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Multi-performance Target Collaborative Optimization Methods for Battery Electric Vehicle

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Abstract: The present studies on battery electric vehicles (BEVs) has mainly focused on the single-objective or weighted multi-objective optimization based on energy management, which can not manifest the coupling relationship among the vehicle performance objectives essentially. To optimize the handling stability, ride comfort and economy of BEV, this paper built the stability dynamics analysis model, ride comfort simulation half-car model and power consumption calculation model of BEV, as well as two-point virtual random excitation model on Level B road and proposed related evaluation indexes, including vehicle handling stability factor, weighted acceleration root-mean-square (RMS) value of vertical vibration at the driver's seat and power consumption per 100 m at a constant speed. The Pareto optimum principle–based multi-objective evolutionary algorithm (MOEA) of BEV was also designed, which was encoded with real numbers and obtained the target values of all optional schemes via MATLAB/Simulink simulation software. The merits and demerits of alternative schemes could be judged according to the Pareto dominance principle, so that alternative schemes obtained after optimization were realizable. The results of simulation experiment suggest that the proposed algorithm can perform the multi-objective optimization on BEV, and obtain a group of Pareto optimum solutions featured by high handling stability, favorable ride comfort and low energy consumption for the decision-makers.

Keywords: Battery Electric Vehicle (BEV); Multi-objective Optimization; Pareto Optimum Principle; Evolutionary Algorithm

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0 Introduction

The efficient operation of BEV entails the coordination of handling stability, ride comfort and economy, with non-differentiable, discontinuous, hybrid, multidimensional, constrained and nonlinear characteristics in its mocel, which is a typical hybrid nonlinear multi-objective optimization issue. Els et al. optimized the suspension characteristic parameters with dynamic-Q algorithm, for the multi-objective optimization of vehicle handling stability and ride comfort, and provided a set of suspension parameters which can improve vehicle handling stability and ride comfort for decision makers [1]. Yang Guangci et al. optimized the fuel consumption, HC+NOx emissions and CO emissions of hybrid electric vehicle (HEV), and proposed a multi-objective optimization evolutionary algorithm based on the Pareto optimum principle for HEV, thus obtaining the Pareto optimum solution set with low fuel consumption and low emissions [2]. Zhang Jingmei et al. improved the genetic algorithm to realize the multi-objective comprehensive optimization of ride comfort, handling stability and road-friendliness of vehicles, and obtained the best matching value of suspension stiffness and damping [3]. Yang Rongshan et al. balanced and optimized handling stability and ride comfort of vehicles with approximate model, and then obtained the optimum value of suspension stiffness, damping and stabilizer bar [4]. Ding Xiaolin et al. proposed a multi-objective optimization matching method for driving system parameters, to improve the ride comfort of four-hub motor-driven electric vehicles and reduce the energy consumption [5]. Song Kang et al. conducted the optimized analysis on suspension and seat parameters based on ride comfort of vehicles, and built a multi-objective optimization model of vehicle dynamic performance. Non-dominated sorting genetic algorithm (NSGA-II) with elite strategy was selected to solve the optimization model, and the Pareto optimum solution set and Pareto frontier were obtained [6]. Chen Yikai et al. determined the optimum control parameters to make road friendliness and ride comfort of vehicles comprehensively through range and variance analysis, in order to improve road friendliness and ride comfort of vehicles at the same time. The simulation results show that the

multi-objective optimum control strategy can make the vehicle comfortable and robust to the change of pavement grade [7]. Zhang Zhifei et al. took the vertical acceleration of the driver and the frame and the sum of the 95th percentile to the fourth power as the performance optimization indexes, to normalize the weight of indexes to a single-objective function by analytic hierarchy process for improving ride comfort and road friendliness of commercial vehicles, as well as optimizing the stiffness and damping of suspension by genetic algorithm. The simulation results show that ride comfort and road friendliness of optimized vehicles are improved effectively [8]. Yang Kun et al. conducted parameter sensitivity analysis on ride comfort and road friendliness of six-axle semitrailer with the optimal Latin hypercube experimental design method, selected appropriate parameters combined with the actual situation and optimized ride comfort, road friendliness, the comprehensive performance of ride comfort and road friendliness with neighborhood cultivated multi-objective genetic optimization algorithm. The research results show that under the common driving speed, the evaluation indexes of selected optimization scheme, smoothness and road friendliness can also be better optimized [9]. Zhou Feikun et al. carried out multi-objective optimization on parameter matching of dynamical system with the optimization method of SAPSO with average mileage under multiple working conditions, average total energy consumption under multiple working conditions and complete vehicle kerb mass as the specific targets. The simulation results show that the weight of vehicles can be reduced and the economic performance on the premise of ensuring the dynamic performance can be improved [10]. Zhang Kangkang et al. compared and selected the 3 dynamical system matching projects with maximum speed, acceleration time and power consumption per 100 km as the specific targets, solved the problem of conflicting among indexes to be optimized with the multi-objective genetic algorithm, described the competitive relationship between indexes with the Pareto matrix, and clearly defined the constraints and scope of application of policies [11].

Most of the above studies transformed the multi-objective optimization to single-objective optimization through weighting or other methods, and then obtained the solution through mathematical programming.

Therefore, they have the following weaknesses: (1) The decision-makers were needed to provide profound preference knowledge (i.e. weight coefficient of each target), to build single-objective evaluation function; (2) A majority of single-objective optimization technologies were based on local optimization search algorithm. Despite the local or global optimum solution obtained for single-objective optimization, several optimum solutions that are available couldn't be searched concurrently, thus, the flexible requirements of multi-objective decision can be hardly met.

In addition, most of the optimization objectives in the researches on single-objective or multi-objective optimization were vehicle handling stability or ride comfort but the researches about the multi-performance target collaborative optimization of handling stability, ride comfort and economy of BEVs could be seldom found. For this reason, this paper built the stability dynamics analysis model, the ride comfort simulation half-car model and the power consumption calculation model, as well as the two-point virtual random excitation model of Level B road surface, respectively, with BEV as the research object, and proposed the evaluation indexes corresponding to the multi-performance objectives by highlighting the multi-objective optimization of BEVs' handling stability, ride comfort and economy under the turning condition, with simulation verification on handling stability, ride comfort and economy of BEVs based on Pareto optimal algorithm. The simulation results show that the proposed Pareto optimal algorithm can collaboratively optimize the safety, ride comfort and economy of BEVs, with the improvement of handling stability, ride comfort and economy to a certain extent.

The innovation points of this paper include: 1) Based on the improved optimization algorithm of non-dominated genetic algorithm, the elite strategy was introduced, with congestion distance and its comparison operator as the basis of secondary sorting. Finally, the global optimal Pareto optimum solution and Pareto front edge were obtained. 2) With handling stability, ride comfort and economy of BEVs as optimization objectives for the first time, the key parameters related to multiple performance were selected as design parameters, to realize the multi-objective optimization of dynamical performance of BEVs, and the optimal matching scheme of several

key parameters was obtained. 3) The optimization ideas and methods have important theoretical significance and engineering practical application value for the optimization design of multi-objective parameters including other mechanical properties of BEVs, such as handling stability transient response analysis and transmission performance.

1 Vehicle Dynamics Models

1.1 Vehicle Dynamics Half-car Model

Vehicles receive inputs from longitudinal, vertical, and transverse directions, from which, the motion response characteristics are definitely interactive and coupled mutually. The influence of vertical coupling motion generated by the listing under the working condition of uniform turning movement on the vertical comfort of the driver can be ignored. Therefore, this paper considered the vertical motion of vehicles alone when building ride comfort model. First of all, the complex vehicle system was properly simplified and assumed:

1) Vehicles are symmetrical to the longitudinal symmetry plane and road unevenness corresponding to the four tires is the same; 2) It is assumed that the road unevenness conforms to the normal distribution of each state after a stationary random process, the road unevenness corresponding to each tire on the same side is different, with a response time delay caused by the wheelbase; 3) Both the stiffness of tires and seats are simplified into linear function; Suspension damping is a linear function of speed; 4) Each tire has a single contact with the ground , without any bounce; Road excitation acts on the central point of contact between tires and the road surface..

After linearizing the automobile system into a half simplified model approximately, front and rear tires will bear 2 random inputs, and the free-body diagram is shown as Figure 1.

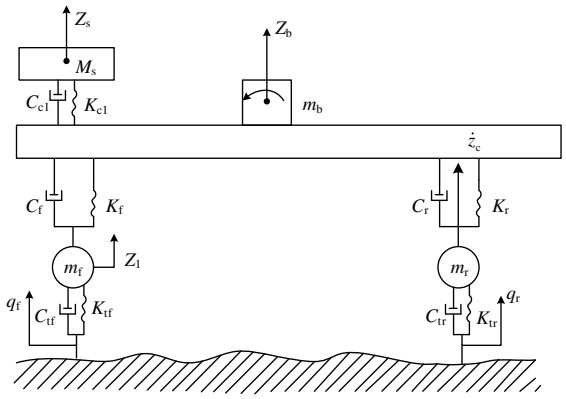


Figure 1 Vehicle 4-DOF Model

All parameters in Figure 1 are set as follows: m_b is curb weight; I_b is vehicle turning inertia; m_f and m_r are unsprung mass of front suspension and rear suspension, respectively; K_{c1} and C_{c1} are spring stiffness and damping of driver seat, respectively; K_f and C_f are spring stiffness and damping of front suspension, respectively; K_r and C_r are spring stiffness and damping of rear suspension, respectively; K_{tf} and C_{tf} are stiffness and damping of front tires, respectively; K_{tr} and C_{tr} are stiffness and damping of rear tires, respectively; q_f and q_r are vertical displacement excitation of front and rear tires, respectively.

According to D'Alembert's principle, the differential equation of vibration motion of 4-DOF can be expressed as:

$$M\ddot{Z} + C\dot{Z} + KZ + C_q\dot{Q} + K_qQ = 0 \qquad (1)$$

Where, $Z = [Z_1, Z_b, Z_c, Z_s]^T$; Z_s, Z_b,Z_1 and Z_c are vertical vibration displacement of driver seat, vehicle body, front suspension and rear suspension, respectively; M is mass matrix; C is system damping matrix; K is system stiffness matrix; K_q is road excitation stiffness; and Q is road excitation displacement. According to Literature [12], the linear inhomogeneous equation set of 4 frequency response functions within the range of frequency domain can be obtained from Formula (1):

$$A_{6\times6} \times \begin{bmatrix} H_1 & H_2 & H_3 & H_4 \end{bmatrix}^T = \begin{bmatrix} Q_1 & Q_2 & Q_3 & Q_4 \end{bmatrix}^T \qquad (2)$$

$A_{6\times6}$ is the response coefficient matrix of each response frequency. It has been verified that its rank is

related to its augmented matrix $B_{4\times5}$, so the equation set has a solution. In the formula, $[H_1\ H_2\ H_3\ H_4]$ correspond to 4 vibration responses relative to the frequency response function vector of the front tire random excitation input $\left[H_{\tilde{z}1-\tilde{q}f}, H_{\tilde{z}b-\tilde{q}f}, H_{\tilde{z}c-\tilde{q}f}\ and\ H_{\tilde{z}s-\tilde{q}f}\right]^T$, and the frequency response function of seat acceleration can be finally obtained.

1.2 Handling Stability Model

Handling stability of vehicles when driving mainly includes longitudinal stability and lateral stability. Longitudinal stability may be out of control mainly in course of longitudinal driving on slope. Lateral stability is mainly reflected in the form of cross slip or rollover. Listing motion is produced when vehicle makes a turn at a uniform speed and the vehicle inclination leads to lateral deformation of the suspension system. The complete vehicle model simplified into a 2-DOF system with lateral oscillation rotating z axis and lateral motion rotating y axis alone is shown in Figure 2 [13]. Then, vehicle listing dynamics model was established, i.e., the relation between the listing stability factor, the listing characteristics of suspension and the dynamic load generated by the road random excitation.

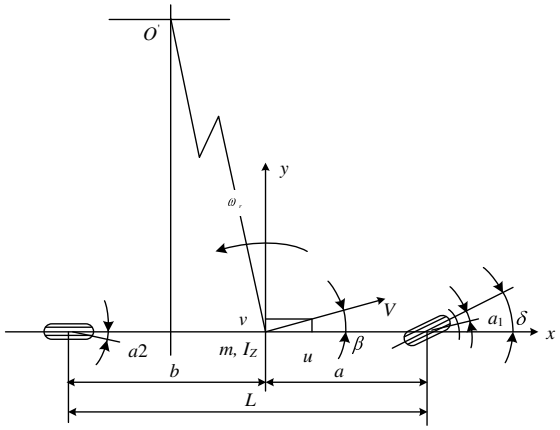


Figure 2 Vehicle Model of 2-DOF

In Figure 2, α_1 and α_2 are slip angle of front and rear tires; β is slip angle of vehicle centroid; δ is front wheel angle; ω_r is speed of heading angle; m is total weight of vehicles; I_z is rotational inertia of vehicle rotating z axis; a and b are the distance from front axis and rear axis to vehicle centroid, respectively; u and v

147 are weight of speed V of vehicle centroid on x axis and y axis.

148 Supposed that vehicle vertical displacement and lateral displacement are all zero, the systematic differential
149 equation of motion can be expressed as below by ignoring the influence of suspension temporarily under the input
150 of front wheel, and considering the planar motion of vehicle alone.

151 $$(k_1+k_2)\beta+\frac{1}{u}(ak_1-bk_2)\omega_r-k_1\delta=m(\dot{\upsilon}+u\omega_r) \quad (3)$$

152 $$(ak_1-bk_2)\beta+\frac{1}{u}(a^2k_1+b^2k_2)\omega_r-ak_1\delta=I_Z\dot{\omega}_r \quad (4)$$

153 When the vehicle is moving at a constant circular motion type, $\dot{\omega}_r=0$ and $\dot{u}=0$, and the vehicle steering
154 sensitivity, $\gamma=\omega_r/\delta$, can be obtained. k_1 and k_2 are the cornering stiffness of front and rear tires, respectively.

155 According to Formula (3) and Formula (4), stability factor can be expressed as:

156 $$K=\frac{m}{L^2}\left(\frac{a}{k_2}-\frac{b}{k_1}\right) \quad (5)$$

157 The tire cornering stiffness is closely related to the tire vertical load, which can be expressed as:

158 $$k_{il(r)}=0.06778F'^{\,2}_{zil(r)}-9.144F'_{zil(r)}+5.129 \quad (6)$$

159 Where, $F'_{zil(r)}$ is the tire load of front and rear axles, respectively. l and r mean the left side and the right
160 side.

161 $$F'_{zil(r)}=F_{zil(r)}+\Delta F_{zil(r)}+F_{id} \quad i=1,2 \quad (7)$$

162 Where, $F_{zil(r)}$ is the vertical reaction force of ground of front and rear axles and left (right) tire under an
163 idle status. The amount of change of vertical load includes two parts: F_{id}, i.e., the dynamic load applied to front
164 and rear axles respectively by road random excitation and $\Delta F_{zil(r)}$, the amount of change of vertical reaction
165 applied to front and rear axles and left (right) tire by the centrifugal force. Therefore, the improved stability factor
166 can be expressed as:

167 $$K_{l(r)}=\frac{m}{L^2}\left(\frac{a}{k_{2l(r)}}-\frac{b}{k_{1l(r)}}\right) \quad (8)$$

2 Two-point Virtual Random Excitation Model of Road Surface

The road excitation born by vehicles in driving belongs to multiple-support excitation. In consideration of the large wheel base, front and rear tires have receive stable and hysteresis road excitation of different phrases. A road model is built within the frequency domain by taking Level B road surface as an example [14]. Suppose that front and rear tires receive the same related stable road excitation, the two excitation points of road surface can be expressed as:

$$\left\{Q_{(t)}\right\}=\begin{bmatrix}Q_1\\Q_2\end{bmatrix}=\begin{bmatrix}Q(t-t_1)\\Q(t-t_2)\end{bmatrix} \quad (9)$$

$Q_{(t)}$ can be regarded as the generalized single point excitation. Suppose that the auto-spectral density of $Q_{(t)}$ is a known constant, and the exciting moment born by front and rear tires is t_1 and t_2, respectively, the two-point virtual excitation model obtained with pseudo excitation method can be expressed as:

$$\left[\tilde{q}(\omega)\right]=\sqrt{S_{qq}(\omega)}\begin{bmatrix}e^{-j\omega t_1}\\e^{-j\omega t_2}\end{bmatrix}e^{j\omega t}=\begin{bmatrix}\tilde{q}_f\\\tilde{q}_r\end{bmatrix} \quad (10)$$

Where, $\tilde{q}_f$ and $\tilde{q}_r$ are virtual excitations born by front and rear tires, respectively.

3 Vehicle Multi-performance Evaluation Indexes

3.1 Evaluation Index of Handling Stability

Handling stability of vehicles covers a broad range, which is mainly manifested by the time-frequency response characteristics of vehicles in curve driving. When a vehicle turns a corner at a constant speed, the ratio of yaw velocity to the turning angle of front wheel at a stable state is used as the response evaluation standard. Differently, the value of stable state factor manifests the stable response of vehicles. Generally speaking, the influence of vehicle structure parameters is considered only in the research analysis of stable state response of vehicle when turning a corner. Hence, the influence of dynamic load caused by road random excitation and suspension stiffness and damping and obtaining the improved stability factor was introduced in this paper, so that

the research of vehicle stability can be more accurate. The improved stability factor $K_{l(r)}$ in Formula (8) was taken as the evaluation index of listing handling stability here in this paper.

3.2 Evaluation Index of Ride Comfort

According to GB/T 4970-2009 *Test Method of Vehicle Ride Comfort*, this paper analyzed the vertical acceleration of the driver's seat instead of human body acceleration with the weighted acceleration RMS value corresponding to the human body acceleration transferred through seat as the evaluation index of ride comfort. Taking the weighted acceleration RMS value $\sigma_{\ddot{z}s}$ of the vertical vibration at driver's seat as the evaluation index of ride comfort, then the formula can be expressed as:

$$\sigma_{\ddot{z}s} = \sqrt{\int_0^\infty W_{zs}^2(\omega)\left|H_{\ddot{z}s-\tilde{q}f}\right|^2 G_{\tilde{z}_{qf}}(f)df} \qquad (11)$$

Where, $W_{zs}(\omega)$ is weighting function (the value is 1 here); $G_{\tilde{z}_{qf}}(\omega)$ is power spectral density inputted by front axle road excitation; $H_{\tilde{z}s-\tilde{q}f}$ is vertical acceleration frequency response function of driver's seat.

3.3 Evaluation Index of Economy

As the research object, the economy of BEVs is generally evaluated by its power consumption per 100 km at a constant speed. Under the uniform driving condition, the driving force required by the vehicle F includes listing resistance F_f and air resistanceF_w, i.e., $F = F_f + F_w$. The power consumption per 100 km of vehicle driving at a constant speed can be calculated with the following formula:

$$E_{drive} = \frac{(F_f + F_W)S}{\eta_{mc}\cdot\eta_T\cdot\eta_q} = \frac{\left(mgf + \frac{C_D A u_a^2}{21.15}\right)S}{\eta_{mc}\cdot\eta_T\cdot\eta_q} = \frac{mgf + \frac{C_D A u_a^2}{21.15}}{36(\eta_{mc}\cdot\eta_T\cdot\eta_q)} \qquad (12)$$

Where, $S = 100km$, f is listing resistance coefficient, C_D is air resistance coefficient, A is windward area, u_a is vehicle driving speed, η_{mc} is the efficiency of motor and controller, η_T is the total efficiency of drive system and η_q is the average discharging efficiency of accumulator.

4 Mathematical Modeling of Multi-objective Optimization

4.1 Mathematical Description of Multi-objective Optimization

BEV optimization in this paper means optimizing the parameters of suspension system and battery control strategy on the basis of satisfying all constraints, so as to make the vehicle safe, comfortable and energy-saving under certain conditions and make several target functions in conflict realize the optimal status within a feasible region. Suppose that X is the decision space of n-dimension and Y is the target space of n-dimension on the basis of ensuring the loss of generality, then its mathematical modeling of multi-objective optimization can be expressed as [11]:

$$\begin{aligned} &\min\ y = F(x) = \left[f_1(x) f_2(x) \cdots f_m(x)\right] \\ &s.t.\ g_i(x) \le 0 \quad (i = 1,2,\cdots,q_1) \\ &\quad h_i(x) = 0 \quad (j = 1,2,\cdots,q_2) \end{aligned} \tag{13}$$

Where,$x = [x_1 x_2 \cdots x_n] \in X \subset R^n$ is decision vector; $y = [y_1 y_2 \cdots y_n] \in Y \subset R^m$. The objective function $F_{(x)}$ means m mapping functions $f: X \to Y, g_1(x) \le 0 (i = 1,2,\cdots q_1)$ and $h_j(x) = 0 (j = 1,2,\cdots q_2)$ are the q_1 inequation constraints and q_2 equation constraints that the objective function $F_{(x)}$ needs to satisfy.

4.2 Optimization of Objectives

The driving conditions set for optimization play a key role, for the speed and road conditions of the vehicle always change in driving. According to the driving conditions set in this paper, the vehicle can be driven stably at a constant speed (30 km/h) along Level B curved road with a 50 m turning radius. Generally speaking, vehicle vibration becomes the most obvious and even resonance may be produced when excitation frequency is 3.15 Hz. In other words, the vehicle's ride comfort and handling stability become the most sensitive. Therefore, the analysis on multi-performance optimization was optimized at a road excitation frequency of 3.15 Hz [12].

This paper took function $min\sigma_{\ddot{z}s}$ (acceleration RMS value $\sigma_{\ddot{z}s}$ of the vertical vibration at the driver's seat), $minE_{dirve}$ (power consumption per 100 km at a constant speed) and handling stability factor $K_{l(r)}$ >0, which mean

reducing the acceleration RMS value of the vertical vibration at the driver's seat and power consumption per 100 km at a constant speed and making the vehicle lack of turning characteristics properly, as the optimization objectives to meet the requirements of handling stability and ride comfort, and minimize power consumption as much as possible. Set the following functions:

$$\begin{cases} f_1(x) = K_{l(r)} \\ f_2(x) = \sigma_{\ddot{z}s} \\ f_3(x) = E_{drive} \end{cases} \quad (14)$$

Where, x is decision variables (or parameters to be optimized), decision variables and corresponding constraint conditions, all of which vary along with specific optimized objects.

4.3 Selection of Design Variables

The parameters which exert significant influence on the optimization objectives were optimized in this paper. The stiffness of front and rear suspensions and damping of the vehicle are closely related to ride comfort of the vehicle; Meanwhile, vertical load of each vehicle axle changes when the vehicle is listing under the effect of road excitation, moment resulting from sidesway and centripetal force, which means the load that each axle bears has been allocated again in listing, causing the change of cornering stiffness of left and right tires or inside and outside tires, and finally changing the steady state response of the vehicle, as well as the stability factor. Therefore, the stiffness and damping of front and rear suspensions can be regarded as variables of optimization analysis. In consideration of the significant influence of related parameters of BEV's motor and battery on battery energy consumption, some parameters selected also serve as design variables. All optimized parameters and their selection range are shown in Table 1.

Table 1 Parameters to Be Optimized and Constraint Range

Type of Parameters	Constraint Range
Maxmum power of motor/kw	$Pe \in [20, 100]$
Power coefficient of motor	$R_s \in [0.6, 1.5]$

Number of battery pack modules/piece	$N_b \in [20,30]$
Axle ratio	$R_m \in [0.5,2.5]$
Upper limit of battery status/%	$H_{SOC} \in [0.55,0.8]$
lower limit of battery status/%	$L_{SOC} \in [0.2,0.55]$
Drive limiting speed/(kw/h)	$V_e \in [5,100]$
Front suspension stiffness/(N/m)	$K_f \in [10475,37046]$
Front suspension damping/$(N \cdot s/m)$	$C_f \in [2500,6000]$
Rear suspension stiffness/(N/m)	$K_r \in [16800,46320]$
Rear suspension damping/$(N \cdot s/m)$	$C_r \in [1200,3600]$
Suspension dynamic deflection/(mm)	$f_d \in [30,60]$

4.4 Pareto Optimum Principle

Pareto optimum principle serves as a key concept in game theory. Several key concepts are given below based on the symbol definitions in 4.1 [15].

Definition 1 Pareto dominance. For random vector $u = [u_1 u_2 \cdots u_m] \in Y, v = [v_1 v_2 \cdots v_m] \in Y$, if and only if $\forall i \in \{1,2,\cdots m\}: u_i \geq v_i \wedge \exists j \in \{1,2,\cdots m\}: u_j > u_j$ is true, v is superior to u, or v dominates u, which can be written as $u \prec v$.

Definition 2 Pareto optimum solution. $x \in X$ is called Pareto optimum solution (or non-dominated solution and non-inferior solution), if and only if $\rightarrow \exists x' \in X: F(x') = [f_1(x') f_2(x') \cdots f_m(x')] \succ F(x) = [f_1(x) f_2(x) \cdots f_m(x)]$. Pareto optimum solution is not dominated by other solutions with the least goal conflict, which can provide decision-makers with a better space for choosing, and can help them make decisions according to the environment or requirements when it is applied to engineering.

5 Algorithm Design

Taking the handling stability factor $f_1(x) = K_{l(r)} > 0$, acceleration RMS value of vertical vibration at the driver's seat $f_2(x) = min\sigma_{\ddot{z}s}$ and power consumption per 100 km at a constant speed $f_3(x) = minE_{dirve}$, which mean making the vehicle lack of turning characteristics properly and reducing the acceleration RMS value of the vertical vibration at driver's seat and power consumption per 100 km at a constant speed as the optimization objectives, this paper proposed the Pareto Optimum Principle-based Multi-Objective Evolutionary Algorithm of EV (EV-MOEA), which is an improvement of non-dominated genetic algorithm (NSGA), with the optimization considering each target equally important and dealing with multi-objective problems, i.e. introducing the elite strategy in the evolutionary process, with the crowding distance and its comparison operator as the basis of the secondary sorting. Finally, the global Pareto optimum solution and the Pareto frontier are obtained.

The advantages of EV-MOEA designed in this paper include good exploration performance, used the fast non dominated sorting, reduce the complexity of the non inferior sorting genetic algorithm, with fast non-dominant ranking, complexity of noninferior sorting genetic algorithm, replacing sharing radius with crowding distance and crowding distance comparison operator, as well as fast running speed, which improve the accuracy of the optimization results in a limited way, so that the individuals in the quasi-Pareto domain can extend to the whole Pareto domain and distribute evenly. Introducing the elite strategy maintained the diversity of the population, with good convergence of the solution set, which improved the rapidity and robustness of the optimization algorithm.

EV-MOEA has an evolution population, and each candidate solution is expressed by real number encoding. The main procedures of the algorithm are shown in Figure 3.

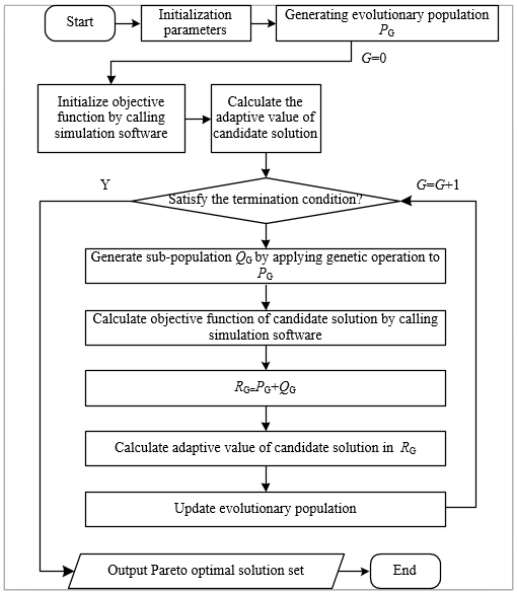


Figure 3 Flow Chart of EV-MOEA

The algorithm is calculated as the steps below:

(1) Initialization. Contents in need of initialization mainly include: Scale of evaluation population N, crossover probabilityP_c,, mutation probabilityP_m, maximum generation G_{max}, vehicle model parameters to be optimized, vehicle driving conditions required for simulation, specific performance indexes to be optimized required for the vehicle model, decision space R^m of m decision variables ($X_1, X_2, \cdots X_m$), i.e. X_i $[L_i, H_i]$*(i=1,2,...m)* (where, L_i and L_i mean lower limit and upper limit of X_i, respectively). For the engineering application, the precision that can be realized by each parameter of BEV is limited certainly, which is significant only when the value of decision variables is within the range of realizable precision. The significant digit of variables in this paper is set according to precision limitation and maximum generation, with the maximum evolutionary algebra as the condition for judging the completion of evolutionary process. Therefore, the evolutionary algebraic counter G needs to be set and initialize into $G = 0$.

(2) Evolutionary population generation. The candidate solution is represented by real coding. The process of generating candidate solution gene is as below: First, generate the evaluation population $P_G = \{x_j = (x_1 x_2 \cdots x_i \cdots x_m) \mid x_i \in [L_i, H_i], j = (1,2,\cdots N), i = (1,2,\cdots,m)\}$ with uniform random number generator, and then truncate the value exceeding the significant digit in x_i (rounded-off) according to the

299 set significant digit.

300 (3) Simulation software calling to initialize the objective function value. Let $\forall x_j \in P_G$, call $MATLAB/$
301 $Simulink$ software to test the performance of vehicle model corresponding to x_j. Simulate the status of the
302 vehicle when driving under specified road conditions and obtain function values of each objective according to the
303 returned results if the performance constraint conditions can be met. To be specific, $f_1(x_j)$ is stability factor,
304 $f_2(x_j)$ is the acceleration RMS value of vertical vibration at driver's seat and $f_3(x_j)$ is the power consumption
305 per 100 km at a constant speed; Otherwise, apply a large enough value to $f_1(x_j)$, $f_2(x_j)$ and $f_3(x_j)$.

306 (4) Calculation of fitness values of candidate solutions. Judge relative advantages and disadvantages of
307 candidate solutions via a specific method. The method applied in the simulation experiments of this paper: First
308 implement non-dominated sorting of P_G, and then calculate the crowding distance of candidate solutions.

309 (5) Genetic operation to generate new candidate solutions. Select $[0.5N]$ from P_G with the two-match
310 method, and then carry out SBX and polynomial variation to generate new population Q_G.

311 (6) Simulation software calling to calculate the objective function value of descendant candidate solutions.
312 Let $\forall x_j \in Q_G$, call $MATLAB/Simulink$ software to test the performance of vehicle model corresponding tox_j.
313 Simulate the driving status of the vehicle under the specified road conditions and obtain function values of each
314 objective according to the returned results if performance constraint conditions can be met. To be specific, $f_1(x_j)$
315 is stability factor, $f_2(x_j)$ is the acceleration RMS value of vertical vibration at driver's seat, $f_3(x_j)$ is the power
316 consumption per 100 km at a constant speed; Otherwise, apply a big enough value to $f_1(x_j)$, $f_2(x_j)$ and $f_3(x_j)$.

317 (7) Evaluation population updating. Obtain new evaluation population with specific strategies. The method
318 applied in the simulation experiments of this paper: First, let $R_G = Q_G \cup$, implement non-dominated ranking of
319 P_G and calculate the crowding distance of candidate solutions; then, select N candidate solutions from R_G based
320 on the ranking results to generate new population P_{G+1}; finally, circulate through $G = G + 1$.

321 (8) Output Pareto optimum solution set $P_{G+1}$and finish evaluation if the end conditions can be met;

Otherwise, turn to Step (5).

In Step (3) and Step (6), assign a value large enough to $f_1(x_j)$, $f_2(x_j)$ and $f_3(x_j)$, respectively, which means that due to its unsuitable handling stability, poor ride comfort and economy, this solution is not directly eliminated for storing diverse genes for subsequent evolutions.

6 Simulation Verification and Relate Analysis

6.1 Experiment Related Settings

$MATLAB/M-File$ was used to program realization for EV-MOEA, with the scale of evaluation population as 32, maximum generation as 100, mutation probability as 0.1 and crossover probability as 0.9. The basic parameter configuration of simulated the whole vehicle is shown in Table 3.

Table 3 Basic Parameters of the Vehicle

Item	Parameter	Value
Drive the Motor	Maxmum power/kW	75
	Maxmum output torque/$(N \cdot m)$	275
	Maxmum speed/$(r \cdot min^{-1})$	10 000
Accumulator	Type	
	Qty./pcs	25
	Single module index	$12V, 25A \cdot h$
Parameters of the Vehicle	Total weight of vehicle (kg)	1350
	Windward area (m^2)	1.9
	Air resistance coefficient	0.335

6.2 Optimization Results and Analysis

The distribution of the final Pareto optimum solutions after making statistics on the results of 10 operations

and combining all solutions is shown in Figure 4, as well as the data of design variables. Let the working efficiency of motor be E_{MC} and the efficiency of drive system be E_G. The statistical results of the stability factor f_1 corresponding to the final Pareto optimum solutions, the root mean square value of vertical vibration acceleration at driver's seat, the power consumption per 100 km at a constant speed and system performance are shown in Table 5. The data in Group 0 in Table 4 and Table 5 are default settings and performance indexes of the selected vehicle.

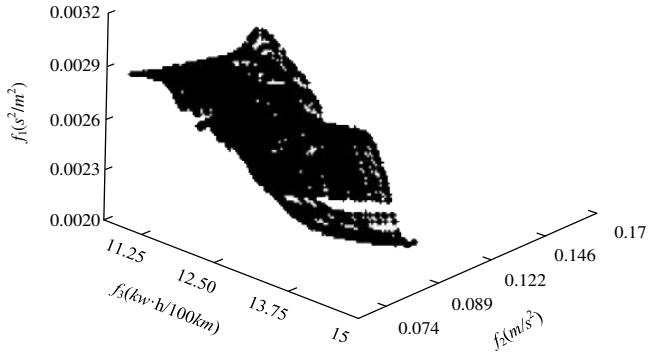


Figure 4 Distribution of Pareto Optimum Solutions after Combining the Results of 10 Operations

Table 4 Specific Parameters of Optimum Solutions after Combining the Results of 10 Operations

No.	$K_f/$ (N/m)	$C_f/$ $(N\cdot S/m)$	$K_r/$ (N/m)	$C_r/$ $(N\cdot S/m)$	f_d (mm)	P_e (kw)	R_S	N_b	R_m	H_{soc}	L_{soc}	v_e (km/h)
0	26460	5063	37183	2532	50	41.017	1.01	25	1.00	0.71	0.60	30.00
1	24819	5129	29015	2624	55	68.916	0.61	25	0.75	0.68	0.54	31.02
2	24905	5207	29643	2601	53	69.703	0.61	25	0.74	0.71	0.46	31.21
3	25134	5473	28349	2718	47	41.569	0.65	20	1.16	0.56	0.38	32.70
4	25685	5318	28710	2794	43	36.213	0.61	20	1.08	0.68	0.41	32.64
5	24986	5067	27965	2591	51	35.951	0.60	20	1.12	0.67	0.41	30.69
6	27359	6137	29047	2548	49	69.218	0.61	25	0.75	0.81	0.45	30.95
7	26741	6243	27934	2501	45	69.026	0.61	25	0.76	0.81	0.44	32.95
8	25834	6154	26075	2856	39	41.001	0.67	20	1.18	0.56	0.40	32.74
9	24378	5409	28437	2673	41	68.667	0.59	25	0.75	0.80	0.45	30.93
10	24953	5173	25712	2613	57	36.759	0.62	20	1.23	0.68	0.42	32.52

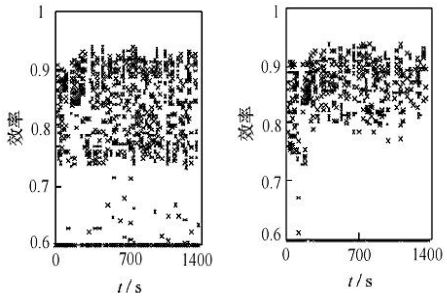
Table 5 System Performance Corresponding to Pareto Optimum Solutions after Combining the Results of 10 Operations

No.	Objective Function Value			System Performance	
	$f_1/$ (s^2/m^2)	$f_2/$ (m/s^2)	f_3 $(kw \cdot h/100km)$	E_{MC}	E_G
0	0.0023	0.114	15.89	0.79	0.89
1	0.0026	0.101	13.73	0.91	0.91
2	0.0027	0.112	13.95	0.89	0.93
3	0.0029	0.109	13.96	0.75	0.94
4	0.0025	0.112	14.25	0.86	0.93
5	0.0023	0.111	14.37	0.85	0.92
6	0.0021	0.110	13.98	0.89	0.91
7	0.0029	0.109	13.29	0.71	0.92
8	0.0023	0.106	13.17	0.88	0.94
9	0.0024	0.108	14.56	0.85	0.93
10	0.0025	0.104	14.59	0.79	0.91

It can be found from the data in Table 5 that the optimized system has reduced the acceleration RMS value of vertical vibration at driver's seat and the power consumption per 100 km at a constant speed under the premise of guaranteeing vehicle handling stability. In the optimized system, stability factors have increased by 9.5%, the acceleration RMS value of vertical vibration at driver's seat has decreased by 5.1% and the power consumption per 100 km at a constant speed has decreased by 8.8% on average, respectively.

As for the efficiency of the system, the efficiency of motor and driving system has increased by 6.1% and 3.8% on average, respectively, which implies that the working efficiency of major components of the vehicle has increased after optimization and each subsystem has better matched, so the multi-performance optimization proposed in this paper can improve the total working efficiency of BEVs.

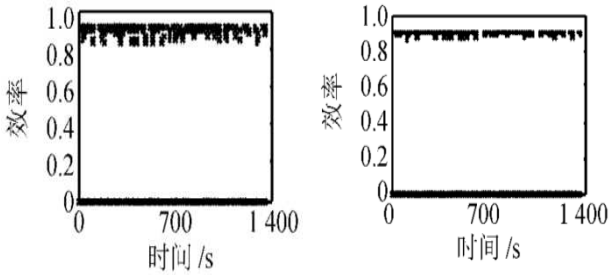
As an example, the optimization solution of Group 1 was compared with the system before optimization. Figure 5 and Figure 6 show the comparison results of the efficiency of motor and driving system, respectively.



(a) Before optimization (b) After optimization

Figure 5 Comparison Figure on Working Efficiency of Motor

According to Figure 5, the efficiency of motor was mainly within [0.7, 0.95] before optimization but within [0.8, 0.95] after optimization, while the working points of optimized motor were highly distributed in the high efficient areas after comparing the distribution diagram on working points of motor, which indicates that the efficiency of optimized motor has been significantly improved, which is further helpful to improve the economy of BEVs.



(a) Before optimization （b）After optimization

Figure 6 Efficiency Comparison of Driving System

According to Figure 6, the efficiency of driving system was within [0.8, 0.9] approximately before optimization but mainly within [0.85, 0.95] after optimization, which shows that the efficiency of driving system after optimization is superior to that before optimization, which is helpful to improve the comprehensive efficiency of BEVs.

7 Conclusions

To address the multi-performance optimization of BEVs, this paper proposed the corresponding model and algotithm for the multi-objective evaluation based on Pareto optimum principle with handling stability, ride comfort and economy as optimization objectives and improved ride comfort and economy under the premise of guaranteeing vehicle handling stability. The effectiveness of the method has been verified through simulation test and the following conclusions have been made.

(1) Multi-objective optimization algorithm of BEVs proposed based on Pareto optimum principle can improve ride comfort of vehicles and reduce energy consumption of batteries under the premise of guaranteeing handling stability. According to the simulation experiment, the algorithm has optimized multi-performance target collaboratively such as the safety, comfort and energy conservation of BEVs.

(2) The working efficiency of motor and driving system of BEVs have been improved differently after optimization, which means that each subsystem has been better matched after optimization and BEVs show a better performance.

(3) The method proposed in this paper makes it unnecessary to simplify the multi optimization objectives into one, which avoids the adverse influence caused by the weighted sum of different objectives, providing many groups of optimum solutions.

Availability of data and materials

All data generated or analysed during this study are included in this published article [and its supplementary information files].

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Authors' Contributions

Yawei Chen and Qian Cheng wrote the manuscript; Jurui Liu was in charge of the whole trial, review and edition; Xixiang Hao and Chenheng Yuan assisted with review. All authors read and approved the final manuscript.

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Competing Interests

The authors declare no competing financial interests.

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