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Optimal Design of Vehicle Upper-equipment Mounting System Based on Improved Particle Swarm Optimization

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Abstract. Applying the multi-dynamic theory, a dynamic model of the upper-equipment mounting system of some vehicle is established. An optimization model for the upper-equipment mounting system is constructed, in which the driver's vertical acceleration RMS value and upper equipment vertical acceleration, pitch angle acceleration and roll angle acceleration of the RMS value are selected as objective function, and the mounted stiffness and damping as design variables of optimization.

Introduction

Military vehicle upper-equipment mounting system is the assembly structure used to reduce and control the transmission of the vehicle's mounted vibrations and to support it[1]. At present, the structure type of military vehicle upper-equipment mounting system between the chassis and the upper equipment is mainly rigid[2]. Research shows that the vibration of the excitation source without attenuation, is directly transmitted through the frame to the upper equipment, and the deformation of the frame will be caused. The relative displacement of the upper equipment and the chassis, seriously affects the reliability of the connection structure. The use of unreasonable modified connection structure will worsen the structural stress distribution, cause the resonance phenomenon, and affect the vehicle safety and reliability. In addition, the rigid suspension caused by the installation of high vibration strength, so we have to take vibration isolation measures for the carrier equipment which require higher vibration environment. These will result in a large number of waste space and increased transportation costs.

According to the analysis of upper-equipment mounting system, this paper infers the formula of upper-equipment mounting system in detail. From solving the equation set with Matlab and using improved particle swarm optimization, the upper-equipment mounting system is analyzed[3].

Dynamic model of upper-equipment mounting system

A 13 DOF dynamic model of the upper-equipment mounting system of some vehicle is established ignoring the flexible deformation and parts friction of the vehicle frame, axle and van, and considering the vertical, pitch and roll movement of the vehicle body relative to the frame[4-6]. The model is shown in Figure 1. The 13 DOF are defined as the vertical movement of the left front wheel, the vertical movement of the right front wheel, the vertical movement of the center of gravity of the left-back two wheels, the vertical movement of the center of gravity of the right-back two wheels, the pitch movement of the left-back two wheels relative to the center of gravity,. the pitch movement of the right-back two wheels relative to the center of gravity,. the vertical movement of the frame, the pitch movement of the frame, the roll movement of the frame, the vertical movement of the cab, the vertical movement of the upper-equipment, the pitch movement of the upper-equipment and the roll movement of the upper-equipment.
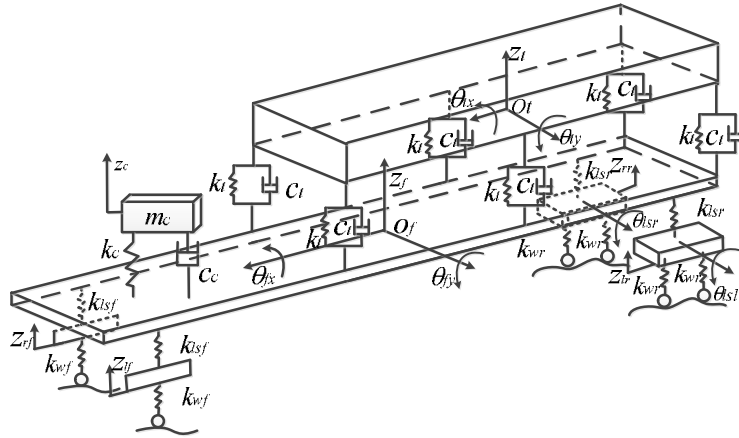
Figure 1 the 13 degrees of freedom vehicle model

Newton's second law mathematical model calculation

The kinetic equation is established according to Newton's second law.

$$m_w \ddot{x}_{lf} + k_w \left(x_{lf} - x_{r1} \right) + k_{lsf} \left(x_{lf} - \left(x_f - L_{fy1}\theta_{fy} + L_{fx}\theta_{fx} \right) \right) = 0 \tag{1}$$

$$m_w \ddot{x}_{rf} + k_w \left(x_{rf} - x_{r2} \right) + k_{lsf} \left(x_{rf} - \left(x_f - L_{fy1}\theta_{fy} - L_{fx}\theta_{fx} \right) \right) = 0 \tag{2}$$

$$m_{ls} \ddot{x}_{lr} + k_w \left(x_{lr} - L_{ls}\theta_{sl} - x_{r3} \right) + k_w \left(x_{lr} + L_{ls}\theta_{sl} - x_{r4} \right) + k_{lsr} \left(x_{lr} - \left(x_f - L_{fy2}\theta_{fy} + L_{fx}\theta_{fx} \right) \right) = 0 \tag{3}$$

$$I_{ls}\ddot{\theta}_{sl} - k_w \left(x_{lr} - L_{ls}\theta_{sl} - x_{r3} \right) \cdot L_{ls} + k_w \left(x_{lr} + L_{ls}\theta_{sl} - x_{r4} \right) \cdot L_{ls} = 0 \tag{4}$$

$$m_{ls} \ddot{x}_{rr} + k_w \left(x_{rr} - L_{ls}\theta_{sr} - x_{r5} \right) + k_w \left(x_{rr} + L_{ls}\theta_{sr} - x_{r6} \right) + k_{lsr} \left(x_{rr} - \left(x_f - L_{fy2}\theta_{fy} - L_{fx}\theta_{fx} \right) \right) = 0 \tag{5}$$

$$I_{ls}\ddot{\theta}_{sr} - k_w \left(x_{rr} - L_{ls}\theta_{sr} - x_{r5} \right) \cdot L_{ls} + k_w \left(x_{rr} + L_{ls}\theta_{sr} - x_{r6} \right) \cdot L_{ls} = 0 \tag{6}$$

$$
\begin{aligned}
&m_f \ddot{x}_f + k_{lsf} \left(x_f - L_{fy1}\theta_{fy} + L_{fx}\theta_{fx} - x_{lf} \right) + k_{lsf} \left(x_f - L_{fy1}\theta_{fy} - L_{fx}\theta_{fx} - x_{rf} \right) + k_{lsr} \left(x_f + L_{fy2}\theta_{fy} + L_{fx}\theta_{fx} - x_{lr} \right) \\
&+ k_{lsr} \left(x_f + L_{fy1}\theta_{fy} - L_{fx}\theta_{fx} - x_{rr} \right) + k_c \left(x_f - L_{fc}\theta_{fy} - x_c \right) + k \left(x_f - L_{ftf}\theta_{fy} + L_{fx}\theta_{fx} - \left(x_t - L_{ty}\theta_{ty} + L_{tx}\theta_{tx} \right) \right) \\
&+ k \left(x_f - L_{ftf}\theta_{fy} - L_{fx}\theta_{fx} - \left(x_t - L_{ty}\theta_{ty} - L_{tx}\theta_{tx} \right) \right) + k \left(x_f + L_{ftm}\theta_{fy} + L_{fx}\theta_{fx} - \left(x_t + L_{tx}\theta_{tx} \right) \right) \\
&+ k \left(x_f + L_{ftm}\theta_{fy} - L_{fx}\theta_{fx} - \left(x_t - L_{tx}\theta_{tx} \right) \right) + k \left(x_f + L_{ftr}\theta_{fy} + L_{fx}\theta_{fx} - \left(x_t + L_{ty}\theta_{ty} + L_{tx}\theta_{tx} \right) \right) \\
&+ k \left(x_f + L_{ftr}\theta_{fy} - L_{fx}\theta_{fx} - \left(x_t + L_{ty}\theta_{ty} - L_{tx}\theta_{tx} \right) \right) = 0
\end{aligned}
\tag{7}
$$

$$
\begin{aligned}
&I_{fx}\ddot{\theta}_{fx} + k_{lsf} \left(x_f - L_{fy1}\theta_{fy} + L_{fx}\theta_{fx} - x_{lf} \right) \cdot L_{fx} - k_{lsf} \left(x_f - L_{fy1}\theta_{fy} - L_{fx}\theta_{fx} - x_{rf} \right) \cdot L_{fx} \\
&+ k_{lsr} \left(x_f + L_{fy2}\theta_{fy} + L_{fx}\theta_{fx} - x_{lr} \right) \cdot L_{fx} - k_{lsr} \left(x_f + L_{fy2}\theta_{fy} - L_{fx}\theta_{fx} - x_{rr} \right) \cdot L_{fx} \\
&+ k \left(x_f - L_{ftf}\theta_{fy} + L_{fx}\theta_{fx} - \left(x_t - L_{ty}\theta_{ty} + L_{tx}\theta_{tx} \right) \right) \cdot L_{fx} - k \left(x_f - L_{ftf}\theta_{fy} - L_{fx}\theta_{fx} - \left(x_t - L_{ty}\theta_{ty} - L_{tx}\theta_{tx} \right) \right) \cdot L_{fx} \\
&+ k \left(x_f + L_{ftm}\theta_{fy} + L_{fx}\theta_{fx} - \left(x_t + L_{tx}\theta_{tx} \right) \right) \cdot L_{fx} - k \left(x_f + L_{ftm}\theta_{fy} - L_{fx}\theta_{fx} - \left(x_t - L_{tx}\theta_{tx} \right) \right) \cdot L_{fx} \\
&+ k \left(x_f + L_{ftr}\theta_{fy} + L_{fx}\theta_{fx} - \left(x_t + L_{ty}\theta_{ty} + L_{tx}\theta_{tx} \right) \right) \cdot L_{fx} - k \left(x_f + L_{ftr}\theta_{fy} - L_{fx}\theta_{fx} - \left(x_t + L_{ty}\theta_{ty} - L_{tx}\theta_{tx} \right) \right) \cdot L_{fx} = 0
\end{aligned}
\tag{8}
$$

$$
\begin{aligned}
&I_{fy}\ddot{\theta}_{fy} - k_{lsf} \left(x_f - L_{fy1}\theta_{fy} + L_{fx}\theta_{fx} - x_{lf} \right) \cdot L_{fy1} - k_{lsf} \left(x_f - L_{fy1}\theta_{fy} - L_{fx}\theta_{fx} - x_{rf} \right) \cdot L_{fy1} \\
&+ k_{lsr} \left(x_f + L_{fy2}\theta_{fy} + L_{fx}\theta_{fx} - x_{lr} \right) \cdot L_{fy2} + k_{lsr} \left(x_f + L_{fy2}\theta_{fy} - L_{fx}\theta_{fx} - x_{rr} \right) \cdot L_{fy2} \\
&- k_c \left(x_f - L_{fc}\theta_{fy} - x_c \right) \cdot L_{fc} - k \left(x_f - L_{ftf}\theta_{fy} + L_{fx}\theta_{fx} - \left(x_t - L_{ty}\theta_{ty} + L_{tx}\theta_{tx} \right) \right) \cdot L_{ftf} \\
&- k \left(x_f - L_{ftf}\theta_{fy} - L_{fx}\theta_{fx} - \left(x_t - L_{ty}\theta_{ty} - L_{tx}\theta_{tx} \right) \right) \cdot L_{ftf} + k \left(x_f + L_{ftm}\theta_{fy} + L_{fx}\theta_{fx} - \left(x_t + L_{tx}\theta_{tx} \right) \right) \cdot L_{ftm} \\
&+ k \left(x_f + L_{ftm}\theta_{fy} - L_{fx}\theta_{fx} - \left(x_t - L_{tx}\theta_{tx} \right) \right) \cdot L_{ftm} + k \left(x_f + L_{ftr}\theta_{fy} + L_{fx}\theta_{fx} - \left(x_t + L_{ty}\theta_{ty} + L_{tx}\theta_{tx} \right) \right) \cdot L_{ftr} \\
&+ k \left(x_f + L_{ftr}\theta_{fy} - L_{fx}\theta_{fx} - \left(x_t + L_{ty}\theta_{ty} - L_{tx}\theta_{tx} \right) \right) \cdot L_{ftr} = 0
\end{aligned}
\tag{9}
$$

$$m_c \ddot{x}_c + k_c \left(x_c - \left(x_f - L_{fc} \theta_{fy} \right) \right) = 0 \tag{10}$$

$$m_t \ddot{x}_t + k \left(x_t - L_{ty} \theta_{ty} + L_{tx} \theta_{tx} - \left(x_f - L_{ftf} \theta_{fy} + L_{fx} \theta_{fx} \right) \right) + k \left(x_t - L_{ty} \theta_{ty} - L_{tx} \theta_{tx} - \left(x_f - L_{ftf} \theta_{fy} - L_{fx} \theta_{fx} \right) \right)$$

$$+ k \left(x_t + L_{tx} \theta_{tx} - \left(x_f + L_{ftm} \theta_{fy} + L_{fx} \theta_{fx} \right) \right) + k \left(x_t - L_{tx} \theta_{tx} - \left(x_f + L_{ftm} \theta_{fy} - L_{fx} \theta_{fx} \right) \right) \tag{11}$$

$$+ k \left(x_t + L_{ty} \theta_{ty} + L_{tx} \theta_{tx} - \left(x_f + L_{ftr} \theta_{fy} + L_{fx} \theta_{fx} \right) \right) + k \left(x_t + L_{ty} \theta_{ty} - L_{tx} \theta_{tx} - \left(x_f + L_{ftr} \theta_{fy} - L_{fx} \theta_{fx} \right) \right) = 0$$

$$I_{tx} \ddot{\theta}_{tx} + k \left(x_t - L_{ty} \theta_{ty} + L_{tx} \theta_{tx} - \left(x_f - L_{ftf} \theta_{fy} + L_{fx} \theta_{fx} \right) \right) \cdot L_{tx} - k \left(x_t - L_{ty} \theta_{ty} - L_{tx} \theta_{tx} - \left(x_f - L_{ftf} \theta_{fy} - L_{fx} \theta_{fx} \right) \right) \cdot L_{tx}$$

$$+ k \left(x_t + L_{tx} \theta_{tx} - \left(x_f + L_{ftm} \theta_{fy} + L_{fx} \theta_{fx} \right) \right) \cdot L_{tx} - k \left(x_t - L_{tx} \theta_{tx} - \left(x_f + L_{ftm} \theta_{fy} - L_{fx} \theta_{fx} \right) \right) \cdot L_{tx} \tag{12}$$

$$+ k \left(x_t + L_{ty} \theta_{ty} + L_{tx} \theta_{tx} - \left(x_f + L_{ftr} \theta_{fy} + L_{fx} \theta_{fx} \right) \right) \cdot L_{tx} - k \left(x_t + L_{ty} \theta_{ty} - L_{tx} \theta_{tx} - \left(x_f + L_{ftr} \theta_{fy} - L_{fx} \theta_{fx} \right) \right) \cdot L_{tx} = 0$$

$$I_{ty} \ddot{\theta}_{ty} - k \left(x_t - L_{ty} \theta_{ty} + L_{tx} \theta_{tx} - \left(x_f - L_{ftf} \theta_{fy} + L_{fx} \theta_{fx} \right) \right) \cdot L_{ty} - k \left(x_t - L_{ty} \theta_{ty} - L_{tx} \theta_{tx} - \left(x_f - L_{ftf} \theta_{fy} - L_{fx} \theta_{fx} \right) \right) \cdot L_{ty} \tag{13}$$

$$+ k \left(x_t + L_{ty} \theta_{ty} + L_{tx} \theta_{tx} - \left(x_f + L_{ftr} \theta_{fy} + L_{fx} \theta_{fx} \right) \right) \cdot L_{ty} - k \left(x_t + L_{ty} \theta_{ty} - L_{tx} \theta_{tx} - \left(x_f + L_{ftr} \theta_{fy} - L_{fx} \theta_{fx} \right) \right) \cdot L_{ty} = 0$$

In order to simplify derivation process, there is no damping force included in the above equations. In fact, there is a damping in the location of the stiffness, the coordinates corresponding to the coordinates of the derivative. Correspondingly, the stiffness matrix change into a damping matrix. Now we only consider the damping of the cab and upper equipment.

Define $X = \left[x_{lf}, x_{rf}, x_{lr}, x_{rr}, q_{lsl}, q_{lsr}, x_f, q_{fx}, q_{fy}, x_c, x_t, q_{tx}, q_{ty} \right]^T$

The equation can be expressed as:

$$M\ddot{X} + C\dot{X} + KX = F \cdot X_r$$

where

$$M = diag \left(m_w, m_w, m_{ls}, m_{ls}, I_{ls}, I_{ls}, m_f, I_{fr}, I_{fy}, m_c, m_t, I_{tx}, I_{ty} \right)$$

$$K = \begin{bmatrix} k_w + k_{lsf} & 0 & 0 & 0 & 0 & 0 & -k_{lsf} & -k_{lsf} L_{fx} & k_{lsf} L_{fy1} & 0 & 0 & 0 & 0 \\ & k_w + k_{lsf} & 0 & 0 & 0 & 0 & -k_{lsf} & k_{lsf} L_{fx} & k_{lsf} L_{fy1} & 0 & 0 & 0 & 0 \\ & & 2k_w + k_{lsr} & 0 & 0 & 0 & -k_{lsr} & -k_{lsr} L_{fx} & -k_{lsr} L_{fy2} & 0 & 0 & 0 & 0 \\ & & & 2k_w + k_{lsr} & 0 & 0 & -k_{lsr} & k_{lsr} L_{fx} & -k_{lsr} L_{fy2} & 0 & 0 & 0 & 0 \\ & & & & k_w L_{ls}^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ & & & & & k_w L_{ls}^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ & & & & & & k_{77} & 0 & k_{79} & -k_c & -6k & 0 & 0 \\ & & & & & & & k_{88} & 0 & 0 & 0 & -6kL_{tx}L_{fx} & 0 \\ & & symmetrical & & & & & & k_{99} & k_c L_{fy1} & k_{911} & 0 & k_{913} \\ & & & & & & & & & k_c & 0 & 0 & 0 \\ & & & & & & & & & & 6k & 0 & k_{1113} \\ & & & & & & & & & & & k_{1212} & 0 \\ & & & & & & & & & & & & k_{1313} \end{bmatrix}$$

where

$$k_{79} = -2k_{lsf} L_{fy1} + 2k_{lsr} L_{fy2} - k_c L_{fc} - 2k \left(L_{ftf} + L_{ftm} + L_{ftr} \right)$$

$$k_{913} = -2kL_{tyf} L_{ftf} - 2kL_{tyr} L_{ftr}$$

$$k_{1113} = -2kL_{tyf} + 2kL_{tyr}$$

$$k_{88} = 2 \left(k_{lsf} L_{fx}^2 + 3kL_{fx}^2 + k_{lsr} L_{fx}^2 \right)$$

$$k_{99} = 2 \left(k_{lsf} L_{fy}^2 + k_{lsr} L_{fy}^2 + kL_{ftf}^2 + kL_{ftm}^2 + kL_{ftr}^2 + \frac{1}{2} k_c L_{fc}^2 \right)$$

$$k_{911} = -2kL_{ftm} + 2kL_{ftf} - 2kL_{ftr}$$

$$k_{1212} = 2 \left(kL_{fx}^2 + 2kL_{tx}^2 \right)$$

$$k_{1313} = 2 \left(kL_{tyf}^2 + kL_{tyr}^2 \right)$$

C is the damping matrix which change the stiffness matrix k for c, the other parameters unchanged,. Except the upper equipment and the cab damping are not 0, the others are 0.

$$F = \begin{bmatrix} k_w & 0 & 0 & 0 & 0 & 0 \\ 0 & k_w & 0 & 0 & 0 & 0 \\ 0 & 0 & k_w & k_w & 0 & 0 \\ 0 & 0 & 0 & 0 & k_w & k_w \\ 0 & 0 & -k_w L_{ls} & k_w L_{ls} & 0 & 0 \\ 0 & 0 & 0 & 0 & -k_w L_{ls} & -k_w L_{ls} \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Six wheel road motions:

The pavement inputs are the ground elevation of the left and right front wheels respectively. The delay is considered when considering the rear wheel ground input.

The optimization algorithm of upper equipment mounting system[7-9]

In this paper, the vertical acceleration, the pitch acceleration, the roll acceleration and the vertical acceleration of the cab are taken as the objectives. The optimization parameters are taken with the stiffness and damping at each suspension point. The improved particle swarm optimization algorithm is used to optimize the model.

Fundamentals

PSO algorithm simulates the predation behavior of birds. Imagine a scene where a group of birds searches for food at random, and there is only one piece of food in the area. All birds do not know where the food is, but how far is their current location from food. Then the best strategy to find food is to search for the distance from the nearest bird around the food.

The PSO algorithm is inspired by this model and is used to solve practical problems. In PSO algorithm, the solution of each optimization problem is to search a bird called "particle" in some space. All particles have a fitness value determined by the optimized function, the greater the fitness value (the smaller) the better the result. Each particle also has a velocity that determines the direction and distance of their flight, and the particles follow the current optimal particle to search in the solution space.

The PSO algorithm first initializes a set of random particles, and then finds the optimal solution by iteration. In each iteration, the particle updates its position by tracking two "extremes". The first extreme is the optimal solution found by the particle itself, which is called the individual extremum. The other extreme is the optimal solution currently found by the population, and this extreme is called the global extremum.

Parameter setting

The driver's vertical acceleration RMS value and upper equipment vertical acceleration, pitch angle acceleration and roll angle acceleration of the RMS value are optimized by weight. Optimization parameters are mounted damping, The particles of this optimization problem can be encoded directly in the form of fitness, ie, the weighted sum. The fitness function can be expressed as:

$$f(C,K) = \sum_{n=1}^{4} w_n a_n \qquad n = 1,2,3,4$$

Where a_n, w_n $\quad n = 1,2,3,4$ are successively the vertical acceleration of the cab root mean square and its weight, the vertical acceleration of the upper equipment root mean square and its weight, the pitch angle acceleration of the upper equipment root mean square and its weight, the roll angle acceleration of the upper equipment root mean square and its weight.

● Particles selected. Generally take 20-40, for more difficult problems, the particles can be taken to 100 or 200. The number of particles in this model is 100.

● The maximum speed. The maximum travel distance of a particle in a cycle, is usually less than the scope of the particle. Larger V_{max} can guarantee the global search ability of particle population, and the smaller ones ensure that the local search ability of particle population is strengthened.

● learning factors. c_1 and c_2 can usually be set as 2.0. c_1 is local learning factor. c_2 is the overall learning factor, generally take c_2 larger. This article takes $c_1 = 1.2$ and $c_2 = 1.8$.

● Inertia weight. A large inertia weight value is beneficial to the global optimization, while a small inertia value favors local optimization. When the maximum velocity V_{max} of the particle is small, an inertia weight is close to 1; when the maximum velocity V_{max} of the particle is not very small, a weight is close to 0.8. In order to better balance the algorithm's global search with local search capabilities, we can use time-varying weights and linearly decreasing inertia weights as follows:

$$w(i) = w_{start} - (w_{start} - w_{end}) i / T_{max}$$

i is the current iteration, T_{max} is the largest number of iterations. In general, the inertia value $w_{start} = 0.9$, $w_{end} = 0.4$. The inertia weight decreases from 0.9 to 0.4 with the iteration, and the larger inertia weight at the beginning of the iteration keeps the algorithm strong global search capability, while smaller inertia weights facilitates more accurate local search capability.

● adaptive variation. Particle swarm optimization algorithm is fast and has a strong versatility, but there are shortcomings such as easy convergence and low precision. In this paper, we introduce the mutation in the PSO algorithm, that is, reinitialize some variables with certain probability. The mutation operation extends the search space that is constantly shrinking in the iteration so that the particles can jump out of the best position previously searched, and expand the search in the larger space while maintaining the diversity of the population, and improving the algorithm to find the better result.

Algorithm flow

(1)Initialization: Set the parameters of the range of motion. Set the learning factor c_1 and c_2, the maximum evolutionary algebra G, i is the current evolutionary algebra. In the search solution space of a D-dimension parameter, the population size of the particle is $Size$, and each particle represents the solution of the solution space, where the position of the k particle in the whole space is identified as X_k, the velocity expressed as V_k. The optimal solution of the k particle from the initial to the current iteration number, the individual extreme value, the current optimal solution of the whole population is $BestS$. Randomly generate $Size$ numbers of particles, randomly generate the initial population position matrix and velocity matrix.

(2)Individual evaluation: The initial position of each particle is thought as the individual extremum. The initial fitness $f(X_k)$ of the individual particles in the population is calculated. The optimal location of the population is found.

(3)The speed and location of the particles are updated, and new populations are generated. Then the speed and location of the particles are cross-border inspected. It should be noted that in the optimization of the stiffness and damping process of the suspension system, only the stiffness and damping limits are set to be greater than zero. However, due to the frame structure of the frame and

the upper equipment, it is also necessary to set an optimization constraint that is constrained by the vertical distance from the frame in the mounting position of the mounting system. Moreover, in order to avoid the algorithm into the local optimal solution, a local adaptive mutation operator to adjust is added.

$$V_k^{i+1} = w(i)V_k^i + c_1 r_1 \left(p_k^i - X_k^i \right) + c_2 r_2 \left(BestS_k^i - X_k^i \right)$$

$$X_k^{i+1} = X_k^i + V_k^{i+1}$$

Where $i=1,2,...G$, $k=1,2,...Size$, r_1 and r_2 are random number during 0 to 1, c_1 is the local learning factor, c_2 is the global learning factor.

(4)Compare the current fitness value $f(X_k)$ of the particle and its own history of the best p_k. If $f(X_k)$ is better than p_k, then set p_k as the current value $f(X_k)$, and update the particle position.

(5)Compare the current fitness value $f(X_k)$ with the population optimal value $BestS$. If $f(X_k)$ is better than $BestS$, set $BestS$ as the current value $f(X_k)$ and update the global optimal value and position.

(6)Check the end condition, if satisfied, then end the optimization. Otherwise, $i=i+1$, go to (3). The end conditions for the optimization is to achieve the maximum evolutionary algebra, or the evaluation value is less than a given accuracy.

Under the excitation of the random road, the weight value of the seat support surface in the automobile theory, the vertical acceleration of the upper equipment, the acceleration angle and the roll angle acceleration of the upper equipment are $w_2=1, w_3=0.4, w_4=0.63$: consider putting the cab and the upper equipment in the same important position, the weight of the vertical acceleration of the cab is the sum weight of the three directions of the upper equipment, $w_1=2.03$. Optimization of the process selected in the road input for the B-level 40km/h road conditions

The optimized parameters of the suspension system are: (K, C) = (1524,8916).

Conclusions

After constructing the upper-equipment mounting system dynamic model, Newton's second law mathematical model calculation is taken to solve the model. Then the driver's vertical acceleration RMS value and upper equipment vertical acceleration, pitch angle acceleration and roll angle acceleration of the RMS value as objective function are selected, and the mounted stiffness and damping as design variables of optimization are selected. Furthermore, an improved PSO method is put forward to obtain the result. According to the method, improved PSO method has advantage on the ability to global search optimized in solving the problem of optimizing upper equipment mounting system.

Acknowledgements

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