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Optimization Strategy of the Electric Vehicle Power Battery Based on the Convex Optimization Algorithm

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Abstract: With the development of the electric vehicle industry, electric vehicles have provided more choices for people. However, the performance of electric vehicles needs improvement, which makes most consumers take a wait-and-see attitude. Therefore, finding a method that can effectively improve the performance of electric vehicles is of great significance. To improve the current performance of electric vehicles, a convex optimization algorithm is proposed to optimize the motor model and power battery parameters of electric vehicles, improving the overall performance of electric vehicles. The performance of the proposed convex optimization algorithm, dual loop DP optimization algorithm, and nonlinear optimization algorithm is compared. The results show that the hydrogen consumption of electric vehicles optimized by the convex optimization algorithm is 95.364 g. This consumption is lower than 98.165 g of the DCDP optimization algorithm and 105.236 g of the nonlinear optimization algorithm before optimization. It is also significantly better than the 125.59 g of electric vehicles before optimization. The calculation time of the convex optimization algorithm optimization is 4.9 s, which is lower than the DCDP optimization algorithm and nonlinear optimization algorithm. The above results indicate that convex optimization algorithms have better optimization performance. After optimizing the power battery using a convex optimization algorithm, the overall performance of electric vehicles is higher. Therefore, this method can effectively improve the performance of current electric vehicle power batteries, make new energy vehicles develop rapidly, and improve the increasingly serious environmental pollution and energy crisis in China.

Keywords: convex optimization algorithm; electric vehicle; power battery; energy management strategy; motor model

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1. Introduction

With the acceleration of China's economy and urban construction, the number of domestic motor vehicles is growing rapidly [1]. The environmental pollution and energy crisis due to the increase in the number of cars have posed a great threat to the natural environment on which humankind depends [2]. More new clean energy vehicles have been put into the market. Among them, the fuel cell electric vehicle (FCEV) is regarded as the new energy vehicle with the best development prospect at present because of its environmental protection and high performance [3]. In fuel cell electric vehicles, the advantages of fuel cells lie in high energy utilization, low pollution, and renewability. They can be used in fields such as automobiles, ships, and household appliances, greatly improving energy utilization efficiency and reducing environmental pollution. As a new type of power battery, the lithium battery has the characteristics of high energy density, lightweight, long service life, good low-temperature performance, safety, and reliability. However, the performance of most FCEVs on the market is limited by the lack of power cell efficiency. Therefore, it is crucial to develop a technique that can efficiently improve the performance of electric vehicle (EV) power batteries [4,5]. The convex optimization algorithm (COA) is an optimization method based on convex sets (CS) and convex functions

(CF). The algorithm has good performance in nonlinear optimization problems. It has been widely used in automobile intelligent control and smart home systems [6–9]. Therefore, in this study, COA is used to optimize the energy management strategy (EMS) and power batteries of EVs. It is expected to improve the vehicle performance of EVs and promote the development of FCEVs. In addition, this study also provides new ideas for the field of EV performance optimization. At present, there is relatively little research on the application of convex optimization algorithms in fuel cell efficiency optimization. In order to fill the research gap in the combination of convex optimization algorithms and fuel cell efficiency optimization, this study aims to use convex optimization algorithms to optimize the power cell parameters of electric vehicles, thereby improving the overall performance of electric vehicles. This study utilizes convex optimization algorithms to model the power battery and motor models of electric vehicles, avoiding the influence of other factors in the parameter optimization process. Furthermore, the application of a convex optimization algorithm in the optimization of electric vehicle power battery parameters achieved an efficient and accurate optimization process, overcoming the shortcomings of traditional methods. In addition, the convex optimization algorithm improves the range and safety performance of electric vehicles by reasonably adjusting parameters such as battery capacity, voltage, and current. In addition, the study also proposed this method to fill the gap in optimization methods for electric vehicle power batteries in China, making contributions to promoting the development of the field of electric vehicle power battery optimization.

2. Related Work

For the energy control of EVs and hybrid EVs, scholars have put forward quite mature theoretical results. Zhang et al. designed a new EMS to improve the stable operation of FC hybrid EVs. They optimized the strategy through the Q-learning algorithm of the double reward function and analyzed the parameters from the overall power demand of the vehicle. The outcomes demonstrated that this technique enhanced the average overall efficiency of the system to 52% [10]. Taking the hybrid EV as the research object, Wang et al. analyzed the effect of waste heat recovery on the optimization of vehicle thermal efficiency. The control parameters were optimized using a deep reinforcement learning algorithm. The experiment showed that this method saved 2% energy for the vehicle and optimized the state parameters of the battery [11]. To improve the endurance of the hybrid EV and take into account the power performance and economic efficiency of the vehicle, Hu et al. proposed a strategy of using deep reinforcement learning (DRL) for real-time energy management. Through model simulation experiments, they confirmed the effective performance of this method [12]. Guo et al. built the power demand model of a hybrid EV on road cruises and ramps by analyzing the vehicle power performance. The energy was controlled by the ARIMA method of data prediction. The simulation experiment demonstrated that the energy consumption of the vehicle could be effectively reduced by about 5–7% after using this method [13]. Coban et al. proposed the concept of vehicle to grid (V2G) to promote the development of electric vehicles and their energy storage systems. The characteristic of V2G charging points is the ability to have bidirectional energy flow when charging electric vehicles/pure electric vehicles. Applying this concept to practical applications, it has been found that after applying V2G, electric vehicles/pure electric vehicles have the ability to manage power flow, and also improve the economic energy balance. This study can find practical applications in evaluating the role of electric vehicles and their integration into power system vehicle network systems [14].

In terms of EV battery management and battery parameter optimization, the Fouladi team proposed an intelligent charging scheme based on a multi-objective optimization algorithm to solve the correct charging for plug-in hybrid vehicles. This scheme minimized energy consumption during charging and extended the battery life. The simulation analysis of the charging scheme showed that the proposed scheme ensured the correct charging of plug-in hybrid vehicles [15]. Zhang et al. discussed the system of plug-in hybrid EVs through the internal combustion engine. The dynamic framework of vehicles was analyzed by scenarios, and the ecological impact of communication equipment and transportation facilities on the driving of networked vehicles was also emphasized [16]. In view of the current situation of EV energy scheduling and distribution, Mehrabi et al. proposed the optimal scheduling of EVs in a large-scale intelligent energy distribution system to achieve EV charging and discharging flexibility. The findings demonstrated that this method achieved 20% of the final power load flattening improvement, which was conducive to the economy of large-scale vehicle energy management [17]. Hannan et al. focused the method of automobile energy management on the optimization of the EV's lithium-ion battery. A battery management system was proposed to evaluate the overall performance of automotive batteries. The experiment demonstrated that the system improved the efficiency of energy use and the battery life of new energy power vehicles, and provided a reference for future EV manufacturing [18]. Mangoni et al. also proposed to optimize the vehicle powertrain depending on the lightweight model. They analyzed the efficiency of the vehicle transmission system by evaluating the battery status of EVs. Experiments showed that this method could be effectively applied to the current EV [19].

In summary, the research results of domestic and foreign researchers on the power energy system of EVs tend to mature. The methods of model construction and parameter analysis are widely used. However, in the optimization, only simulation vehicle models are used for experimental analysis, and the computational complexity is not paid attention. The diversified combination of dynamic parameters in model construction often increases the calculation cost. Therefore, this research proposes an EV energy optimization method based on convex optimization, which is expected to provide a scientific reference for the future new energy vehicle market. To highlight the advantages of the proposed method in this study, the advantages and disadvantages of the above related works are compared with the methods proposed in this study. The comparison results are shown in Table 1.

Table 1. Comparison of the proposed methods with previous methods.

Method	Swot	Concrete Content
Dual reward function Q-learning algorithm implementation strategy	Advantage	The overall efficiency improvement of automobiles is significant
	Shortcoming	High energy consumption
Deep reinforcement learning algorithm optimization	Advantage	Significant energy savings
	Shortcoming	Low efficiency enhancement
Vehicle to network concept based on virtual inertial control	Advantage	Stronger ability to maintain voltage and frequency stability
	Shortcoming	Not much improvement in overall vehicle performance
Intelligent charging scheme based on multi-objective optimization algorithm	Advantage	Reduce energy consumption and improve battery life
	Shortcoming	Not much improvement in overall vehicle performance
Optimal scheduling of EVs in large-scale intelligent energy distribution systems	Advantage	Improvement of power load flattening effect
	Shortcoming	Not much improvement in overall vehicle performance
Energy optimization method based on convex optimization algorithm	Advantage	It can improve the performance of power batteries, reduce energy consumption, and thereby enhance the overall performance of EVs
	Shortcoming	Insufficient performance improvement

3. EV Power Battery Optimization Based on COA

3.1. Establishment of EV Power System Mathematical Model

FCEVs can be separated into pure FC vehicles and hybrid EVs according to the energy composition [20]. The hybrid power system of the FC and the power cell is the power system widely used by major automobile manufacturers [21]. Among them, the power cell is the auxiliary energy source, and the FC is the primary energy source. The FC is the average power required by the vehicle system. The power battery provides the difference between the maximum power and the average power, which greatly reduces the volume of the FC and reduces the cost of the vehicle [22]. The power battery module has good continuous tracking output performance under the condition of drastic load changes. This can effectively compensate for the transient changes of the FC and effectively reduce the dynamic changes of the FC, thus improving the service life [23,24]. The energy generated by the automobile brake is input to the battery through the bus, thus reducing the hydrogen consumption of the system and improving the economy of the whole vehicle. Figure 1 depicts the hybrid system structure of a FCEV.

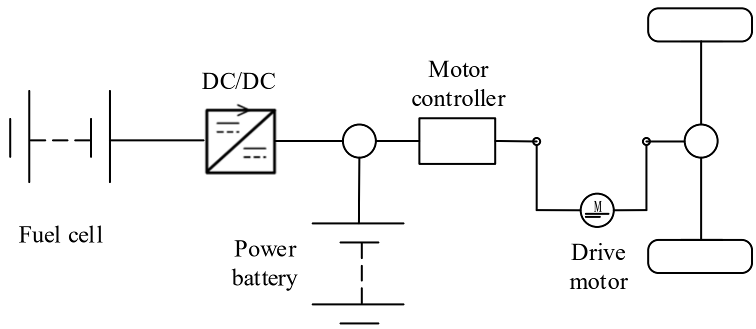

Figure 1. Power System Structure of a FCEV.

The cost-effectiveness of the hybrid system of the FC and the power battery is higher than that of the pure FC. Therefore, the power system is selected for optimization [25]. In this power system, the energy of the vehicle is provided by the power battery, FC, and DC/DC converter. The power battery's primary purpose is to supply the momentary maximum power demand so that the system can maintain stable output power for a long time. To optimize the capacity of the power battery better, the power system model of the vehicle is built first. Considering the economy and practicability of FCEVs, the constructed vehicle dynamics model includes only the longitudinal dynamics model of driving and braking, not the vehicle's vibration and driving stability. The expression of vehicle demand torque T is shown in Formula (1) [26].

$$T(t) = \frac{(\delta m\dot{v}(t) + 0.5\rho C_D A_f v(t)^2 + fmg\cos\theta(t) + mg\sin\theta(t))R_w}{i_0\eta_t} \tag{1}$$

In Formula (1), R_w represents the wheel radius and the unit is m. The EV's mass is m and the unit is kg. g is the acceleration of gravity and the unit is $\mathrm{m/s^2}$. The rolling resistance coefficient is f and the unit is N/kN. v is the speed of the EV and the unit is km/h. C_D is the air resistance coefficient and the unit is ns/m. The windward area is A_f and the unit is $\mathrm{m^2}$. ρ is the air density and the unit is $\mathrm{kg/m^3}$. θ is the road slope. i_0 is the final drive ratio. η_t represents the transmission efficiency. δ represents the coefficient of rotation. To optimize the capacity of the power battery, the vehicle's total mass is made up of the mass of the vehicle itself and the mass of the power battery pack. The expression of the total vehicle mass m is shown in Formula (2).

$$m = m_0 + m_b N_b \tag{2}$$

In Formula (2), the basic mass of the car is m_b and the unit is kg. m_b is the mass of a single power battery and the unit is kg. N_b represents the number of power batteries. Table 2 shows the main parameters of a FCEV [27].

Table 2. Main Parameters of a FCEV.

Parameter	Character	Numerical Value	Unit
Vehicle foundation quality	m_0	1768.6	kg
Wheel radius	R_w	326	mm
Windward area	A_f	2.58	m^2
Air drag coefficient	C_D	0.367	-
Rolling resistance coefficient	f	0.0071	-
Final drive ratio	i_0	9.215	-
Maximum power of fuel cell	$P_{fc,\max}$	61	KW
Maximum voltage of fuel cell	$U_{fc,\max}$	340	V
Rated power of fuel cell	$P_{fc,rat}$	42	KW
Rated voltage of fuel cell	$U_{fc,rat}$	180	V

The drive motor is an important part of new energy vehicles and also a source of power [28,29]. Special drive motors for new energy vehicles include DC motors, asynchronous motors, permanent magnet synchronous motors, and switched reluctance motors. Due to their high efficiency, easy control, wide speed range, high reliability, and high specific power, permanent magnet synchronous motors are commonly applied in new energy vehicles. Therefore, a permanent magnet synchronous motor is selected as the driving motor. Power batteries and fuel cells together power the drive motor. The two are effectively converted into mechanical energy to meet the torque T_M required by the vehicle. In addition, the friction brake T_{brk} can be supplemented when the maximum battery current or torque is reached. The selected drive motor model is TX115MS156. The maximum torque, minimum torque, and maximum speed are 330 Nm, −330 Nm, and 12,000 rpm, respectively. The torque and required power of the motor are shown in Formula (3).

$$\begin{cases} T_M(t) = T(t) - T_{brk}(t) \\ P_M(t) = T_M(t)\omega_M(t) \end{cases} \tag{3}$$

In Formula (3), P_M represents the motor power and the unit is kw. ω_M represents the motor speed and the unit is r/min. The transmission system outputs the motor power to the wheels, giving the car power its needs. The relationship between the required power P_{dem} of the car and the motor power P_M is shown in Formula (4).

$$P_{dem}(t) = P_M(t)\eta_M \tag{4}$$

In Formula (4), η_M represents the efficiency of the motor system. Formula (5) represents the dynamic system balance.

$$P_{fc}(t) + P_b(t) - P_{bloss}(t) = P_M(t) + P_a \tag{5}$$

In Formula (5), P_{fc} represents the fuel cell power. P_b denotes the battery power in watts. P_{bloss} is the power battery power loss. P_a is a constant representing the auxiliary power of the vehicle. All three power units are kw. The primary goal of the research is to improve the power battery of the hybrid power system. The power battery usually refers to the battery that provides the power source for pure EVs, hybrid EVs, fuel cell EVs, etc. At present, power batteries include lead acid, lithium ion, nickel metal hydride, etc. [28]. The lithiumion battery is an ideal power battery for EVs at present due to its high voltage, long charging and discharging time, high specific energy, wide working range, safety and reliability, and fast charging. As the core component of a FCEV, the power battery can not only overcome the defect of poor dynamic characteristics but also effectively control the brake mechanism to make sure the car runs reliably and safely [30,31]. Detailed information of the selected power batteries is shown in Table 3.

Table 3. Specific parameters of power batteries selected for the study.

Parameter	Character	Numerical Value	Unit
Individual mass	m_b	0.275	kg
Total mass	m_1	38	kg
Battery capacity	E	2.1	kw·h
Nominal voltage	$U_{b,nom}$	350	V
Maximum power	$p_{b,\max}$	70	kw
Minimum power	$p_{b,\min}$	−70	kw
Maximum SOC	$SOC_{\max}$	0.8	/
Minimum SOC	$SOC_{\min}$	0.3	/
Average power	$\eta_{b,ave}$	0.9	/

The existing equivalent models mainly include RC, Rint, lead acid (LA), and neural network (NN). The Rint model can reflect both the open-circuit voltage (OCV) and the charging/discharging internal resistance, making it convenient for conducting this experiment. Therefore, the Rint model is used as the equivalent model for this experiment. The Rint model is composed of a voltage source and a variable resistor. The equivalent model and structure of the power battery pack are shown in Figure 2.

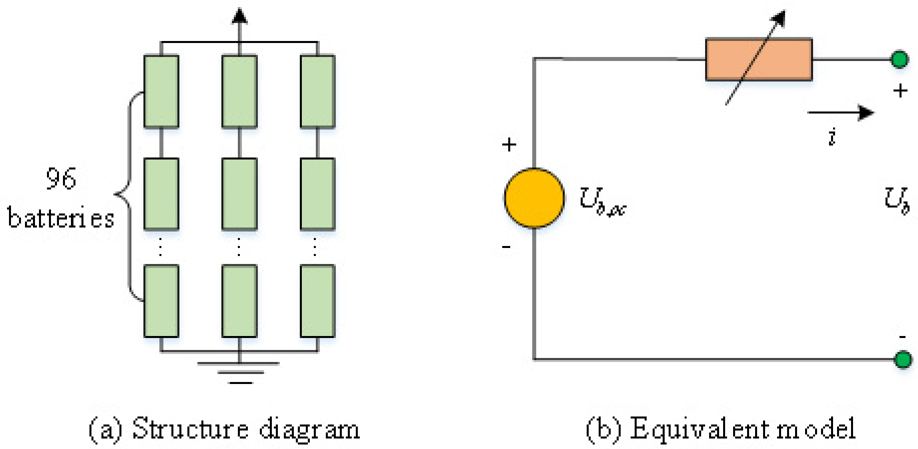

Figure 2. Equivalent Model and Structure Diagram of the Power Battery Pack.

The structure of the power battery pack is shown in Figure 2a. Figure 2b is an equivalent model. From Figure 2a, the quantity of batteries in series is 96 and the batteries in parallel are 3. According to Kirchhoff's voltage law, Formula (6) displays the equivalent circuit's equation.

$$U_b = U_{b,oc} - iR_b \tag{6}$$

In Formula (6), $U_{b,oc}$ represents the OCV of the power battery and the unit is V. R_b represents the internal resistance of the power battery and the unit is Ω. U_b represents the terminal voltage of the power battery and the unit is V. i represents the internal current of the power battery and the unit is A. The internal resistance R_b of the power battery is a function of the state of charge (SOC). The expression is shown in Formula (7).

$$R_b = \begin{cases} R_{cha}(SOC), i < 0 \\ R_{dis}(SOC), i \geq 0 \end{cases} \tag{7}$$

In Formula (7), $R_{cha}(SOC)$ is the internal resistance of power battery charging and the unit is Ω. $R_{dis}(SOC)$ is the internal resistance of power battery discharge and the unit is Ω.

When charging an electric vehicle, the resistance of the battery gradually decreases. When discharging an electric vehicle, the resistance of the battery gradually increases [32]. The expression of the power battery OCV is shown in Formula (8).

$$U_{b,oc} = N_b f_2(SOC) \tag{8}$$

In Formula (8), $f_2(SOC)$ is the lookup function of the SOC. Depending on the established mathematical model, a method for solving the optimal control problem of the dynamic model is proposed. It is to achieve the optimal matching of energy through the energy distribution within a certain driving time. On the premise of ensuring energy density, hydrogen consumption is reduced. The kinetic equation of the system is shown in Formula (9).

$$SOC(t+1) = SOC(t) - \frac{U_{b,oc}(t) - \sqrt{U_{b,oc}^2(t) - 4R_b(t)(P_M(t) - P_{fc}(t) - P_a(t) + P_{bloss}(t))}}{2QR_b(t)}\Delta t \tag{9}$$

In Formula (9), Q represents the battery capacity and the unit is Wh. Formula (9) is the model of the dynamic system. Based on this model, an optimization operation is carried out to improve the performance of the power battery.

3.2. Power Battery Optimization Strategy Based on COA

COA is the most commonly used mathematical method in optimal control at present. This optimization strategy is based on CS and CF. It has been widely used in automobile intelligent control, smart home systems, financial statistics, etc. COA is a method to study the minimum problem of convex function under the given form [33]. COA is more likely to be able to solve a problem if it can be made into a convex optimization problem or if it already is one. At present, local approximation of the general nonlinear optimization model by the convex optimization model is the main way to study problems with nonlinear optimization. In the optimization control of new energy vehicles, the COA also gradually shows its advantages. The CS in the COA means that if a set still contains the line segment connecting any two points, this set is called a CS. Generally speaking, if each point in a set can be reached by a line segment composed of any other point, the set is called a CS. Figure 3 shows some typical convex and non-convex sets.

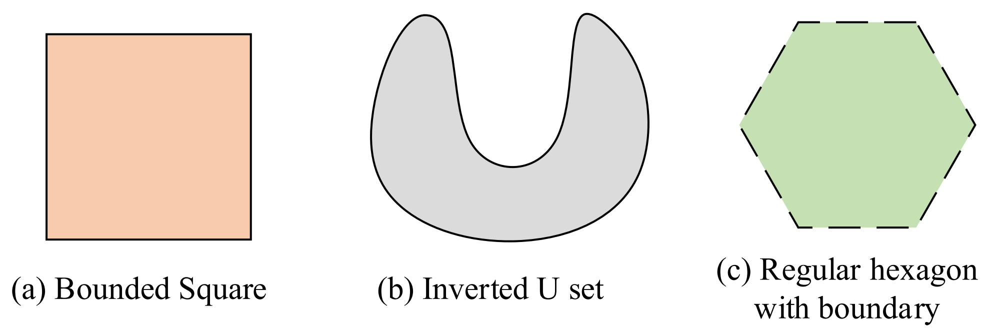

Figure 3. Typical Convex and Non-convex Sets.

Figure 3a–c show the set of squares with boundaries, the regular U, and the regular hexagons with partial boundaries, respectively. Figure 3a,c are non-convex sets, and Figure 3b is CS. The following defines the CF of the COA. In function $f : R^n \rightarrow R$, if $dom f$ is a CS. (x, y) in the set satisfies $x, y \in dom f, 0 \leq \theta \leq 1$. The expression is shown in Formula (10).

$$f(\theta x + (1-\theta)y) \leq \theta f(x) + (1-\theta)f(y) \tag{10}$$

In Formula (10), f represents a convex function. From a two-dimensional perspective, the inequality shown in Formula (10) can be regarded as the connection of two points, $(x_1, f(x_1))$ and $(x_2, f(x_2))$, on a convex function. The line is on the curve formed by the convex function f. If $x_1 \neq y, 0 \leq \theta \leq 1$, Formula (10) is valid. In this case, f is strictly a CF. Assuming that CF f is differentiable, the CS of CF f is $domf$. The CF f needs to satisfy the expression shown in Formula (11).

$$f(y) \geq f(x) + \nabla f(x)^T (y - x) \tag{11}$$

If Formula (11) satisfies any $x, y \in domf$, for the first order of the CF, the theorem is a necessary and sufficient condition. COA is a developed area of mathematics. The minimum and minimum of CF on the CS can be found using this optimization technique. This method can not only optimize the EMS but also optimize the capacity of the power battery. Three conditions must be satisfied to solve the problem by using COA. First, the objective must be a convex function when seeking the minimum optimization. When seeking the maximum optimization, the objective must be a concave function. Second, inequality constraints must be convex functions. The third condition is that the formula constraint must be affine. In the dynamic system model of an EV, most variables are not convex functions. To better use the COA to optimize variables, these variables are processed to fulfill the demands of convex optimization. To optimize the power battery capacity while optimizing the EMS of an EV, the battery proportion factor S_b is added in Formula (2). The scale factor is the optimization variable in the COA to obtain the optimal capacity of the power battery. The quantity of parallel power batteries affects the power battery capacity. The power battery's overall quality is also impacted by the scale factor. Therefore, the calculation expression of vehicle mass is shown in Formula (12).

$$m = m_0 + s_b m_b N_b \tag{12}$$

The efficiency of electric vehicle motors is a discrete value. Therefore, the formula describing the electric vehicle motor model is a non-convex function. To better utilize the COA of the motor model, the motor model is fitted to improve convexity. The assembled motor model is shown in Figure 4.

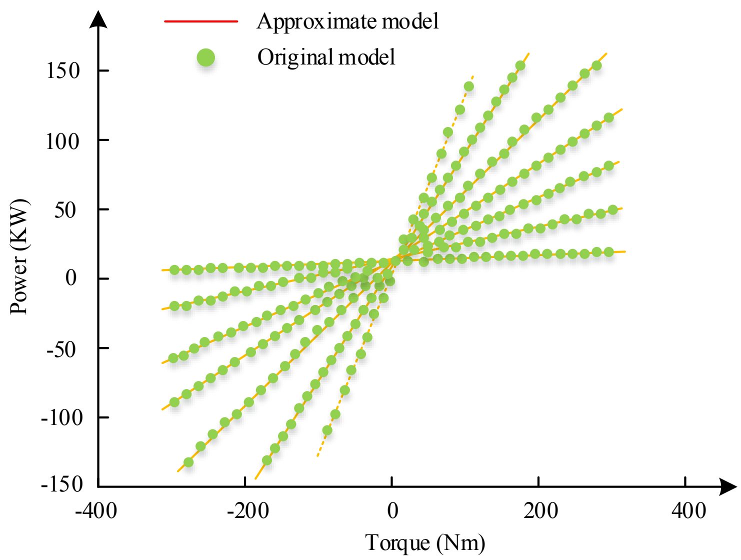

Figure 4. Motor Model after Fitting.

The motor power in the fitted motor model is a quadratic function of torque. The quadratic function is constrained to be convex. The expression of the constrained motor power is shown in Formula (13).

$$P_M(T_M(t), t) \geq b_0(\omega_M(t)) + b_1(\omega_M(t))T_M(t) + b_2(\omega_M(t))T_M^2(t) \cdots \tag{13}$$

In Formula (13), b_0, b_1, and b_2 are coefficients of different dimensions. In the motor model, the motor torque, as well as speed, are also related to the threshold value. The specific relationship is shown in Formula (14).

$$\begin{cases} T_{M,\min}(\omega_M(t)) \leq T_M(\omega_M(t)) \leq T_{M,\max}(\omega_M(t)) \\ 0 \leq \omega_M(t) \leq \omega_{M,\max} \end{cases} \tag{14}$$

In Formula (14), $T_{M,\min}(\omega_M(t))$ is the minimum torque at speed ω_M. $T_{M,\max}(\omega_M(t))$ is the maximum torque at ω_M speed. The power battery model proposed in the study is non-convex. Firstly, to optimize the power battery model, the OCV of the power battery should be approximated as a linear function. Formula (15) is the linear function expression.

$$U_{b,oc}(t) = c_1 SOC(t) + c_0 \tag{15}$$

Secondly, the dynamic equation for a power battery is also simplified because the current function is not convex. SOC is replaced by the battery energy E as the state variable for the optimization problem. At this time, Formula (16) illustrates the power battery's dynamic equation.

$$E(t+1) = E(t) + \Delta t P_b(t) \tag{16}$$

Finally, the approximate expression for the loss of power is shown in Formula (17).

$$P_{b,loss}(t) = (1 - \eta_b)|P_b(t)| \tag{17}$$

In Formula (17), η_b represents the average efficiency of the power battery. The energy E and PB of the power battery meet the constraint inequality shown in Formula (18).

$$\begin{cases} SOC_{\min}E \leq E(t) \leq SOC_{\max}E \\ P_{b,\min} \leq P_b(t) \leq P_{b,\max} \end{cases} \tag{18}$$

The goal of FCEV EMS based on COA and power cell optimization is also to minimize the hydrogen consumption of the system. Formula (19) is the cost function of the optimization problem.

$$J = \sum_{k=1}^{N} (a_2 P_{fc}(k)^2) + a_1 P_{fc}(k) + a_0) \tag{19}$$

In Formula (19), a_2, a_1, and a_0 are the coefficients used to fit the quadratic term, the primary term, and the constant term, respectively. P represents fitting the quadratic function. By calculating this formula, the minimum hydrogen consumption of the system can be obtained. In summary, the COA is used to enhance the parameters of the motor model and the power battery model, respectively. Figure 5 depicts the precise procedure.

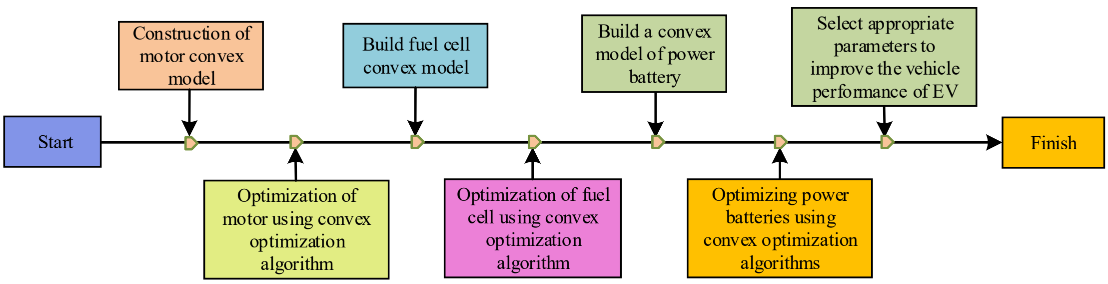

Figure 5. COA for EV Performance Optimization Process.

From Figure 5, the general process of using convex optimization algorithms for optimizing the performance of electric vehicles is as follows. Firstly, a convex model of the electric vehicle motor is constructed and the optimization model based on the convex optimization algorithm is established. Secondly, a convex model of the electric vehicle fuel cell is constructed and optimized through convex optimization algorithms. Then, a convex model of the electric vehicle power battery is constructed and optimized using convex optimization algorithms. Finally, appropriate parameters are selected to improve the vehicle performance of the electric vehicle.

4. Analysis of COA Performance Test Results

EVs often encounter various driving conditions in the actual driving process. To better analyze the optimization effect of electric vehicles proposed in the study, representative cycle test conditions are selected to test vehicle performance. The New European Driving Cycle (NEDC) is based on the new European testing standards for electric vehicles, which include many driving conditions and habits similar to the actual driving environment. The purpose of this cycle is to evaluate the actual performance and range of electric vehicles, making it more suitable for testing in actual driving environments. The WLTP cycle is based on American automotive testing standards, which include more road driving conditions and driving habits, making it more suitable as a testing standard for electric vehicles when driving on actual roads. However, due to the fact that this cycle does not fully simulate the actual driving environment, other factors need to be considered during testing, such as the vehicle's battery capacity, motor power, etc. Furthermore, the commonly used operating conditions for domestic new energy vehicles are NEDC and the Urban Dynamometer Driving Schedule (UDDS) cycle, rather than the WLTP cycle. Therefore, the NEDC cycle and the UDDS cycle are selected as the standard cycle conditions for testing. The speed–time curves of the two cycle conditions are shown in Figure 6.

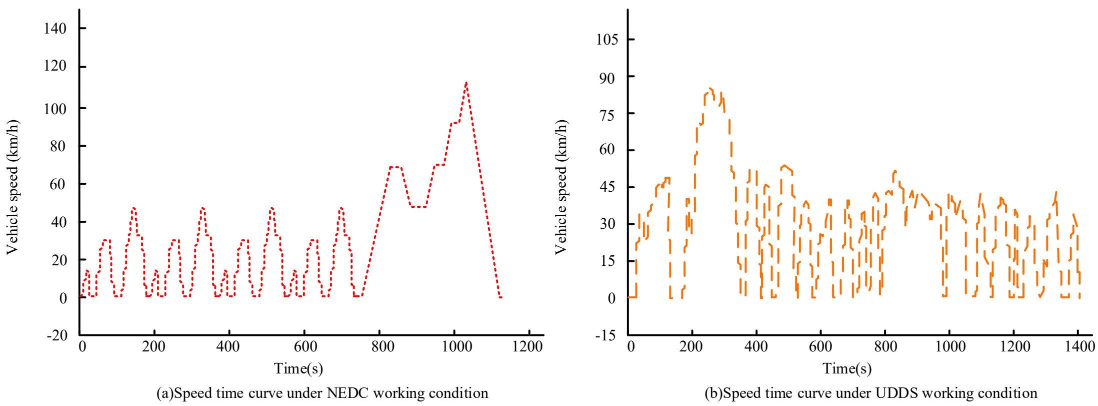

Figure 6. Speed–Time Curve under Two Cycle Conditions.

From Figure 6a, the NECD cycle includes 780 s of urban cycles. The process includes four stages: starting, accelerating, slowing, and decelerating. The maximum speed is 50 km/h. In addition, it also includes the maximum speed of 400 s. The suburban working condition is 120 km/h. From Figure 6b, the UDDS cycle also includes four stages: starting, accelerating, slowing, and decelerating. The speed distribution is uniform. In this cycle, the maximum speed is 92 km/h. The ADVISOR simulation software is used to simulate electric vehicles. To analyze the optimization effect of the algorithm, the hydrogen consumption and optimal battery capacity of the unoptimized electric vehicle under two cycle conditions are tested. The test results of unoptimized electric vehicles under two cycle conditions are shown in Table 4.

Table 4. Comparison of the test results of the three algorithms.

Test Indicators	First Test		Second Test		Third Test	
	NEDC	UDDS	NEDC	UDDS	NEDC	UDDS
Hydrogen consumption (g)	123.216	125.482	122.335	126.154	123.057	125.134
Optimal power battery capacity (KW·h)	3.125	3.216	3.136	3.208	3.141	3.209

In Table 4, the average hydrogen consumption of electric vehicles without optimization under the NEDC cycle is 122.869 g. The average hydrogen consumption under the UDDS cycle is 125.590 g. The average optimal battery capacity under the NEDC and UDDS cycles is 3.134 KW·h and 3.211 KW·h, respectively. To test the performance of the convex optimization algorithm proposed in this study, comparative experiments are conducted with the dual loop DP optimization algorithm and the nonlinear optimization algorithm. Hydrogen consumption, computational time, power, etc. are used as comparison indicators. The experimental parameters are: the capacity of the power battery is fixed at 2.1 kWh; the quantified value of SOC is 2×10^{-4}. The electric vehicles optimized by three optimization algorithms were tested under the NEDC and UDDS cycle conditions. The test results are shown in Table 5.

Table 5. Comparison of the test results of the three algorithms.

Algorithm	Double Loop DP Algorithm		Convex Optimization Algorithm		Linear Optimization Algorithm	
	NEDC	UDDS	NEDC	UDDS	NEDC	UDDS
Hydrogen consumption (g)	98.162	100.358	101.364	106.963	105.236	110.69
Optimal power battery capacity (KWh)	2.769	2.769	2.036	2.159	2.556	2.634
Operation time (s)	10,986	12,368	4.9	5.5	406.6	463.9

Table 5 compares the optimization results of three optimization algorithms in terms of hydrogen consumption, optimal battery capacity, and calculation time. In the NEDC working condition, the average hydrogen consumption optimized by the convex optimization algorithm is 95.364 g. It is lower than the 98.165 g consumption of the double cycle dynamic programming algorithm and the 105.236 g consumption of the linear optimization algorithm. In addition, the optimal battery capacity and running time optimized by the convex optimization algorithm are 2.094 KW·h and 4.9 s, respectively, which are superior to the DCDP optimization algorithm and the linear optimization algorithm. In the UDDS working condition, the average hydrogen consumption after convex optimization algorithm optimization is 96.963 g, which is lower than the 100.358 g consumption of the DCDP algorithm and 110.629 g consumption of the linear optimization algorithm. In addition, the optimal battery capacity and running time optimized by the convex optimization algorithm are 2.159 KW·h and 5.5 s, respectively, which are superior to the DCDP optimization algorithm and the linear optimization algorithm. Through the above comparative analysis, the performance of electric vehicles optimized by the convex optimization algorithm is better. In addition, comparing Tables 4 and 5, the hydrogen consumption and optimal power battery capacity of electric vehicles optimized by convex optimization algorithms significantly decreased. Therefore, convex optimization algorithms can improve the performance of electric vehicle power batteries. To better analyze the performance of the convex optimization algorithm, the power of the DCDP algorithm and convex optimization algorithm in two two-cycle conditions is compared. In addition, in order to better compare and analyze the performance of the convex optimization algorithm, the power of the dual cycle dynamic programming algorithm and the convex optimization algorithm in two two-cycle conditions is compared and analyzed. Sliding filters were used to filter data during the optimization process. Figure 7 displays the power distribution diagram of the two algorithms in the NEDC cycle.

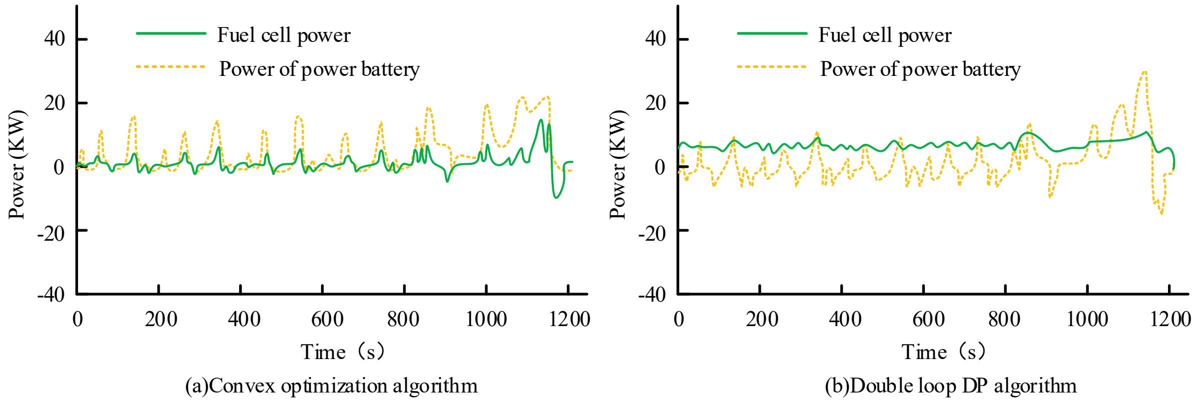

Figure 7. Power of Two Algorithms under the NEDC Condition.

Figure 7a shows the power curve of the COA under the NEDC condition. From Figure 7, the power of a fuel cell is greater than 0, while the power of a power cell may be less than 0. This phenomenon exists because when the maximum transient response power of the fuel cell cannot meet the load demand, the power cell will switch to a discharge mode to provide the remaining power. Therefore, the power of the fuel cell is always positive, while the power of the power cell can be negative. From Figure 7a, the fuel cell power fluctuates greatly during this cycle. The power range varies between 0–22 kW, and the power of the power battery also fluctuates slightly. Figure 7b shows the power curve of the DCDP under the NEDC condition. From Figure 7b, the power of the fuel cell fluctuates greatly during this cycle, with a power range of −18–30 KW. The power of the power cell fluctuates very little. The application effect of the power battery optimized by the COA is better than that optimized by the DCDP algorithm under the NEDC condition. Figure 8 depicts the FC efficiency curves of the two optimization algorithms under the NEDC condition.

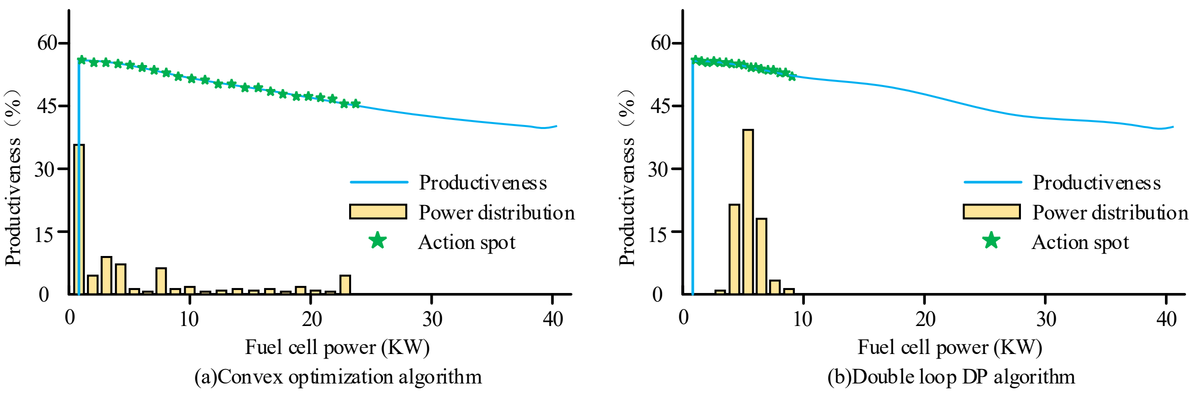

Figure 8. Efficiency Curve of FC under the NEDC Condition.

Figure 8a shows the efficiency curve of the COA under the NEDC condition. From Figure 8a, under this cycle condition, the FC's working points are focused in the high-efficiency area. The working points are relatively scattered, and the power range varies from 0 to 22 kW. Figure 8b shows the efficiency curve of the DCDP under NEDC. From

Figure 8b, the fuel cell's working points are focused in the high-efficiency area. The working points are relatively concentrated in the power range of 3–10 kW. According to the above results, the application effect of the power battery optimized by COA is better than the optimized DCDP under NEDC conditions. Figure 9 shows the power distribution diagram of the two algorithms in the UDDS cycle.

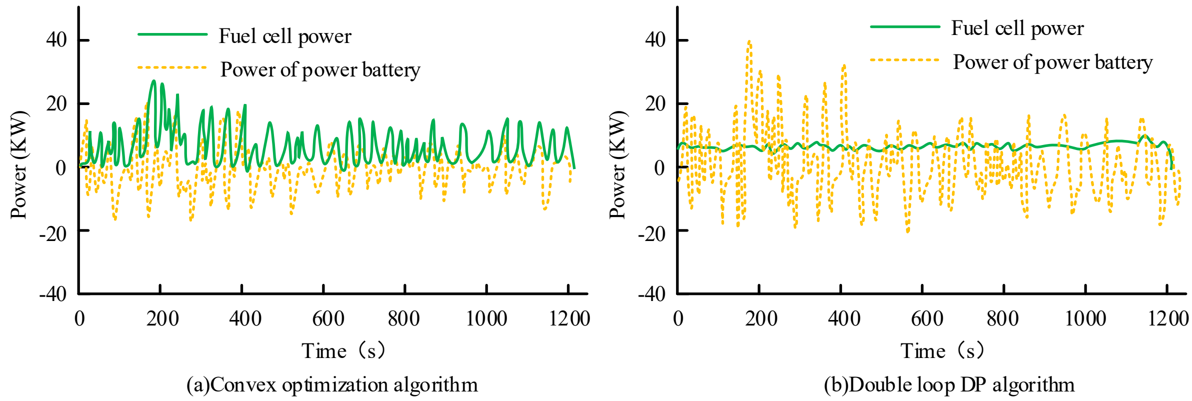

Figure 9. Power of Two Algorithms under the UDDS Condition.

Figure 9a shows the power curve of the COA under the UDDS condition. From Figure 9a, the FC power fluctuates greatly during the UDDS working condition, and the power range varies between 0–28 kW. The power of the power battery also fluctuates greatly, ranging from −19 KW to 18 KW. Figure 9b shows the power curve of the DCDP under UDDS. From Figure 9b, the power fluctuation of the FC is very small during the UDDS working condition. Most of the power is below 7 KW. The power of the power battery fluctuates greatly, ranging from −19 KW to 38 KW. From the above results, the application effect of the power battery optimized by the COA is better than the DCDP under the UDDS condition. Figure 10 shows the fuel cell efficiency curves of two optimization algorithms under the UDDS condition.

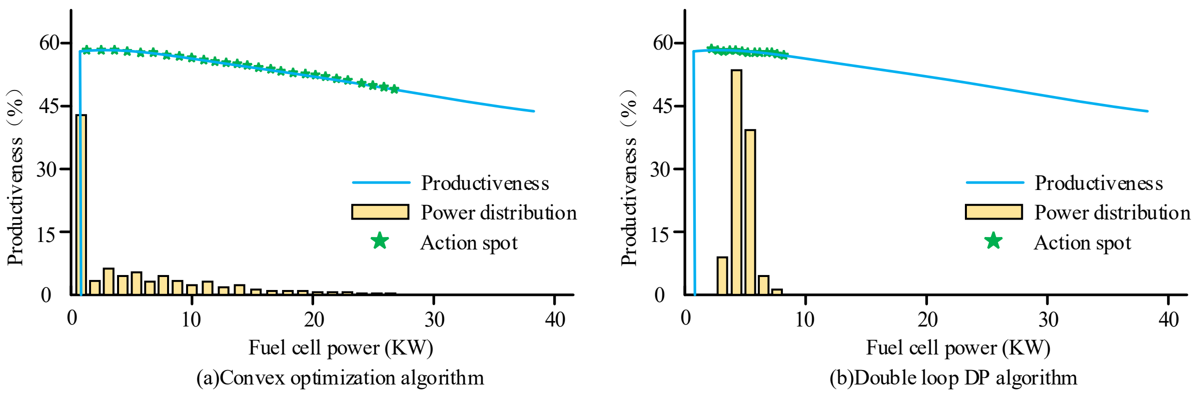

Figure 10. Efficiency Curve of Fuel Cell under the UDDS Condition.

The COA's efficiency curve under the UDDS condition is depicted in Figure 10a. The working points of the fuel cells are relatively concentrated under the UDDS condition. The working points are relatively scattered, and the power range varies between 0–28 kW. Figure 10b depicts the efficiency curve of the DCDP under the UDDS condition. From Figure 10b, the working points of fuel cells are very concentrated under the UDDS condition, basically between 3 KW and 10 KW. According to the above results, the application effect of the power battery optimized by COA is better than that optimized by DCDP under the UDDS condition. In general, the COA can realize the synchronous optimization of battery capacity and EMS. The optimal results of the two methods are not different. Although the capacity of the power battery solved by COA is different, this method has a high computing speed. The power and efficiency are better than the DCDP. Therefore, the COA is used to optimize the power battery, which can effectively improve the battery performance of EVs.

5. Conclusions

With the emergence of alternative fuel vehicles, the development of FCEVs has generated concerns because of the high-cost of performance. However, at present, the absence of energy consumption mechanism optimization hinders the development of new energy vehicles. To solve this problem, a convex optimization algorithm was studied to optimize the motor model and power battery of FCEVs, aiming to improve the overall performance of electric vehicles in this way. The convex optimization algorithm, double loop dynamic programming algorithm, and nonlinear optimization algorithm were compared. The hydrogen consumption of electric vehicles optimized by the convex optimization algorithm is 95.364 g. It is significantly better than the hydrogen consumption of electric vehicles optimized by the dual cycle DP optimization algorithm of 98.165 g. The hydrogen consumption of the nonlinear optimization algorithm is 105.236 g. In addition, the computation time of the convex optimization algorithm optimization is 4.9 s, which is much lower than the 10,986 s of the dual loop DP optimization algorithm and the 406.6 s of the nonlinear optimization algorithm. The above results indicate that the application of the convex optimization algorithm in the battery optimization of electric vehicles can effectively improve the overall performance of electric vehicles. Overall, this article provides new contributions and prospects for the following fields. (I) It can further improve the application fields of convex optimization algorithms and promote the development of optimization algorithm fields. (II) The overall performance of electric vehicles was improved, promoting the development of new energy vehicles. (III) The power battery solution was optimized to promote the development of the power battery field. Fuel cell electric vehicles are an important direction of the global energy technological revolution, which is also an important means to alleviate the energy crisis and reduce environmental pollution. Research was conducted on the optimization of fuel cells. The convex optimization algorithm was used for optimization design, achieving reasonable allocation of energy and power, and obtaining the optimal power battery capacity. The convex optimization algorithm was compared with the dual loop DP optimization algorithm and the nonlinear algorithm. The research results are as follows. Firstly, by analyzing the topological structures of various fuel cell electric vehicle power systems, a hybrid structure of a fuel cell and a power battery was selected and a mathematical model of the hybrid power system was established. Secondly, the relevant knowledge of convex optimization algorithms was described. The convexity of the dynamic system model was ensured through approximate processing. The effectiveness of convex modeling in this paper was verified through simulation experiments. Finally, the convex optimization algorithm proposed in this study has good optimization effects on electric vehicle power batteries. By optimizing electric vehicles through this method, the overall performance of electric vehicles can be significantly improved. Due to the limitations of the experimental conditions, the performance of this method was only verified in simulation experiments. Verifying the algorithm's performance in a real vehicle is the focus of our next work.

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Abbreviations

Abbreviation	Specific meanings
DP	Dynamic programming
FCEV	Fuel cell electric vehicle
COA	Convex optimization algorithm
CS	Convex sets
CF	Convex functions
EMS	Energy management strategy
EV	Electric vehicle
DRL	Deep reinforcement learning

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