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Optimization of suspension of rail vehicles with coil springs using marine predators algorithm

Milan Bižić, Radovan Bulatović and Dragan Petrović[AQ: 1]

Abstract

The topic of this paper is the usage of the algorithm of marine predator (MPA) in the optimization of the suspension of rail vehicles with coil springs. The aim is to reduce the mass of set of coil springs as the main parts of rail vehicles suspension. The optimized set of coil springs must satisfy the appropriate conditions related to the suspension characteristics, with the aim of achieving the required operation quality and running security of the observed rail vehicle. Starting from the bi-linear characteristic of rail vehicles suspension and the analytical description of its parameters, an optimization problem is formulated. It is composed of six optimization parameters, an objective function and 16 constraints (eight for each coil spring in the set). The developed approach is applied in two specific examples of suspension optimization of four-axled freight wagons, the first with axle load of 200 kN and the second with axle load of 225 kN. The optimization problem is resolved using MPA. The acquired results showed that the given optimization approach with MPA provide a significant mass decrease compared to conventional design method of rail vehicles suspension with coil springs. The mass decrease of one set of coil springs in both examples is about 15.5%. Given that each considered four-axled freight wagon has 16 sets of coil springs, the decrease of the total coil springs mass per wagon in both examples is more than 60 kg. Since certified rail vehicles are commonly produced in large series, the proposed approach can be very significant for increasing profitability in the rail vehicles industry.

Keywords

Coil spring optimization, suspension optimization, rail vehicles suspension, marine predators algorithm, MPA

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Introduction

The suspension has greatest impact on the dynamic behavior quality of rail vehicles, that is, on quiet running and running safety, whose tests are mandatory in the certification process in accordance with valid international standards EN and UIC.[1,2] Therefore, problems of suspension design are always a current topic in the literature and research in the field of railway engineering. In some of the most popular books today, such as Iwnicki[3] and Andersson et al.,[4] great attention is paid to suspension issues and their importance is particularly emphasized.

The most common method of suspension of rail vehicles is based on set of two coil springs of different diameters, that allows their placement one inside the other. Since the length of the inner spring is shorter than the length of outer spring, when the vehicle is empty, only the outer spring is active. When the vehicle is loaded above a certain limit, both springs are active, and such suspension has a bi-linear stiffness characteristic. Conventional method of the calculation and design of this type of suspension involves determining the dimensions of the inner and outer spring with the aim of satisfying the required characteristics of the suspension behavior. These required characteristics can be met with many different combinations of dimensions of inner and outer spring. However, not enough attention is paid to the optimization of dimensions with the aim to reduce mass and save material for production of coil springs.

Contemporary research in this area mainly refers to analysis the stresses and strains, as well as the durability and reliability of rail vehicles coil springs. Orlova et al.[5] have studied the usage of the method of finite elements (FEM) in determining the stress and

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structural strength of the coil spring for suspension of rail vehicles. Dai et al.[6] have investigated new techniques for modeling the coil springs and proposed a new flexible model of spring that is more suitable for analyzing the dynamic performances of rail vehicles. The static analysis of the coil spring of primary suspension of the locomotive and the improvement of its strength by introducing new material, has been studied by Kumar et al.[7] The method of dynamic matrix of stiffness has been applied for determining the coil spring dynamic stiffness in the primary suspension of railway vehicle by Sun et al.[8] Kumbhalkar et al.[9] and Reddy and Reddy[10] have investigated the failure of coil springs of railway vehicles taking into account material properties and types of loading. Sharma et al.[11] have studied the origin of coil spring failures in the suspension of railway vehicles taking into account the influence of vehicle-truck interaction. The specific causes of fractures of coil springs which caused malfunctions of suspensions of wagons have been investigated by Rocha et al.[12] and Joshi et al.[13] However, there is insufficient research dealing with optimization of coil springs design with the aim of materials savings. Given that coil springs are made of very expensive spring steels, the possibilities of reducing their mass are of great practical importance. This was the motive for the study presented in this paper, with the aim to find the possibility to optimize the coil springs design in rail vehicles suspension.

Solving practical problems of design and optimization in engineering today is most often based on the application of different optimization algorithms.[14] There are many examples of successful application of optimization algorithms in solving problems of structural design of machine elements and constructions, such as those presented in Pavlović et al.,[15] Abderazek et al.,[16] Bižić et al.,[17] Pavlović et al.,[18] and Atanasovska and Momčilović.[19] Recent years, one of the most popular algorithms in solving the engineering and technical problems is Marine Predators Algorithm – MPA.[20–22] There are many examples of its efficiency in solving different types of problems, such as those exposed in Islam et al.,[23] Shaheen et al.,[24] Sun and Gao,[25] Owoola et al.,[26] and Pan et al.[27] Based on all this, the idea was born to apply MPA in the coil springs design optimization used in rail vehicles suspension. The basic goal is to reduce the mass of the set of coil springs and provide the opportunities to increase profitability in the industry of rail vehicles.

Stiffness characteristics of suspension with coil springs

In the identification the stiffness characteristics of the suspension of rail vehicles with coil springs, the car-body vertical vibrations must be analyzed. The frequency of vibrations of the basic dynamic model of the car-body shown in Figure 1 is specified by the solution of the equation:

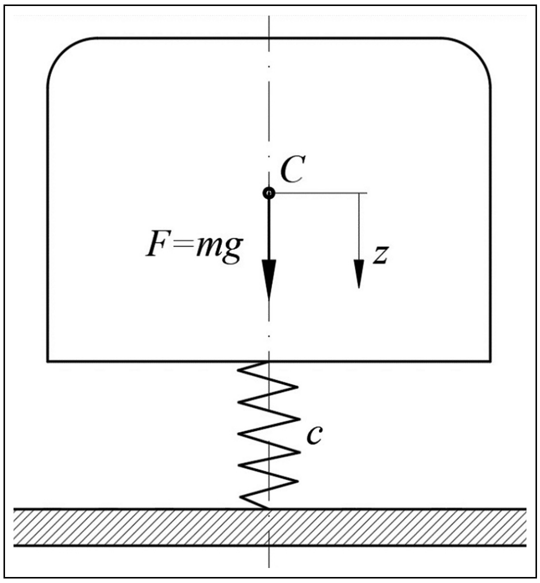

Figure 1. Basic dynamic model of vibration of car-body.[28]

$$m \cdot \ddot{z} = F - c(f_{st} + z) \tag{1}$$

In the previous expression are: m– car-body mass, g– gravitational acceleration, f_{st}– static deflection of spring, c– suspension stiffness, and z– vertical movement of car-body.

The static condition of equilibrium is:

$$F = m \cdot g = f_{st} \cdot c \tag{2}$$

Equation (1) can now be written succinctly as:

$$\ddot{z} + \omega^2 \cdot z = 0 \tag{3}$$

The angular frequency is:

$$\omega = \sqrt{\frac{c}{m}} = 2 \cdot \pi \cdot \nu \tag{4}$$

The frequency of vertical oscillations is:

$$\nu = \frac{1}{2 \cdot \pi}\sqrt{\frac{c}{m}} = const. \tag{5}$$

By equating the expressions for stiffness $c = k_1 \cdot F$ and $c = dF/df$, the following relation is obtained:

$$\frac{dF}{F} = k_1 \cdot df \tag{6}$$

After integration, the following relationship between force and deflection is obtained:

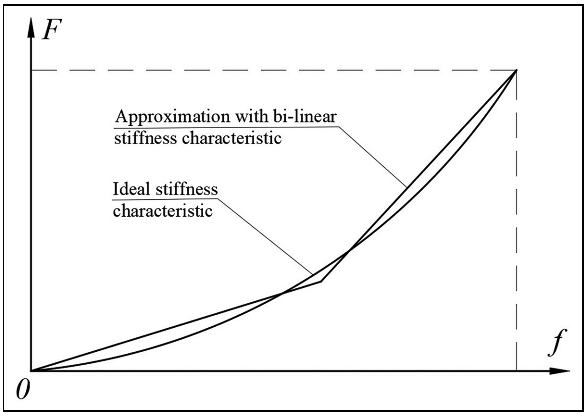

Figure 2. Diagram of ideal suspension characteristic and its approximation using set of two coil springs.

Figure 3. Set of coil springs in rail vehicles suspension.

$$F = e^{k_1 \cdot f + k_2} = k_3 \cdot e^{k_1 \cdot f} \tag{7}$$

The previous expression shows that, from the aspect of rail vehicle dynamic behavior, the ideal stiffness characteristic of suspension is exponential (Figure 2). Therefore, the suspensions of rail vehicles should be designed to have stiffness characteristic as close to exponential as possible. That is why a set of two coil springs is usually used in rail vehicles suspension (Figure 3). Both have a linear relationship between force and deflection, but with a different slope in the stiffness diagram (Figure 2).

The diagram of the bi-linear stiffness characteristic of the set of coil springs is given in Figure 4. The diagram shows the following sizes: c_o– stiffness of outer spring; c_i– stiffness of inner spring; c_s– stiffness of set of springs (parallel connection of outer and inner spring); f_c– deflection of outer spring for empty

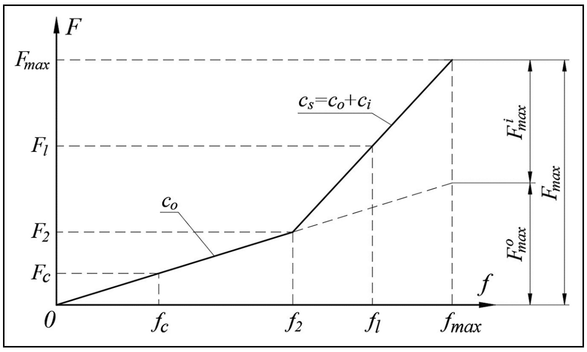

Figure 4. Diagram of bi-linear stiffness characteristic of the set of coil springs.

vehicle; F_c– force due weight of empty vehicle; f_2– deflection when inner spring starts working; F_2– force when inner spring starts working; f_l– deflection of set of springs due weight of vehicle and load; F_l– force due weight of vehicle and load; $f_{\max}$– maximal deflection of set of springs with addition of dynamic impacts; $F_{\max}$– maximal force with addition of dynamic impacts; $F^o_{\max}$– maximal force at outer spring with addition of dynamic impacts and $F^i_{\max}$– maximal force at inner spring with addition of dynamic impacts.

Therefore, the main goal of design the suspension system of rail vehicles with coil springs is to provide stiffness characteristics for the proper operation of the vehicle and to meet the criteria of quiet running and running safety according to international standards.[1,2]

Parameters for design of set of coil springs

The basic dimensions of the set of coil springs used in rail vehicles suspension are shown in Figure 5 and those are: D_o– outer spring diameter, d_o– outer spring wire's diameter, H^{fr}_o– free height of the outer spring, D_i– inner spring diameter, d_i– inner spring wire's diameter, H^{fr}_i– free height of the inner spring, α_o– outer spring coil angle, α_i– inner spring coil angle and m– gap between coils of outer and inner spring.

The load of one set of coil springs for an empty vehicle (see Figure 3 and the diagram in Figure 4)[28]:

$$F_c = \frac{G_{ev} - n_{ws} \cdot G_{ws} - n_s \cdot G_{sa}}{n_s} \tag{8}$$

where:

G_{ev}– weight of empty vehicle
n_{ws}– number of wheelsets on vehicle
G_{ws}– weight of one wheelset
n_s– number of sets of coil springs on vehicle

G_{sa}– assumed weight of one set of coil springs (since the exact value is unknown at this design stage, it must be assumed)

The assumed weight of one set of coil springs is determined as a function of the assumed masses of the outer and inner spring m_{oa} and m_{ia}:

$$G_{sa} = (m_{oa} + m_{ia}) \cdot g \tag{9}$$

The load of one set of coil springs for a fully loaded vehicle (see Figure 3 and the diagram in Figure 4):

$$F_l = F_c + \frac{G_{cc}}{n_s} \tag{10}$$

The load weight (carrying capacity of the vehicle) G_{cc} can be determined as follows:

$$G_{cc} = n_{ws} \cdot P_{ws} - G_{ev} \tag{11}$$

where:

P_{ws}– axle load

The load of one set of coil springs for a fully loaded vehicle with addition of dynamic impacts (see diagram in Figure 4):

$$F_{\max} = k_d \cdot F_l \tag{12}$$

where:

$k_d = 1.3$ – coefficient of dynamic influence (takes into account the dynamic influence due to vehicle running)

The load when the inner spring starts working (see the diagram in Figure 4)[28]:

$$F_2 = \sqrt{F_c \cdot F_l}$$

The maximum permissible suspension deflection of vehicle due load:

$$\Delta f_{s\max} = (h_{\max} - h_{\min}) - \Delta h_w \tag{13}$$

where:

$h_{\max} = 1060^{\pm 5} mm$– maximum distance between buffer and rail top for an empty vehicle defined by UIC regulations

$h_{\min} = 960 mm$– minimum distance between buffer and rail top for a fully loaded vehicle defined by UIC regulations

The maximum possible vehicle lowering due to wear of the wheels Δh_w is:

$$\Delta h_w = \frac{d_n - d_w}{2} \tag{14}$$

where:

d_n– new wheel diameter

d_w– completely worn wheel diameter

The necessary stiffness of the outer spring is described by expression[28]:

$$c_o = \frac{2}{\Delta f_{s\max}} \cdot (F_2 - F_c) \tag{15}$$

The necessary stiffness of set of coil springs is:

$$c_s = c_o + c_i = \frac{F_l}{F_2} \cdot c_o \tag{16}$$

The necessary stiffness of the inner spring is determined as:

$$c_i = c_s - c_o \tag{17}$$

The designed deflection of the outer spring for empty vehicle is (see the diagram in Figure 4):

$$f_c = \frac{F_c}{c_o} \tag{18}$$

The designed maximal deflection of set of coil springs with addition of dynamic impacts:

$$f_{\max} = \frac{F_2}{c_o} + \frac{F_{\max} - F_2}{c_s} \tag{19}$$

The designed deflection when inner spring starts working (see the diagram in Figure 4):

$$f_2 = \frac{F_2}{c_o} \tag{20}$$

The designed deflection of set of springs due weight of vehicle and load (see the diagram in Figure 4):

$$f_l = f_2 + \frac{F_l - F_2}{c_s} \tag{21}$$

Parameters for design of outer spring

The active coils number of the outer spring is specified by the expression:

$$z_{oa} = \frac{G \cdot d_o^4}{8 \cdot D_o^3 \cdot c_o} \tag{22}$$

where:

G– shear modulus

d_o– outer spring wire's diameter (see Figure 5)

D_o– outer spring diameter (see Figure 5)

The active coils number of the outer spring z_{oa} must be greater than three. The maximum diameter of the outer spring is restricted by the lateral space L available for installation in the bogie. Thus, the following condition must be satisfied:

$$(D_o + d_o)_{\max} = L \tag{23}$$

The free height of the outer spring is restricted by the vertical space V available for installation in the bogie, that is,:

$$H_o^{fr} = V + f_c \tag{24}$$

The total coils number of the outer spring:

$$z_o = z_{oa} + z_n \tag{25}$$

where:

$z_n = 1 \div 1.5$ – non-active coils number

The condition of the outer spring stability must be satisfied, as follows:

$$\frac{H_o^{fr}}{D_o} \leqslant 3 \tag{26}$$

The maximal force in the outer spring:

$$F_o^{\max} = f_{\max} \cdot c_o \tag{27}$$

The maximal stress in the outer spring:

$$\tau_o = \frac{8 \cdot F_o^{\max} \cdot D_o}{\pi \cdot d_o^3} \cdot k_o \tag{28}$$

The maximal stress in the outer spring must be less than the permissible stress for a given spring material ($\tau_o \leqslant \tau_{per}$). The coefficient of Chernyshev of the outer spring:

$$k_o = 1 + \frac{1.252}{w_o} + \frac{0.876}{w_o^2} \tag{29}$$

Index of the outer spring:

$$w_o = \frac{D_o}{d_o} \tag{30}$$

Index of outer spring w_o must have value between 4 and 12. The outer spring coil angle must be less than 10°, and it is specified by the expression:

$$\alpha_o = arctg\frac{H_o^{fr}}{(z_{oa} + 2) \cdot \pi \cdot D_o} \tag{31}$$

Parameters for design of inner spring

The active coils number of the inner spring:

$$z_{ia} = \frac{G \cdot d_i^4}{8 \cdot D_i^3 \cdot c_i} \tag{32}$$

where:

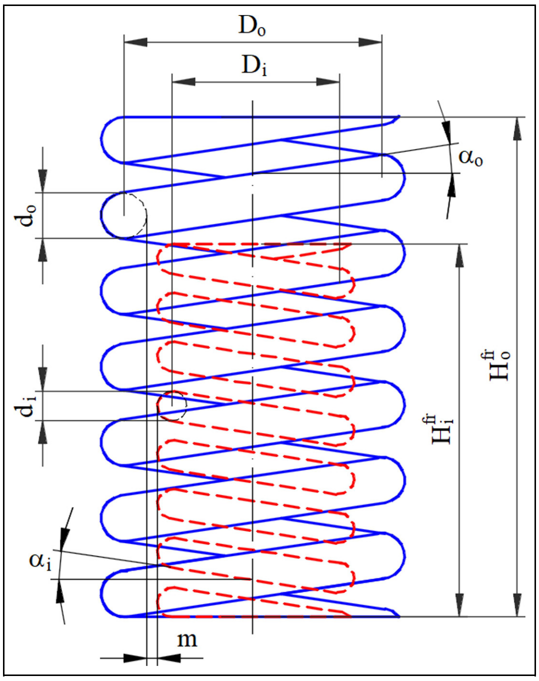

Figure 5. Basic dimensions of set of coil springs used in rail vehicles suspension.

d_i– inner spring wire's diameter (see Figure 5)

D_i– inner spring diameter (see Figure 5)

The number of active coils of the inner spring z_{ia} also must be greater than three. The maximum diameter of the inner spring is restricted by the lateral space available for installing the inner spring into the outer spring. Therefore, the following condition must be satisfied:

$$D_i + d_i \leqslant D_o - d_o - 2 \cdot m \tag{33}$$

where:

$m = 3 \div 5\,\text{mm}$ – gap between coils of outer and inner spring (see Figure 5)

The free height of the inner spring (see Figure 5):

$$H_i^{fr} = H_o^{fr} - f_2 \tag{34}$$

The inner spring total number of coils:

$$z_i = z_{ia} + z_n \tag{35}$$

The condition of the inner spring stability must be satisfied, that is,:

$$\frac{H_i^{fr}}{D_i} \leqslant 3 \tag{36}$$

The maximal force in the inner spring:

$$F_i^{\max} = F_{\max} - F_o^{\max} \tag{37}$$

Table 1. Variables to be optimized with boundaries.

Variable	Unit	Boundary
x_1 (=D_o)	[m]	0.05 ÷ 0.3
x_2 (=d_o)	[m]	0.005 ÷ 0.05
x_3 (=z_{oa})	–	2 ÷ 20, (rounded to first smaller tenth)
x_4 (=D_i)	[m]	0.04 ÷ 0.25
x_5 (=d_i)	[m]	0.005 ÷ 0.05
x_6 (=z_{ia})	–	2 ÷ 20, (rounded to first smaller tenth)

The maximal stress in the inner spring:

$$\tau_i = \frac{8 \cdot F_i^{\max} \cdot D_i}{\pi \cdot d_i^3} \cdot k_i \tag{38}$$

The maximal stress in the inner spring must be less than the permissible stress for a given spring material ($\tau_i \leqslant \tau_{per}$). The coefficient of Chernyshev of the inner spring:

$$k_i = 1 + \frac{1.252}{w_i} + \frac{0.876}{w_i^2} \tag{39}$$

Index of the inner spring:

$$w_i = \frac{D_i}{d_i} \tag{40}$$

Index of inner spring w_i must also have value between 4 and 12. The inner spring coil angle must be less than 10°, and it is specified by the expression:

$$\alpha_i = arctg \frac{H_i^{fr}}{(z_{ia} + 2) \cdot \pi \cdot D_i} \tag{41}$$

The conventional method of designing of set of coil springs in rail vehicles suspension usually involves determining the given parameters, in order to satisfy the required conditions from the previous expressions. However, not enough attention is paid to the fact that the required conditions can be met with many different combinations of parameters of outer and inner spring. In this way, there is often an unnecessary increase in the coil springs mass, which is very unfavorable from many different aspects.

Optimization problem and MPA

The key task of the optimization is to ensure the mass decrease of set of coil springs, while satisfying all the required conditions defined by previous relations. Generally, the problem may be described mathematically as follows:

$$\begin{aligned} &\text{minimization} f(\mathbf{X}), \\ &\text{subjectingto} : g_c(\mathbf{X}) \leqslant 0, \ c = 1, ..., k \end{aligned} \tag{42}$$

In the previous expression $f(X)$ is objective function, $g_c(X) \leqslant 0$ is constraint function, k is number of constraints and X is design vector composed of D design variables ($\mathbf{X} = \{x_1, ..., x_D\}^T$). The variables are being optimized with boundaries are given in the Table 1 and those are: $x_1 = D_o$– outer spring diameter, $x_2 = d_o$– outer spring wire's diameter, $x_3 = z_{oa}$– active coils number of the outer spring, $x_4 = D_i$– inner spring diameter, $x_5 = d_i$– inner spring wire's diameter and $x_6 = z_{ia}$– active coils number of the inner spring. All parameters in the optimization problem must be considered in units of the International System of Units. The boundaries are defined based on experience from the technical practice of manufacturing of coil springs of rail vehicles. They are related to the production of coil springs taking into account the possibility for procurement of given spring wires, measurement of dimensions in production, etc.

Objective function

To formulate the objective function, an analytical expression for accurate calculation of the mass of set of coil springs is derived. Due to limited space, only the final expression is given here. It has been assumed that the coil springs are made of standard spring steel with a density of 7850 kg/m^3. Therefore, the mass of set of coil springs, that is, objective function $f(X)$ is specified by the expression:

$$\begin{aligned} m_s &= 1962.5 \cdot \pi^2 \left[d_o^2 \cdot D_o \cdot (z_{oa} + 2) + d_i^2 \cdot D_i \cdot (z_{ia} + 2) \right] \\ m_s &= 1962.5 \cdot \pi^2 \left[x_2^2 \cdot x_1 \cdot (x_3 + 2) + x_5^2 \cdot x_4 \cdot (x_6 + 2) \right] \end{aligned} \tag{43}$$

Given that there are six optimization parameters, the design vector is:

$$\mathbf{X} = \{x_1, x_2, x_3, x_4, x_5, x_6\}^T = \{D_o, d_o, z_{oa}, D_i, d_i, z_{ia}\}^T \tag{44}$$

Constraints for outer spring

Based on expression (22), the constraint to fulfill the outer spring necessary stiffness can be written as:

$$g_1(x) = \frac{G \cdot x_2^4}{8 \cdot x_3 \cdot x_1^3} - c_o = 0 \tag{45}$$

The constraint that refers to fulfillment the limitation of space for installation ($D_o + d_o \leqslant L$):

$$g_2(x) = x_1 + x_2 - L \leqslant 0 \tag{46}$$

The constraint that refers to fulfillment of condition of minimum active coils number of outer spring ($z_{oa} \geqslant 3$):

$$g_3(x) = 3 - x_3 \leqslant 0 \tag{47}$$

The constraint that refers to fulfillment of condition of spring stability:

$$g_4(x) = \frac{H_o^{fr}}{x_1} - 3 \leqslant 0 \tag{48}$$

The constraints that refer to fulfillment of condition for the value of outer spring index ($w_o = 4 \div 12$):

$$g_5(x) = 4 - w_o < 0 \tag{49}$$

$$g_6(x) = w_o - 12 < 0 \tag{50}$$

The constraint that refers to fulfillment of condition of permissible stress ($\tau_o \leqslant \tau_{per}$):

$$g_7(x) = \tau_o - \tau_{per} \leqslant 0 \tag{51}$$

The last constraint for outer spring that refers to fulfillment of maximum allowable coil angle ($\alpha_o \leqslant 10°$):

$$g_8(x) = \alpha_o \cdot \frac{360}{2 \cdot \pi} - 10 \leqslant 0 \tag{52}$$

Constraints for inner spring

Based on expression (32), the constraint to fulfill the inner spring necessary stiffness can be written as:

$$g_9(x) = \frac{G \cdot x_5^4}{8 \cdot x_6 \cdot x_4^3} - c_i = 0 \tag{53}$$

The constraint that refers to fulfillment the limitation of space for installation of inner spring into outer spring ($D_i + d_i \leqslant D_o - d_o - 2 \cdot m$):

$$g_{10}(x) = x_4 + x_5 - (x_1 - x_2 - 2 \cdot m) \leqslant 0 \tag{54}$$

The constraint that refers to fulfillment of condition of minimum active coils number of inner spring ($z_{ia} \geqslant 3$):

$$g_{11}(x) = 3 - x_6 \leqslant 0 \tag{55}$$

The constraint that refers to fulfillment of condition of spring stability:

$$g_{12}(x) = \frac{H_i^{fr}}{x_4} - 3 \leqslant 0 \tag{56}$$

The constraints that refer to fulfillment of condition for the value of inner spring index ($w_i = 4 \div 12$):

$$g_{13}(x) = 4 - w_i < 0 \tag{57}$$

$$g_{14}(x) = w_i - 12 < 0 \tag{58}$$

The constraint that refers to fulfillment of condition of permissible stress ($\tau_i \leqslant \tau_{per}$):

$$g_{15}(x) = \tau_i - \tau_{per} \leqslant 0 \tag{59}$$

The last constraint for inner spring that refers to fulfillment of maximum allowable coil angle ($\alpha_i \leqslant 10°$):

$$g_{16}(x) = \alpha_i \cdot \frac{360}{2 \cdot \pi} - 10 \leqslant 0 \tag{60}$$

For solving the specific examples of design of rail vehicles suspension and the formulated optimization problem, MPA is applied.

MPA

Metaheuristic optimization algorithms have the ability to produce novel solutions that are more quality compared to the previous, that is, they go toward the space where the global minimum lies. They also recognize the pitfall of entrance into a local optimum and possess mechanisms to avoid that region. This provides a higher algorithm effectiveness, through proper ratio of the most important parts of any metaheuristic – exploration and exploitation or intensification and diversification. Diversification implies that various solutions are generated for global searching, while intensification focuses on searching a local area through data about right solutions discovered in that region. Searching or intensification usually use randomization that gives the ability for leaving the space of local minimum. Besides, it may be applied to search the local space round the instantly finest solution, if the footstep is limited to the local area. Otherwise, randomization can search the space globally. Too much diversification and too little searching means that the system may converge much faster, but the probability of finding the global optimum may be low. On the other hand, too much searching and too little diversification causes the search path to wander around with very slow convergence. The optimal balance should indicate the right amount of searching and diversification, leading to optimal algorithm performance. Therefore, the balance of these two quantities is of crucial importance.

A new highly efficient metaheuristic algorithm of marine predator (MPA) has been proposed in Faramarzi et al.[20] It was created on the basis of features marine predators that use Lévy and Brownian movement in search of prey. In this algorithm, searching efficiency is achieved by better balancing of exploration and exploitation.

As with other metaheuristic algorithms, the initial population is formed as follows:

$$\vec{X}_0 = \vec{X}_{min} + rand \cdot \left(\vec{X}_{max} - \vec{X}_{min}\right) \tag{61}$$

where:

$\overrightarrow{X}_{min}$, $\overrightarrow{X}_{max}$– below and top limits for project variables

rand – random number in the interval from 0 to 1

Further, two matrices are formed, one of which refers to the predator and the other to the prey. The best solution is nominated as a top predator and serves for formation of matrix which is called *Elite* and has the following form:

$$Elite = \begin{bmatrix} X^I_{1,1} & X^I_{1,2} & \cdots & X^I_{1,d} \\ X^I_{2,1} & X^I_{2,1} & \cdots & X^I_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ X^I_{n,1} & X^I_{n,2} & \cdots & X^I_{n,d} \end{bmatrix}_{n \times d} \tag{62}$$

Based on matrix (62), the prey is found based on information about its position. The vector $\vec{X}^I$ is the predator vector that is multiplied n times, and in this way the given matrix is constructed. The parameter n is the number of searching agents, while d is the number of design variables. It is significant to emphasize that prey and predator are searching agents – the prey is searching for food while the predator is searching for him. The prey updates its positions based on the *Prey* matrix which is:

$$Prey = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,d} \\ X_{2,1} & X_{2,1} & \cdots & X_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n,1} & X_{n,2} & \cdots & X_{n,d} \end{bmatrix}_{n \times d} \tag{63}$$

The algorithm's initial phase is the exploration stage that refers to the period in which the predator is getting around slower than prey. This phase is mathematically described by the following three expressions:

$$while\ Iter < \frac{1}{3} Itermax \tag{64}$$

$$\overrightarrow{stepzize_i} = \overrightarrow{R_b} \otimes \left(\overrightarrow{Elite_i} - \overrightarrow{R_b} \otimes \overrightarrow{Prey_i}\right), i = 1, 2, ..., n \tag{65}$$

$$\overrightarrow{Prey_i} = \overrightarrow{Prey_i} + P \cdot \vec{R} \otimes \overrightarrow{stepsize_i} \tag{66}$$

where:

$\overrightarrow{R}_b$– vector consisting of random numbers which are generated on the basis on Brownian motion (have a uniform distribution)

$P = 0.5$– constant

$\overrightarrow{R}$– uniformly distributed vector of random numbers that lie in the interval between 0 and 1

$\otimes$– symbol of entry-wise multiplications

In the second phase, both the predator and the prey move in a similar way. It represents the central part of the optimization process where both research phases are included – exploration and exploitation, while the first one gradually turns into the second one. This phase can be mathematically described by the following expressions:

$$while\ \frac{1}{3} Itermax < Iter < \frac{2}{3} Itermax \tag{67}$$

$$\overrightarrow{stepsize_i} = \overrightarrow{R_l} \otimes \left(\overrightarrow{Elite_i} - \overrightarrow{R_l} \otimes \overrightarrow{Prey_i}\right), i = 1, 2, ..., n/2, \tag{68}$$

$$\overrightarrow{Prey_i} = \overrightarrow{Prey_i} + P \cdot \vec{R} \otimes \overrightarrow{stepsize_i} \tag{69}$$

$$\overrightarrow{stepsize_i} = \overrightarrow{R_b} \otimes \left(\overrightarrow{R_b} \otimes \overrightarrow{Elite_i} - \overrightarrow{Prey_i}\right), i = n/2 + 1, ..., n, \tag{70}$$

$$\overrightarrow{Prey_i} = \overrightarrow{Elite_i} + P \cdot CF \otimes \overrightarrow{stepsize_i} \tag{71}$$

where:

$\overrightarrow{R}_l$– random numbers vector of Lévy motion (based on Lévy distribution)

CF– adaptable parameter that regulates the predator's movement size, described by the expression:

$$CF = \left(1 - \frac{Iter}{Itermax}\right)^{\left(2\frac{Iter}{Itermax}\right)} \tag{72}$$

In the last third phase, the prey is getting around slower than predator, that is, algorithm's exploitation stage is finished. The mathematical formulation of this phase is described by the following expressions:

$$while\ Iter > \frac{2}{3} Itermax \tag{73}$$

$$\overrightarrow{stepsize_i} = \overrightarrow{R_l} \otimes \left(\overrightarrow{R_l} \otimes \overrightarrow{Elite_i} - \overrightarrow{Prey_i}\right), i = 1, 2, ..., n \tag{74}$$

$$\overrightarrow{Prey_i} = \overrightarrow{Elite_i} + P \cdot CF \otimes \overrightarrow{stepsize_i} \tag{75}$$

Also, it is significant to take into account the effects of fish aggregating devices (FADs), that cause changes in the behavior of marine predators. Marine predators are located in FADs vicinity longer than

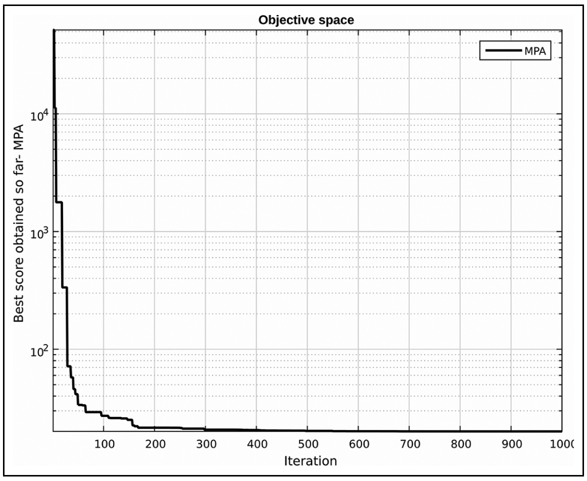

Figure 6. The diagram of convergence in example 1.

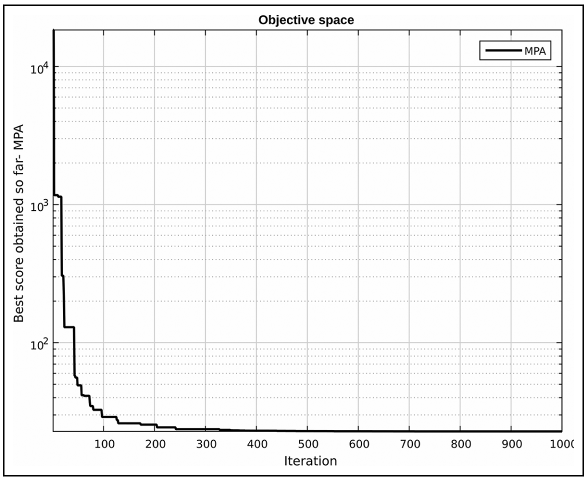

Figure 7. The diagrams of convergence in example 2.

80% of period, while in 20% of period they take on longer movements in various directions with the aim of discovering the spaces with various prey distribution. Thus, FADs can be treated as local optimums with the feature of capturing in the space of search. They can be mathematically described as:

$$\overrightarrow{Prey_i} = \begin{cases} \overrightarrow{Prey_i} + CF\left[\vec{X}_{min} + \vec{R} \otimes \left(\vec{X}_{max} - \vec{X}_{min}\right)\right] \otimes \vec{U}; & if\ r \leqslant FADs \\ \overrightarrow{Prey_i} + [FADs(1-r) + r] \cdot \left(\overrightarrow{Prey_{r1}} - \overrightarrow{Prey_{r3}}\right) & if\ r > FADs \end{cases} \tag{76}$$

where:
$\vec{U}$– binary vector with arrays that include 0 and 1
r_1, r_2– random label of prey matrix

It is important to note that the Elite matrix is created in such a way that the best position of the predator or the best solution in the current iteration is copied n times, so that the Elite matrix has the dimensions of the initial population x number of variables, as shown in expression (62).

The presentation of MPA pseudocode and flowchart is avoided due to limited space. They are well known and can be found in numerous literature such as Zhong et al.,[22] Islam et al.,[23] Shaheen et al.,[24] and Sun and Gao.[25]

Specific examples and optimization results

The proposed approach is applied in two specific examples of suspension optimization of four-axled freight wagons. The first is for axle load of 200 kN, and the second is for axle load of 225 kN. The input parameters values are presented in the Table 2, and the results for the six optimization parameters obtained by the MPA are specified in the Table 3.

The parameters used in MPA are: $n = 40$, $d = 6$, Itermax = 1000, $p = 0.5$ and FADs = 0.2. The diagrams of the convergence are given in Figures 6 and 7.

Table 2. Input parameters values.

Input parameter	Example 1	Example 2
P_{ws} [N]	200,000	225,000
G_{ev} [N]	205,000	220,000
n_{ws}	4	4
G_{ws} [N]	12,000	12,000
n_s	16	16
m_{oa} [kg]	18	18
m_{ia} [kg]	8	8
d_n [m]	0.92	0.92
d_w [m]	0.84	0.84
G [N/m^2]	7.8×10^{10}	7.8×10^{10}
τ_{per} [N/m^2]	8×10^8	8×10^8
L [m]	0.2	0.2
V [m]	0.242	0.242

Table 3. Values of optimization parameters obtained by MPA.

Parameter	Example 1	Example 2
x_1 (=D_o)	0.12386	0.12715
x_2 (=d_o)	0.02728	0.02864
x_3 (=z_{oa})	6.74790	6.70260
x_4 (=D_i)	0.07154	0.07234
x_5 (=d_i)	0.01904	0.02017
x_6 (=z_{ia})	6.85310	7.18180
f_{min} (=m_s)	20.06219	22.81031

A comparative overview of the results acquired by the given optimization approach and MPA, and by the conventional method of designing the suspension of rail vehicles is presented in the Table 4. It is significant to emphasize that some of the sizes, such as wire diameters and numbers of active coils, are rounded due to technical limitations in the production of coil springs (rounded values are marked with *).

The acquired results showed that in both examples a significant decrease of mass of set of coil springs is achieved. In the first example, the mass of

Table 4. Comparative overview of results acquired by proposed optimization approach and MPA, and conventional method of design for examples 1 and 2.

Parameter	Example 1			Example 2		
	Required	Conventional method	Optimization MPA	Required	Conventional method	Optimization MPA
x_1 (=D_o) [m]	0.05 ÷ 0.3	0.17	0.12386	0.05 ÷ 0.3	0.168	0.12715
x_2 (=d_o) [m]	0.005 ÷ 0.05	0.03	0.0273*	0.005 ÷ 0.05	0.032	0.02870*
x_3 (=z_{oa})	⩾3	3.8	6.7*	⩾3	4.5	6.7*
x_4 (=D_i) [m]	0.04 ÷ 0.25	0.1	0.07154	0.04 ÷ 0.25	0.1	0.07234
x_5 (=d_i) [m]	0.005 ÷ 0.05	0.0225	0.01910	0.005 ÷ 0.05	0.022	0.02020
x_6 (=z_{ia})	⩾3	4.8	6.9	⩾3	3.8	7.2
f_{min} (=m_s) [kg]	–	23.83	20.03	–	27.07	22.89
F_c [N]	9557.44	9557.44	9557.44	10,494.94	10,494.94	10,494.94
F_2[N]	21,136.74	21,234.77	21,353.82	23,583.44	23,741.83	23,798.98
F_l [N]	46,744.94	46,744.94	46,744.94	52,994.94	52,994.94	52,994.94
F_{max} [N]	60,768.42	60,768.42	60,768.42	68,893.42	68,893.42	68,893.42
f_c [m]	0.0227	0.0226	0.0225	0.0221	0.0219	0.0219
f_2 [m]	0.0502	0.0502	0.0502	0.0496	0.0496	0.0496
f_l [m]	0.0777	0.0772	0.0772	0.0771	0.0766	0.0767
f_{max} [m]	0.0928	0.0921	0.0922	0.0919	0.0914	0.0915
c_o [N/m]	421,065.61	423,018.42	425,389.90	475,945.51	479,141.92	480,295.27
c_i [N/m]	510,141.51	520,578.16	513,620.31	593,563.52	610,051.58	595,582.71
c_s [N/m]	931,207.12	943,596.58	939,010.21	1,069,509.03	1,089,193.5	1,075,877.98
F_o^{max}[N]	39,057.07	39,057.07	39,057.07	43,746.98	43,746.98	43,746.98
F_i^{max}[N]	21,711.35	21,711.35	21,711.35	25,146.45	25,146.45	25,146.45
H_o^{fr}[m]	0.2647	0.2647	0.2647	0.2641	0.2641	0.2641
H_i^{fr}[m]	0.2145	0.2145	0.2145	0.2145	0.2145	0.2145
H_o^{fr}/D_o	⩽3	1.56	2.14	⩽3	1.57	2.08
H_i^{fr}/D_i	⩽3	2.15	3	⩽3	2.15	2.97
w_o	–	5.6667	4.5370	–	5.25	4.4303
w_i	–	4.4444	3.7455	–	4.5455	3.5812
k_o	–	1.2482	1.3185	–	1.2703	1.3272
k_i	–	1.3260	1.3967	–	1.3178	1.4179
τ_o [N/m^2]	$\leqslant 8\times10^8$	7.82×10^8	7.98×10^8	$\leqslant 8\times10^8$	7.25×10^8	7.96×10^8
τ_i [N/m^2]	$\leqslant 8\times10^8$	6.43×10^8	7.93×10^8	$\leqslant 8\times10^8$	7.93×10^8	7.97×10^8
α_o [°]	⩽10	4.89	4.48	⩽10	4.41	4.35
α_i [°]	⩽10	5.74	6.13	⩽10	6.72	5.86

set of coil springs is reduced by 3.8 kg or 15.95%, while in the second example it is reduced by 4.18 kg or 15.44%. Given that each considered four-axled wagon has 16 sets of coil springs, the decrease of their total mass per one wagon in the first example is 60.8 kg and in the second example 66.88 kg. It should be emphasized that the optimized sets of coil springs fully satisfy all the required suspension characteristics and conditions. This is confirmed by the comparative diagrams of the required stiffness characteristics of suspension and stiffness characteristics obtained by the conventional design method and the developed optimization approach and MPA, which are given in Figures 8 and 9.

The algorithm code is written in the Matlab R2015a software package. The calculation time for each individual example in the paper is about 2.4 s, while the computer performances are: AMD Ryzen 5 PRO 4650G, Radeon Graphics 3.70 GHz, 12.0 GB of RAM, 64-bit operating system and x64-based processor. Each time the algorithm is run, the same objective function value is obtained with a very small deviation of up to 10^{-4}.

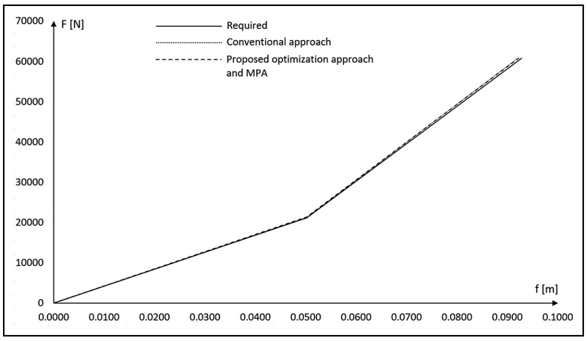

Figure 8. Comparison diagram of stiffness characteristics of suspension in example 1.

Therefore, the obtained results have shown that the MPA proved to be very effective in solving the given examples.

Conclusion

The topic of the paper is usage of the algorithm of marine predator (MPA) in the optimization of design

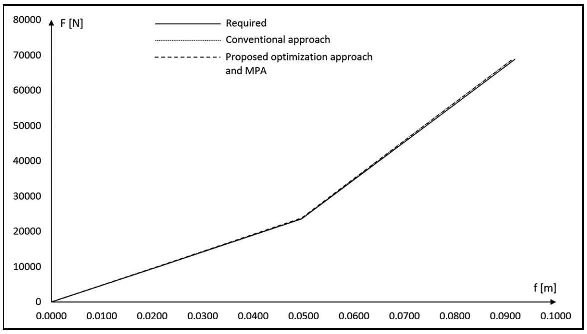

Figure 9. Comparison diagram of stiffness characteristics of suspension in example 2.

of set of coil springs in suspension of rail vehicles. The MPA algorithm belongs to the group of biologically inspired algorithms that are very successful in finding the global minimum. It searches the space based on stochasticity and it is not necessary for the objective function to be continuous and differentiable, as in the case of applying the gradient-based methods. The initial values for the design variables can be set in any range, so the algorithm will always give the optimal values regardless of the initial values of the lower and upper bounds of the design variables. In addition, the MPA algorithm has no restrictions on the number of variables that can be of any type – integer, discrete, etc.

The primary target of the optimization is to reduce the mass of set of coil springs with the simultaneous satisfaction the required conditions and stiffness characteristics of rail vehicles suspension. Based on the analytical expressions for determining the suspension parameters, an optimization problem composed of six optimization parameters, an objective function, and 16 constraints is formulated. The proposed approach is applied in two specific examples to optimize the suspension of four-axled freight wagons with sets of coils springs, while MPA is used for solution the optimization problem. A significant decrease of mass has been accomplished compared to the conventional method of suspension design. In both examples, the mass decrease per one set of coil springs is about 15.5%, that is, the total mass of coil springs per one wagon is reduced by over 60 kg. Therefore, the obtained results show that the proposed optimization approach and MPA may be efficiently used in designing of rail vehicles suspension with coil springs. The approach is universal, has no restrictions and may be used in solving the problems of design and optimization of the suspension of every rail vehicle with coil springs. Only minimal settings are required such as entering input parameters, boundaries of variables, etc. The proposed approach ensures the optimal design of the suspension system of rail vehicles with coil springs in order to provide the proper operation of the vehicle and meet the criteria of quiet operation and driving safety according to the international standards.[1,2] Given the fact that rail vehicles are produced in large series, the proposed approach provide significant material savings and can be very valuable for increasing profitability in the rail vehicles industry. Further research should be focused primarily on investigating the possibility of applying other optimization algorithms to resolve the defined optimization problem in order to achieve better results.

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