ARAŞTIRMA, GELİŞTİRME VE UYGULAMA MAKALELERİ

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Design and Optimization of an EV Battery Enclosure Using Machine Learning

In this study, structural optimization of an enclosure under bending and torsional constraints was carried out. Machine learning (ML) approach was used to calculate the objective and constraint functions in the optimization problem. The ML model was trained and validated with data obtained from finite element analyses. The optimization model was then solved by the differential evolution algorithm. Five thicknesses, which are the design parameters in the enclosure, were optimized for minimum mass, and according to the results, the enclosure's mass decreased by 18.29%.

Keywords: Battery enclosure, design optimization, machine learning, differential evolution algorithm

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1. INTRODUCTION

Today, in parallel with the development of battery charging infrastructure, the share of electric vehicles in the automobile market is increasing. In these vehicles, there is a prismatic battery enclosure that carries the battery packs at the bottom of the vehicle. The design of the battery enclosure used in these vehicles is expected to fulfill the desired functions under certain boundary conditions, such as bending stiffness, torsional stiffness, Noise-Vibration-Harshness (NVH), and crashworthiness. At the same time, optimization studies are required for vehicles to be lightweight.

Many researchers in the literature have carried out studies on the structural analysis of battery enclosures. Long et al. [1] conducted a crash damage-based mitigation study for long-range electric vehicles. The Ls-Dyna software was used in the finite element analyses. The effect of the system on bending and torsion modes was examined, and the findings were summarized. Ruan et al. [2] performed finite element analyses to obtain a reliable battery enclosure design that meets the relevant technical standards through a lightweight design. In this context, the created three-dimensional model was analyzed under different operating conditions by means of Ansys and HyperMesh software. The study confirmed the battery enclosure structure obtained as a result of the structural optimization in terms of static stiffness and modal behavior. Li et al. [3] analyzed the rigidity of the electric vehicle battery enclosure by means of the finite element model they developed. In the study, the finite element analysis module of the welding points of the battery enclosure was created with the help of HyperMesh and Nastran softwares.

In the literature review, it was seen that different researchers examined the modal properties of both the battery enclosure assembly and its subcomponents. Wang and Zhao [4] examined the modal properties of the battery box in their study. Yang et al. [5] aimed to improve the dynamic and static performance of the battery pack. Li et al. [6] examined the body of the battery enclosure in their study. As a result of static and modal analyzes, it has been seen that the body has sufficient rigidity but low in terms of natural frequency.

There are also optimization studies on battery enclosure in the literature. The studies are generally related to optimizing the sheet material thickness values. Pan et al. [7] carried out size optimization for lightening on the battery enclosure made of steel material Shui et al. [8] performed the mass minimization of the battery enclosure, the maximization of the first natural frequency, and the minimization of the maximum deformation. Thicknesses were chosen as design parameters. It has been stated that the parameter that affects the mass the most is the bottom base thickness of the enclosure. In order to reduce the weight of the battery pack system, an optimization study was carried out by using the experimental design and the response surface method [9]. Lin et al. [10] chose panel and beam thicknesses on the battery enclosure as design parameters and defined a multi-objective optimization problem. In addition to the objective functions selected as mass minimization, and first natural frequency maximization, the stress value is defined as the constraint and the response surface function is defined and solved with the global optimization algorithm.

In this study, finite element models were created, and an optimization study was carried out by considering the 7th natural frequency, bending and torsional stiffnesses boundary conditions. While the response surface method is frequently used for the objective functions and constraint functions required for optimization in the literature, the artificial neural network model is used in this study. No similar study was found in the literature.

2. MATERIALS AND METHODS

In this study, structural optimization of a battery enclosure under frequency, bending and torsional stiffness constraints was carried out. It has been observed that aluminum alloys are primarily used in the current situation due to their lightness as battery enclosure material. 6000 series aluminum material was chosen as the battery enclosure material.

2.1. Finite Element Simulations

Mid surfaces of the battery enclosure’s solid model are obtained to perform static bending and torsion analysis, as shown in Figure 1. The solid model is designed in a CAD software called SolidWorks, and mid surfaces are extracted with a commercial software Hypermesh. Battery enclosure design is box-shaped and has reinforcing structures to keep modules safe under any external loads. Hypermesh software is used to mesh the mid surfaces of the EV battery enclosure. In order to reduce the computational expense of analyzing a complete solid model, midsurface model used for the finite element model.

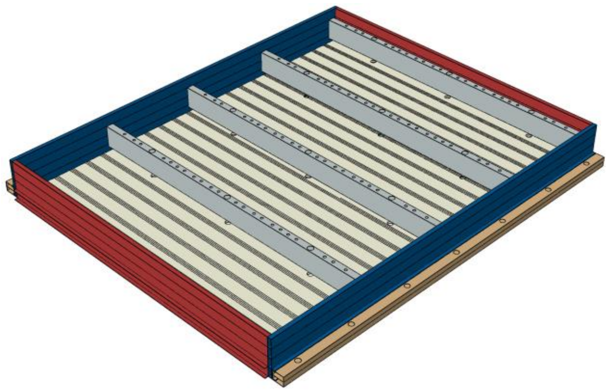

Figure 1. Mid surfaces of the battery enclosure

The whole model is divided into the 2D quad elements as much as possible (Figure 2). Element size set to 5 mm, and the finite element model has 309547 elements (1188 of them are linear triangular elements) and 316352 nodes. The model is exported as a Nastran Input File (*.bdf). The Nastran file is imported, and all boundary conditions are defined in Abaqus software. As shown in Figure 3a, the battery enclosure is constrained with all degrees of freedom at points 1, 2, 3, and 4, and 500 N is applied at points 5 and 6, 1000 N in total, for bending boundary condition. A sample static bending analysis has been run, and the result is shown in Figure 4. As expected, the maximum bending displacements are near the 5th and 6th points. In torsion analysis (Figure 3b), the battery enclosure is constrained with all transitional degrees of freedom at points 1 and 4. 1500 Nm moment is applied at point 7. Reference point 7 is coupled to points 2 and 3 with a rigid connection to apply the moment properly. Once again, a sample static torsion analysis has been run, and the result is shown in Figure 5. The maximum angle of rotations is near the 2nd and 3rd points, as expected. The modal analysis performed with the free-free conditions therefore, 7th mode is considered since the first six mode (transitional and rotational) is close to zero.

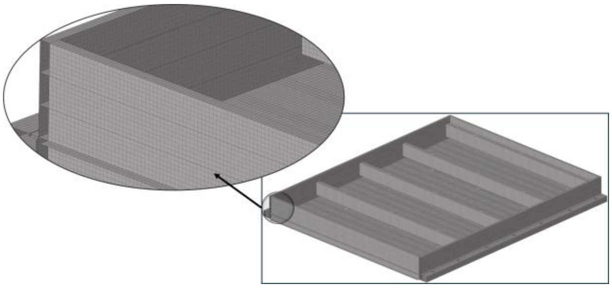

Figure 2. Finite element model of the battery enclosure

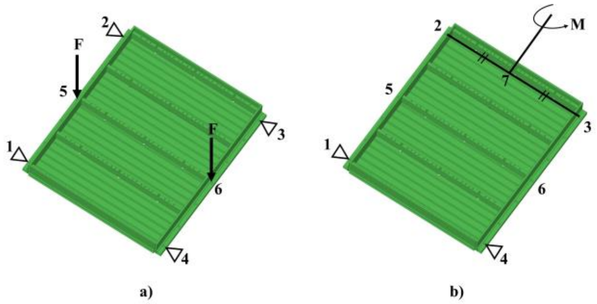

Figure 3. Boundary conditions; a) Bending, b) Torsion

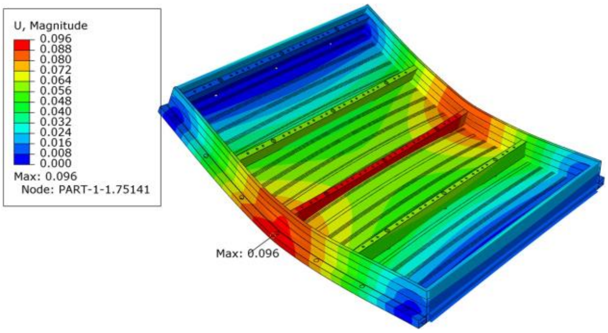

Figure 4. Maximum bending displacement

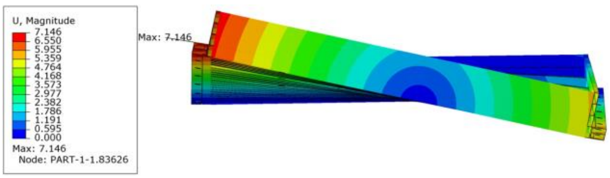

Figure 5. Maximum angle of rotation

6063-T6 aluminum alloy has been chosen in this study, and the Young Modulus and Poisson Ratio are assumed to be 70 GPa and 0.35, respectively, as shown in Table 1. Since it is easier to control thickness values using mid surfaces, thickness values have been changed with Python programming language using Abaqus/CAE's coding infrastructure to perform many finite element analyses. The dataset required for neural network training has been gathered by finite element analysis. Latin Hypercube Sampling in the pyDOE module is applied in this study, and 300 designs are selected using Python programming language. Three hundred analyses for modal, bending and torsion boundary conditions, 900 in total, were carried out, and the results were saved in a CSV file. The file contains five thicknesses which are design parameters in this study; mass which will be minimized; bending stiffness, torsional stiffness and 7th natural frequency.

The bending stiffness is calculated by dividing applied force to maximum deformation as given in Eq. 1 where F_{total} is equal to 1000 N. To calculate the torsional stiffness (Eq. 2), the applied moment (1500 Nm) is divided to maximum angle of rotation (Eq. 3), which is the angle between the deformed and undeformed shape of the battery enclosure as shown in Figure 6.

$$Bending\ Stiffness = \frac{F_{total}}{U_{max}} \tag{1}$$

$$Torsional\ Stiffness = \frac{M_{total}}{\theta_{max}} \tag{2}$$

$$\tan\theta_{max} = \frac{U_y}{0.5 * Width} \tag{3}$$

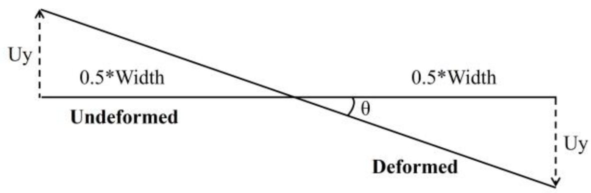

Figure 6. Calculating the maximum angle of rotation

The design parameters (from T_1 to T_5) of the EV battery enclosure are shown in Figure 7. The bottom plate is modeled as having a hollow section in order to lighten the battery enclosure and the shell equivalent of the section is shown in Figure 8. Vertical surface thicknesses of the bottom plate are set to 5 mm.

Table 1. Aluminum 6063-T6 alloy properties

Density, gr/cm^3	2.7
Young Modulus, MPa	70000
Poisson Ratio	0.35
Yield Stress, MPa	250

2.2. Machine Learning

Machine learning, which is a part of artificial intelligence, allows us to achieve the results we want simply and quickly. Even though we may not be able to define the process completely, we still can have a good and useful relationship between inputs and outputs [11]. Deep learning, a specific subfield of machine learning, is an approach to learning representations from data with sequential layers. Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) are the most common deep learning algorithms. They can deal with complex and non-linear relationships such as image classification, speech recognition, autonomous driving, etc. The use of neural networks has become increasingly popular in recent years, particularly in data analysis and prediction. Therefore, artificial neural networks, a sub-branch of machine learning, were preferred instead of a surrogate model to predict structural behaviors of the EV battery enclosure.

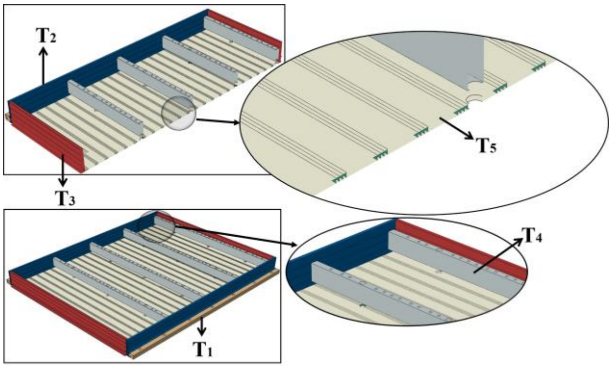

Figure 7. Design parameters, T_1-T_5

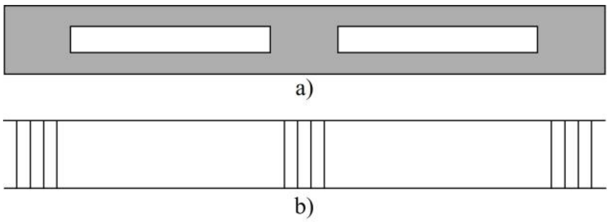

Figure 8. Bottom plate, a) Solid, b) Shell

Artificial neural networks are trained using two-thirds of the dataset obtained by performing finite element analysis. The thicknesses of the battery enclosure are determined as inputs. There are four neural network models with the same structure as shown in Figure 9 (5 inputs, two hidden layers with 32 and 16 nodes, and output) to predict mass, 7th natural frequency, bending and torsional stiffness. ReLU (rectified linear unit) is chosen as the activation function of the layers. Adam, MSE (Mean Square Error), and MAE (Mean Absolute Error) are used in this study as the optimization function, the loss function, and the success metric, respectively.

2.3. Optimization

Differential Evolution (DE) is an evolutionary population-based optimization algorithm, and it is developed to find the global optimum instead of a local optimum in an optimization problem. This study uses the DE algorithm in the pymoo module [12] to obtain both objective and constraint functions. Among the strategies in the DE algorithm, DE/rand/1/bin DE strategy was used. Population size, generation number, and crossover rate are chosen as 50, 50, and 0.3, respectively. The default values defined in the module are used for all the other parameters.

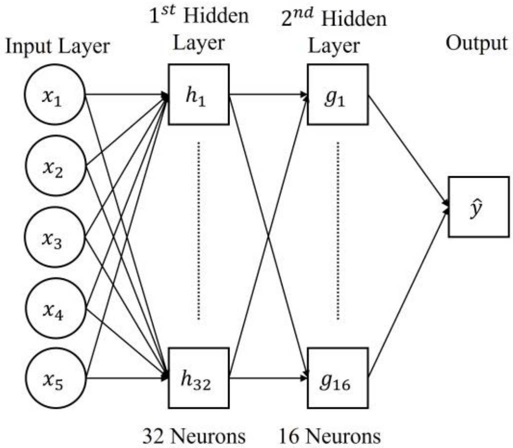

Figure 9. ANN structure for battery enclosure

The objective of the size optimization is to find the minimum mass under the frequency, bending and torsional stiffness expected from the EV battery enclosure. The structural properties were selected in accordance with the requirements of the TÜBİTAK project. The size optimization problem is defined as follows:

Obj. min mass

St. Bending stiffness $\geq$ 13000 N/mm,
Torsional stiffness $\geq$ 2000 Nm/°,
7th Natural Frequency $\geq$ 50 Hz,
$2 \leq T_1 \leq 5$ mm,
$2 \leq T_2 \leq 5$ mm,
$2 \leq T_3 \leq 5$ mm,
$2 \leq T_4 \leq 5$ mm,
$2 \leq T_5 \leq 5$ mm.

The methodology which is used to minimize the mass of the battery enclosure is shown in Figure 10. Latin Hypercube Sampling was used for the design of experiment study. After that, finite element analysis for modal, bending and torsion was run, and the results, which will be used to train ANNs, were saved in a CSV file. Two-thirds of the dataset was used to train neural networks, and the rest was used to test ANN models. Once the DE algorithm initializes the first population (thicknesses), mass, 7th mode, bending and torsional stiffnesses will be predicted by trained neural networks for each individual.

3. RESULTS AND DISCUSSION

3.1. Artificial Neural Network

The R^2 scores of the trained neural network models are given in Table 2, which demonstrates the success rates of the five neural networks in predicting the outputs of the dataset. It is evident from the tables that all the neural networks have a significant ability to predict the outputs with high success rates, as indicated by the high R^2 values. These results highlight the effectiveness and reliability of neural networks in predicting complex datasets accurately. Moreover, the close success rates observed between the training and test indicate that the researchers did not encounter any overfitting problems during the training process. The absence of overfitting in this study demonstrates the effectiveness of the training process and the suitability of the structures for the task at hand. Figures 11 illustrate the comparison between the predicted values and the actual test data. In addition to R^2 scores, it is evident from the figures that the developed neural network models successfully predict the test data, which the network has not processed before, as indicated by the close alignment between the predicted values and the actual test data.

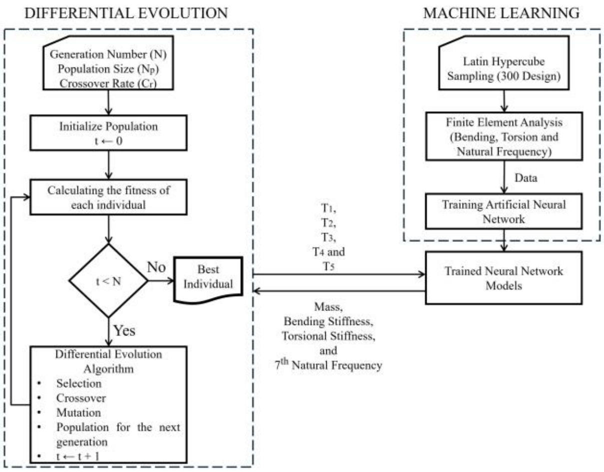

Figure 10. Flowchart of the optimization study

3.2. Differential Evolution-Based Size Optimization

The optimization study performed with the DE algorithm successfully minimized the mass under the constraints. Convergence history of the optimization study is illustrated in Figure 12, and it can be seen that the optimization algorithm reaches its optimum point since the fitness function is not getting any lower. As seen in Table 3, the mass of the battery enclosure has decreased from 67.09 kg to 54.82 kg. According to the results, the mass decreased by 18.29%, and the 7th mode, bending and torsional stiffnesses were obtained as 51.06 Hz, 13018.0 N/mm and 2000.4 Nm/°, respectively (Table 3). According to the optimization study, the structural properties meet the constraint functions and have hit their limits, an outcome that is expected. With appropriate thicknesses, in addition to minimizing the mass, there is an increase in both bending and torsional stiffness. Table 3 shows us that the increase of the 1st thickness from 3.0 to 4.20 has a crucial role in meeting design targets. The 3rd, 4th, and 5th thicknesses approached the lower boundaries and contributed significantly to the mass reduction.

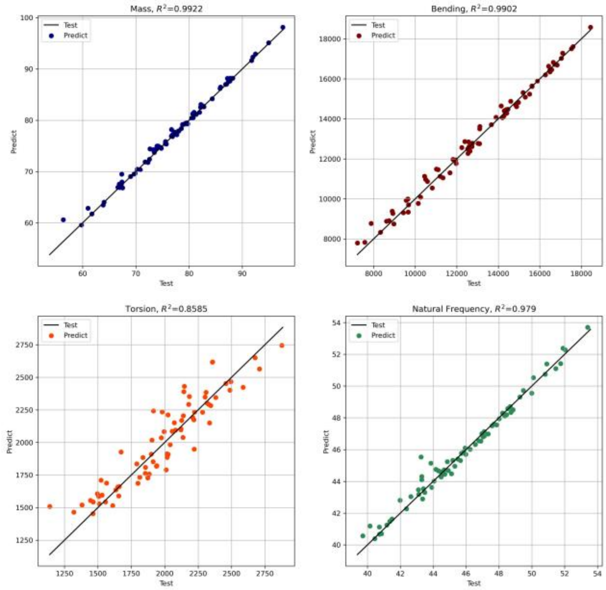

Figure 11. Comparing test and predicted results

Table 2. R^2 coefficient of determination score of each model

Output	Epoch	Train	Test
Mass, kg	329	0.9974	0.9922
Bending Stiffness, N/mm	500	0.9908	0.9902
Torsional Stiffness, Nm/°	434	0.8095	0.8585
7th Natural Frequency, Hz	328	0.9887	0.9790

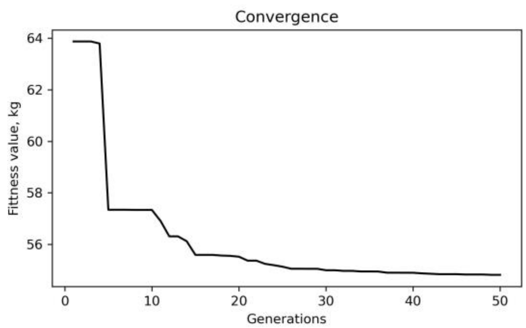

Figure 12. Convergence history

To see the validation of trained neural networks, a comparison between neural networks (NN) predicts and finite element (FE) results is made. The comparison is shown in Table 4. As can be seen, the highest error was encountered in the torsional stiffness which has the lowest R^2 value. Even though, both bending and torsional stiffness are violated the requirements, the optimization result clearly shows us which thicknesses should be focused on to satisfy the constraints with a minimum mass increase.

Table 3. Comparing the base and optimized model

	Base Model	Optimized Model
T_1, mm	3.00	4.20
T_2, mm	3.00	3.46
T_3, mm	3.00	2.00
T_4, mm	3.00	2.03
T_5, mm	3.00	2.00
Mass, kg	67.09	54.82
Bending Stiffness, N/mm	10956.68	13018.00
Torsional Stiffness, Nm/°	1588.74	2000.40
7^{th} Natural Frequency, Hz	45.559	51.065

Table 4. Comparison between FE and NN

	Mass, kg	Bending Stiffness, N/mm	Torsional Stiffness, Nm/°	7^{th} Natural Frequency, Hz
FE	55.13	12511.65	1865.79	51.527
NN	54.82	13018.00	2000.40	51.065
%Error	0.56	4.05	7.21	0.90

The proposed methodology has proven to be highly effective in the size optimization problem of EV battery enclosures. This innovative approach provides a systematic and reliable guide for designers to optimize the size of the battery enclosures, which are essential components of electric vehicles. With this approach, designers can easily and quickly find the optimal size of the battery enclosure, which ensures efficient performance. Overall, the proposed methodology represents a significant advancement in the field of automotive design and engineering. Its effectiveness and versatility make it an essential tool for designers and engineers who are looking to optimize the performance and efficiency of automotive products. By utilizing this approach, designers can save time and resources for a variety of products in the automotive industry.

4. CONCLUSION

The successful application of the proposed methodology highlights the importance of robust and reliable battery enclosures in electric vehicles. The optimization of battery enclosure design will continue to be crucial in the development of electric vehicles with the increasing demand for sustainable transportation solutions.

In the present work, a finite element-based machine learning algorithm has been successfully applied to EV battery enclosure optimization under modal, bending and torsion constraint. It is required to research the behavior of battery enclosure under different loading and boundary conditions, including ground impact and pole crash. Those conditions will be considered in the further studies.

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MAKİNE ÖĞRENMESİ KULLANILARAK BİR ELEKTRİKLİ ARAÇ BATARYA TAŞIYICISININ TASARIMI VE OPTİMİZASYONU

Bu çalışmada, eğilme ve burulma kısıtlamaları altında bir batarya muhafazasının yapısal optimizasyonu gerçekleştirilmiştir. Optimizasyon problemindeki amaç ve kısıt fonksiyonlarını hesaplamak için makine öğrenmesi yaklaşımı kullanılmıştır. Sonlu eleman analizlerinden elde edilen veriler ile makine öğrenmesi modeli eğitilmiş ve doğrulanmıştır. Optimizasyon modeli daha sonra diferansiyel evrim optimizasyon algoritması ile çözülmüştür. Batarya taşıyıcısındaki tasarım parametresi olan beş kalınlık minimum kütle için optimize edilmiş ve elde edilen sonuçlara göre taşıyıcı kütlesi %18,29 azalmıştır.

Anahtar Kelimeler: Batarya taşıyıcısı, tasarım optimizasyonu, makine öğrenmesi, diferansiyel gelişim algoritması

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