

Energy Consumption Monitoring and Intelligent Analysis Technology under Dynamic Working Conditions of Vehicles

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Abstract

This article deeply studies the energy consumption monitoring and intelligent analysis technology of vehicles under dynamic working conditions, aiming to improve the energy management level of vehicles under different driving conditions. The research focuses on the complex impact mechanism of dynamic operating conditions on energy consumption, especially the differences in energy consumption performance under typical operating conditions such as urban driving and high-speed driving. By proposing an energy consumption monitoring technology based on multi-sensor fusion, combined with high-precision real-time monitoring and intelligent analysis models, the effectiveness of the system in terms of real-time performance, accuracy, and environmental adaptability was experimentally verified. The system utilizes big data and artificial intelligence technology to construct an energy consumption prediction model and anomaly detection method. Research shows that the energy-saving rate under urban driving conditions can reach 15%, while the energy-saving rate under high-speed driving is 8%. Through practical application cases, it has been verified that the system can effectively reduce vehicle exhaust emissions and fuel consumption, with significant energy-saving effects, providing feasible solutions and important reference basis for automotive energy management.

Keywords

Dynamic Working Conditions; Energy Consumption Monitoring; Multi-Sensor Fusion; Intelligent Analysis; Energy Consumption Optimization.

1. Introduction

In recent years, with increasingly stringent environmental regulations and growing consumer demand for vehicle fuel efficiency, energy consumption management has become a key focus in the automotive industry. Traditional energy consumption monitoring technologies are mostly based on laboratory or static testing under specific conditions, which fail to comprehensively reflect the complex and variable energy performance of vehicles during real-world driving. Under dynamic working conditions, vehicles exhibit significant differences in energy consumption across various driving scenarios such as urban roads, highways, and congested traffic. Therefore, energy monitoring and analysis tailored to these conditions are particularly important.

At the same time, with the advancement of technologies such as big data and artificial intelligence, energy consumption monitoring techniques based on multi-sensor fusion and intelligent analysis have emerged as research hotspots. By collecting and analyzing real-time energy consumption data of vehicles under diverse conditions, it is possible to more accurately assess energy efficiency performance and provide drivers with energy-saving recommendations, thus enabling optimized energy consumption management.^[1]

2. Energy Consumption Monitoring Technology under Dynamic Working Conditions of Vehicles

2.1 Impact of Dynamic Working Conditions on Vehicle Energy Consumption

Under dynamic working conditions, vehicle energy consumption is influenced by a variety of factors, leading to complex and diverse performance outcomes. In urban driving, frequent starts, stops, and low-speed travel significantly increase energy consumption, primarily due to lower efficiency during acceleration and low-speed phases, as well as energy losses caused by frequent gear shifting.

During high-speed driving, aerodynamic drag becomes the dominant factor in energy consumption. As vehicle speed increases, air resistance rises exponentially, causing a sharp increase in energy use. Additionally, road gradients, traffic conditions, and load variations also significantly impact energy performance. The differences in vehicle energy consumption under different operating conditions are summarized in Table 1.

Table 1. Impact of Driving Conditions on Energy Consumption

Driving Condition	Speed Range (km/h)	Average Fuel Consumption (L/100km)	Primary Influence
Urban Driving	0-50	45580	Frequent start-stop
Highway Driving	80-120	45451	Dominated by air resistance
Mountain Road Driving	20-60	45644	Road gradient effects

The data in Table 1 indicate that energy consumption is generally higher during urban driving due to frequent start-stop operations. Although engine efficiency tends to be higher during highway driving, the increase in aerodynamic drag at higher speeds leads to a significant rise in energy consumption. In the case of mountain road driving, energy consumption is notably affected by road conditions and gradients-greater inclines result in higher fuel usage.

2.2 Technical Requirements for Energy Consumption Monitoring under Dynamic Working Conditions

Energy consumption monitoring under dynamic working conditions must meet several technical requirements, including high accuracy, real-time capability, and environmental adaptability. High accuracy ensures that the monitoring system can precisely capture the vehicle's energy consumption across different operating conditions, minimizing deviations caused by measurement errors. Real-time capability requires the system to acquire and process energy data during vehicle operation promptly, enabling timely energy efficiency optimization decisions. Environmental adaptability demands that the system operate reliably under varying environmental conditions—such as temperature, humidity, and altitude—as well as adapt to different road conditions and driving behaviors.^[2]

The core technology of energy consumption monitoring lies in data acquisition and processing. The data acquisition process involves collecting a variety of parameters, including vehicle speed, engine RPM, fuel consumption, aerodynamic drag, and road gradient. A commonly used formula for energy consumption calculation is:

$$E(t) = \frac{P(t) \times V(t)}{\eta} \tag{1}$$

where, $E(t)$ denotes the energy consumption at time t , $P(t)$ is the engine output power, $V(t)$ is the vehicle speed, and η represents the transmission system efficiency.

2.3 Energy Consumption Monitoring Technology based on Multi-Sensor Fusion

To enhance the accuracy and reliability of energy consumption monitoring, multi-sensor fusion technology has been widely adopted in vehicle energy management systems. The selection and proper deployment of different sensors are key to the effectiveness of this approach. Commonly used sensors include accelerometers, GPS modules, fuel flow sensors, air flow meters, and engine management system sensors. Accelerometers and GPS modules are used to obtain real-time speed and location information of the vehicle, while fuel sensors measure fuel consumption. Air flow meters and engine management sensors provide critical data on engine operating conditions.

During the data fusion process, advanced algorithms such as Kalman filtering are employed to integrate data from multiple sensors, thereby improving the accuracy of monitoring results. The Kalman filter is a recursive algorithm that provides optimal state estimation by combining prior knowledge of the system with real-time sensor measurements. Its fundamental equations are as follows:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k [z_k - H_k \hat{x}_{k|k-1}] \quad (2)$$

In the above equations, $\hat{x}_{k|k}$ denotes the estimated state at time k , $\hat{x}_{k|k-1}$ represents the predicted state from the previous time step, K_k is the Kalman gain matrix, z_k is the measurement value, and H_k is the measurement matrix.

Through continuous iteration, the algorithm effectively fuses multi-dimensional data from various sensors, reducing measurement errors and system noise that may arise from relying on a single sensor.

3. Intelligent Analysis Technology for Vehicle Energy Consumption

3.1 Overview of Intelligent Analysis Techniques

The importance of intelligent analysis technologies in vehicle energy consumption monitoring is increasingly prominent, especially under complex and dynamic working conditions. Intelligent analysis enables the accurate identification of energy consumption patterns, facilitating refined energy management. During vehicle operation, energy consumption data is influenced by multiple interacting factors such as speed, acceleration, road gradient, load variation, and ambient temperature. These factors introduce a high degree of nonlinearity and randomness into energy consumption behavior.^[3]

Traditional analysis methods struggle to handle such complex data patterns. In contrast, intelligent analysis, by integrating big data and artificial intelligence technologies, enables deep mining and real-time analysis of large-scale data. Big data technologies provide a solid foundation for intelligent analysis by allowing the system to store and process high-frequency, multi-dimensional data across various operating conditions. For instance, energy consumption prediction models based on neural networks can leverage multi-layer nonlinear mappings to accurately predict vehicle energy consumption under different driving scenarios. The mathematical representation is as follows:

$$\hat{E}(t) = f(W^L \cdot \sigma(W^{L-1} \cdot \sigma(\dots \sigma(W^1 \cdot X + b^1)\dots) + b^{L-1}) + b^L) \quad (3)$$

In the above expression, $\hat{E}(t)$ denotes the predicted energy consumption at time t , X is the input feature vector, W^1 and b^1 represent the weight matrix and bias vector of the first layer, respectively, σ is the activation function, f denotes the output layer function.

Through intelligent analysis techniques, the system can achieve high-precision energy consumption prediction and dynamically adjust based on real-time data, thereby improving the effectiveness of energy consumption management.

3.2 Machine Learning-Based Energy Consumption Prediction Models

The construction of machine learning-based energy consumption prediction models begins with dataset creation and feature selection, aiming to capture the complexity and variability of energy consumption data. Under dynamic driving conditions, commonly used datasets include vehicle speed, acceleration, engine RPM, fuel consumption rate, and ambient temperature.

To model nonlinear relationships and iteratively refine prediction accuracy, tree-based models—such as decision trees and random forests—have shown excellent performance. For high-dimensional regression problems, Support Vector Machines (SVMs) are particularly effective, identifying the optimal hyperplane in the feature space to minimize prediction error.

Deep learning, or more specifically deep neural networks (DNNs), leverage multiple layers of neurons to perform nonlinear mappings, further enhancing the model's ability to predict complex energy consumption patterns with high accuracy. During model training, gradient descent is typically used to optimize the loss function:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N \left(\hat{E}(t_i) - E(t_i) \right)^2 + \lambda \|\theta\|^2 \quad (4)$$

In the above equation,, (θ) denotes the loss function, $\hat{E}(t_i)$ is the predicted value for the i -th sample, $E(t_i)$ is the corresponding actual energy consumption value, θ represents the model parameters, and λ is the regularization parameter.

Through this optimization process, the model incrementally improves its prediction accuracy and becomes capable of adapting to energy consumption variations under different driving conditions, thereby achieving precise forecasting.

3.3 Anomaly Detection and Handling in Energy Consumption Data

Anomaly detection and handling are critical components of vehicle energy consumption monitoring systems. This process not only ensures the accuracy and reliability of energy data but also enables the timely identification of anomalies caused by external interference or system malfunctions. Under complex and dynamic working conditions, factors such as vehicle faults, sensor failures, or abrupt environmental changes can lead to abnormal fluctuations in energy consumption data. If such anomalies are not promptly addressed, they may significantly compromise the accuracy of prediction models and lead to erroneous decision-making.^[4]

To effectively identify anomalies, deep learning-based detection methods have increasingly become mainstream. Among them, autoencoders and variational autoencoders are widely adopted due to their capacity to learn latent representations of normal data distributions. These methods can robustly detect deviations indicative of anomalous behavior.

Under different operating conditions, anomaly detection results using autoencoder-based models exhibit richer data coverage, capturing various types of anomalies across multiple scenarios, as illustrated in Table 2.

The data in Table 2 indicate significant differences in anomaly detection results across various operating conditions. Notably, mountain road driving exhibits the highest anomaly detection rate, suggesting a more complex operating environment with greater data variability. The statistical values of average, maximum, and minimum reconstruction errors further support the reliability of the anomaly detection process.

Table 2. Anomaly Detection Results of Energy Consumption Data under Different Operating Conditions

Driving Condition	Total Samples	Anomalous Samples	Detection Rate (%)	Avg. Reconstruction Error	Max Reconstruction Error	Min Reconstruction Error
Urban Driving	5000	75	1.5	0.03	0.075	0.01
Highway Driving	4000	60	1.5	0.022	0.065	0.008
Mountain Roads	3000	120	4	0.035	0.08	0.012
Rural Roads	3500	90	2.6	0.028	0.07	0.009
Mixed Conditions	6000	130	2.2	0.032	0.078	0.011

4. Real-Time Energy Optimization and Driving Assistance Technologies

4.1 Energy Optimization Strategies based on Real-Time Monitoring

Under dynamic driving conditions, the accurate acquisition of multi-dimensional vehicle energy data—such as speed, acceleration, engine RPM, and fuel consumption—relies heavily on real-time monitoring systems. These systems provide a solid foundation for formulating energy optimization strategies. In urban driving environments, frequent start-stop operations lead to increased fuel consumption. To address this, technologies such as intelligent start-stop systems and electrified low-speed driving can be employed to reduce fuel use. In highway scenarios, where aerodynamic resistance becomes a major factor, solutions like active grille shutters, low rolling resistance tires, and intelligent cruise control can effectively minimize driving drag. [5]

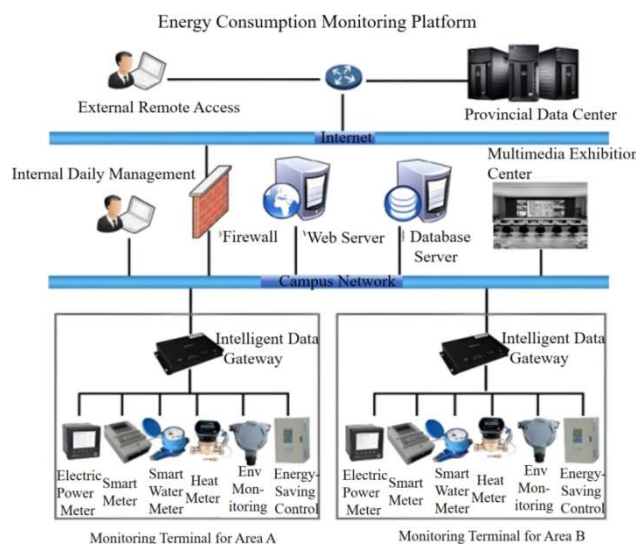


Figure 1. Schematic Diagram of the Adaptive Energy Management System Architecture

Comprehensive optimization also targets more challenging conditions, such as mountain roads or complex terrains, where managing torque output and coordinating four-wheel systems is critical. For such scenarios, specialized strategies are designed to dynamically adjust control parameters to

achieve maximum energy efficiency with minimal cost. For instance, under certain transport conditions, reducing engine power during descent can increase the proportion of regenerative energy, thereby lowering fuel consumption. On highways, optimizing aerodynamic properties can further reduce resistance. The overall architecture and operational flow of the adaptive energy management system are illustrated in Figure 1.

4.2 Intelligent Analysis of the Relationship between Driving Behavior and Energy Consumption

Vehicle energy consumption is closely related to driving behavior, with a significant and direct correlation between the two. Different driving habits-such as acceleration patterns, braking frequency, and speed control-have distinct impacts on fuel consumption. Intelligent analysis techniques help uncover and interpret these influences by collecting and analyzing large volumes of driving data to quantitatively assess how various behaviors affect fuel efficiency.

For instance, frequent hard braking or rapid acceleration can be quantified in terms of fuel loss, whereas smooth throttle control and appropriate braking contribute to improved fuel economy. Four typical driving behaviors-sudden acceleration, gradual acceleration, abrupt braking, and steady cruising-exhibit clearly distinguishable effects on energy consumption, providing numerical evidence of their impact on fuel efficiency. Data analysis reveals that both sudden acceleration and abrupt braking lead to significantly higher energy consumption compared to smooth and steady driving, as shown in Table 3.

Table 3. Impact of Different Driving Behaviors on Vehicle Energy Consumption

Driving Behavior	Increase in Fuel Consumption (%)	Remarks
Sudden Acceleration	30	Significant fuel wastage
Smooth Acceleration	10	Fuel-saving
Abrupt Braking	25	Low energy recovery efficiency
Constant Speed Driving	5	Optimal fuel economy

Based on these data, the energy optimization recommendation system can provide drivers with real-time feedback and improvement suggestions.

4.3 Energy Management in Intelligent Driving Assistance Systems

The integration of intelligent driving technologies with energy management systems has led to the development of advanced driver-assistance systems (ADAS) aimed at optimizing vehicle energy performance without compromising driving safety. Autonomous driving functions-such as route planning, speed control, and traffic condition prediction-enable optimal energy utilization through the support of intelligent algorithms.

Real-time driving data is continuously analyzed and applied within the driver-assistance interface to provide diverse guidance options, including recommendations for speed, acceleration, braking, and route selection. In addition to offering real-time suggestions during a trip, these systems also generate personalized efficiency reports based on historical driving behavior, helping drivers progressively improve habits and achieve long-term fuel savings.

The interface design and functional schematic of the energy efficiency optimization recommendation system are illustrated in Figure 2.

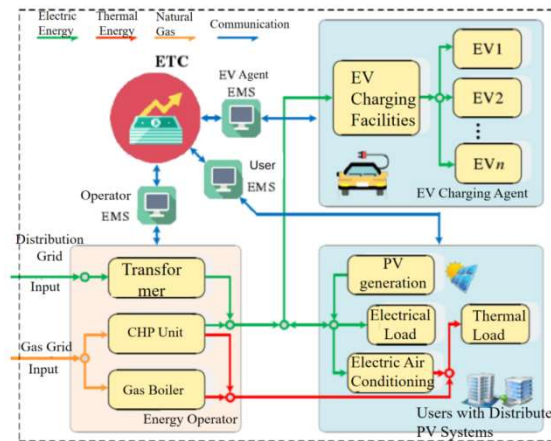


Figure 2. Energy Efficiency Optimization Design

5. Development and Application of Vehicle Energy Consumption Monitoring and Analysis System

5.1 System Design and Architecture

Targeting high accuracy and real-time performance, the hardware architecture of the system integrates multiple sensors, data processing units, and communication modules to enable comprehensive data acquisition. Various sensors-including accelerometers, fuel sensors, and environmental sensors-collect real-time vehicle data under different operating conditions. Initial filtering and preprocessing are handled by the data processing unit to ensure consistency and accuracy. The processed data is then transmitted to a central control unit or cloud server via wireless networks or in-vehicle bus systems.^[6]

The system adopts a compact and modular configuration, consisting of several functional units: a data acquisition module, a data analysis module, an energy consumption prediction module, and an optimization recommendation module. Leveraging a large-scale database, the system aggregates and stores data from all hardware components, enabling in-depth analysis of energy usage patterns and the identification of key influencing factors. Furthermore, it generates intuitive feedback reports for drivers or automated maintenance systems.

5.2 Case Analysis of Practical Applications

In real-world applications, the vehicle energy consumption monitoring and analysis system has been widely deployed across several typical driving scenarios. Urban driving is one of the primary use cases, where complex and congested traffic conditions, coupled with frequent stop-and-go behavior, cause significant fluctuations in energy consumption. The system monitors real-time driving data to detect frequent acceleration and braking patterns, and it provides optimized driving suggestions through an energy analysis model to effectively reduce fuel consumption.

Table 4. Performance Analysis of the System Under Different Driving Scenarios

Driving Scenario	Energy Saving Rate (%)	Response Time (ms)	Data Processing Capacity (data points/s)
Urban Driving	15	50	1000
Highway Driving	8	40	1500
Mountain Road Driving	12	60	800
Rural Road Driving	10	55	900
Mixed Driving Conditions	13	45	1200

On highways, the system utilizes aerodynamic analysis and speed control to determine the most fuel-efficient cruising speed. It also adjusts vehicle power output based on upcoming traffic conditions, thereby improving fuel economy. The system's performance across various scenarios is presented in Table 4.

The data show that the system achieves significant energy savings in both urban and highway driving scenarios. Specifically, the energy saving rate reaches 15% in urban environments and 8% on highways.

5.3 System Integration

System integration plays a crucial role in the development of vehicle energy consumption monitoring and analysis systems. In the complex in-vehicle environment, achieving seamless integration among multiple sensors, data processing units, and communication modules poses significant technical challenges and remains one of the major obstacles in system development.

Key technical issues include data synchronization among heterogeneous sensors, compatibility across different communication protocols, and enhancing the system's resistance to interference. To ensure system stability and reliability, it is essential to employ advanced signal processing and data fusion techniques during the integration process. Rigorous hardware and software testing is also required to evaluate the system's performance under various driving conditions.

6. Conclusion

This study conducted an in-depth investigation into energy consumption monitoring and intelligent analysis technologies under dynamic vehicle operating conditions. A big data-driven solution based on multi-sensor fusion and intelligent analysis was proposed. Experimental results demonstrated that the system achieved significant energy savings across various driving scenarios: 15% in urban driving, 8% on highways, and 12% in mountain road conditions.

Moreover, the anomaly detection module achieved a maximum detection rate of 4%, with average reconstruction errors ranging from 0.01 to 0.08, ensuring data reliability. By optimizing driving behaviors and energy management strategies, the system effectively combined real-time monitoring with energy consumption prediction. This provides strong technical support and a valuable reference for the future advancement of energy-saving and emission-reduction technologies in the automotive sector.

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