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Optimal design of the floor panel for an automotive platform under uncertainty of the vehicle length

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Abstract. Length of a vehicle is an important variation to generate different variants of an automotive platform. This parameter is usually adjusted by embedding dimensional flexibility into different components of the Body in White (BIW) including the floor pan. Due to future uncertainties, it is not necessarily possible to define certain values of wheelbase for the future products of a platform. This work is performed to add flexibility into the design process of a length-variable floor pan. By means of this analysis, the cost and time consuming process of optimization is not necessary to be performed for designing the different variants of a product family. Stiffness and mass of the floor pan are two important functional requirements of this component which directly affect the occupant comfort, dynamic characteristics, fuel economy and environmental protection of the vehicle. A combination of Genetic algorithm, GMDH-type of artificial neural networks and TOPSIS methods is used to optimally design the floor pan associated with arbitrary length of the variant in the defined system range. The correlation between the optimal results shows that for a constant mass of the floor pan, the first natural frequency decreases by increasing the length of this component.

Keywords: platform; floor plan; design; FEM; genetic algorithm; artificial neural networks

1. Introduction

The breathtaking volume of production requires an extremely high level of industrial and management technology to remain in the highly competitive market of automotive manufacturing. A very necessary reaction of any automotive manufacturer against the market changes is diversification of the products. This variety occurs in two dimensions: spatial and developmental. Spatial variety is referred to the range of different products the company offers at a specific point of time, such as Hatchback, Sedan and mini SUV products of an automotive platform. On the other hand, developmental variety is referred to the range of different developmental stages (Suistorana 2003). Due to these inevitable changes, a flexible design method is needed to minimize the costs and time of replacing the old product with a new one or redesigning a variant to obtain a new variant of a modular product platform. Martin and Ishii (2002) described the Design for Variety (DFV) method, to develop standardized and modularized product platforms. The authors used the Generational Variety Index (GVI) and Coupling Index (CI) to aid in designing a modular product platform that can be easily changed in the future. They also showed that reducing these indices leads to a robust design against the future changes; Meaning that applying changes to the design parameters imposes minimum effects to satisfaction of the functional requirements. However, while the functional requirements are satisfied, diversification may lead to reduce the performance and total efficiency of the system in different variants. Hence, the quality of operation of the system is also important to be investigated in platform product design.

The floor panel is a component of the underbody structure of Body in White (BIW) system which plays an important role in foundation of the architecture of the automotive platform. From DFV point of view, extending the floor pan is an effective solution to absorb the uncertainties of wheelbase variation in different variants of a modular platform. In this case, the design range is the range of variations of the floor pan's length which is considered to support the variety of products which are supposed to be produced based on the current platform. If the floor pan's length is changed, the overall characteristics of this component will be also changed as a result. So it is important to know and to control these characteristics over variations of floor pan's length. The stiffness of floor pan is important due to structural reasons and its effect on passengers' comfort and feeling of solidness (Suh *et al.* 2007). A conventional approach to judge about stiffness of the floor panel is vibration analysis (Mignery). Due to the direct relation between the natural frequencies and stiffness, the higher the natural frequency, the stiffer structure of the panel is expected. On the other hand, weight reduction is an important task in automotive engineering which usually has conflict with stiffening the structure. Therefore, a compromised solution is required to have a road vehicle with light weight and high stiffness simultaneously. In such cases, a multi-objective optimization problem is needed to be solved to obtain the best compromising solution of the

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objective functions. Classical numerical optimization methods are only applicable to continuously differentiable functions. So to consider all these objectives, a complex multi-objective optimization problem (MOP) must be solved. Many different methods were proposed by previous researchers for solving MOPs (Lee *et al*. 2011 and Guillen 2011). Non-dominated Sorting Genetic Algorithm (NSGA-II) proposed by Srinivas and Deb (1994), which is a Pareto based approach is one of the efficient algorithms for solving MOPs. It generates a set of non-dominated solutions (Pareto solutions), where a non-dominated solution performs better on at least one criterion than the other solutions. To improve NSGA-II, Nariman-Zadeh proposed modified NSGA-II which uses epsilon-elimination algorithm rather than crowding factor (Jamali *et al*. 2009). This method is employed successfully in many recent studies (Khalkhali *et al*. 2011, 2012). A set of non-dominated optimal solutions are proposed by NSGA-II after convergence of the solutions. One of the main advantages of this method is to propose a variety of optimal design vectors to the designer. Hence, the designer is able to choose the trade-off solution according to his priorities and preferences. In this case, a Multi-Criteria Decision Making Method (MCDM) is needed to help to choose the best optimal design among the non-dominated points of Pareto based on weight coefficients which are given to the objective functions according to their priorities. Technique for Ordering Preferences by Similarity (TOPSIS) is a commonly used and successful MCDM method (Khalkhali *et al*. 2014, 2016). TOPSIS is based on simultaneous minimization of distance from an ideal point and maximization of distance from a nadir point.

Analytical mathematical equations are the most exact way of calculating the objective functions in terms of the design variables in the multi-objective optimization problems. In cases that these equations are expensive and time-consuming to solve or it is not possible to find such equations and relations (most of the complex physical problems such as automotive analyses are included in this category), Artificial Neural Networks could help to create a linkage between design variables and objective functions in a quick way. Artificial Neural Networks (ANNs) are computational modeling tools which are able to predict a relation between inputs and outputs of a function. Using these network leads to take advantage of eliminating a large number of experiments or simulations especially in parametric studies or multi-objective optimization problems. Group Method of Data Handling (GMDH) type of neural network algorithm is the heuristic self-organization method for modeling complex systems. This method is successfully being used to shortage the run-time of multi-objective optimization algorithms in the recent years (Khalkhali *et al*. 2010, 2012).

In this paper, the floor pan of a modular automotive platform is considered to be variable in length in order to cover the changes of wheelbase in different product variants. Due to the future uncertainties, a 150 mm range is considered for variations of the floor pan’s length. Since it is desired to have the optimum characteristics of the floor pan including stiffness and weight of the panel simultaneously, a multi-objective optimization is needed for different lengths of the floor pan in the design range. For this purpose, geometrical parameters of the floor pan are chosen as the design variables. Artificial neural networks are employed in this paper to find the mathematical relation between the objective functions (First natural frequency and mass of the panel) and the design variables. NSGAII algorithm is then used to find a set of non-dominated optimum design vectors which offers the compromised solution of the problem for each designated panel length. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is then used as a Multi-Criteria Decision Making (MCDM) method to choose the trade-off designs among these non-dominated optimum design vectors. Since a limited number of length levels are considered to be analyzed, a linear interpolation between the trade-off designs is assumed as the final guideline of design for the future uncertainties of the wheelbase.

2. Design process overview

Two logical strategies to extend the length of wheelbase of an automotive are extending the front floor and extending the center floor as modular parts respectively. These two concepts are shown in Fig. 1. As a DFV investigation of the design team, the first strategy is selected to be used in this study. The case study is the new National Platform project (NP01) which is under development by Iran University of Science and Technology (IUST). Position of the floor panel which is supposed to be considered as a modular part to be used to extend or shorten the wheelbase is shown in Fig. 2 which also depicts the overall BIW model of NP01 sedan product. To cover the range of shortest to longest variants of this platform which are the hatchback and mini SUV cases respectively, the length of floor pan (Le) is supposed to lie in the following range

$$1400 \leq Le \leq 1550 \tag{1}$$

The previous researches have shown that a flexible BIW platform will be more profitable when the degree of future uncertainty increases (Suh 2005). Therefore, in the design process it is assumed that the design parameter (Le) could have any arbitrary real values in the range of Eq. (1).

First natural frequency of the panel as a criteria to judge about the overall stiffness and weight of the panel as a parameter which has capability of influencing fuel economy and environmental protection of the final product are considered as the functional requirements of this component which are being submitted to a multi-objective optimization to obtain the best compromised combination of the objective functions (mass and first natural frequency of the floor pan). Thickness of the floor pan and geometrical details of the floor pan’s embossments are considered as the design variables. Since known mathematical relations between the design variables and the objective functions are not available in this problem such as many other industrial problems, artificial neural networks of GMDH type are employed to use estimating models and relations predicting the first natural frequency and weight of the floor pan in terms of the geometrical design variables.

A Finite element model of the floor pan is created and submitted to the modal analysis. To verify the FE model

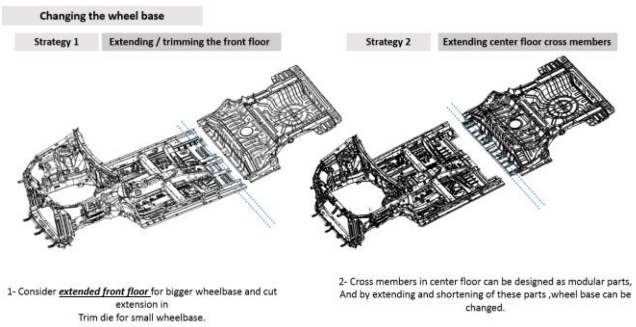


Fig. 1 Different strategies for extending the length of wheelbase

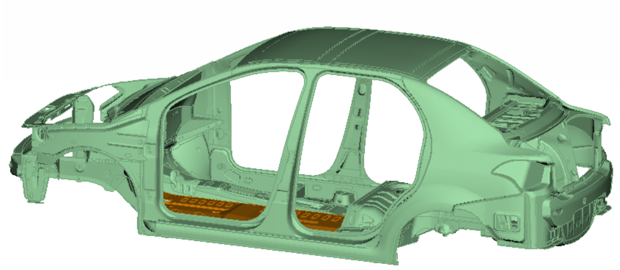


Fig. 2 Position of the floor pan in the BIW of NP01 project

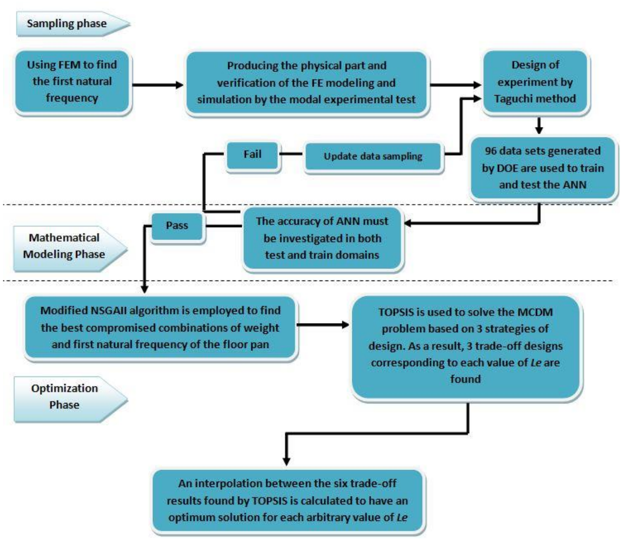


Fig. 3 Proposed flexible design process algorithm

Table 1 Designated levels of the design features

Level Number	t (mm)	w (mm)	l (mm)	d (mm)
1	0.65	20	80	2
2	0.8	30	103	5
3	0.9	40	143	10
4	1.2	48	173	15

Table 2 Configuration of the experiments proposed by Taguchi L_{16} orthogonal array

Analysis number	Level of (t)	Level of (w)	Level of (l)	Level of (d)
1	1	1	1	1

Table 2 Continued

Analysis number	Level of (t)	Level of (w)	Level of (l)	Level of (d)
2	1	2	2	2
3	1	3	3	3
4	1	4	4	4
5	2	1	2	3
6	2	2	1	4
7	2	3	4	1
8	2	4	3	2
9	3	1	3	4
10	3	2	4	3
11	3	3	1	2
12	3	4	2	1
13	4	1	4	2
14	4	2	3	1
15	4	3	2	4
16	4	4	1	3

and simulation, the real model is produced and an experimental modal test is performed on it. Taguchi method is then used to generate the training samples of the GMDH type of ANN. After extracting the mathematical relations between the design variables and objective functions, modified NSGA-II algorithm is used to find the non-dominated design vectors. The optimization problem is configured and solved for six different values of *Le* to cover the 150 mm range of changes of the wheelbase. Then, TOPSIS as a commonly used MCDM method is employed to find the trade-off design vectors proposed based on three different strategies of design, among the all of non-dominated proposed design vectors found by modified NSGA-II. Finally, an interpolation between the six obtained trade-off designs corresponding to different *Le* values is calculated to find the optimum design relations of the floor pan for any arbitrary wheelbase lengths. The simplified flowchart of the explained procedure is shown in Fig. 3.

3. Design of experiment

Four geometrical parameters are considered as the design features affecting two output functions: first natural frequency and total mass of the floor pan. These design features are shown in Fig. 4. Based on design and production restrictions, the upper and lower bounds for variations of the design features are supposed as follows

$$\begin{gathered} 0.65mm < t < 1.2mm \\ 20mm < w < 48mm \\ 80mm < l < 173mm \\ 2mm < d < 15mm \end{gathered} \tag{2}$$

where *t* is the thickness of the panel and *w*, *l* and *d* are the width, length and depth of the panel's embosses. The higher the number of levels, the lower effects of nonlinearity error in the parametric study becomes. However, four levels of variations are considered for each geometrical feature based on time and financial resources including t (0.65, 0.8, 0.9, and 1.2), w (20, 30, 40, and 48), l (80, 103, 143, and 173) and d (2, 5, 10, and 15). Values of the four variables corresponding to each level are summarized in Table 1. The total number of possible combinations of these variables according to number of levels and variables is equal to 256. In Taguchi method, two main parameters are needed to be specified. First is control factor or the vector of design features; another is the noise factor that denotes all factors that cause variation.

Taguchi proposed orthogonal arrays to acquire the attribute data and to analyze the performance measure of the data to decide the optimal process parameters (Senthil Kumar, Kalidas, Sivakumar, Hariharan, Fautham, Ethiraj 2013). In this study, L_{16} orthogonal array is employed. This array is suitable for the cases with four design variables and four levels for each design variable. The total number of experiments is 16 and the corresponding configuration of the experiments is shown in Table 2. To investigate the effect of length uncertainties, the platform wheelbase variation parameter (Le) is subjected to six levels (1400, 1430, 1460, 1490, 1520 and 1550) in such a way that uniformly covers the range of Eq. 1. Therefore, the total number of simulation samples is equal to 96. Note that Le is not supposed to be considered as a design variable in the optimization process. But the variation of this factor is considered to generate data samples for training the Artificial Neural Networks.

4. Experimental modal analysis

In this section, details of the modal experiment on the floor pan of the new developing platform (NP01) are explained. The aim of this experiment is to validate the results of the FE modeling and simulation with the real values. A physical model of the floor pan is generated and submitted to modal experimental test. The fabrication method is stamping by soft tools, drawing operation and trimming is carried out by laser cut. The experiment details are explained as follows. A roving hammer test is the most common type of impact test. An accelerometer is fixed at a single DOF, and the structure is subjected to impacts at as many DOFs as desired to define the mode shapes of the structure. Using a two channel Fast Fourier Transform (FFT) analyzer, Frequency Response Functions (FRFs) are computed between each impact DOF and the fixed response DOF. A suitable grid is usually marked on the structure to define the impact points.

In this research, the charge type hammer has been used to excite the frame. To cover frequency ranges of interest, a rubber tip has been utilized. Excitation point has been selected so that the maximum mode shapes could be obtained (It must not be on the nodal points of any mode of interest). In order to reduce the noises in the measurements, each of the stage results have been obtained by averaging 10 measurements of the same kind.

The frame was suspended using cables having the elasticity suitable enough for the natural mode extraction. In order to get first 4 natural frequencies of the panel, 48 points were marked on it for accelerometers installation locations. A geometrical model of the system was created using six coordinates required for each node. Each node corresponds to a point on the panel. The tri-directional accelerometers were attached to these points.

The most general purpose parameter estimation technique called Time Domain MDOF Analysis has been used. It provides a complete and accurate modal model from single input multiple output frequency response functions. It uses global estimators; means that it analyzes all the data records simultaneously in order to estimate the structure’s characteristics. With this approach, a unique estimation of the pole values (natural frequencies) is obtained.

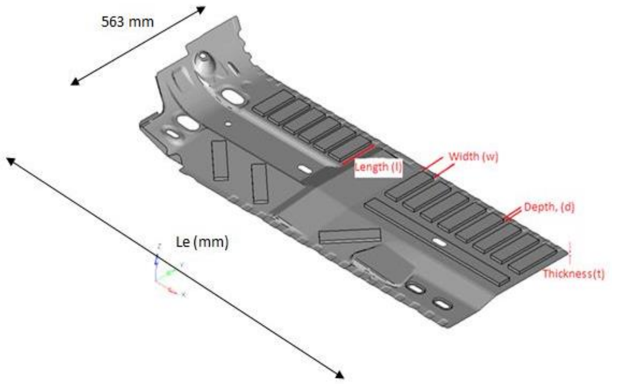


Fig. 4 Geometrical shape, overall dimensions and design features of the basic floor pan

Table 3 Geometrical configuration of the base design

Thickness of the floor panel (t) (mm)	Width of the embosses (w) (mm)	Length of the embosses (l) (mm)	Depth of the embosses (d) (mm)
0.65	20	80	2

5. Finite element modeling and simulation

The geometrical shape and overall dimensions of the floor pan are shown in Fig. 4. Geometrical details of the basic model of floor pan are presented in Table 3. This model is supposed to be compared in finite element simulation and experimental test to verify the FE model and simulation. Steel is considered as the constituting material of the panel with mechanical properties of $\rho = 7800\frac{kg}{m^3}, E = 210GPa\ and\ \nu = 0.3$ (Sun *et al.* 2015). The boundary edges of the model are supposed to be free. Due to the low aspect of thickness to the other dimensions, the complex 3D model is replaced by 2D shell elements. As a result of a mesh independence investigation, the model is divided to 6309 elements including 5966 quadratic and 343 triangular elements.

6. Artificial neural networks

GMDH-type of artificial neural networks is employed in this paper to find an approximated mathematical relation between geometrical features of the floor pan and final characteristics of this component including the first natural frequency and mass. GMDH finds the output function in terms of the input parameters and a set of cascaded neurons which are found in terms of the prior level neurons or input variables. In other words, the structure of network has a cascaded form and composition of two neurons results in generation of a new neuron. The final neuron represents the output of the network. In GMDH-type of neural networks, this composition is performed using (usually) the quadratic form of Ivakhnenko polynomial (Ivakhnenko 1971) as follows. The general and quadratic forms of Ivakhnenko polynomial are described in Eqs. (3) and (4) respectively

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \cdots \tag{3}$$

$$y = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \tag{4}$$

7. Artificial neural networks

A multi-objective optimization problem (MOP) is defined when it is desired to optimize more than one objective functions simultaneously. In these problems, there are several objectives or cost functions (a vector of objectives) to be optimized (minimized or maximized) simultaneously. These objectives often conflict with each other so that improving one of them will deteriorate another. Therefore, an optimization algorithm is needed to find the best values of design variables in order to achieve the best compromising values of the objective functions. In such cases, there is not a single optimal solution which satisfies all of the objective functions at the same time, instead there is a set of optimal solutions, known as Pareto front which proposes a set of solutions in the space of objective functions that are non-dominated to each other. Having a stiffer panel without improving material is usually possible with section improvement and mass enhancement. Therefore, we face to a multi-objective optimization problem in this study. Non-dominated sorting genetic algorithm (NSGA-II) is a Pareto-based evolutionary algorithm that is employed here to solve the MOP. The current problem is configured as follows

Objective functions:

Maximize f_1, Is calculated using the ANN model (Appendix A)

Minimize *m*, Is calculated using the ANN model (Appendix A) (5)

Design Variables:

As described in Eq. (2)

It is important to note that the length of Panel (L_e) is assumed to be constant in the optimization process. Therefore, six MOP problems associated with six different values of L_e are solved separately.

Table 4 Strategy definition and corresponding weight factors

Strategy	Weight Coefficient of f_1	Weight Coefficient of *m*
St1	0.2	0.8
St2	0.5	0.5
St3	0.8	0.2

8. Multi-criteria decision making (MCDM)

MCDM is widely applied to select one or more alternatives among the available ones. In this paper, three different strategies for selecting the trade-off design among a set of non-dominated optimal designs are investigated. The three strategies are described in Table 4.

The first strategy (St1) is describing the situation that importance of weight reduction is in priority with respect to importance of stiffness. The second strategy (St2) corresponds to the situation that mass reduction and stiffness improvement have equal importance for designer. The third strategy (St3) is reversed of the first case. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Khalkhali *et al.* 2014) is an MCDM method which is employed in this study. The objective of TOPSIS is to determine the best compromised solution based on its distance from the positive, (S^+), and negative, (S^-), ideal solutions according to the weights appointed for every criterion. The best solution is the closest one to the positive ideal solution and the farthest one from the negative ideal solution.

9. Results and discussion

9.1 Experimental results and Validation of the FE model

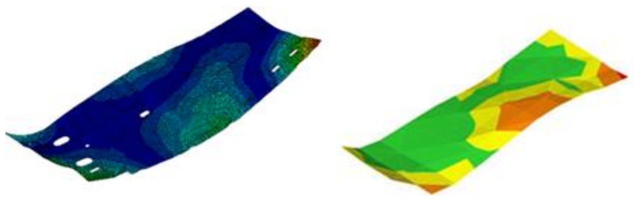
First four natural frequencies of the floor panel found by the experiment and FE simulation are listed in Table 5. A comparison with the FEM results shows the maximum and average error of 4.2% and 2.67% respectively. Furthermore, first natural mode shapes of the panel found by the FE simulation and test are depicted and compared in Fig. 5. A good accordance between the results is observed. Therefore, the finite element model and simulation method are accurate along with a reasonable error. A good accordance between the results is observed.

9.2 ANN modeling

Among the 96-sized set of data samples generated by Taguchi and simulated by FEM , the first 76 samples are used to train the network and the last 20 ones are used as the testing data. The good ability of GMDH-type neural networks for modeling and prediction of numerically obtained first natural frequency (f_1) data are depicted in Fig. 6 both for training and testing data. Such behaviors are also shown for the mass of panel both for training and testing data in Fig. 7. Distribution of ANN modeling and FE simulation results with respect to $y = x$ line shows the accuracy of models. It is evident in these figures that the evolved GMDH-type neural network in terms of quadratic equations can successfully model and predict the output of testing data that are not used during the training process. As a more quantitative criterion, the MAPE error in modeling the training and testing samples of mass and the first natural frequency of panel are shown in Table 6. The corresponding polynomial representation for both of the objective functions is given in Appendix A.

Table 5 First four natural frequencies of the floor pan's basic model of NP01 project found by FEM and Experiment

Mode Number	Frequency (Hz) FEM	Frequency (Hz) Experiment	Error (%)
1	4.14	4.24	2.36
2	7.76	7.91	1.90
3	12.99	13.56	4.20
4	13.66	13.97	2.22
Average	-	-	2.67



(a) (b)

Fig. 5 First natural mode shapes of the panel found by the FE simulation and test (a) FEM and (b) Experiment

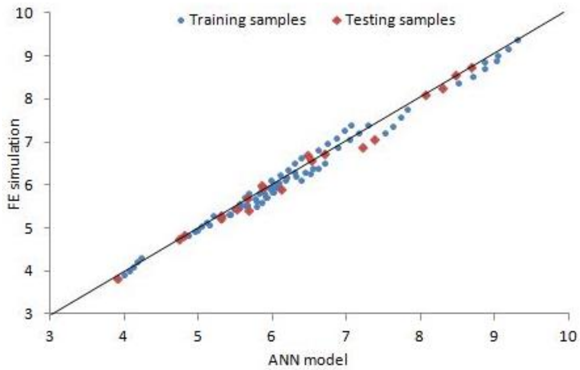


Fig. 6 Accuracy of the ANN model in predicting the first natural frequency of floor pan (f_1) for training and testing data samples

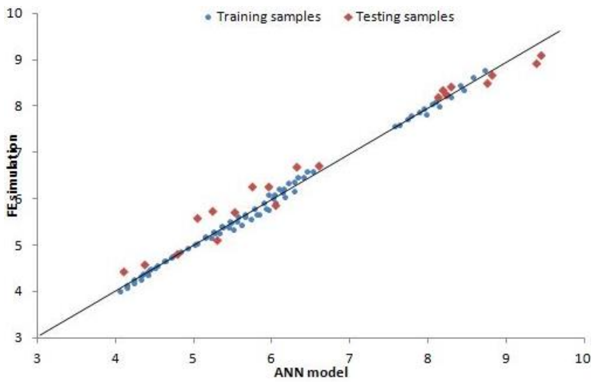


Fig. 7 Accuracy of the ANN model in predicting the total mass of floor pan (m) for training and testing data samples

Table 6 The MAPE error in modeling the training and testing samples of mass and the first natural frequency of the floor panel

	Training Samples	Testing Samples
f_1	1.70%	1.78%
m	0.99%	4.12%

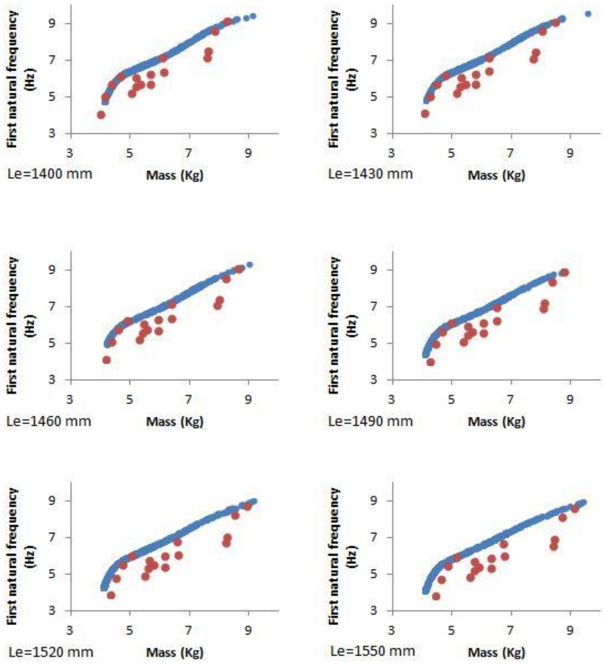


Fig. 8 Pareto front for mass and the first natural frequency of the panel along with 16 Taguchi proposed designs

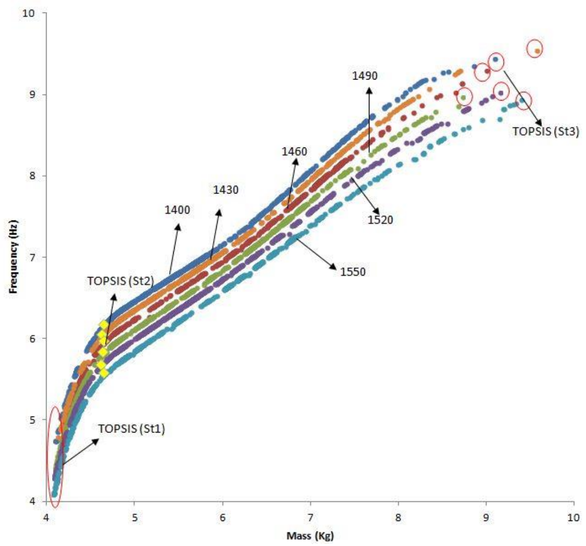


Fig. 9 Comparison of Pareto fronts associated with different values of *Le* and TOPSIS proposed trade-offs

9.3 Finding the optimal solution

Six different optimization problems are solved in this study. Each problem corresponds to a different variant of the platform. As previously stated, each variant differs from the

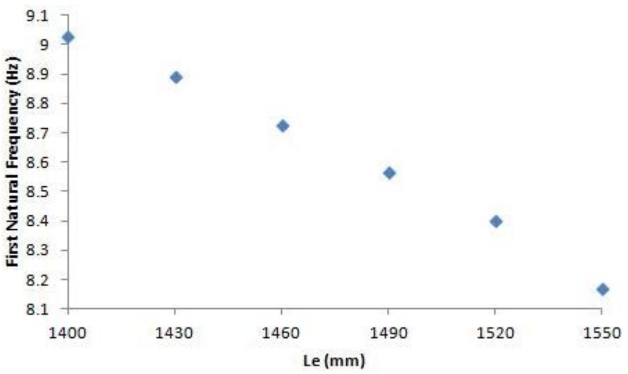


Fig. 10 Optimal value of the first natural frequency for constant mass of 8.07 Kg

Table 7 The trade-off design proposed by TOPSIS according to three different strategies

	t (mm)	W (mm)	L (mm)	D (mm)	m (Kg)	f_1 (Hz)
St1	0.65	47.96	160.41	1.64	4.098813	4.74173
	0.65	48	163.34	2.23	4.126017	4.793088
	0.65	47.98	160.51	3.21	4.188861	4.958074
	0.65	47.98	165.8	2.06	4.090929	4.418275
	0.65	47.98	159.55	2.04	4.084548	4.281189
	0.65	47.98	160.31	2.02	4.07324	4.089555
St2	0.65	48	171.48	8.29	4.649049	6.164929
	0.65	47.98	169.23	8.33	4.63433	6.049131
	0.65	47.99	167.66	8.71	4.654005	5.964145
	0.65	48	166.15	8.79	4.646252	5.835863
	0.65	48	162.84	8.71	4.624371	5.680929
	0.65	48	160.63	9.12	4.650419	5.570853
St3	1.2	41.05	120.54	13.74	9.100755	9.434678
	1.2	45.75	160.79	14.66	9.575601	9.538923
	1.19	47.28	121.87	12.73	8.996694	9.296525
	1.17	47.96	125.76	11.48	8.725228	8.971377
	1.19	47.72	138.22	12.31	9.154848	9.019497
	1.2	47.77	138.25	12.98	9.39708	8.937752

Table 8 Different values of parameter y with respect to the number of design variable and length of the floor pan based on TOPSIS results and St2

Le	y_1	y_2	y_3	y_4
1400	0.65	48	171.48	8.29
1430	0.65	47.98	169.23	8.33
1460	0.65	47.99	167.66	8.71
1490	0.65	48	166.15	8.79
1520	0.65	48	162.84	8.71
1550	0.65	48	160.63	9.12

other variants by the length of wheelbase which is embedded to length of the floor pan (L_e) as explained in Section 2. The Pareto fronts associated with the different values of L_e are depicted in Fig. 8. As it is obvious in this figure, the initial designs suggested by Taguchi are laid below the Pareto in all of the cases. This fact shows the improvement of results in the way of reducing the mass and increasing the first natural frequency of the floor pan. This comparison demonstrates that using NSGA-II for optimization not only gives a set of optimum designs which the designer is able to choose the best one among them according to priorities of the objective functions, but also the final results are remarkably improved and more trustable compared to the initial samples.

Fig. 9 shows a comparison between the Pareto fronts presented in the previous figure. According to this figure, an obvious correlation exists between the optimal designs of different product variants. This correlation is further demonstrated in Fig. 10 by a comparison between the optimal value of first natural frequency for a fixed value of mass in different lengths of the floor pan. As a result, the higher the value of L_e, the lower value of the first natural frequency of the panel is expected for a fixed value of weight. The trade-off designs found by TOPSIS for the three different strategies are shown in Fig. 9 and further described in Table 7. It is shown in this figure, that the left and right ends of the Pareto front for different values of L_e are related to trade-off designs of St1 and St3 respectively. Furthermore, a point near the fracture location of the Pareto fronts is related to St2 trade-off design in all values of L_e.

Due to future uncertainties, a product with a definite wheelbase length is not necessarily predictable. This fact originates form different roots of uncertainty which is always inevitable in designing an automotive platform. Hence, a solution to find the optimum design for an arbitrary length of wheelbase in the defined range of Eq. (1), is a linear interpolation between the results found for six different values of L_e. This interpolation is performed and the interpolated optimal values of the four design variables are presented in Eq. 6.

$$DP_i = \begin{cases} \frac{Le-1400}{30}\left(y_{i,1430}-y_{i,1400}\right)+y_{i,1400} & 1400 < Le < 1430 \\ \frac{Le-1430}{30}\left(y_{i,1460}-y_{i,1430}\right)+y_{i,1430} & 1430 < Le < 1460 \\ \frac{Le-1460}{30}\left(y_{i,1490}-y_{i,1460}\right)+y_{i,1460} & 1460 < Le < 1490 \\ \frac{Le-1490}{30}\left(y_{i,1520}-y_{i,1490}\right)+y_{i,1490} & 1490 < Le < 1520 \\ \frac{Le-1520}{30}\left(y_{i,1550}-y_{i,1520}\right)+y_{i,1520} & 1520 < Le < 1550 \end{cases} \tag{6}$$

In this equation, DP_i denotes the interpolated value of *i*-th design parameter ($DP_1 = t\,, DP_2 = w\,, DP_3 = l\,, DP_4 = d$. Furthermore, $y_{i,L}$ is the *i*-th design parameter Corresponding to each length range which is determined based on TOPSIS analysis and St2. Different values of this parameter are described in Table 8.

10. Conclusions

In this paper, the floor pan of a modular automotive platform was subjected to variation in length. This variation was considered to change the wheelbase in order to generate different product variants with different lengths such as hatchback, sedan and mini-SUV. Due to wanted and unwanted uncertainties in definite length of the future products, it is important to propose a solution which covers all of the possible values of the floor pan's length. For this purpose, the variation range of the platform length was replaced by six different values of this parameter which are uniformly distributed in the range. To investigate the operation quality of the floor pan, two important parameters were considered: 1- The first natural frequency 2- The mass of the panel. A finite element model was developed to perform the modal analysis. Validation of this modeling and simulation was investigated by an experimental test on the real model of the floor pan. Maximum error of 4.2% showed the good accuracy of the FE model and simulation. Multi-objective optimization was then performed to optimize the quality of operation of the floor pan. To improve the running time and simplifying the operations, an artificial neural network of GMDH-type was trained and tested using 96 data samples which were generated using Taguchi method and FE simulation. The accuracy of this model was also investigated and the MAPE error observed to be less than 4.12%. This study is also concluded to the following results:

1- A set of optimal designs exist for a multi-objective optimization problem such as the current case. The designer is free to use an optimum design among these non-dominated solutions. The priorities of the objective functions determine the trade-off design. MCDM methods such as TOPSIS could be employed in this situation to assign weights to the objective functions to sort the final results.

2- A correlation between the optimum solutions of the floor pans with different lengths exists. The correlation shows that the longer the floor pan's length, the worse the optimum solution is.

3- As a comparison between the optimum results, for a constant mass of the panel, the optimal first natural frequency decreases by reduction of the floor pan's length.

4- A good method to make robust the optimality of the results against to the future uncertainties is a linear interpolation between the optimal results associated with the different values of the variable parameter if a good correlation exists between the optimal solutions of different variable values.

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