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Automotive rubber part design using machine learning

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Abstract. In rubber products design finite element analysis is a widely used technique. In many cases, the pre-defined operating conditions can be achieved by changing the geometric dimensions of the product which is the well-known iterative design method. Using more than one design parameter the number of possible combinations will increase significantly. The application of Support Vector Machine (SVM) can handle the large number of data in a special way and helps to find the optimal design parameters. In this paper an optimization process of a rubber jounce is presented using nonlinear finite element analysis and SVM.

1. Introduction

In rubber bumper design one of the most important technical characteristics of the product is the force-displacement curve under compression load. This behaviour is the most critical customer need, in many cases its fulfilment requires general iterative design method. Design engineers can handle this task with the modification of the product shape. This kind of shape optimization problem can be solved with several standard optimization methods, if the parametrization of the design process is determined. As it can be seen in the following chapter, the numerical method is a good way to evaluate the working characteristics of the rubber part. Automation of the whole process feasible with the use of Visual Basic for Applications (VBA) which allows to directly access Femap from Excel. Thereby the finite element model pre- and post-processing were controlled with macro running in excel.

The application of SVM in optimization process has the advantage that the transformation function between the input space (D) and so-called feature space (E) can be hidden, and supervised machine learning procedures can be applied to find an appropriate regression function.

2. Finite element model of the rubber bumper under compression load set

Rubber behave as a nonlinear, elastic, isotropic and incompressible material, which can be described accurately with hyperelastic constitutive model. Within this several material models and material constants can be found. The material models for rubbers are generally given by the strain energy potential. A successful finite element simulation of rubber parts hinges on the selection of an appropriate strain energy function and on the accurate determination of material constants. Because of material incompressibility, the strain energy function can be divided [1]

$$W = W_D(\bar{I}_1, \bar{I}_2) + W_b(J) \quad (1)$$



where $W_b(J)$ denotes the volumetric terms of the strain energy function and J is for the Jacobian and $W_D(\bar{I}_1, \bar{I}_2)$ is for the deviatoric terms of the strain energy function. The polynomial form of the strain energy potential is based on the first \bar{I}_1 and second \bar{I}_2 strain invariants of the right Cauchy-Green tensor [2]

$$W = \sum_{i+j=1}^N c_{ij}(\bar{I}_1 - 3)^i(\bar{I}_2 - 3)^j + \sum_{k=1}^N \frac{1}{d_k} (J - 1)^{2k} \quad (2)$$

where determination of c_{ij} and d_k material constants are required in material model. The κ bulk modulus can be calculated as

$$\kappa = \frac{2}{d} \quad (3)$$

where d is the material compressibility parameter.

Mooney-Rivlin, Yeoh and Neo-Hookean material models are available within the polynomial form of the strain energy potential. There are two-, three-, five- and nine-term Mooney Rivlin models. With $N=1$ substitution the expression of the polynomial form is equivalent with the two-term Mooney-Rivlin model.

$$W_{MR} = c_{10}(\bar{I}_1 - 3) + c_{01}(\bar{I}_2 - 3) + \frac{1}{d} (J - 1)^2 \quad (4)$$

According to [3-4] two-term Mooney-Rivlin model with $c_{10} = 1,28801 \text{ MPa}$, $c_{01} = 1,1371 \text{ MPa}$ and $\kappa = 1000 \text{ MPa}$ values were selected for the finite element investigation of the rubber part.

The geometry of the he investigated rubber specimen is axisymmetric, furthermore the boundary conditions are symmetric as well, thereby the deformation of the shape is independent from the ϕ axis. In such a case it is worth choosing axisymmetric element (isoparametric quadrilateral elements) for meshing. The size of the element was 1 mm . The investigated geometry can be seen on 'Figure 1' and it was created with $H = 40 \text{ mm}$, $\alpha = 3^\circ$, $D_1 = 108 \text{ mm}$ and $D_2 = 33 \text{ mm}$ dimensions. Under working conditions, the rubber jounce comes into contact on the bottom and on the top with flat steel parts. Therefore, frictional contact was defined between the surfaces of the product and the steel parts. The coefficient of static friction was selected $\mu_s = 0,6$ according to [5]. At boundary conditions it is given 12 mm prescribed displacement for the top edge of the upper one steel plate, furthermore the bottom curve nodes on the lower one steel were constrained along z axis. Finally finite element analysis was run and as a result the 'Figure 1' shows the deformation state of the rubber jounce while the named 'Optimum characteristics' curve on 'Figure 2' shows the load displacement characteristics of the investigated product.

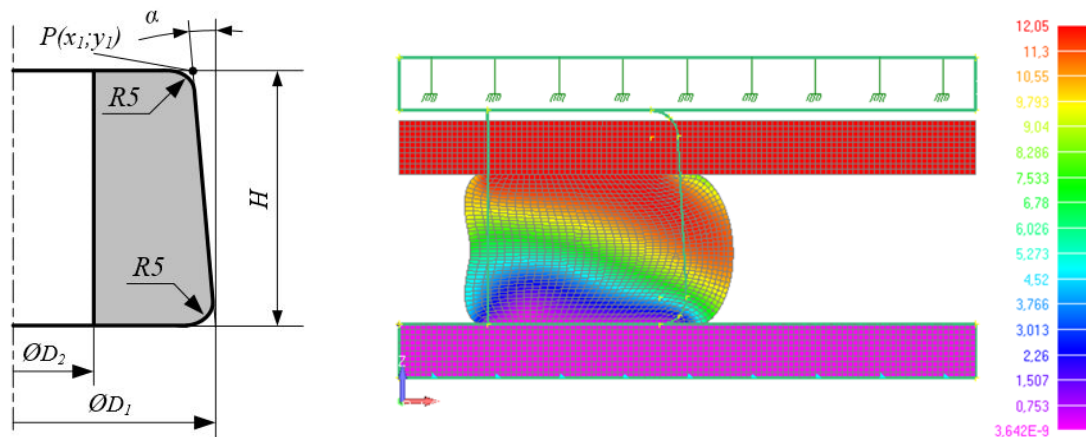


Figure 1. The investigated rubber jounce's geometry and the obtained deformation state from finite element analysis.

3. Two-Dimensional Shape Optimization Problem

In many cases the dimensions of the rubber bumper built in air spring are constrained by other parts. During the current investigation, the product's height ($H = 40 \text{ mm}$) and draft angle ($\alpha = 3^\circ$) were fixed while D_1 outer diameter and D_2 hole diameter are variables, see in 'Figure 1'. Thus in the shape optimization the design parameters are defined in mm , according to the following conditions:

$$\mathbf{D} = (D_1; D_2), \text{ where } \begin{cases} D_1 \in [70, 71, \dots, 130] \\ D_2 \in [10, 11, \dots, 60] \end{cases} \text{ and } x_1 - \frac{D_2}{2} \geq 15 \quad (5)$$

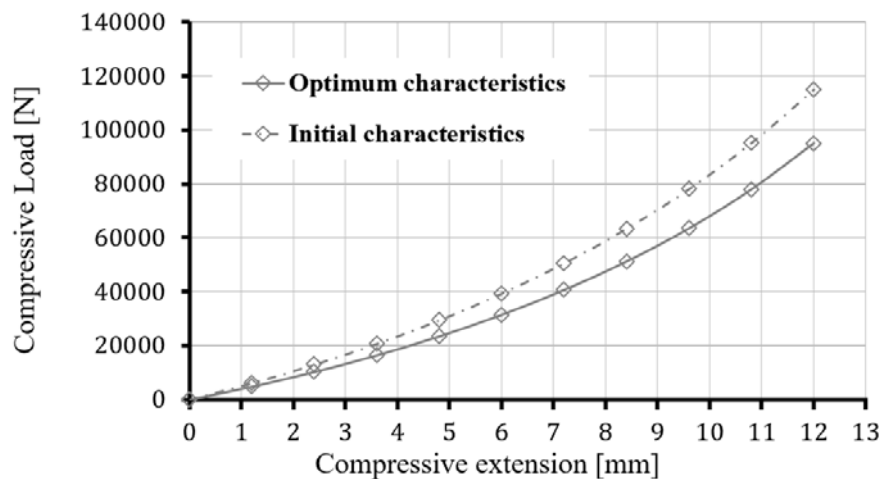


Figure 2. Working characteristics of rubber jounces with optimum shape and a possible initial shape.

The goal of the shape optimization process is to minimize the difference between the initial characteristics and the desired characteristics see on 'Figure 2'. The aim of this research is to investigate the applicability of support vector regression machine, therefore the desired characteristics determined from predefined optimum shape $\mathbf{D}_{opt} = (108; 33) \text{ mm}$. The finite element analysis was solved in 100 step and every 10th step was created as output. The difference was calculated as sum of the square error (SSE):

$$E(\mathbf{D})_{FEA} = \sum_{i=1}^{10} (F_i(\mathbf{D}_{opt}) - F_i(\mathbf{D}))^2 \text{ [kN}^2\text{]} \quad (6)$$

where $E(\mathbf{D})$ is the error value in an investigated design point, $F_i(\mathbf{D}_{opt})$ is the i^{th} results of required compression force value in the optimal design point while $F_i(\mathbf{D})$ is the i^{th} results of required compression force value in the initial design point. Table 1 contains the calculated error value for an initial design point $\mathbf{D} = (130; 60) \text{ mm}$. The objective function of the shape optimization process is to minimize this error value.

Table 1. Calculated Error values in different design points.

	$D_1[\text{mm}]$	$D_2[\text{mm}]$	E_{FEA}
Optimum Shape	108	33	0
Initial Shape	130	60	1275,84

4. Train support vector regression models

The objective of the machine learning is to discover a function $E = f(\mathbf{D})$ that best predict the value of E associated with each value of \mathbf{D} . At the first step 128,36,22 and 8 pieces of vertex pairs (Learning

Points) were selected from D according to 'Figure 3', than E values were determined by using finite element analysis. Thereby the training set was produced for the machine learning algorithm.

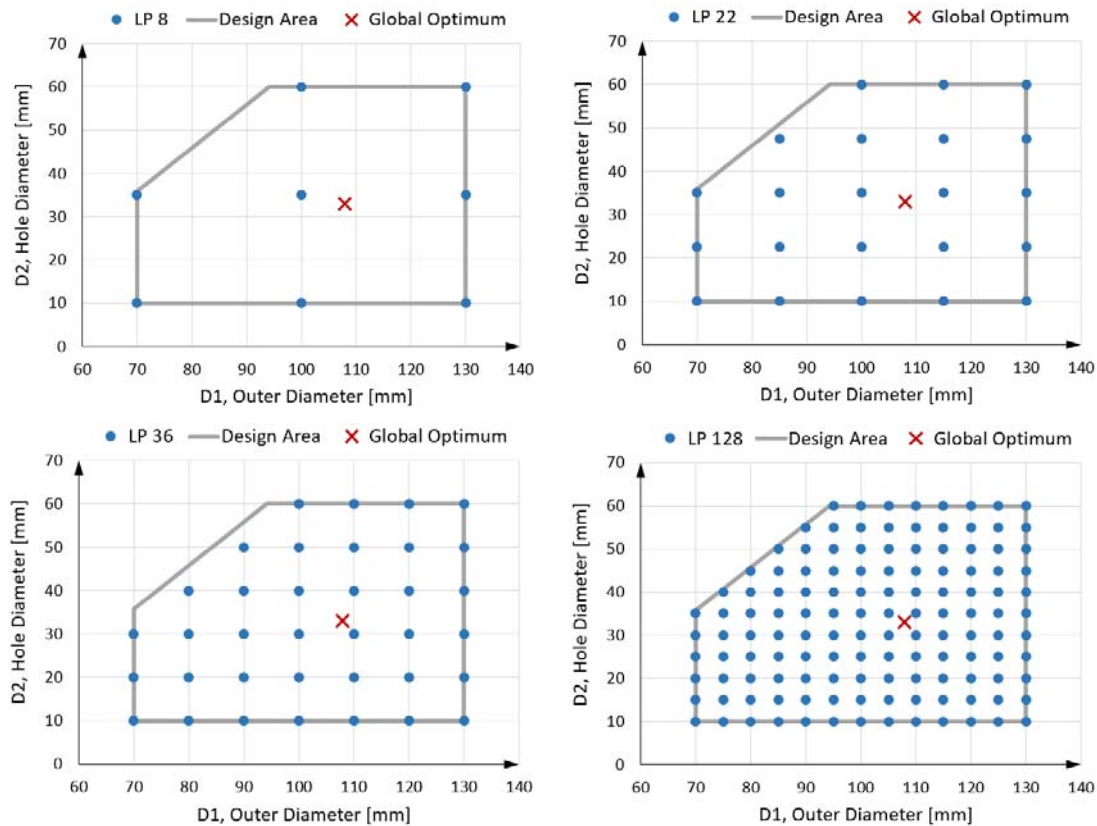


Figure 3. The selection of different learning points set from the design area.

Matlab has a Regression Learner application. With the use of this application we could perform automated training to search for the best regression model type, including linear regression models, regression trees, Gaussian process regression models, support vector machines, and ensembles of regression trees. Manual regression model training was ran without validation data set for all available SVM types.

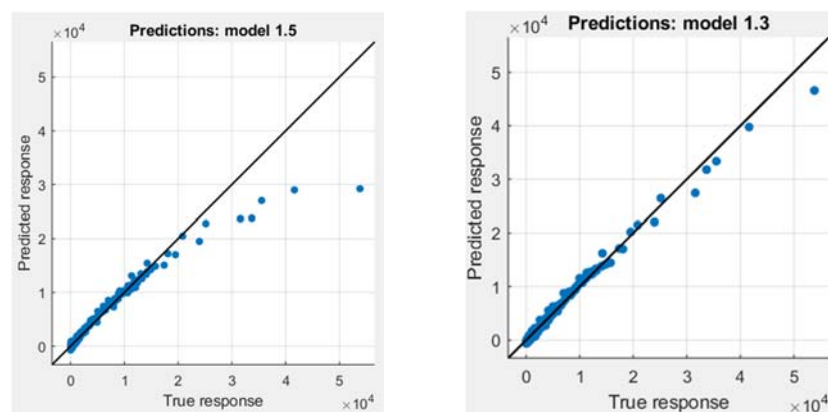


Figure 4. Predicted response versus true response by the use of different kernel function.

The predicted response of Medium Gaussian SVM model is plotted against the actual, true response, see the left one picture in 'Figure 4', while the right one shows the Cubic SVM model's predicted values. A perfect regression model has a predicted response equal to the true response, so all the points lie on diagonal line. The vertical distance from the line to any point is the error of the prediction for that point. The predictions are scattered more farther from the line with the use of Gaussian model like with Cubic model so this has smaller errors for the data set.

As it could see, the goodness of the prediction highly hinges on the kernel function type. To choose the best model, the root mean square error (RMSE) value was calculated on the predicted set. As it can be seen below in the Table 2, the best trained model was the Cubic SVM for each set of Learning Points.

Table 2. Comparison the goodness of the kernel functions with the use of different number of Learning Points and root mean square error calculation.

kernel function	RMSE			
	LP 8	LP 22	LP 36	LP 128
Linear SVM	15765	12972	11516	9526
Quadratic SVM	11968	9053	5598	3751
Cubic SVM	8645	5304	2619	1012
Fine Gaussian SVM	11695	9135	7643	3514
Medium Gaussian SVM	12202	8419	6382	2903
Coarse Gaussian SVM	16553	12710	11123	8520

5. Investigate the minimum number of required learning points

Using the different trained Cubic SVM models for different data sets, predictions were made for each combination of design parameters. Table 3 contains the smallest predicted object function value for each data set and the associated design parameters. Based on the values, the minimum error of the possible solution is $E = -660,84$ for which the optimum design parameters are $\mathbf{D}_{opt}^{SVM} = (108; 33) \text{ mm}$. This object function value is not possible because of the SSE calculation method, but this cannot be eliminated. Thereby and due to the verification the error values were calculated by finite element method as well, see in Table 3. As it was expected these numbers are different, however the error values are close to zero except for that predictions which one was made by the data set containing 8 pieces of learning points. The rubber bumper working characteristics were also determined for each predicted optimum shape, see in 'Figure 5'. Compared the different possible optimum shape with the known optimum, it can be stated that each geometry shows nearly the desired characteristics except for the *LP 8*.

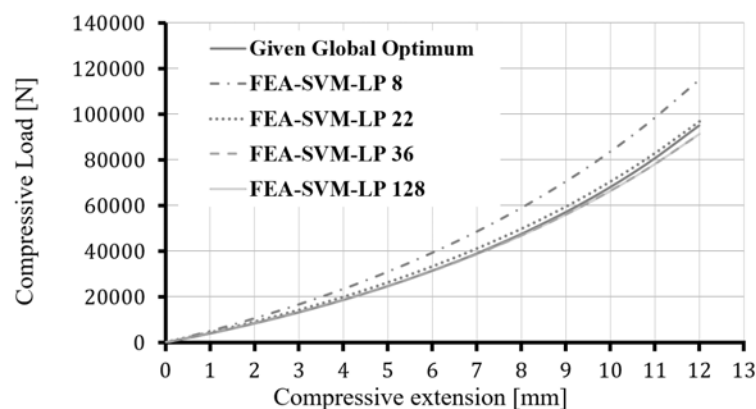


Figure 5. Comparison of the predicted different optimum shape's working characteristics.

Table 3. The smallest predicted and calculated object function value for each data set and the associated design parameters.

Method	$D_1[mm]$	$D_2[mm]$	E_{SVM}	E_{FEA}
Global Optimum	108	33	-	0
LP 8	130	60	2409,65	1275,84
LP 22	124	60	-282,65	30,02
LP 36	122	60	-625,44	23,54
LP 128	119	55	-660,84	23,28

6. Conclusion

Foremost the finite element model of the rubber jounce was built with the use of prescribed displacement as load set. The deformation and working characteristics of the product were determined from the analysis results. Next step was the introduction of two-Dimensional Shape Optimization Problem, where the design parameters and object functions has been defined also. Training data set with different number of learning points was created for supervised machine learning. Support vector regression method was selected to predict the optimum shape of the rubber jounce. With the use of calculated training data set several kernel functions were trained. Root mean square error (RMSE) value was calculated to choose the best model. For every data set the Cubic kernel function shows the best match, therefore it was chosen for the prediction of each combination of design parameters. From the predicted values the optimum shape was determined for each data set. The predicted values did not agree with the finite element calculations, however the determined optimum shape was sufficiently accurate if the number of the learning points are at least 22. As a result, it can be stated that support vector machine is a good way to predict the optimum shape of rubber products. It would be worth in the future to test the efficiency of the algorithm for more complex design problem.

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