Research on Whole-Vehicle Energy Efficiency Analysis and Optimization Based on Multi-Sensor Data Acquisition

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Abstract. This study addresses the existing issues in energy management of traditional automobiles and proposes a series of optimization approaches. Currently, the application of sensors in the automotive field is becoming increasingly extensive. Various types of sensors are arranged in different vehicle systems according to their functions to realize the monitoring of the vehicle's overall energy flow. Furthermore, by combining with artificial intelligence, real-time management of the vehicle's overall energy flow is achieved. In this paper, the functions of various sensors are elaborated in detail, along with their selection and arrangement; the connection between data transmission and CAN bus is discussed to realize signal frequency modulation and transmission; and prospective suggestions for combining with artificial intelligence neural networks are put forward to promote the further development of energy management. Meanwhile, this research establishes connections with studies related to intelligent connected vehicles, facilitating the intelligent development of fuel-powered vehicles, battery electric vehicles, and hybrid electric vehicles. It aims to achieve the clean and energy-efficient development of various types of automobiles and enhance the efficiency of energy utilization.

Keywords: Energy Management, Sensor, CAN Bus, Intelligent Connectivity.

1. Introduction

As global energy crises and environmental pollution worsen, improving energy utilization gains more attention, especially for new energy vehicles that grow yearly with "dual carbon" goals. A vehicle’s energy management affects its range, power, and environmental impact, but traditional models have flaws: ICEVs only optimize engine efficiency; BEVs focus on battery charging; HEVs rely on fixed power distribution, lacking flexibility for changing road or weather conditions.

Sensor technology, key for intelligent connected vehicles, advances environmental sensing and provides real-time data for energy management, though it still needs improvement. AI brings new solutions: combining multi-source sensor data with machine learning enables dynamic energy adjustment, fixing traditional strategy flaws.

To boost vehicle energy efficiency, this work proposes a real-time system fusing multi-node sensor data and AI. It uses deployed sensors for distributed data collection, plus reinforcement learning for energy flow modeling and optimal decisions. This offers new methods for NEV energy management and cuts ICEV consumption, aiding green automotive transformation.

2. System Design

2.1. Selection and Deployment of Sensors

2.1.1. Temperature Sensors

First, it is necessary to clarify the application scenarios and modules where temperature sensors are deployed. In whole-vehicle energy analysis, temperature sensors are primarily used in three modules: the power battery system, the drive motor and electric control system, and the thermal management system, with the common function of temperature monitoring.

In the power battery system, battery temperature directly influences charging and discharging efficiency. For instance, low temperatures reduce lithium-ion activity, leading to increased internal resistance, risks of thermal runaway, and accelerated battery aging. Thus, high-precision, rapid-response multi-point temperature monitoring is required. For this module, high-precision negative temperature coefficient thermistors (NTCs) are recommended. NTCs operate within a wide temperature range of -40°C to 125°C, which adequately covers the operating temperatures of vehicles. High-precision NTCs, fabricated using laser trimming technology, achieve a precision of ±0.2°C to ±1°C, with lower costs compared to platinum resistors, making them suitable for large-scale deployment. As contact-type sensors, NTCs with metal or ceramic packaging exhibit high thermal conduction efficiency, enabling rapid capture of local temperature rises during battery charging and discharging processes—for example, temperature changes of ≥5°C/min at the surface of battery cells during fast charging. Sealed via glass encapsulation or epoxy resin, high-precision NTCs demonstrate strong resistance to humidity and thermal aging, with a service life of ≥10 years under conditions of 85°C and 85% relative humidity, which aligns with the rigorous operational environment of battery packs.

By deploying NTCs in the power battery system and analyzing their advantages, it is found that NTCs are also applicable to the drive motor and electric control system as well as the thermal management system. In general, high-precision NTCs feature a broad application range, high measurement accuracy, rapid response speed, strong anti-interference capability, and low cost.

In summary, for temperature sensor selection in whole-vehicle energy efficiency analysis, high-precision NTCs are chosen and deployed in the power battery system, drive motor and electric control system, and thermal management system.

Figure 1 is High-precision NTC.

Figure 1. High-precision NTC

2.1.2. Pressure Sensors

First, it is necessary to clarify the application scenarios and modules where pressure sensors are deployed. In whole-vehicle energy analysis, pressure sensors are primarily used in two modules: the powertrain system and the thermal management system, both serving the function of pressure monitoring.

In the powertrain system, which includes internal combustion engines in traditional fuel vehicles and motor-generators in new energy vehicles, the energy conversion efficiency is directly related to parameters such as intake air volume, exhaust backpressure, and turbocharger pressure ratio. This requires high-precision, wide-range, and high-temperature/ high-pressure-resistant pressure measurement to calculate air-fuel ratios, turbocharger efficiencies, and mechanical power losses. Under China VI emission standards, the monitoring range for engine exhaust backpressure is 5–50 kPa. Ceramic piezoresistive sensors, such as those with NGK/NTK ceramic diaphragms, exhibit excellent high-temperature resistance, with an operating temperature range of -40°C to 800°C, effectively avoiding sensor failure caused by high exhaust temperatures. Additionally, ceramic piezoresistive sensors are based on Al_2O_3 ceramic substrates, whose thermal expansion coefficient matches that of engine components, minimizing zero-point drift induced by thermal stress.

In the thermal management system, ceramic piezoresistive sensors first demonstrate superior medium compatibility. The coolant in thermal management systems is typically an ethylene glycol aqueous solution with a pH value of 6–8, containing corrosive ions. The isolation diaphragm of ceramic piezoresistive sensors is made of 316L stainless steel and treated with nano-coatings (e.g., diamond-like carbon (DLC) films), ensuring corrosion resistance of ≥10 years and no performance degradation under 85°C/85%RH aging tests. The coolant system operates within a pressure range of 0–300 kPa, and ceramic piezoresistive sensors achieve a measurement accuracy of ±0.5%FS, capable of detecting pressure fluctuations at the 5 kPa level to provide a basis for water pump speed adjustment. During sudden air blockages in the coolant system, pressure peaks reach ≤400 kPa, and ceramic piezoresistive sensors exhibit an overload capacity of ≥200%FS, preventing pipe bursts.

In summary, ceramic piezoresistive sensors meet the requirements for dynamic measurement under high-temperature and high-pressure conditions in the powertrain system while ensuring precision. In the thermal management system, they also balance medium compatibility and sensitivity. Therefore, ceramic piezoresistive sensors are selected as the pressure sensors for whole-vehicle energy analysis and deployed in the powertrain system and thermal management system. Figure 2 is Ceramic Piezoresistive Sensor.

Figure 2. Ceramic Piezoresistive Sensor

2.1.3. Flow Sensors

First, it is necessary to clarify the application scenarios and modules where flow sensors are deployed. In whole-vehicle energy analysis, flow sensors are primarily used in the thermal management system, with the core function of flow monitoring.

In the thermal management system, the coolant is typically an ethylene glycol aqueous solution with an electrical conductivity of ≥200μS/cm. Electromagnetic flow sensors, based on Faraday’s law of electromagnetic induction, measure volumetric flow rate by leveraging the medium’s electrical conductivity, eliminating the need for contact measurement. This design avoids seal aging, a common issue in contact-based sensors. The measurement range of such sensors generally spans 0.1–10 m^3/h, which adequately covers the coolant circulation volume in passenger vehicles. With an accuracy of ±0.5%–±1%FS (full scale) and a response time ≤1 s, they can effectively capture sudden flow rate changes during water pump start-stop operations—for example, adjusting from 0 to 5 m^3/h within ≤2 s. Furthermore, the lining materials of electromagnetic flow sensors (e.g., polytetrafluoroethylene, PTFE) and electrodes (made of Hastelloy) exhibit strong corrosion resistance, enabling long-term tolerance to ethylene glycol corrosion. This aligns with the high-reliability requirements of battery pack and motor cooling systems. Therefore, electromagnetic flow sensors are selected for monitoring coolant flow in thermal management systems. Figure 3 is Electromagnetic Flow Sensor.

Figure 3. Electromagnetic Flow Sensor

In the thermal management system, refrigerants such as R134a and R1234yf exist in a non-conductive gas-liquid mixture state. Traditional contact-type sensors are prone to failure due to frosting or corrosion. Ultrasonic flow sensors measure flow velocity by detecting the time difference of ultrasonic wave propagation in the refrigerant, with a measurement range covering 0.01–10 m^3/h, which adapts to the flow rates of air conditioning pipelines. They achieve an accuracy of ±1%–±2%FS and are unaffected by refrigerant phase changes (i.e., gas-liquid two-phase transitions), making them suitable for dynamic flow monitoring in evaporators and condensers. Therefore, ultrasonic flow sensors are selected for monitoring refrigerant flow. Figure 4 is Ultrasonic Flow Sensor.

Figure 4. Ultrasonic Flow Sensor

2.2. Data Acquisition and Transmission

From the analysis in Section 1.1, it is evident that whole-vehicle energy efficiency analysis involves diverse types of sensors, including temperature, pressure, flow rate, wind speed, and current/voltage sensors. These sensors are deployed in distinct modules (e.g., power battery, motor and electric control, thermal management) and serve specialized functions (e.g., temperature monitoring, pressure measurement, flow rate statistics). However, to achieve efficient energy analysis and management, the primary challenge lies in reliably transmitting these dispersed and heterogeneous sensor data to a unified system, and integrating multi-source information through multi-sensor fusion technology to form a comprehensive understanding of the vehicle’s energy flow.

From the perspective of data transmission, different sensors output signals in varying forms.These signals require conditioning (e.g., filtering, isolation, amplification, and analog-to-digital conversion) before being transmitted via on-board communication networks.

Multi-sensor fusion is critical for improving the accuracy of energy efficiency analysis. Single sensors can only reflect local states—for example, a temperature sensor measures temperature at a specific point—whereas the vehicle’s energy flow involves multi-physical field coupling , where motor efficiency is jointly influenced by temperature, current, and rotational speed. By fusing multi-source data and combining algorithms such as Kalman filtering, Bayesian estimation, or machine learning, noise errors from individual sensors can be eliminated, enabling the reconstruction of a more accurate energy flow model.

2.2.1. Multi-sensor Data Integration

Driven by the rapid development of the autonomous driving field, multi-sensor fusion technology has achieved relatively mature advancement. In autonomous driving applications, the core objective of multi-sensor fusion lies in acquiring information regarding the external environment of vehicles and their driving states, without directly involving the utilization of multi-sensors for monitoring the energy usage of various vehicle components. Nevertheless, the multi-sensor data integration technology employed in autonomous driving can be fully applied to the monitoring of energy utilization across all parts of a vehicle.

As illustrated in Figure 7, this presents a multi-sensor fusion framework utilized in autonomous driving. Multi-sensor fusion technology enhances the overall performance and robustness of the system by integrating information collected from different sensors installed in various components. In practical applications, sensor fusion primarily encompasses three strategies: data-level fusion, feature-level fusion, and decision-level fusion.

Data-level fusion directly merges raw sensor data. Techniques such as weighted average or Kalman filtering are adopted to reduce measurement errors, making it particularly suitable for state estimation in dynamic environments. This characteristic highlights the real-time nature of data monitoring, enabling the measurement of energy flow under all circumstances.

Feature-level fusion involves the synthesis of data after feature extraction. It is commonly applied in tasks such as target recognition, while in the context of energy management, its primary function is to accurately determine the rationality of energy utilization.

Decision-level fusion, on the other hand, consolidates the independent judgments made by each sensor in accordance with predefined decision rules to derive the final detection result. For instance, it may determine that the air conditioning system should consume more energy while the drive system should appropriately reduce its energy supply [1]. Figure 5 is Technical Process and Framework of Multi-Sensor Fusion.

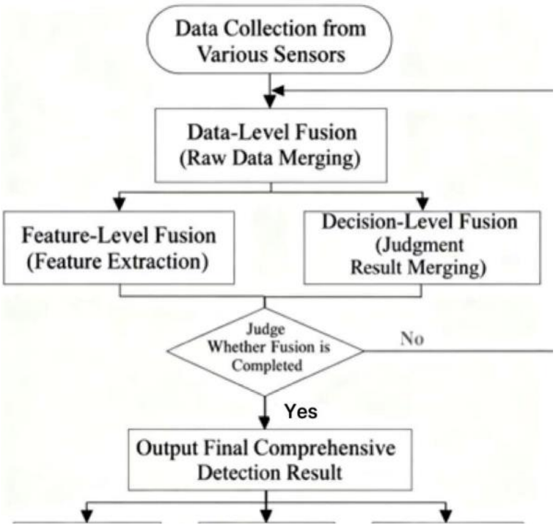


Figure 5. Technical Process and Framework of Multi-Sensor Fusion

The aforementioned figure depicts the process of multi-sensor data fusion and processing in autonomous driving applications. However, in vehicle energy efficiency analysis based on multi-sensors, the only difference lies in the final stage. In autonomous driving applications, the integrated data is utilized for tasks such as path planning, target recognition, and collision warning. In contrast, within vehicle energy efficiency analysis, the integrated multi-sensor data is employed to realize the rational reallocation of overall vehicle energy.

For example, battery management system (BMS) monitoring has already been implemented in electric vehicles, where multi-sensor fusion technology plays a crucial role in BMS and energy recovery systems. The BMS monitors the state of the battery in real-time by fusing data from temperature, current, pressure, and voltage sensors. This ensures that the battery operates within a safe temperature range and optimizes charging and discharging strategies, thereby extending the battery lifespan.

Vehicle energy efficiency analysis, in essence, extends the application of multi-sensor fusion technology—previously utilized in BMS—to all vehicle systems related to energy utilization. This extension enables more optimized management of the overall vehicle energy.

2.2.2. Multi-sensor Data Processing

After the deployment of all the aforementioned sensors, the implementation of data transmission involves signal conditioning, in-vehicle network transmission, and multi-sensor data integration. The entire process is designed to reliably transmit scattered sensor data to the central system, thereby supporting the analysis of the vehicle's energy efficiency. As multi-sensor data integration has been elaborated in Section 1.2.1, this section will focus on explaining how signal conditioning and in-vehicle network transmission are conducted after sensors collect data.

It can be inferred from Section 1.1 that a large number of sensors are deployed for the analysis of vehicle energy efficiency. These sensors are of different types and output signals in various forms, so signal conditioning is required before they can output valid data. For instance, temperature sensors output analog voltage signals, while current/voltage sensors may produce digital signals. These signals are vulnerable to noise interference, such as electromagnetic interference from the powertrain system. Therefore, it is necessary to eliminate high-frequency noise through filtering, ensure electrical safety via isolation, enhance signal strength by means of amplification, and convert analog signals to digital format through analog-to-digital conversion to adapt to the digital communication network. Taking the power battery system as an example, the closed-loop Hall current sensor outputs current signals, which need to be converted into digital quantities via ADC for the calculation of State of Charge. Signal conditioning serves as a prerequisite for data transmission, ensuring the accuracy and real-time performance of data.

The principles and methods of signal conditioning applied to photoelectric sensors can be similarly adopted for other sensors. During vehicle operation, due to factors such as vibration,bumpiness, and sensor manufacturing processes, the actual sensor signals always contain considerable harmonic interference, accompanied by DC components with waveform distortion. Although a special optical path design has been incorporated into the sensor manufacturing process to account for bumps within a range of ±100 mm—ensuring that the center of the light beam incident on each photosensitive strip is strictly parallel to the main optical axis of the lens, and that the center distance of the diffused spots generated on the focal plane remains unchanged even when the object distance varies—the noise and amplitude variation of the signals are still significant. Such signals must be processed by a conditioning circuit before they can be utilized by the microcomputer system [2].

Consequently, each sensor, similar to the aforementioned photoelectric sensor, must undergo redesign based on its specific signal output characteristics and potential sources of errors to achieve accurate signal conditioning.

After signal conditioning is implemented for each sensor, data transmission is carried out. In the analysis of vehicle energy efficiency, the Controller Area Network bus is employed for the signal transmission of sensors. The message transmission of CAN technology operates in a multi-master mode, where any node in the network can actively send information to other nodes in the network at any time, without distinguishing between master and slave nodes. A CAN node can realize data transmission and reception in several modes, including point-to-point, one-to-multipoint, and global broadcast, simply by filtering the identifiers of messages [3]. Therefore, the CAN bus serves as a standard solution for the efficient and reliable transmission of sensor data.

As a serial communication protocol with low latency and high reliability, the CAN bus is suitable for processing multi-sensor data. For example, in the thermal management system, the digital signals output by the flow sensor after conditioning can be broadcast to the central gateway via the CAN bus, supporting real-time monitoring of changes in coolant flow with a response time of ≤ 1 second.

The CAN bus adopts a multi-master architecture, allowing sensor nodes to participate in data transmission using a frame format. The frame format is divided into standard frames with 11-bit identifiers and extended frames with 29-bit identifiers. The frame types of the CAN bus include data frames, remote frames, error frames, and overload frames. For example, sensors deployed in the power battery or motor system directly transmit data frames. Each piece of sensor data, such as temperature and pressure, is encapsulated into a CAN message with a unique identifier to ensure priority-based processing.

Meanwhile, the CAN bus supports high-speed transmission, with a typical rate of 1 Mbps, which meets the requirements for transient data capture. For instance, when the motor starts, the current change rate can reach 1000 A/ms, and the transmission rate of the CAN bus is fully capable of meeting the signal transmission rate requirements of various parts of the vehicle.

Data transmission is achieved through signal conditioning, CAN bus transmission, and multi-sensor fusion. Signal conditioning ensures data reliability; the CAN bus, as the core of the in-vehicle network, efficiently transmits heterogeneous data; and multi-sensor fusion improves the accuracy of energy analysis, providing support for the optimization of the vehicle's energy performance.

3. Energy Utilization of Automobiles

3.1. Current Status of Energy Utilization

To understand the energy utilization of fuel - powered vehicles, it is first necessary to clarify their energy flow path: fuel chemical energy → engine combustion → mechanical energy→ transmission system → wheel drive → effective work.

Energy utilization and loss are mainly distributed in the following links:

Engine combustion link: Taking mainstream gasoline engines as an example, approximately 60% - 70% of the fuel energy is lost in this link. The forms of loss include incomplete combustion (e.g., uneven mixture concentration and ignition delay, which lead to insufficient release of chemical energy), heat loss, and mechanical friction. The friction loss between components such as pistons and cylinder walls, crankshafts and bearings accounts for 10% - 15%.

Transmission system link: About 15% - 20% of the engine output energy is lost here. The loss forms include gear meshing friction, slippage of the torque clutch , and torsional vibration of the drive shaft .

Auxiliary system link: Approximately 10% - 15% of the fuel energy is used for non - driving purposes. The main energy - consuming items are as follows: air - conditioning system (the power consumption of the compressor accounts for 5% - 8%); lighting and electronic equipment (headlights, air - conditioning panels, in - vehicle entertainment systems, etc., account for 3% - 5%); and tire rolling resistance (accounting for 5% - 7%, which is strongly related to tire pressure and road surface conditions).

To understand the energy utilization of electric vehicles, it is first essential to grasp their energy flow path: battery electrical energy → motor controller → drive motor → transmission system → wheel drive → effective work. The energy distribution is shown in Figure 6. In terms of energy consumption, the main drive system accounts for approximately 3/4 of the total energy consumption. This proportional relationship gradually increases to a basically stable state as the electric vehicle is used for a longer time during driving [4].

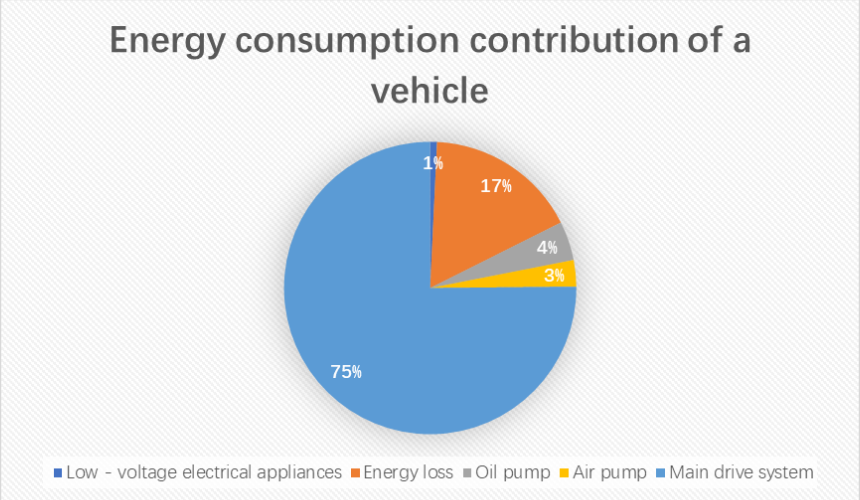


Figure 6. Energy consumption contribution of a vehicle

The driving efficiency of electric vehicles is presented in Figure 7. It can be seen from Figure 7 that in the initial stage of vehicle driving, it is necessary to complete tasks such as battery preheating, air circuit air supplementation, and achieving good lubrication. That is to say, a certain amount of energy is consumed for the vehicle to enter a good working state. After about 1 hour, the driving efficiency of the electric vehicle will reach a basically stable level. Under the condition of similar working conditions, the energy consumption level of the air pump largely depends on the airtightness of the air circuit [4].

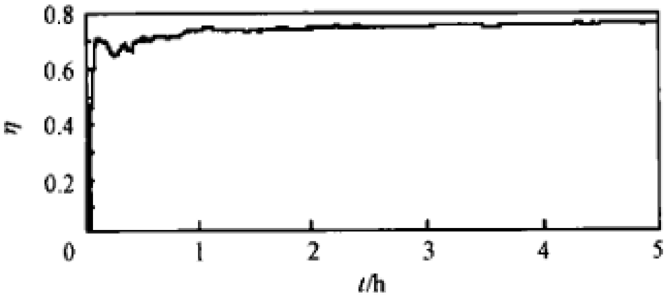
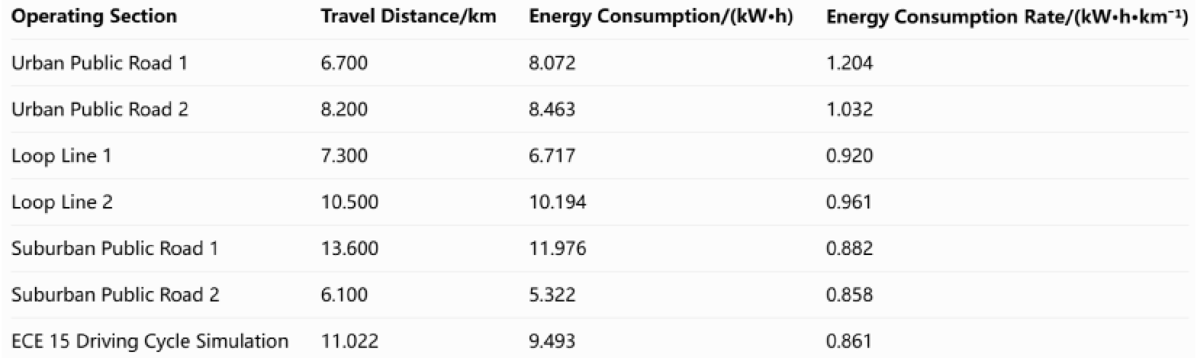


Figure 7. Driving efficiency vs.time

3.2. Current Data Analysis Methods

To optimize the energy utilization of automobiles using multi-sensors, it is also necessary to understand how the current vehicle energy-related data are processed and the differences in vehicle energy utilization under different working conditions.

First, for electric vehicles, it is essential to understand the impact of different working conditions on their energy consumption. Taking public transportation as an example, due to urban congestion, a large number of stops, and extremely high passenger flow, public transportation in Beijing generally exhibits characteristics such as low average speed, short average driving cycle, high idle speed ratio, and low constant-speed driving ratio. Consequently, public transportation vehicles in Beijing frequently accelerate and decelerate, with short durations of constant-speed and quasi-constant-speed driving. During the same time period, the traffic flow and pedestrian flow vary significantly across different road sections, leading to corresponding changes in the energy consumption of electric vehicles [4]. Figure 8 shows the energy consumption rate of the BJD6100 electric bus when driving under public transport working conditions along different road sections. All tests were conducted from 9:00 to 10:00 a.m.



Operating Section	Travel Distance/km	Energy Consumption/(kW•h)	Energy Consumption Rate/(kW•h•km^{-1})
Urban Public Road 1	6.700	8.072	1.204
Urban Public Road 2	8.200	8.463	1.032
Loop Line 1	7.300	6.717	0.920
Loop Line 2	10.500	10.194	0.961
Suburban Public Road 1	13.600	11.976	0.882
Suburban Public Road 2	6.100	5.322	0.858
ECE 15 Driving Cycle Simulation	11.022	9.493	0.861

Figure 8. The influence of driving mode to energy consumption

It can be observed that the energy consumption rate varies considerably across different road sections. Overall, the energy consumption during driving in urban areas is significantly higher than that on ring roads. In suburban areas, with low traffic and pedestrian flow, vehicles often travel above the economic speed; the average speed on ring roads ranges from 30 to 40 km/h, which is close to the economic speed of the test vehicle. However, on ring roads, the density of bus stops is higher than that in suburban areas, and the passenger flow is larger, resulting in slightly higher energy consumption when driving on ring roads compared to suburban areas. Within urban areas, the working conditions also differ greatly among various road sections, leading to a significant difference in energy consumption between Urban Bus Route 1 and Urban Bus Route 2. A comparison between the test results and simulation calculations reveals that since the simulated working conditions include a highway cycle with a relatively high average speed, the energy consumption rate is lower, which is close to that of the suburban working conditions.

It can thus be concluded that the energy utilization of electric vehicles is closely related to vehicle working conditions. Factors such as vehicle speed, starting, stopping, and driving habits all affect the energy utilization of vehicles. Therefore, the real-time adjustment of energy distribution is particularly important. Real-time analysis based on multi-sensors and subsequent adjustment of energy distribution are significantly superior to the current practice of only conducting tests before vehicles are launched in batches. From the above analysis, it can be seen that although the current data analysis methods can complete the analysis of the overall vehicle energy utilization, they have the limitations of lag and non-adjustability. In contrast, the vehicle energy efficiency analysis based on multi-sensors should address these issues as much as possible.

4. Vehicle Energy Efficiency Optimization Methods

4.1. Current Energy Management Strategies

At present, different types of automobiles have developed relatively mature energy management solutions respectively. Taking hybrid electric vehicles (HEVs) as an example, they combine the characteristics of fuel-powered vehicles and battery electric vehicles (BEVs). Therefore, analyzing their energy management solutions enables a comprehensive understanding of the current energy management strategies at one time.

The goal of energy management for hybrid electric vehicles is to achieve rational distribution and utilization of driving energy between the engine and the motor, on the premise of meeting various performance indicators of the entire vehicle. Specifically, according to the characteristics of the engine, low fuel consumption and low emissions can be ensured as long as the engine is operated within its high-efficiency range as much as possible. For the motor, the situation is more complex: although the motor efficiency is relatively high, it is largely restricted by the state of charge (SOC) of the battery. When the SOC is relatively high, the vehicle can be operated in the electric driving mode as much as possible to ensure low fuel consumption and low emissions; when the SOC is relatively low, continuing to operate in the electric driving mode will cause irreversible damage to the battery; when the SOC is at an intermediate value, it is optimal to allow the engine and the motor to work in a coordinated manner, so as to achieve the best fuel economy and the lowest emissions while ensuring the good driving performance of the vehicle [5].

It can be seen from the above that the current energy management strategies for hybrid electric vehicles only focus on the coordination between the engine and the motor, and do not involve systems such as the thermal management system, entertainment system, and air conditioning system. There are significant deficiencies in terms of overall energy management.

In contrast, the energy management optimization strategies for battery electric vehicles are more straightforward, which are divided into two aspects: charging optimization and discharging optimization [6]. Moreover, these strategies only focus on energy management optimization for the battery and the motor. Taking Figure 9 as an example, the current optimization focus is still placed on charging and discharging strategies, and there is no involvement in vehicle-wide energy management and distribution.

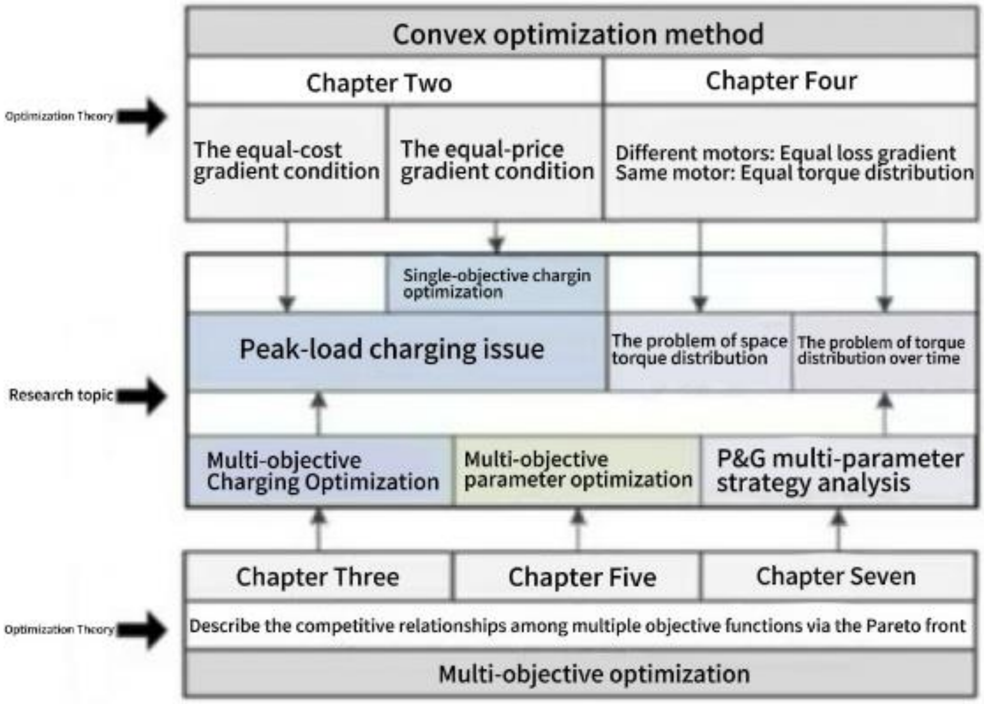


Figure 9. The logical block diagram of research content with convex optimization and multi-objective optimization as the core

In comparison, the energy management strategies for fuel-powered vehicles are relatively underdeveloped, focusing solely on fuel economy and emissions. Specifically, they only concern whether energy management optimization can reduce exhaust emissions and improve driving range. Due to the limited analytical value of pure fuel-powered vehicles, a 48V mild hybrid vehicle is taken as an example for brief analysis here. The electrical consumption throughout the entire cycle condition is converted into fuel consumption to calculate the equivalent fuel consumption. With equivalent fuel consumption and emissions as optimization objectives, the NSGA-II algorithm is applied to optimize the final drive ratio and 5 battery-related control parameters in the control strategy. The results show that under the NEDC cycle condition, the optimized equivalent fuel consumption per 100 kilometers is reduced by 6.5% compared with that before optimization, and the emissions of CO, HC, and NO_x are reduced by 11%, 9.3%, and 10% respectively [7].

It can thus be concluded that the current energy management strategies do not target all vehicle systems; instead, they only conduct detection, analysis, and optimization for key powertrain systems and energy storage systems. In contrast, deploying multi-sensors in various systems according to their functional requirements to achieve vehicle-wide energy management can improve energy utilization efficiency to a greater extent.

4.2. Real-Time Optimization of Whole-Vehicle Energy Efficiency Integrated with Artificial Intelligence

First, we need to briefly understand the tasks that artificial intelligence (AI) can currently perform. Taking artificial neural networks (ANNs) as an example, ANNs are human-engineered dynamic systems with directed graphs as their topological structure, which process information by responding to continuous or intermittent inputs through state transitions [8]. This demonstrates the feasibility and innovativeness of using AI for real-time processing of multi-sensor data. As discussed earlier, multi-sensor data exhibits continuous or intermittent variations due to changes in vehicle operating conditions, road conditions, etc. ANNs can address such data by integrating and analyzing these dynamic inputs.

However, merely integrating and analyzing multi-sensor data cannot achieve real-time energy regulation for the entire vehicle. To realize real-time energy management, AI must make decisions. In current intelligent connected vehicles (ICVs), AI has already developed capabilities for decision-making. ICVs rely on AI to construct decision systems, whose tasks involve determining driving behaviors and action timings based on global driving objectives, self-vehicle status, and environmental information. These decision mechanisms aim to adapt to as many operating conditions as possible while ensuring safety, enabling correct decisions for comfort, energy saving, and efficiency [9]. Although current ICV decision systems are not primarily designed for real-time energy efficiency management, their application direction aligns with sensor-based whole-vehicle energy efficiency optimization. Thus, with the development of ICVs, AI-driven decision systems for whole-vehicle energy management will emerge and mature.

Concurrently, the evolution of ICVs has given rise to intelligent environmentally friendly vehicles. These vehicles integrate three major systems: clean energy powertrains, electronically controlled chassis, and intelligent safety assistance, along with three key technologies: structural sharing, information fusion, and control coordination. They comprehensively achieve three core functions: safety, energy saving, and environmental protection [10]. As shown in Figure 10, key vehicle components, assemblies, and sensing systems (including new energy engines, transmissions, motors, batteries, electro-hydraulic brakes, front-wheel active steering controllers, and environmental perception sensors such as radar, cameras, GPS, yaw rate sensors, longitudinal acceleration sensors, and vehicle controllers) are connected via dual CAN bus lines to enable shared and rapid transmission of vehicle status information. This indicates that amid the development of ICVs, technologies aimed at improving energy utilization efficiency have also advanced. These technologies are closely integrated with AI, leverage multi-sensor capabilities, and hold significant promise when combined with artificial intelligence.

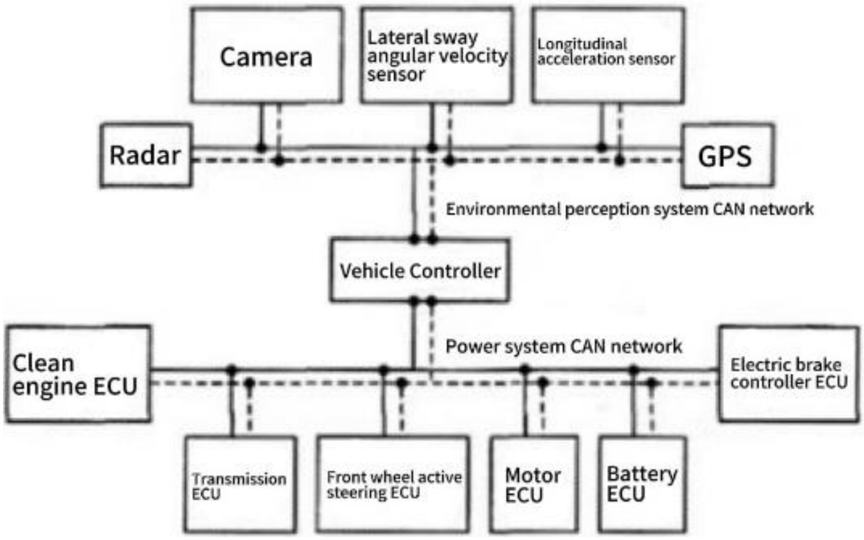


Figure 10. Structural Diagram of Intelligent and Environmentally Friendly Automotive Control System

The application prospects of artificial intelligence vary across different industries, and the new business forms and models it fosters will drive the transformation and upgrading of industrial structures [11]. Therefore, the close integration of AI with vehicle energy efficiency analysis can not only enhance energy utilization efficiency but also boost the development of the industry, propelling the automotive sector toward a cleaner, more environmentally friendly, and more efficient direction.

5. Conclusion

This study proposes an approach to optimize vehicle energy management by utilizing multi-sensor technology. At the current stage, multi-sensors are only applied to visual perception in autonomous driving. Leveraging the relatively mature collaborative application of multi-sensors in this field, this study synchronously applies them to vehicle energy management.

Therefore, a systematic data acquisition network is constructed through the systematic deployment of multi-sensors, including those for temperature, wind speed, pressure, and flow rate. Combined with the CAN bus, this network enables data collection and signal transmission. Meanwhile, artificial intelligence algorithms are integrated to achieve real-time fusion processing of multi-source heterogeneous data and support decision-making, thereby realizing real-time management of the vehicle's overall energy.

In addition, this study establishes detailed connections with various types of vehicles under different working conditions, and summarizes the necessity and advantages of real-time energy management. Thus, it innovatively addresses the issue that traditional energy management strategies have poor adaptability when dealing with complex road conditions and different working conditions.

Different from traditional energy management strategies, which only focus on the management and optimization of the drive system and energy storage system, the multi-sensor-based energy management can monitor additional systems such as the entertainment system and air conditioning system, beyond those monitored by traditional energy management. This enables the monitoring and optimized distribution of the vehicle's overall energy, providing a solution with both engineering practicality and theoretical prospectiveness for the green transformation of various types of vehicles.

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