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Energy Consumption Prediction and Control Algorithm for Hybrid Electric Vehicles Based on an Equivalent Minimum Fuel Consumption Model

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Abstract: The development of hybrid technology can effectively solve the problems of the high pollution and energy consumption levels of automobiles. Therefore, an energy consumption prediction and control algorithm for hybrid vehicles based on a minimum equivalent fuel consumption model is proposed. The model's battery power consumption is equivalent to the fuel consumption, and the sum of the engine fuel consumption and the battery equivalent fuel consumption is established as the objective function. By utilizing these factors, an innovative minimum equivalent fuel consumption model was constructed that could be used to measure the energy efficiency of hybrid vehicles. The longitudinal force result of braking force distribution control was obtained, as well as the energy consumption prediction structure of a hybrid electric vehicle. The rolling resistance, air resistance, and climbing resistance of the hybrid electric vehicles were calculated, and the energy consumption control algorithm for hybrid electric vehicles was constructed according to the calculation results. The experimental results indicated that under this research algorithm, the driving energy consumption of hybrid electric vehicles was relatively low and the energy consumption and energy efficiency measurements effectively met the actual demand, and the energy consumption prediction and control results were good.

Keywords: minimum equivalent fuel consumption model; hybrid electric vehicle; energy consumption forecast; control algorithm; longitudinal force

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Citation: Zhang, Q.; Tian, S. Energy Consumption Prediction and Control Algorithm for Hybrid Electric Vehicles Based on an Equivalent Minimum Fuel Consumption Model. *Sustainability* **2023**, *15*, 9394. https://10.3390/su15129394

Academic Editors: Hamidreza Behi, Danial Karimi, Reza Behi and Masud Behnia

Received: 18 April 2023
Revised: 5 June 2023
Accepted: 7 June 2023
Published: 12 June 2023

1. Introduction

The energy crisis and environmental pollution are becoming more and more serious, and hybrid electric vehicles have gradually become a key topic in the field of automobile research because of their low energy consumption and low emissions [1,2]. Hybrid electric vehicles refer to vehicles whose driving systems are composed of two or more single driving systems that can run at the same time, and the driving power of these vehicles is provided by a single driving system, alone or jointly, according to the actual driving state of such a vehicle [3]. Hybrid electric vehicles, as described, generally refer to vehicles that combine electric motors with traditional internal combustion engines (diesel engines or gasoline engines) and motors that are used as power sources, with some engines being modified to use alternative fuels, such as compressed natural gas, propane, or ethanol. In order to improve the energy consumption predictions for, as well as the control of, hybrid electric vehicles, a minimum equivalent fuel consumption model has been used to replace that of a traditional energy storage system, and energy consumption prediction and control have become the research focus of the authors; the current research achievements in this field are shown in Table 1.

Table 1. Discussion and analysis results from the references.

Reference	Research Findings	Research Limitations
[4]	Based on Lagrangian theory, a mathematical model for the electromechanical coupling vibration of the internal combustion engine and generator for a series hybrid electric vehicle was established.	The actual control effect of the model is inconsistent with the predicted results, and the energy control efficiency is low. The comprehensiveness of the model needs to be improved.
[5]	A global optimization method based on an energy allocation strategy is proposed that effectively solves the optimization problem of the cost and weight of the energy control.	The weight of the system equipment is large, the cost of operation and maintenance is high, and the output efficiency of the entire energy storage system is reduced.
[6]	A neural fuzzy system with real-time offline optimization results was constructed using K-cross allocation, which effectively improves the comprehensiveness of energy control by evaluating vehicle energy efficiency and setting penalty terms for battery energy use.	A large amount of resources need to be used to achieve offline optimization, and the offline optimization results are greatly limited by data and environment, which cannot fully reflect the actual situation, resulting in a poor control effect.
[7]	Joint control of the entire vehicle system avoids additional energy consumption in unexpected situations and improves energy efficiency and battery life.	In practical applications, there are significant limitations regarding computing resources and time that cannot guarantee the real-time running status of vehicles, resulting in poor practical application results.
[8]	This study proposes a vehicle baseline control and vehicle energy optimization management strategy based on the Pontryagin minimum principle that effectively controls the vehicle's baseline driving and optimizes the vehicle's energy control performance.	Without considering whether the equivalent fuel consumption is the minimum value for calculating the real-time energy consumption of vehicles, the optimization effect of vehicle energy configuration and management is not significant.
[9]	Propose an energy management strategy for supercapacitor hybrid power systems to address the issue of battery aging in hybrid electric vehicles. By developing a hierarchical energy optimization management framework, we can effectively improve the operational efficiency of automobiles and reduce battery aging costs.	Focusing solely on reducing economic costs without calculating the weight of vehicle energy consumption factors, it is impossible to monitor and predict vehicle energy consumption in real time.
[10]	This study proposes a fuzzy control strategy to control the load change rate of automotive battery systems. Effectively improving the durability of fuel cells and reducing vehicle operating costs.	The lack of actual simulation of car energy consumption resulted in control strategies being unable to adjust energy allocation and configuration strategies under different driving conditions, resulting in low energy utilization efficiency.

Table 1. *Cont.*

Reference	Research Findings	Research Limitations
[11]	A physical network system based on an energy management strategy is proposed to address the issue of intelligent and electrified upgrades in hybrid electric vehicles. The deep reinforcement learning algorithm was applied to visualize and analyze the energy consumption parameters in dynamic vehicle systems, thus effectively improving the energy efficiency.	In the process of training network data, factors such as road conditions, driving speed, starting and acceleration, and the vehicle's own energy supply and consumption were not comprehensively considered, making it impossible to control the energy consumption of hybrid vehicles in real-time.
[12]	In order to achieve the electrification of vehicle energy drive systems, a hybrid electric vehicle energy management system design is proposed to reduce the energy consumption levels and extend the service life of energy storage.	Unable to predict the future energy consumption of the vehicle before its operation, without controlling and optimizing the conversion and distribution of different energy sources during vehicle operation, energy utilization efficiency needs to be improved.
[13]	This study applies the open-circuit voltage method to estimate the power output of lithium-ion batteries in electric vehicles. The particle swarm energy management algorithm is applied to control the battery output power, allocate battery energy fuzzy quantities, effectively reduce energy consumption rate, and improve the real-time performance of vehicle energy management.	Without combining actual driving data to optimize the energy consumption structure of automobiles, only optimizing and adjusting the electric vehicles cannot achieve the synchronous development of automobile energy prediction and control.

Although the above research produced some results, certain problems still remain. From an analysis of the content in Table 1, a hybrid electric vehicle energy consumption prediction and control algorithm was proposed to improve the current situation. Taking the sum of the engine fuel consumption and battery equivalent fuel consumption as the objective function, a minimum equivalent fuel consumption model for hybrid electric vehicles was established to predict the energy efficiency of a vehicle, establish an energy consumption prediction structure for hybrid electric vehicles, and improve the comprehensiveness of energy consumption control results and energy utilization efficiency. By calculating the rolling resistance, air resistance, and climbing resistance of hybrid electric vehicles, we could establish an energy consumption control algorithm for hybrid electric vehicles, improve the energy control efficiency, and reduce the energy consumption and emissions of vehicles. Based on this, the innovative application of hybrid electric vehicle energy consumption prediction algorithms and hybrid electric vehicle energy consumption control algorithms can be used to predict the future operation of a vehicle, adjust the vehicle's energy management system in real time, achieve optimized energy management, and achieve the best energy utilization efficiency and performance.

2. Energy Consumption of a Hybrid Electric Vehicle under a Minimum Equivalent Fuel Consumption Model

2.1. Building a Minimum Equivalent Fuel Consumption Model

The minimum equivalent fuel consumption model uses an instantaneous optimization strategy. Its main idea is to equate battery power consumption with fuel consumption, establish the sum of the engine fuel consumption and the battery equivalent fuel consumption as the objective function, determine the equivalent factor coefficient, and distribute the engine and battery power reasonably at every moment to minimize fuel consumption. For an HEV with energy maintenance, the difference between the initial state of charge and the terminal state of charge of the battery needs to be very small [14], and the energy consumed by the battery can be ignored relative to the total energy. As an auxiliary energy storage element, a battery acts as an energy buffer where all energy comes from the engine's fuel consumption. Any electric energy consumed in a battery's discharge stage must be supplemented by engine fuel at a later stage. In the future, the amount of electric energy increased by a battery in a charging stage can be used to drive a vehicle through a pure electric working mode, which is equivalent to saving fuel consumption by using a hybrid controller [15,16]. Therefore, the equivalent fuel consumption of a minimum equivalent fuel consumption model can be expressed as follows:

$$A_A = A_B + A_C \tag{1}$$

where A_A represents the equivalent fuel consumption of the engine and battery, A_B represents the engine's fuel consumption, and A_C represents the fuel consumption converted from the battery's energy consumption [17].

The fuel consumption of the engine and the fuel consumption converted by the battery can be obtained by Formulas (2) and (3):

$$A_B = D_F \times D_H \tag{2}$$

$$A_C = \frac{G_H}{G_J} \times \lambda \tag{3}$$

where D_F represents the fuel consumption rate of the engine, %; D_H is the expression of the engine's power, kW; G_H is the expression of the battery's power, kW; G_J represents the low calorific value of the fuel; and λ stands for an equivalent factor.

For hybrid electric vehicles, energy management can be regarded as an optimal control problem, and its optimization goal is to minimize fuel consumption [18]. The performance index function can be expressed by the following formula:

$$D_S = \int (A_B + A_C) \times E(t)dt \tag{4}$$

where $E(t)$ represents the system control variable, taking the battery power as the system control variable and the battery state of charge as the state variable, namely,

$$\begin{aligned} E(t) &= P_{DG}(t) \times D_S \\ X(t) &= S_{CV}(t) \times D_S \end{aligned} \tag{5}$$

where $P_{DG}(t)$ represents the peak power of the engine, %, and $S_{CV}(t)$ represents the initial value of the battery's SoC. According to the minimum principle, if the control variable $E(t)$ is the global optimal solution of the optimal control problem, then $\hat{E}(t)$ must be satisfied so that the Hamiltonian function takes the minimum value, that is:

$$\hat{E}(t) = \text{argmin} H(E(t), F(t), t) \tag{6}$$

where $H(E(t), F(t), t)$ stands for the Hamiltonian, and its formula is:

$$H(E(t), F(t), t) = A_A + \zeta E(t) \tag{7}$$

In Formula (7), ζ represents a covariant. By comparing the equivalent fuel consumption expression of this minimum equivalent fuel consumption model [19], the relationship between ζ and the equivalent factor λ can be obtained as follows:

$$\zeta = \frac{-\lambda G_H}{G_J} \tag{8}$$

where ζ can be regarded as the equivalent factor after conversion. Then, the minimum equivalent fuel consumption model can be constructed, and its expression is as follows:

$$M_X = \zeta \times \lambda \times H(E(t), F(t), t) \tag{9}$$

The model regards a hybrid electric vehicle as a multi-input and multi-output system. By modeling and analyzing the power flow of each energy component in a hybrid electric system, the energy flow of a hybrid electric system can be controlled and optimized. An energy management strategy is responsible for controlling and optimizing the hybrid power system to achieve the goal of minimizing the equivalent fuel consumption [20]. In practice, this equivalent minimum fuel consumption model, combined with real-time vehicle data, can dynamically control and optimize the energy flow of a hybrid power system, which can realize optimal control.

2.2. Energy Efficiency Measurement of a Hybrid Electric Vehicle

The elements of each level were compared to obtain a comparative judgment matrix between every two elements, and, finally, the consistency of this matrix was checked and the energy efficiency measurement results of hybrid electric vehicles were measured.

Firstly, the element comparison matrix was constructed. On the basis of the minimum equivalent fuel consumption model, it was assumed that the relative importance between the energy-consuming node i and node j in a hybrid electric vehicle network is M_{ij}. In the minimum equivalent fuel consumption model, the calculation formula of M_{ij} is as follows:

$$M_{ij} = \frac{1}{M_{ji}} \times M_X \tag{10}$$

In Formula (10), M_{ij} has seven criteria, namely, 1, 3, 5, 7, 9, 2468, and reciprocal values. These standards were set based on the above algorithms, combined with models and practical application scenarios, by analyzing the energy consumption of different nodes, the functional requirements undertaken by each node in the network, the location of the central node in the network, and the comprehensive security requirements. Here, 1 holds the same importance for both node i and node j, 3 indicates that node i is slightly more important than node j, 5 indicates that node i is more important than node j, 7 indicates that node i is much more important than node j, 9 indicates that node i is much more important than node j, and 2468 indicates the middle value near the standard. The reciprocal values indicate that the ratio of the importance between node i and node j is inversely proportional to that between node j and node i.

The formula for calculating the weight $\widetilde{M}_i$ of each index is as follows:

$$\widetilde{M}_i = \sum_{i=1, j=1}^{n} M_{ij} \tag{11}$$

When calculating the weight, a consistency check is needed to maintain the consistency of the overall thinking. The calculation expression for this consistency check is as follows:

$$C_I = \frac{\lambda_{\max} - n}{n - 1} \tag{12}$$

where C_I represents the weight consistency index and $\lambda_{\max}$ represents the eigenvalue of the judgment matrix.

When the consistency index C_I is less than or equal to 0.1, the judgment matrix meets the consistency requirements; otherwise, it needs to be corrected. With the help of the minimum equivalent fuel consumption model, the energy efficiency levels of the energy-consuming nodes of hybrid electric vehicles are measured, and the calculation formula for the i power system characteristic ratio under the j index is as follows:

$$N_{ij} = \frac{n_{ij}}{\sum\limits_{i=1,j=1}^{n} n_{ij}} \tag{13}$$

where N_{ij} represents the characteristic matrix and n_{ij} represents the i-th hybrid vehicle network characteristic under j indexes.

Based on the above analysis, the energy efficiency measurement formula for hybrid electric vehicles is as follows:

$$F(x) = \sum_{i=1}^{l} p_i \left[\sum_{z=1}^{n} (q_{z1} + q_{z2}) \right] \times N_{ij} \tag{14}$$

In Formula (13), l represents the number of motors in a hybrid vehicle, p_i represents the weight vector of the energy-consuming nodes in a hybrid vehicle, and q_{z1} and q_{z2} represent the weight vectors of the secondary indicators of the nodes.

2.3. Energy Consumption Prediction Algorithm for Hybrid Electric Vehicles

The energy consumption control algorithm for hybrid electric vehicles monitors the energy management system of a vehicle in real time, adjusts the energy distribution and deployment strategy according to different driving conditions, and achieves the best energy utilization efficiency. The energy consumption prediction algorithm for hybrid electric vehicles refers to an algorithm that simulates and predicts the energy consumption of a hybrid electric vehicle to achieve the best energy utilization efficiency. The algorithm is mainly based on vehicle performance parameters, road conditions, driving conditions, etc., and through predicting the future operation of a vehicle, optimized energy management and maximized economic benefits are realized [21,22]. The core element of the energy consumption prediction algorithm for hybrid electric vehicles is the energy consumption model. The model can predict a vehicle's energy consumption with high accuracy by considering many factors such as vehicle dynamics, the energy flow equation, and the battery's chemical reactions. At the same time, on the basis of a large amount of actual driving data, the energy consumption model has been optimized and trained, which improves its prediction accuracy and precision. The energy consumption prediction algorithm flow of hybrid electric vehicles is shown in Figure 1:

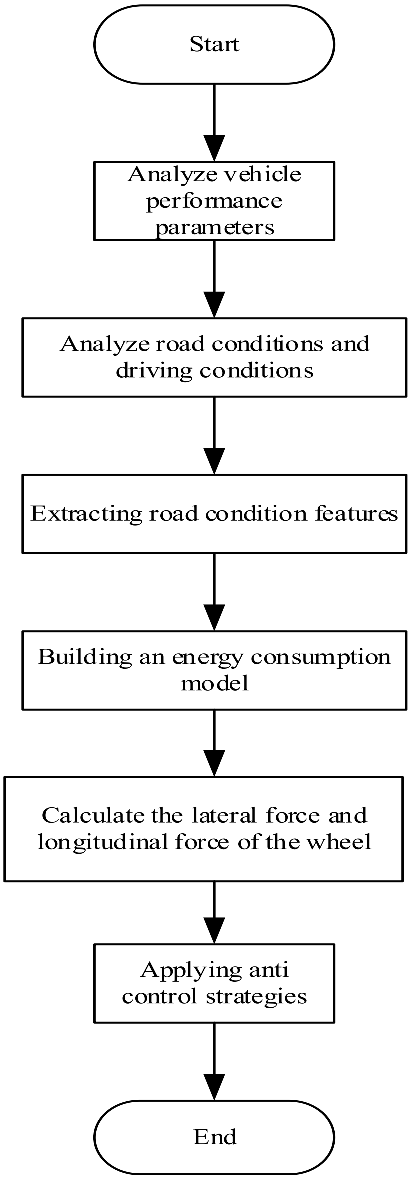


Figure 1. Energy consumption prediction algorithm flow for hybrid electric vehicles.

Through the minimum equivalent fuel consumption model, the stress on the plane during the driving of a hybrid electric vehicle can be obtained, and the lateral forces and longitudinal forces of a hybrid electric vehicle's wheels can be obtained by analyzing the stress in detail. The lateral and longitudinal forces of car wheels refer to the two different directions of force that the wheels are subjected to during driving. Lateral force refers to the force acting on the side of the wheel, also known as lateral force or lateral friction. It is the main force generated when a vehicle turns, with its direction perpendicular to the direction the vehicle is travelling and pointing towards the center of where the vehicle turns. The magnitude of lateral force depends on factors such as vehicle speed, contact angle between wheels and road surface, road roughness, and the height of the vehicle's center of gravity. Longitudinal force refers to the force acting in the front and rear directions of the wheel, also known as longitudinal friction. It is the main force generated by vehicles during acceleration, braking, and climbing, with its direction parallel to the direction of the vehicle movement. The magnitude of longitudinal force depends on factors such as road friction coefficient, contact pressure between the wheels and road surface, and wheel grip. According to the results of the lateral and longitudinal forces of the wheels, feedback control is then adopted to reduce the control error caused by the change in the lateral force of wheels on the braking force distribution. The longitudinal force calculation formula for the braking force prediction distribution of a hybrid electric vehicle is as follows:

$$F_{ud} = F_{bf} \times F_{cf} \times F(x) \tag{15}$$

In Formula (15), F_{ud} represents the longitudinal force of the predicted distribution of the automobile's braking force, F_{bf} represents the matrix parameter for the braking force control efficiency, and F_{cf} represents the initial longitudinal force of the automobile's wheels.

The system obtains the longitudinal force results for the braking force distribution control through calculations, and on this basis, the longitudinal force results of the distribution control to reduce the following error of the braking force's expected target are relaxed. The feasible region of the longitudinal force distribution of the automobile's wheels is set, and the brake actuator in the system is constrained by the wheel friction circle to ensure the stability of the feasible region of the longitudinal force distribution of the automobile's wheels. According to the calculation results, the energy consumption prediction structure of a hybrid electric vehicle can obtained, as shown in Figure 2.

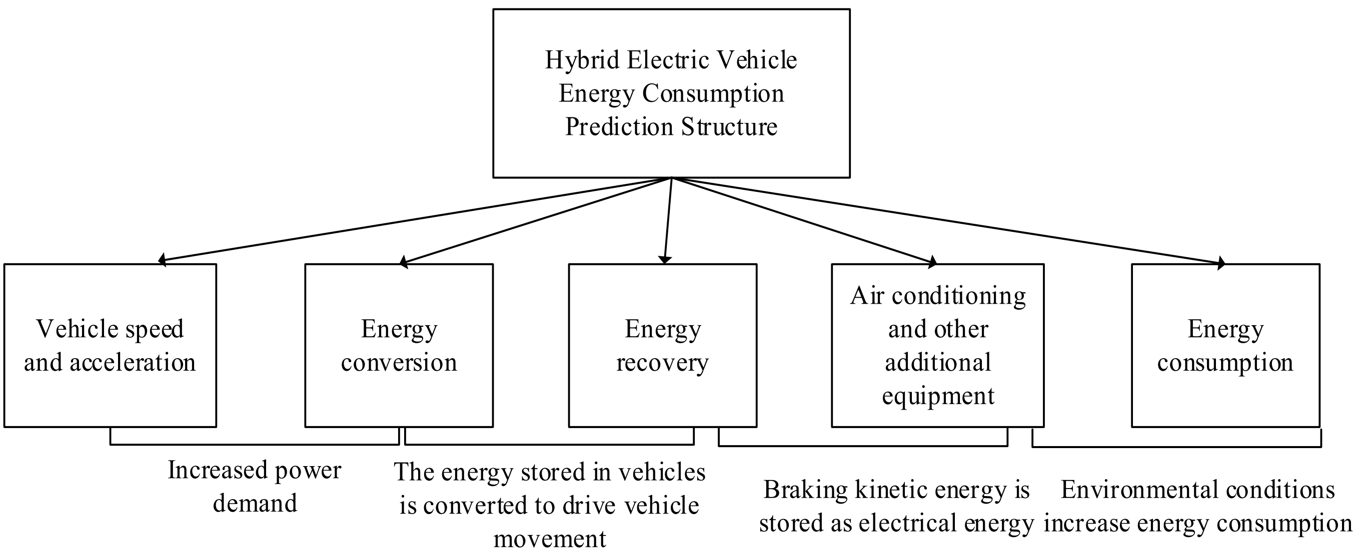


Figure 2. Energy consumption prediction structure of a hybrid electric vehicle.

According to the structure shown in Figure 2, through the energy consumption prediction of a hybrid electric vehicle, the future energy consumption of a vehicle can be predicted before it is run so as to formulate the best energy management strategy, and thus the best energy utilization efficiency and fuel economy are achieved. In the process of realizing the energy consumption prediction for a hybrid electric vehicle, many factors need to be considered, such as road conditions, driving speed, starting and acceleration, and the energy supply and consumption of the vehicle itself. At the same time, the algorithm also needs to control the energy consumption of a hybrid electric vehicle in real time and adjust the energy control strategy according to different driving conditions to achieve the best energy utilization efficiency.

2.4. Energy Consumption Control Algorithm for a Hybrid Electric Vehicle

The energy consumption prediction algorithm of a hybrid electric vehicle realizes optimized energy management by predicting the future operation of a vehicle. The energy consumption control algorithm of a hybrid electric vehicle refers to an algorithm that achieves the best energy consumption and fuel consumption by optimizing and regulating the energy management system of a hybrid electric vehicle. The algorithm mainly controls and optimizes the conversion and allocation of different energy sources during a vehicle's operation so as to achieve the highest utilization efficiency of the vehicle's energy. The core element of the energy consumption control algorithm of a hybrid electric vehicle is the energy management strategy. This strategy aims to achieve the best energy distribution and deployment by monitoring and adjusting the power flow of the internal combustion engine, battery, motor, and other energy components in real time, so as to achieve the goal of minimizing the equivalent fuel consumption of a vehicle. At present, the model-based predictive control algorithm is mainly used for the energy management of hybrid electric vehicles. By modeling and predicting vehicle dynamics and energy flow and combining them with the real-time data from on-board sensors, the algorithm can control and adjust vehicle energy management in real time to achieve the best energy control. The energy consumption control algorithm flow of hybrid electric vehicles is shown in Figure 3.

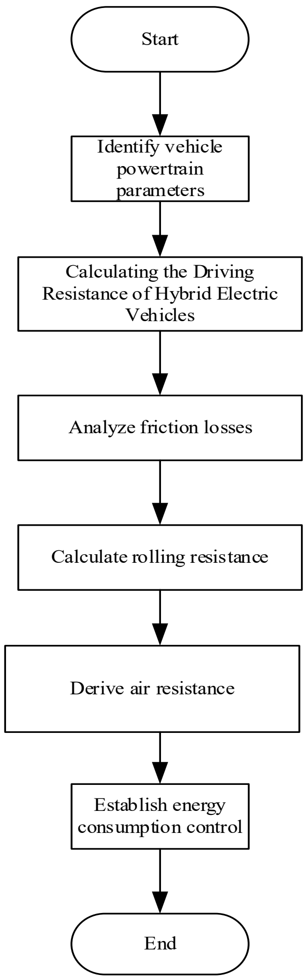


Figure 3. Energy consumption control algorithm flow for hybrid electric vehicles.

The driving process of a hybrid electric vehicle is affected by complex road conditions and the surrounding environment. In order to reasonably distribute driving power, realize the smooth driving of hybrid electric vehicles, and enhance the reliability of the braking energy recovery control system, the identification and power control of an automobile's brake pedal are adopted. Considering the characteristics of the brake pedal energy recovery control signal of a hybrid electric vehicle, the relevant parameters of the power system are calculated according to a real driving situation for the vehicle, and the input signals generated by each parameter are identified. The basic operation theorem of hybrid electric vehicle power systems can be described using mathematical formulas. The vehicle's resistance, traction, and speed are explained below.

We calculated the running resistance of a hybrid electric vehicle, including its tire rolling resistance, air resistance, and climbing resistance. When a vehicle is driving on soft road, the deformation of the road surface is large and the friction loss between the tire and the ground is low. The calculation process of the rolling resistance F_r is recorded as follows:

$$Z_r = P \times f_r \times F_{ud} \tag{16}$$

In Formula (16), P represents the vertical load at the center of the wheel and f_r represents the rolling resistance index. When the vehicle is on a slope, the rolling resistance is as follows:

$$Z_r{}' = P \times f_r \cos\alpha \tag{17}$$

In Formula (17), α represents the inclination angle of the road's surface.

The air resistance is influenced by many factors, with shape resistance having the greatest impact, followed by the interference resistance, internal circulation resistance, induced resistance, and friction resistance caused by the surface protrusions. The derivation process of the air resistance K_w is described as follows:

$$K_w = \rho \times A_f \times C_D (v + v_w)^2 \times Z_r{}' \tag{18}$$

In Formula (18), ρ represents the air density, A_f represents the windward area value, C_D represents the air resistance index, v represents the vehicle speed, and v_w represents the wind speed variable of the vehicle's movement.

When moving uphill, the gravity of a vehicle will move along the slope, resulting in the climbing resistance F_g, which is recorded as follows:

$$F_g = m \times \sin\alpha \times K_w \tag{19}$$

In Formula (19), m represents the volume of the sloped surface. Accounting for the tire rolling resistance, air resistance, and climbing resistance, and thus building the energy consumption control, the calculation formula is as follows:

$$G_K = \frac{\left(Z_r + K_w + F_g\right)}{N_w} \tag{20}$$

In Formula (20), N_w represents the driving tire speed, and according to the control result, the energy consumption control structure of a hybrid electric vehicle is obtained, as shown in Figure 4.

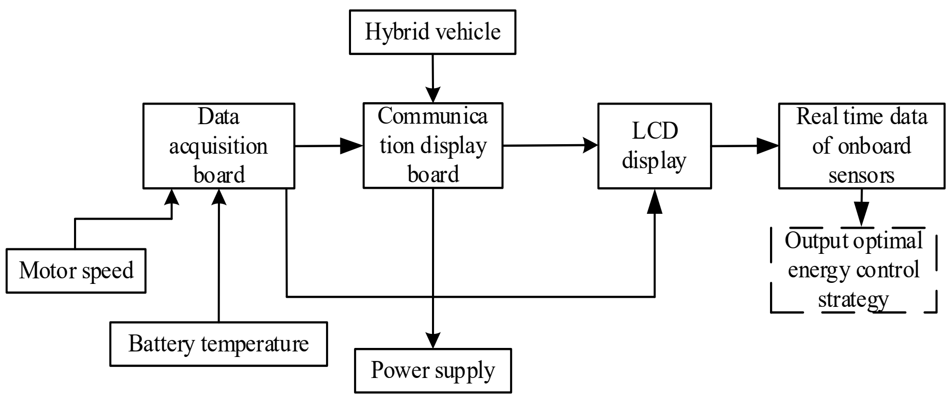


Figure 4. Energy consumption control structure of a hybrid electric vehicle.

The energy consumption control structure of a hybrid electric vehicle can adjust the working state of a motor and engine in real time according to the driving conditions and road conditions of the vehicle so as to achieve the best energy utilization efficiency.

To summarize, there is an interdependence between the energy consumption prediction algorithm and the energy consumption control algorithm for hybrid electric vehicles. The forecasting algorithm provides key forecasting information and a decision-making basis for the control algorithm, and the control algorithm adjusts the vehicle's energy management system in real time according to the results of the forecasting algorithm to achieve the best energy utilization efficiency and performance. Real-time monitoring and adjusting the energy management system of a hybrid electric vehicle achieves the goal of optimizing energy consumption and fuel consumption. The algorithm has the advantages of high efficiency, accuracy, and adaptability, and it has wide application prospects and market demand in the performance index, energy savings, and environmental protection of hybrid electric vehicles.

3. Simulation Experiment and Results

In order to verify the effectiveness of the energy consumption prediction and control algorithm for hybrid electric vehicles using the minimum equivalent fuel consumption model, a simulation experiment was carried out, and the simulation test was carried out by combining CarSim 2020 software and MATLAB 2019b software. The selected hybrid vehicle turned out to be a series−parallel hybrid vehicle with a P1 + P3 structure, as shown in Figure 5.

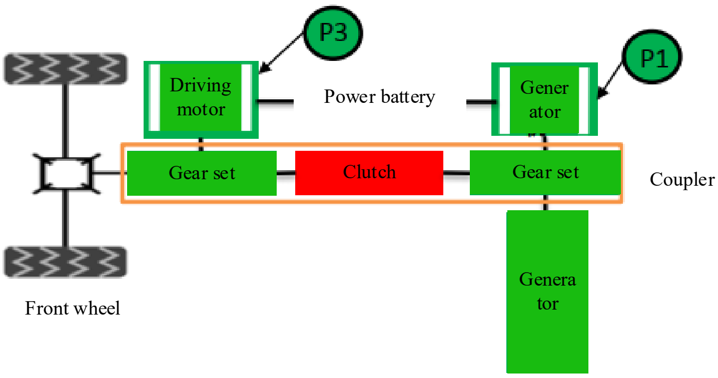


Figure 5. Series−parallel hybrid electric vehicle with a P1 + P3 structure.

A series−parallel hybrid electric vehicle with a P1 + P3 structure (as shown in Figure 5) was used as the simulation experimental object. In CarSim, the constant speed was set to 80 km/h, and the road adhesion index was set to 0.75. The configuration of simulation experiment parameters is shown in Table 2.

The parameter components or corresponding functions built into the experimental test were as shown in Table 2. Vehicle mass (kg) refers to the weight of the vehicle itself, including the body, engine, chassis, tires, etc. The setting of vehicle mass usually takes into account factors such as the vehicle's load-bearing capacity and safety performance. Height of centroid (m) refers to the height of the vehicle's center of gravity, which usually affects the stability, handling, and other aspects of the vehicle. A lower height of the center of mass usually helps improve the stability and handling of the vehicle. Wheelbase (mm) refers to the distance between the centerline of the wheels, which usually affects the smoothness and comfort of the vehicle. A longer wheelbase usually helps to improve the smoothness and riding comfort of the vehicle. Maximum power (kW) refers to the maximum power output of the engine, which usually affects the vehicle's acceleration performance, climbing ability, and other aspects. Higher maximum power usually helps to improve the vehicle's power performance. Maximum speed (r/min) refers to the maximum speed that a vehicle can reach, which usually affects the driving efficiency, fuel consumption, and other aspects of the vehicle. A higher top speed usually helps to improve the driving efficiency of the vehicle. Other parameters used were 16 independent 12-bit resolution double-buffered

D/A converters with an output range of 0~+10 V and a digital input and output capacity of 12 channels.

Table 2. Parameter configuration table for the simulated experimental objects.

Serial Number	Parameter Configuration	Value or Function
1	Vehicle mass (kg)	1100
2	Height of centroid (m)	0.8
3	Wheelbase (mm)	2640
4	Maximum power (kW)	14
5	Maximum speed (r/min)	4620
6	Pressure transducer	Real-time measurement of the pressure of the automobile wheel brake disc
7	Electronic brake pedal position sensor	Collect the position of the brake pedal and use it as an output
8	Engine−generator	22/61
9	Engine−(clutch)−differential	50/61
10	Driving motor−differential	58/21

Before completing the simulation experiment, this study selected 100 sets of training sample data for the simulation platform to simulate the energy consumption of 100 km driven by ordinary cars and hybrid cars, respectively, as shown in Figure 6.

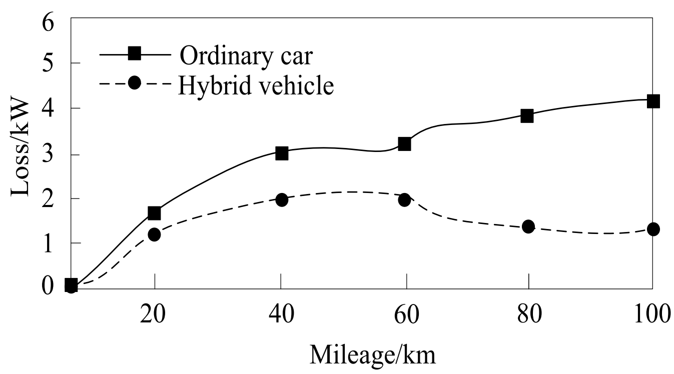
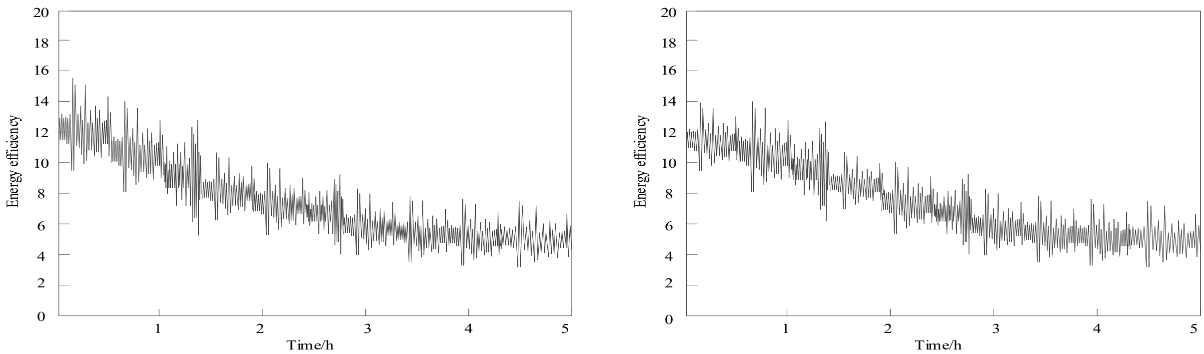


Figure 6. Test results of the different automobiles' driving energy consumption.

According to Figure 6, this experiment was mainly based on the simulation of 100 km, and the energy consumption of the two models could be basically restored. The energy consumption of the ordinary cars was large, and the more mileage, the higher the power consumption, while the driving energy consumption of the hybrid electric vehicles was small. After the mileage exceeded 60 km, the power loss was reduced to less than 1 kW, and the stable power loss was maintained, which could provide a stable driving force for the vehicle.

In the above experimental environment, the fluctuations in the energy consumption and energy efficiency for the different time periods were measured by using the proposed algorithm, and it was compared with the actual fluctuations in the energy consumption and energy efficiency to determine whether the fluctuations in the measurement results obtained by the proposed algorithm were consistent with those of the actual situation. The comparison results for the energy consumption and energy efficiency measurements are shown in Figure 7.



(**a**) (**b**)

Figure 7. (**a**) Measurement results of the actual energy consumption and energy efficiency. (**b**) Energy efficiency measurement results for the proposed algorithm.

According to Figure 7, the energy consumption and energy efficiency measurement results obtained by the proposed algorithm were largely consistent with the actual results, which shows that the energy consumption and energy efficiency measurement results of the proposed algorithm met the actual needs. The reasons for this are that the proposed algorithm used the minimum equivalent fuel consumption model to assign weights to the energy efficiency of the nodes, constructed a hierarchical structure of the energy consumption of hybrid electric vehicles, compared the elements at each level, obtained a comparative judgment matrix between every two elements, and, finally, verified the consistency of the matrix and measured the energy efficiency measurement results of the hybrid electric vehicles.

In order to show the applicability of the proposed algorithm, through simulation experiments, it was compared with the [6] transferable representation control algorithm and the [7] collaborative control algorithm. We set the experimental time to 30 s and the initial speed to 10 m/s, stepped on the vehicle's accelerator pedal to accelerate to 40 m/s, gave the front wheel a 10-degree angle, and maintained the 10-degree angle until the end of the simulation. Taking the energy management efficiency of hybrid electric vehicles as an example, we analyzed the practical application effects of three algorithms. The comparison results for management efficiency are shown in Figure 8:

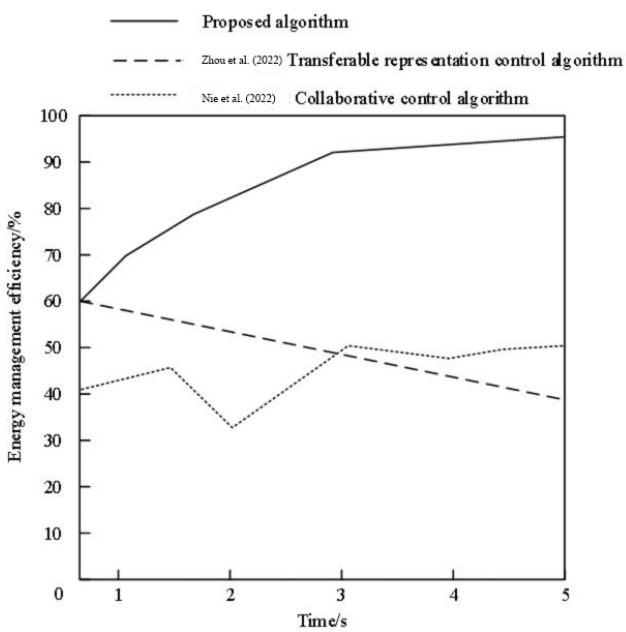


Figure 8. Comparison results of energy management efficiency of different algorithms [6,7].

From Figure 8, it can be seen that after applying the algorithm in this article, the energy management efficiency of automobiles increased with time, and the management efficiency was above 60%, with the highest value reaching 97%. As the authors of [6] show, as the transferable representation control algorithm increases over time, management efficiency gradually decreases, with a minimum value of 40%. The energy management efficiency of the [7] collaborative control algorithm showed irregular changes over time, ranging from 30% to 55%. From this, it can be seen that the energy management efficiency of the method in this article is high and the practical application effect is good. This is because the proposed algorithm adopts an equivalent minimum fuel consumption model for optimization, which can effectively consider the energy flow and loss between different components of hybrid electric vehicles, thereby improving energy utilization efficiency. The model-based predictive control method is adopted to achieve optimal allocation and control of energy by predicting the vehicle's status for a period of time in the future. This method can better adapt to different driving conditions and changes in road conditions, and can be adjusted online based on real-time data, thereby improving energy efficiency. However, the transferable representation control algorithm [6] and the collaborative control algorithm [7] did not fully consider the energy flow and loss between different components of hybrid electric vehicles, resulting in a low energy management efficiency.

The above test conditions remained unchanged; taking the energy consumption of hybrid electric vehicles as an example, the prediction and control results for the three algorithms are shown in Figures 9 and 10, respectively.

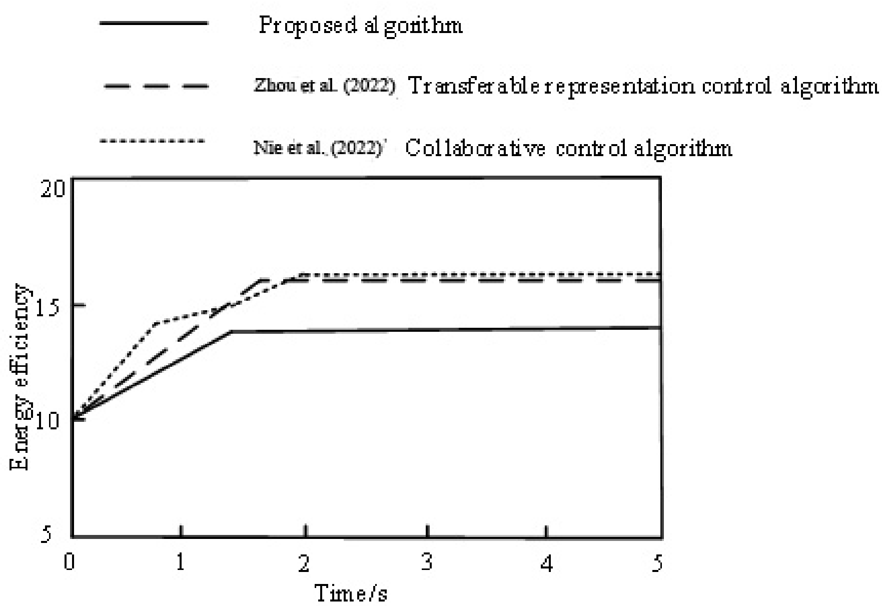


Figure 9. Energy consumption prediction results for the different algorithms [6,7].

As can be seen in Figures 9 and 10, the energy consumption prediction results and control results for the proposed algorithm are good, and could quickly restore stability after short-term oscillation. Reference [6] had a higher peak value for transferable representation control algorithms and reference [7] for collaborative control algorithms, and the oscillation process consumed a lot of time, which increased the probability of vehicle turning failure. The proposed algorithm could achieve the best fuel consumption and energy utilization efficiency, and it reduced vehicle energy consumption and exhaust emissions. At the same time, the energy consumption and fuel consumption were minimized and the use cost was significantly reduced. This is because the algorithms of both [6,7] were based on traditional control theory and modeling methods, which make it difficult to fully consider the nonlinear characteristics and complexity of the vehicle's driving process, resulting in low accuracy and stability for the energy consumption prediction and control results.

The proposed algorithm adopts a model predictive control method that can be adjusted and optimized in real time based on the predicted results, making energy consumption control more accurate and stable. At the same time, the algorithm also considers the optimization of energy management strategies and power allocation strategies, which can enable the vehicle to achieve the best fuel consumption and energy utilization efficiency, while ensuring performance.

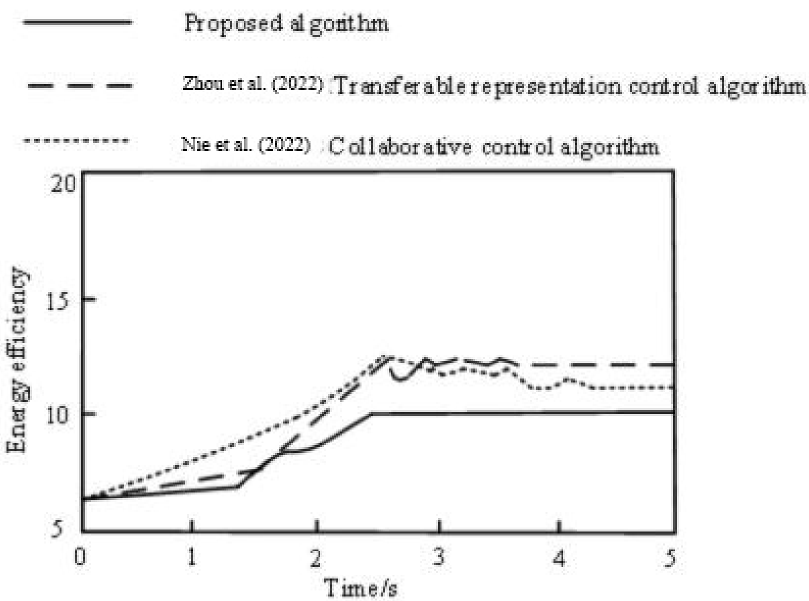


Figure 10. Results for the energy consumption control for the different algorithms [6,7].

4. Conclusions and Prospects

4.1. Conclusions

In this paper, the energy consumption prediction and control algorithm for hybrid electric vehicles based on the minimum equivalent fuel consumption model was proposed, and the following conclusions were obtained through our research:

(1) The driving energy consumption of a hybrid electric vehicle is small, and after the mileage exceeds 60 km, the power consumption is reduced to less than 1 kW. When stable power consumption is maintained, stable driving power for a vehicle can be provided.

(2) The measurement results of the energy consumption and efficiency are largely consistent with the actual results, which shows that the measurement effect of the energy consumption and efficiency of the proposed algorithm meets the actual needs.

(3) The prediction and control results for energy consumption are good, and the algorithm can quickly restore stability after short-term shocks, with good results.

4.2. Prospects

Regarding the problem of energy consumption predictions and control for hybrid electric vehicles, we will continue our research, the specific contents of which are as follows:

(1) The research should analyze the dynamics of the core component—the dual planetary hybrid transmission—and establish a dynamic model of the transmission; integrate it with other component models, including the engine, power battery, dual motors, and vehicle longitudinal dynamic model; and establish a forward simulation model for a power split hybrid mining dump truck.

(2) It is necessary to carry out bench tests and real vehicle tests to verify the control effect of the algorithm. At the same time, whether the model is in the loop or the hardware

is in the loop, there is still a certain gap between the added noise signal and the real signal, and this needs further verification for the control strategy and control effect.

(3) To design the energy management control strategy, it is necessary to fully consider factors such as battery aging and battery peak power, and it is necessary to optimize the design from multiple dimensions in combination with the power battery.

Author Contributions: Q.Z.: building the minimum equivalent fuel consumption model and the proposed energy consumption prediction and control algorithm for hybrid electric vehicles, constructing the minimum equivalent fuel consumption model, measuring the energy efficiency of hybrid electric vehicles using this model, and preparing and writing the draft manuscript. S.T.: calculating the rolling resistance, air resistance, and climbing resistance of hybrid electric vehicles and constructing the energy consumption control algorithm for hybrid electric vehicles according to the calculation results. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study did not require ethical approval.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

Acknowledgments: The authors would like to offer their sincere thanks to those who developed the techniques that contributed to this research.

Conflicts of Interest: The authors declare no conflict of interest.

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