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OPTIMAL DESIGN OF AUTOMOTIVE SUSPENSION SPRINGS USING DIFFERENTIAL EVOLUTION ALGORITHM

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Abstract: The automotive industry has been growing steadily and paying attention to develop technologies and production processes in the world. Automotive companies are facing great competition due to the increasing number of companies and the rapid increase in customer expectations as a result of developing technological products. In order to compete, automotive manufacturers need to meet the expectations of customers and governments, such as vehicle weight, collision safety, fuel emissions and vehicle comfort. In order to ensure that competition is sustainable, companies should design lighter and more efficient parts that require less processing costs with more precise operations. Recently, concerns about fuel consumption and air pollution have been reported. Meta-heuristic optimization methods have been widely used for optimization of vehicle component over the past three decades. In this paper, differential evolution (DE) algorithm is used for optimization of the coil spring design, which is one of the suspension spring types. Using the DE algorithm, the mass of the coil spring decreased by about 29.3 %. The results show that the DE algorithm provides better solutions as previous methods in the literature.

Keywords: Design optimization, Differential evolution algorithm, Spring

Diferansiyel Gelişim Algoritması ile Taşıt Süspansiyon Yaylarının Optimum Tasarımı

Öz: Otomotiv endüstrisi son otuz yıldır istikrarlı bir şekilde büyümekte ve sürekli olarak dünyada teknoloji ve üretim süreçlerini geliştirmek için çalışmalarını devam ettirmektedir. Otomotiv şirketleri, artan sayıda firma ve gelişen teknolojik ürünler sonucunda müşteri beklentilerindeki hızlı artış nedeniyle büyük bir rekabetle karşı karşıyadır. Rekabet edebilmek için otomotiv üreticilerinin, araç ağırlığı, çarpışma güvenliği, yakıt emisyonları ve araç konforu gibi müşterilerin ve hükümetlerin beklentilerini karşılaması gerekiyor. Rekabetin sürdürülebilir olmasını sağlamak için, şirketler daha hassas operasyonlarla daha az işleme maliyeti gerektiren daha hafif ve daha verimli parçalar tasarlamalıdır. Son zamanlarda, yakıt tüketimi ve hava kirliliği ile ilgili endişeler bildirilmiştir. Meta-sezgisel optimizasyon yöntemleri, son yirmi yıl içinde araç bileşeninin optimizasyonu için yaygın olarak kullanılmaktadır. Meta-sezgisel optimizasyon yaklaşımlarından biri olan diferansiyel delişim (DE) algoritması araç süspansiyon sistemlerinde kullanılan yay tasarımının optimizasyonunda kullanılmıştır.
Bu çalışmada kullanılan yayın kütlesi % 29.3 oranında azaltılmıştır. Elde edilen veriler DE algoritmasının literatürde yer alan diğer evrimsel optimizasyon yöntemlerinden, genetik algoritma, yapay arı kolonisi algoritması ve parçacık sürüsü algoritmasından daha iyi çözümler sunduğunu göstermektedir.

Anahtar kelimeler: Tasarım optimizasyonu, Diferansiyel gelişim algoritması, Yay

1. INTRODUCTION

The automotive sector was under pressure due to the increase in the number of cars and the development of technologies to reduce fuel consumption and emissions.

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In particular, reducing vehicle weight and thus minimizing fuel emissions is one of the research areas focused on over the past 20 years. For these purposes, new tools are required to assist the designer in the initial design phase. The efficient use of computer-aided engineering and optimization techniques in design processes enables the design to be verified during the design phase without the need for trial-and-error, thus reducing cycle time and minimizing costs.

Optimization is often used in engineering designs to create less costly and more powerful structures. In engineering designs, the current structure is optimized in order to mitigate the structure studied, to increase its strength, to move to the maximum or to minimize the parameters such as exposure to displacement conditions and constraints.

Evolutionary algorithms inspired by nature are used as a powerful tool to figure out complex optimization problems encountered. For almost a quarter century, many evolutionary methods, such as artificial bee colony algorithm, ant colony algorithm, genetic algorithm, particle swarm algorithm, artificial immune algorithm, have been widely used to minimize computational errors in access to optimum design and analytical optimization (Karaboga and Basturk, 2003; Karaboga and Basturk, 2007; Karaboga and Basturk, 2008; Camp et al., 2005; Eberhart and Kennedy, 1995; Yildiz, 2009; Yildiz and Solanki, 2011; Perez and Behdinan, 2007; Yildiz and Saitou, 2011; Bureerat and Limtragool, 2006; Ferhat et al. 2011).

For instance, Yildiz and Lekesiz (2017) developed a novel charged system search algorithm based approach for optimization of continuum structures. The developed approach is applied to optimization of vehicle component. In (Yildiz , 2017), well-known newly developed optimization methods were used for optimization of machine components.

The differential evolution (DE) algorithm, is the population-based optimization approach (Storn and Price, 1995). The main principle of the DE algorithm is to produce new members by calculating vector differences between members who make up the current population.

Many research works have been made for optimization of automotive components recently. Designers and manufacturers working in the automobile sector are aiming to produce high-quality and cost-effective parts of the suspension system. To achieve these goals, optimization of automobile parts is desirable. Different suspension types for automotive applications are defined (Birch, 1988). Some methods were developed on spring design (Bhateja et al., 1996). The applications of composite materials in the automotive sector to bumpers, engine parts, backplate pans, drive shafts, elliptical springs, leaf springs were discussed(Weeton, 1986). Fiber-reinforced plastics that can be used in the spring industry (Timmins, 1977).

The volume of the wire, the desired spring rate, space restriction, and fatigue life minimizing the optimum design of the package has been obtained by applying fatigue analysis (Pollanen and Martikka, 2010).

Effect of weight reduction on the optimization of the design stage by improving production processes and materials was examined. In studies on leaf spring design to reduce vehicle weight, it is concluded that this can be achieved by using composite materials. By compiling these studies, they analyzed the problems in reducing the total weight of the vehicle by using the springs produced from the composite material and concluded that the contribution of composite springs to the weight reduction according to the steel springs is positive (Sharma and Bergaley, 2014).

Nonlinear optimization method called the "cage search method", was applied to the optimum design of a leaf spring (Liu and Chadda, 1993). Genetic algorithm was used for optimization of composite spring (Rajendran and Vijayarangan, 2001). Another procedure for reliability-based optimization of automobile parts was proposed by researchers (Zhang et al., 2005).

In this study, the optimum design of the helical spring was realized by using the differential evolution algorithm.

2. DIFFERENTIAL EVOLUTION ALGORITHM

The differential evolution (DE) algorithm is a population-based optimization approach. The main principle of the DE algorithm is to produce new members with vector differences calculated among members in a population (Storn and Price, 1995).

The process steps of the DE algorithm are mutation, crossover and selection. The DE algorithm starts with the randomization of an NP solution vector population at the beginning of iterations. The mutation operation, crossover operation, and then selection operation are applied sequentially to this first population. The mutation operation and crossover operation are used to create new vectors, while the selection operation is applied to determine if these new vectors are still kept in the next iteration. The following are the operators of the DE algorithm.

2.1. Mutation

The mutation process is called generating new parameter vectors by adding weight variation to a third vector between two population vectors. The parameters of the mutated vector are then compared to the parameters of the target vector to test the pre-tested vector. A mutant vector is generated corresponding to each $X_{i,G} = 1,2,3,\dots,NP$ target vector.

$$v_{i,G+1} = x_{r1,G} + \left(\left(x_{r2,G} - x_{r3,G}\right) * F\right) \tag{1}$$

$r_1, r_2, r_3, i \in \{1,\dots,NP\}$ is chosen randomly to be different from each other. Equation (1) is the size of the population represented by NP, and F is a scaling factor and controls the magnitude of the different variations of $\left(x_{r2,G} - x_{r3;G}\right)$.

2.2. Crossover

Trial vector $u_{ji,G+1}$, is produced by mixing the vector with the vector mutated with the parent vector.

$$u_{ji,G+1} = \begin{cases} u_{ji,G+1} & \leftarrow \left(rnd_j \le \mathrm{C}\right) \text{or } \mathrm{j} = \mathrm{r}c_i \\ x_{ji,G} & \leftarrow \left(rnd_j > \mathrm{C}\right) \text{ and } \mathrm{j} \ne \mathrm{r}c_i \end{cases} \tag{2}$$

Where $j = 1\!:\!VD\ and\ r_j \in [0,1]$ are determined random ; C is crossover ratio $\in [0,1]$, $rc_i \in \{1\!:\!VD\}$ vector which is chosen random. *VD* refers to the dimensions of a vector.

2.3. Selection

This process is the stage in which the trial vector obtained as a result of mutation and crossing is evaluated. Next, the efficiency of target vector and the trial vector is compared to the better one. If the function value generated by the experiment vector is smaller, the experiment vector is copied to the next generation, on the contrary the target vector takes its place in the next generation.

$$x_{i,G+1} = \begin{cases} u_{i,G+1} & \text{if } f\left(u_{i,G+1}\right) \le f(x_{i,G}) \\ & x_{i,G} \text{ other case} \end{cases} \tag{3}$$

Parameter values accepted in this study; the mutation rate (F) is 0.8 and the crossover rate (CR) is 0.95.

The pseudo code of the DE algorithm is given as follows.

Differential evolution algorithm

Begin

Generate randomly initial population of solutions

Repeat

Mutation

Crossover

Until a termination is satisfied,

End

End.

3. SUSPENSION SPRINGS

The spring is a structure with high elastic deformation function which is compressed when loaded on it and returned to its original form when the load is withdrawn. The springs which are part of the suspension system of a vehicle and the weight of the vehicle are supported. When driving, the vehicle's engine and drivetrain, body and frame will be weighted. If the sprung weight is increased, the springs are compressed further. Weights such as wheels, tires and braking devices are called asymmetrical weights.

The weight of the vehicle is carried by the tires. The transmission of the weights of the sprung components is primarily from springs to non-spring parts and then from tires to ground. The unladen weight of an automobile forms tires, wheels, other suspension parts that move directly with the tires near the brake assembly. The weight of the car consists of engine, transmission, frame, body and other parts connected with this body. The spring-loaded weight is connected to the unladen weight by the suspension springs. The amount of opening of the suspension springs varies depending on the movements during travel. Figure 1 shows the suspension springs, the weight of the spring and the asymmetric weight of a vehicle. The suspension springs are 10-20% by unsprung mass. The advantage of reducing unladen weight is to minimize vibration and increase the driving comfort of the car.

In the automotive industry, different types, shapes, sizes, ratios and capacities of the springs such as torsion bar springs, leaf springs, and coil springs have been used. These springs can be used as a quad for a vehicle or in different combinations with different mounting styles. The suspension springs used in the vehicle design are illustrated in Figure 2.

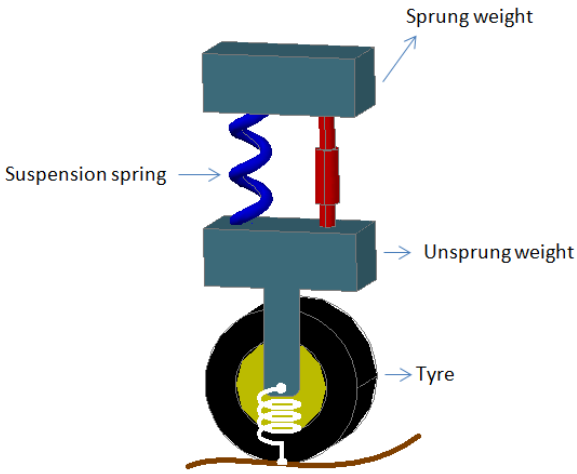
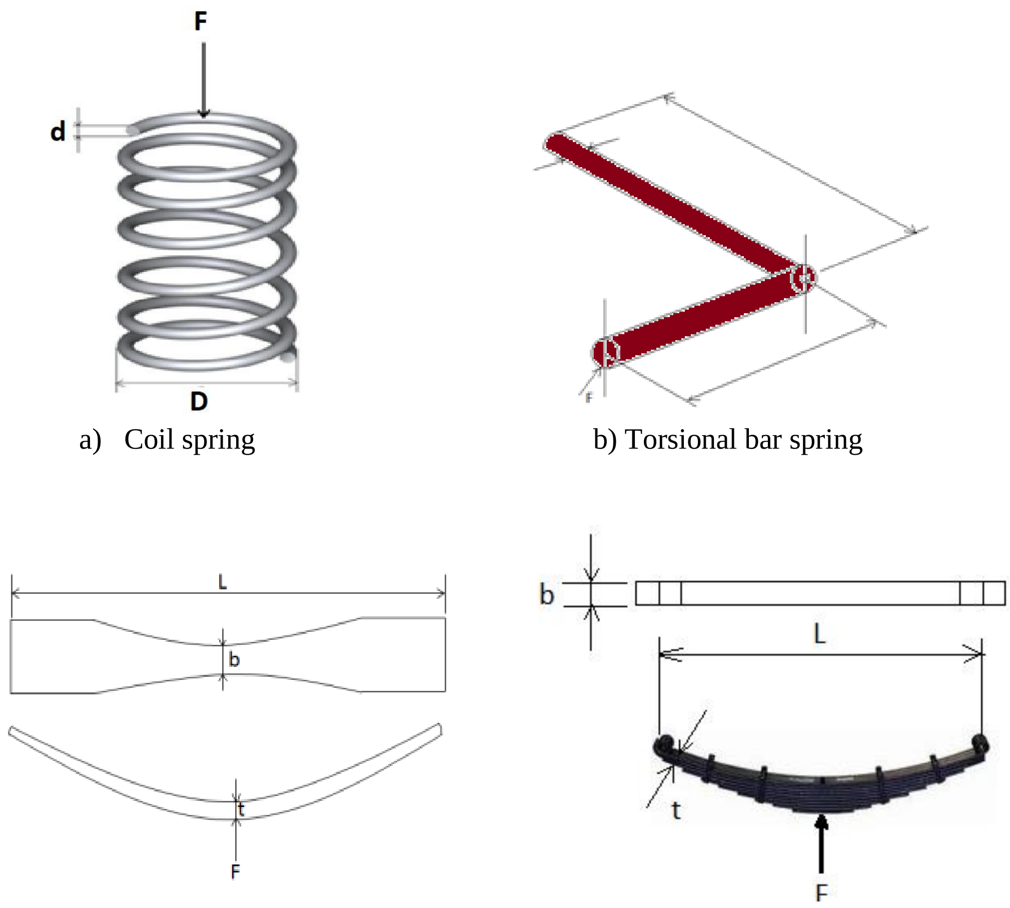


Figure 1:
Display of suspension spring weight, and unladen weight in a vehicle



a) Coil spring

b) Torsional bar spring

c) Composite leaf spring

d) Steel leaf spring

Figure 2:
Different suspension springs

4. MATHEMATICAL MODELING OF THE OPTIMIZATION PROBLEM

4.1. Objective Function

In the optimization of a spring, minimum weight or minimum volume is taken into consideration as objective function. The objective function of the coil spring design problem is minimization of mass (M) of the spring and it is calculated by the following equation;

$$M = \frac{(n+Q)\pi^2 D d^2 \rho}{4} \tag{4}$$

4.2 Design Variables

The variable that significantly changes the value of the objective function is called the design parameters. The design parameters are the variables that must be kept constant. Spring diameter, wire diameter and quantity of active spirals are design variables of the optimization problem solved in this paper. The values of the design variables and the design parameters used in the optimization of this spring design are given in Tables 1 and 2.

Table 1. Design variables values of coil springs

Parameters	**Lower limit (mm)**	**Upper limit (mm)**
Spring diameter (D)	80	89
Wire diameter (d)	14	21
Quantity of active spirals (n)	5	9

Table 2. Design parameters of coil springs

Constants	**Value**
Modulus of rigidity (G)	7800 kgm^{-3}
Load (F)	$85.2x10^3$ MPa
Quantity of inactive turns (Q)	4600 N

4.3 Constraints

First constraint considered in this optimization problem is shear stress. The maximum shear stress τ in a coil spring occurs on the inner face of the spring coils and is equal to:

$$\tau = \frac{8FD}{\pi d^3}\left(\frac{(4D-d)}{(4D-4d)} + \frac{0.615d}{D}\right) \tag{5}$$

The latter constraint is maximum deflection . The maximum deflection (δ) of a coil spring is obtained by the following equation;

$$\delta = \frac{8FD^3N}{d^4G} \tag{6}$$

Side constraints used in this paper are given as following:

$$200 \text{ MPa} \leq \tau \leq 250 \text{ MPa} \tag{7}$$

$$15 \text{ mm} \leq \delta \leq 22 \text{ mm} \tag{8}$$

In this study, differential evolution algorithm is used for optimization of the vehicle suspension springs. In this study, the number of populations was determined as 40 and the number of iterations as 250. TThe results obtained as a result of the optimization of the suspension springs are given in Table 3. The objective function of the optimization problem considered in this paper is the total mass of the suspension spring. The minimum mass is obtained by the best possible combination of design variables.

Table 3. Optimal parameters of coil springs

	Initial	Simulated Annealing	Differential Evolution
Weight(kg)	5.039	4.23	3.8973

5. CONCLUSIONS

This research focuses on the optimum design of an automotive suspension spring. The desired final aim is to reduce the mass of the suspension spring, thereby minimizing the asymmetric mass of the vehicle. The design variables of this optimization study are average wire diameter of the coil spring, the coil diameter and the number of active coils. The coil spring dimensions are optimized using the differential evolution algorithm. According to the result from Table 3, the coil spring mass decreased by approximately 29.3% as initial design. According to the research, it is concluded that the differential development algorithm provides good results when it is at the global optimum. The contribution of the automotive suspension spring to the total mass of the vehicle is approximately 10-20%. The reduction in the mass is related to gas-emissions. As a result, even a small reduction in the mass of the suspension springs contributes to the improvement in passenger comfort and vehicle performance.

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