

The preferable models of P-model 1 and P-model 2 after the optimization studies are shown in Figures 14 and 16, resp. One can easily notice the difference of the preferable designs of P-model 1 and P-model 2. This can also demonstrate the effect of the design parametrization on the obtained models after the GA optimization.

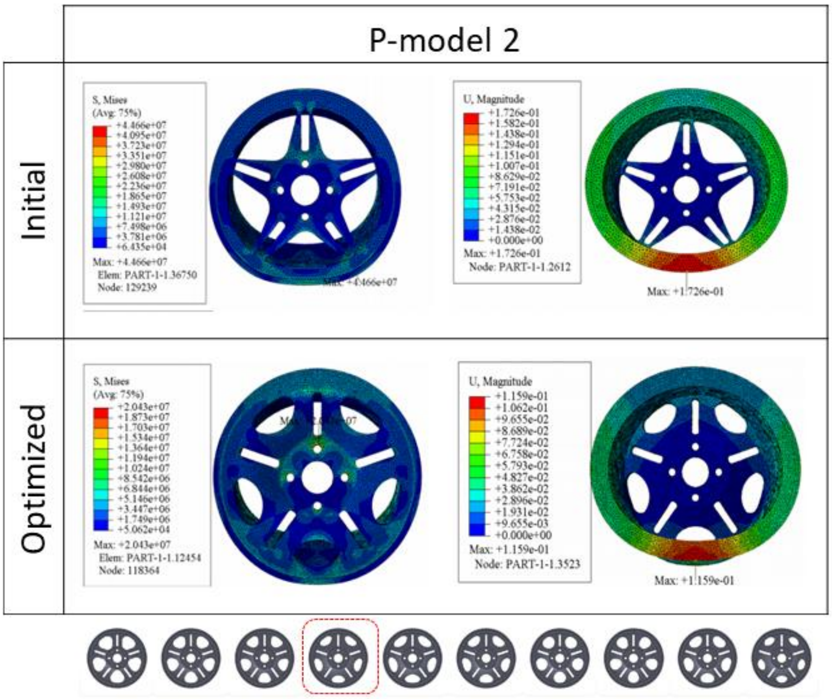



**Figure 18.** Comparison of the initial and optimized models for the P-model 2.

In Figures 17 and 18, the most eligible models selected for P-models 1 and 2 are shown with a red rectangle. For P-model 1, there was no improvement according to the aesthetic criterion, while the displacement value improved by 26% and the stress value by 35%. For the P-model 2, the aesthetic criterion was improved by 20%, the displacement value by 33%, and the stress value by 56%. When both P-models are compared with each other, the aesthetic value of P-model 2 is 14% and its displacement value is 5% worse than P-model 1. But its stress value is 23% better. As a result, design parametrization is crucial and strongly affects the obtained models after optimization. The models having the highest scores according to the aesthetic, displacement and stress scores are shown in Figure 19.

(a) (b) (c)

**Figure 19.** The best models according to aesthetic (a), displacement (b) and stress (c) scores.

## 5. Discussion and Conclusion

This work involves a wheel rim optimization study. A rim was designed and parametrized to generatively obtain 20 new designs. They were then scored according to aesthetic and mechanical criteria. The selected designs were then used as parents in a crossover process of GA in line with mutation operator. After applying a GA-based approach, several wheel rim designs are selected. Distinctly parametrized models are gone under this optimization process. According to the results, optimized models from different parametrizations may have different mechanical and aesthetic properties. This implies that parametrization is an important step, which has to be carefully performed before the optimization process.

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