The study of parametric optimization algorithms on example of vehicle bumper crashworthiness

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Abstract. Different algorithms of parametric optimization (implemented in the program LS-OPT) to solve high-speed and high-nonlinear problems of impact character on the example of vehicle bumper optimization are considered and compared. Different algorithms of response surface optimization such as linear polynomial model, quadratic polynomial model, Feedforward, Radial Basis Function, Kriging and Support Vector Regression were studied and analyzed; algorithms of choosing point selection scheme were considered. The analysis of optimization results allowed us to determine which of these algorithms are most effective in terms of accuracy and computational time. The problem of impact on the vehicle’s bumper is solved in the paper, the optimization is based on the application of metamodel (RBF). The method provided a reduction of its mass by 16% while maintaining the initial parameters of crashworthiness.

1. Introduction

The evolution of the automotive industry has reached such a level that it is impossible to imagine further improvement of structures without using optimization, especially in the field of crashworthiness [1-6].

Parametric optimization methods are divided into direct optimization and metamodel-based optimization. The direct optimization is used to solve single-criteria problems with a relatively small number of variables, the metamodel-based optimization is used to solve complex multi-criteria problems with many variable parameters.

Structural scheme of the optimization algorithm is shown in Figure 1, where you can see that the algorithm of creating a metamodel includes three main stages: the choice point selection scheme, the construction of response surfaces for the criteria and limitations and the search for the optimal solution (minimum target function).

Let’s consider and compare different optimization algorithms based on the construction of a metamodel (implemented in the program LS-OPT) to solve high-speed and high-nonlinear problems of crashworthiness on the example of a vehicle bumper.

The purpose of the work is to select the preferred optimization algorithm based on the construction of the response surface (metamodel) in relation to the processes of impact on the supporting structures of vehicle to reduce their mass and meet the requirements of crashworthiness at acceptable values of accuracy and time of solving.
2. Optimization methods

2.1. The first stage of the optimization algorithm
At the first stage of the optimization it is necessary to choose the model of the response surface, which can be obtained in different ways. Let's consider the following types of approximations: linear polynomial model, quadratic polynomial model, neural networks: Feedforward (FF) and Radial Basis Function (RBF), Kriging and Support Vector Regression (SVR).

Linear polynomial model is the simplest and least costly in terms of computing time. It is built by approximating the $n$-th number of individual test results. Calculations show that the accuracy of such a model is satisfactory only for preliminary evaluations.

The FF and RBF models are based on the principles of the neural networks. The direct-spread neural networks like FF has a clear multilevel topology [7]. Each unit performs a biased weighted sum of their inputs and passes this value through a transfer (activation) function to produce the output. The outputs of each layer of neurons are inputs to the next level. RBF uses radial basic functions as activation functions [8]. The output of the neural network is a linear combination of radial basic functions of inputs and unit parameters.

The Kriging model is based on the interpolation method, for which interpolated values are simulated by the Gaussian process defined by previous covariance.

The SVR model, which is a variation of the reference vector method, has good generalization properties [9]. Instead of minimizing the empirical incoherence, the model is based on the structural minimization of incoherencies.

2.2. The second stage of the optimization algorithm
At the second stage of the optimization problem it is necessary to choose the point selection scheme, which depend on the type of response model under consideration. The set of points and types of response surface determines the metamodel for further optimization. There are many ways to select the point selection scheme. The following methods are known from the theory of experiment planning: factorial design (factor experiment), Koshal design, Central composite design, D-optimal, Latin hypercube design, Space-filling design.
The method of the complete factor experiment involves calculating the number of experiments by
\[ N = m^n, \]
where \( m \) — the number of levels of each factor, \( n \) — number of factors. The disadvantages of this method include its redundancy in terms of the number of experiments, which leads to irrational waste of time.

The D-optimal method, most often used for polynomial models, uses a subset of all possible points of a complete factor experiment [10]. For linear polynomial model, the minimum number of points is determined by \( 1.5(n+1)+1 \), for the quadratic polynomial model, by \( 0.75(n+1)(n+2)+1 \). This method is a compromise of achieving high accuracy of forecasting and low calculation time.

The space-filling method optimizes the minimum distance between experimental design points for a given number of points [11]. This method is convenient to combine with FF, RBF and Kriging models. The disadvantage of this method is that it does not "recommend" the number of necessary experiments.

2.3. The third stage of the optimization algorithm
At the third stage the algorithm of searching for the minimum of the target should be chosen. The program provides three variants of the minimum search: Leap-Frog Optimizer [12] (the algorithm used when the minimum of the target function is searched for only one criterion), genetic algorithm (multi-criteria and multi-parameter algorithm) [13, 14] and Adaptive Simulated Annealing [15, 16] with the ability to switch to Leap-Frog Optimizer to search for the local minimum.

In this paper, the D-optimal method is used for polynomial metamodels, and space-filling method is used for the rest of them [17]. The number of points to obtain an exact solution is generally unknown. The sequential RSM method is used to determine this parameter. As a result, the number of points depended on the convergence of three criteria: the accuracy of the metamodel, the accuracy of the optimization criterion, and the accuracy of the restrictions (the minimum number of points for one iteration cannot be less than \( 1.5(n+1)+1 \)). All criteria are defined by the engineer and depend on the task.

3. Mathematical model and optimization model
In order to determine the most effective algorithm of parametric optimization, a study of the vehicle bumper on impact was conducted. The main purpose of the bumper is to protect against impact by maximizing energy absorption. In the process of impact in the construction of the bumper there are numerous zones with plastic deformations, there comes a loss of stability and buckling. This type of problem is well suited for the analysis of optimization algorithms, because it describes the main nuances of deformation arising in the elements of vehicle construction in road accidents. The test pattern and 3D model of the car bumper are shown in Figure 2.

![Figure 2](image-url)

**Figure 2.** Test pattern (a) and 3D model (b) of the car bumper:
1 - Test bench; 2 - Constraint
Geometric dimensions, properties of materials, conditions of interaction between bumper and drummer are considered in detail in the paper [18].

The loads and simulation results obtained using the LS-DYNA program are shown in Figure 3. The drummer's mass is 25 kg, the speed is 10 m/s, and the calculation time is limited to 0.025 s. The maximum movement of the drummer is 100 mm.

The goal of the optimization is to create a structure similar in crashworthiness to the basic model with a minimum mass. The target function (criterion) is the mass of the bumper. The restriction was the maximum movement of the drummer, which should correspond to the experimental data.

The bumper structure, consisting of external and internal power elements, is broken into parts. Each of them had an independent variable - the thickness of the internal and external t nj parts respectively (i = 1...5, j = 1...5). The range of change of the variable is 0,5...1,5 mm. Figure 4 shows finite element models of bumper power elements broken down into parts.

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**Figure 3.** Simulation results

**Figure 4.** Finite element models of external (a) and internal (b) bumper power elements
The Adaptive Simulated Annealing algorithm is used to optimize the bumper as the most effective algorithm among those related to the crashworthiness [19].

It is important to note that all algorithms are very sensitive in terms of accuracy and duration of the solution to the assignment of criteria of convergence of the optimization task. In this case, the sequential RSM method is used, i.e. the initially unknown number of experiments was determined in the process of iteration solution. The result was obtained when the convergence criteria did not exceed 0.01 values. Setting too high values may lead to inappropriate results due to errors in the solution.

4. Result and discussion

Analysis of the results of application of different metamodels for vehicle bumper optimization is given in the Table.

| Type of metamodel | Bumper’s mass | Moving the drummer | Solution convergence (number of experiments) |
|-------------------|---------------|--------------------|--------------------------------------------|
|                   | Value, kg     | Change, %          | Value, mm | Accuracy, % |                          |
| Base model        | 3.14          | –                  | 100       | –           | –                          |
| linear polynomial | 2.68          | 14.6               | 115       | 15          | No (391)                   |
| quadratic polynomial | 2.25         | 28                 | 162       | 62          | No (391)                   |
| FF                | 2.46          | 22                 | 158       | 58          | No (391)                   |
| RBF               | 2.64          | 16                 | 101       | 1           | Yes (221)                  |
| Kriging           | 2.39          | 24                 | 148       | 48          | No (391)                   |
| SVR               | 2.46          | 22                 | 128       | 28          | No (391)                   |

The results showed that the convergence of the optimization problem solution has been achieved only for the RBF metamodel (221 experience, 13 iterations). For other cases, the Table presents the results of the best intermediate iterations.

Figure 5 shows the response surfaces method [20] obtained with the help of the considered metamodels, where L is the movement of the drummer; \( t_{v1} \) is the thickness of the inner part; \( t_{n1} \) is the thickness of the outer part.

For all types of metamodels, the impactor's movement error (for the best intermediate iterations) varied from 15 % (linear polynomial model) to 62 % (FF), except for the RBF, for which all convergence conditions were met, and the impactor's movement was 101 mm. Consequently, only the RBF model is applicable to optimization tasks related to impacts specific to bumpers, bodies and cabins of vehicles.

For the problem of crashworthiness of the vehicle bumper the use of the optimization allowed to reduce the mass by 16% (from 3.14 to 2.64 kg) while maintaining the crashworthiness of the basic model.
5. Conclusion
The use of control, FF, Kriging or SVR metamodels does not allow to get the result for the solution of the optimization task. The accuracy of the drummer movement for intermediate iterations exceeds 28%, it is too high.

The linear polynomial model with D-optimal is advisable to use only when performing preliminary multi-variant calculations for impact problems, as it is rational in terms of accuracy and machine time.

The use of software based on RBF metamodel allowed to reduce the mass of the vehicle bumper by 16% (from 3.14 to 2.64 kg) while maintaining the initial parameters of crashworthiness.

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