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Hierarchical Control Strategy of Predictive Energy Management for Hybrid Commercial Vehicle Based on ADAS Map

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Abstract

Considering the change of vehicle future power demand in the process of energy distribution can improve the fuel saving effect of hybrid system. However, current studies are mostly based on historical information to predict the future power demand, where it is difficult to guarantee the accuracy of prediction. To tackle this problem, this paper combines hybrid energy management with predictive cruise control, proposing a hierarchical control strategy of predictive energy management (PEM) that includes two layers of algorithms for speed planning and energy distribution. In the interest of decreasing the energy consumed by power components and ensuring transportation timeliness, the upper-level introduces a predictive cruise control algorithm while considering vehicle weight and road slope, planning the future vehicle speed during long-distance driving. The lower-level calculates the future power demand based on the results of speed planning, and a dynamic programming method is utilized to determine the global optimal power distribution rules for the current road and driving condition with the goal of optimal engine fuel consumption. The comparison of simulation and vehicle test results indicates that under the various high-speed cruising conditions with little change in speed range and road slope, the predictive energy management strategy has a significant improvement in fuel saving compared with the rule-based energy management strategy.

Keywords

Hybrid commercial vehicle, predictive energy management, hierarchical control, predictive cruise control, dynamic programming, ADAS map

Introduction

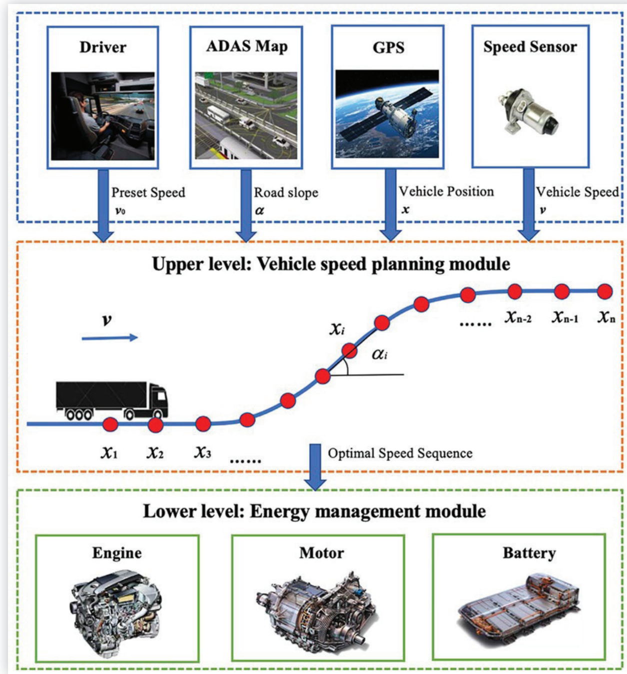
Energy saving and safety are key to the development of automotive technology [1]. Hybrid electric vehicle is currently one of the important research directions in new energy vehicles for its low energy consumption, low emissions, and extended driving range [2]. The advantages of hybrid systems are further highlighted in commercial vehicles due to their longer driving range and greater fuel consumption [3]. Hybrid electric vehicles normally contain two or more power components, resulting in multiple driving modes. Energy management strategies are required to optimize the power distribution to among power components [4]. At present, research on hybrid energy management strategies is mainly carried out regarding static logic threshold energy strategies [5], fuzzy control energy management strategies [6], equivalent consumption minimization strategies [7], global optimal energy management strategies [8, 9, 10], model predictive energy management strategies [11, 12], and artificial intelligence-based energy management strategies [13]. With the development of intelligent transport systems and vehicle connectivity, the predictive energy management strategy that integrates future working conditions information has emerged [14, 15]. This paper aims to address a key issue in the hybrid predictive energy management, which is accurately predicting future power demand of the vehicle during long-distance driving, thereby determining the global optimal energy management strategy suitable for the current road conditions based on the prediction result.

In the hybrid energy management strategy, considering the changes in the future working conditions is promising to improve the vehicle energy-saving potential [16], where the key is how to achieve accurate prediction of future working conditions, and to make rational use of the prediction results to reduce the vehicle fuel consumption. In Ref [17], in order to improve the energy-saving efficiency of hybrid electric buses, the deep neural network (DNN) was applied to predict future vehicle speed given historical vehicle speed, driver type and driver behavior. Then the optimal control strategy within the predicting range was determined by a dynamic programming algorithm. The outcome witnessed a fuel saving rate of 3.34% with driver information considered in energy management strategy. In Ref [18], a velocity predictor and SOC reference generator were introduced. A function neural network algorithm was implemented in the velocity predictor to predict future vehicle speed. SOC reference trajectory was determined by current driven distance and predicted future speed fed by the velocity predictor, which further regulated the energy distribution rules among hybrid power components. Ref [19] proposed a hierarchical model predictive control framework composed of economic and control layers. The economic layer uses Levenberg-Marquardt optimized neural network to predict complex load of fuel cell vehicles, while a model predictive control algorithm was applied to tracking the reference trajectory in the control layer. Ref [20] introduced a method of predicting vehicle speed and passenger number based on deep learning to further anticipate future vehicle power demand. The simulation results demonstrated that the energy efficiency of this energy management strategy could approach 98.02% of the global dynamic programming. Ref [21] proposed to train neural networks using the optimal results of dynamic programming, based on which a velocity prediction-based online model predictive control framework was established. The co-state correction and slacked constraints were applied to solve the real-time optimal energy distribution sequence. In Ref [22], a stochastic speed predictor was developed based on Markov chain model targeted for the issue of vehicle speed changes under actual driving condition, based on which the energy management strategy was developed considering battery electrical-thermal-aging dynamics. Simulation calculation had verified that the energy consumption was reduced with this strategy applied. Ref [23] proposed an optimization strategy based on dual-loop online intelligent programming (DOIP). The deep fuzzy predictor was constructed to realize future speed prediction, and a chaos-enhanced accelerated swarm optimization algorithm was utilized to distribute energy between engine and motor. The outcome of driver-in-the-loop test showed that the algorithm could lower fuel consumption and shorten calculation time. Ref [24] stated that marked and frequent changes of power demand led to adverse scenarios for energy management. Neural networks and Markov chains were employed to predict total power demand, and the rationality of this algorithm was verified by representative driving cycles. Ref [25] constructed a multi-step Markov velocity prediction model, and trained reinforcement learning controller using Q-learning algorithm based on the driving power distribution under typical working conditions. The energy distribution of hybrid power system was determined by the joint application of the speed prediction model and the reinforcement learning controller.

In addition to predicting future working conditions based on neural networks, deep learning, and Markov algorithms, the influence of other factors, such as position, road terrain grade information, traffic information and internal activities of power components, is considered to improve the accuracy of predicting future working conditions and the energy-saving performance of hybrid energy management strategies [26]. Ref [27] proposed to consider the impact of the actual internal activities of power components during the development of energy management strategies, and compared the fuel saving effect of optimization-based strategy without and with using OBD. The results showed that, considering the measurement errors from in-vehicle measurement system and simplicity of the widely used models can improve the fuel saving rate of energy management strategies. Ref [28] proposed dividing the intended driving route into multiple road segments with different spatially averaged driving energy demands, where the vehicle velocity and road grade data were classified based on a ordered sample clustering algorithm and a gap statistic algorithm, hence realizing automate SOC planning. In Ref [29], it was proposed to establish a vehicle speed prediction model based on real driving cycle and road terrain data, and the energy distribution rules were obtained from the model predictive control algorithm. Experimental results indicated that this method reduced fuel consumption by 5-7% compared with energy management strategies with no vehicle speed prediction models applied. In Ref [30], an energy management strategy was established based on the adaptive Pontryagin's Minimum Principle, and the genetic algorithm was used to determine the co-state function between vehicle driving distance and battery SOC. The co-state value was updated in real time according to the route information and the reference SOC to improve the adaptability of the energy management strategy. Ref [31] introduced a road grade recognition model based on GPS/GIS system, calculating the demanded torque at the next moment based on road slope information and determining the operation mode of power system according to the required torque and battery SOC. In Ref [32], future vehicle speed was predicted according to the driver's intention based on the traffic information. The A* algorithm was introduced to search for the optimal energy management strategy within the prediction horizon, thus reducing the computation time. The simulation results showed that its fuel economy was only lower than the global optimal strategy by 1.16%. In Ref [33], considering the influence of various factors such as traffic status, weather, etc., a vehicle power predictive controller was developed combining the real-time information obtained in V2X. This prediction tracked the optimal reference from the cloud to achieve precise prediction of future vehicle power. In Ref [34], the acquisition of road terrain grade information and front vehicles movement prediction were realized by the vehicle-vehicle and vehicle-equipment wireless communication technology, based on which energy distribution between motors was further optimized. In Ref [35], future vehicle speed was predicted based on a vehicle tracking control model, and the rolling dynamic programming algorithm was applied to achieve optimal energy distribution on the promise of safe distance between vehicles. Ref [36] realized power prediction and energy distribution optimization from navigation data and information in V2X system, improving the fuel-saving rate of electric vehicle with range extender.

In the predictive energy management strategy proposed in this paper, in order to accurately predict the future power demand of the vehicle, we combine the predictive cruise control [37] with hybrid energy management. The predictive cruise control is used to realize the vehicle speed planning and control in the process of long-distance driving, then the future power demand of the vehicle can be accurately calculated according to the planning speed, road slope and vehicle load. The predictive energy management strategy is subdivided into two levels. Based on the ADAS map, the upper-level algorithm obtains accurate road slope information in front of the vehicle, and calculates the optimal cruising speed trajectory with the goal of minimizing the energy consumption of vehicle power components. In the lower-level algorithm, based on the optimal cruising speed trajectory, the future power demand of the vehicle is accurately calculated according to the vehicle dynamics, then the dynamic programming algorithm is used to obtain the global optimal energy management strategy with the optimal engine fuel consumption as the objective.

FIGURE 1 Diagram of the hierarchical control algorithm.



The main contributions of this paper are the following. (1) Eliminate the influence of driver control on vehicle speed using predictive cruise instead of manual operation. Therefore, the future vehicle speed can be accurately calculated by the predictive cruise control system to realize "predicting future by the future", instead of predicting the future power demand from summarizing and learning of historical vehicle speed information and driving conditions. (2) Considering the influence of speed control on vehicle fuel saving performance during long-distance cruising, the future vehicle speed is planned with the goal of optimal energy consumption of power components, and the energy saving potential of hybrid vehicles is improved in the aspect of speed planning. (3) Determine future vehicle speed through predictive cruise control, providing working conditions cycles for the dynamic programming algorithm in energy distribution process embedded in the lower layer. It guarantees the optimality of control and satisfies the needs of predictive working conditions in the dynamic programming algorithm, enabling real-time application of dynamic programming algorithm in the follow-up research. (4) Under the high-speed cruising conditions with slightly varying speed range and road slope, the hybrid power system is usually in a stable state, it is difficult to take full advantage of energy-saving features in hybrid power system. Comparing simulation results with actual vehicle experiment results, the PEM proposed in this paper can realize fuel-efficient driving for hybrid commercial vehicles in common highway conditions.

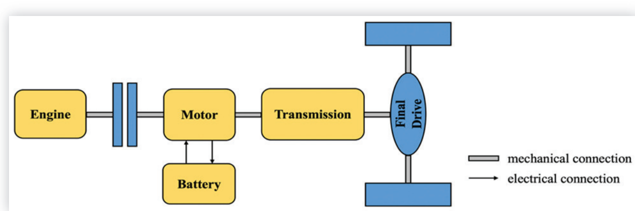
Hybrid Electric Vehicle Model and Issue Description

In the hierarchical control strategy of predictive energy management designed in this paper, vehicle obtains its own state and road information based on the ADAS map, global positioning system and sensors, which are used as input to the upper-level algorithm. In the upper-level vehicle speed planning algorithm, the optimal speed sequence is determined with the objective of minimizing the total energy consumed by the power components and is fed into the lower-level algorithm. In the lower-level energy management algorithm, the energy distribution among the engine, motor and battery is determined based on the optimal speed sequence with the aim of minimizing the fuel consumption of the engine. The diagram is illustrated in Figure 1, where v_0 is preset speed by the driver, v is vehicle speed, x is current position of the vehicle, and x_i is location of each road sampling point, α_i is road slope corresponding to each road sampling point.

Vehicle Power System Structure

This paper takes FAW Jiefang JH6 hybrid vehicle as the sample vehicle for algorithm research. The structure of vehicle power system is shown in Figure 2. JH6 is equipped with P2 hybrid structure, where the power of engine is transmitted to the motor via the clutch, then is coupled with power of motor. The coupled power is transmitted to the wheels through transmission and main reducer. When the clutch is engaged, engine and motor revolve coaxially at the same speed. Motor is employed both as a driving motor and

FIGURE 2 Hybrid powertrain structure.



2, the power demand of the vehicle remains stable, since the main road condition embodies an relatively plain road with slight road slope variation, where uphills and downhills only present at the beginning and ending segments. Therefore, the fuel saving performance in road section 2 is not obvious as road sections with constant uphills and downhills.

From the perspective of energy conversion, gravitational potential energy, kinetic energy, chemical energy of fuel, battery electric energy, and thermal energy generated by mechanical brake can be converted into each other, and the battery plays the role of reservoir in the whole process. Reasonable use of the energy storage function of the battery, increasing the battery energy throughput as much as possible under the premise of ensuring the battery life, can avoid unnecessary waste of energy and improve the fuel saving rate of the vehicle. From the comparison data, under the condition of equipped with the same power components and battery, the battery charging power of the PEM under three road section is 4.56, 7.62, 6.57 kWh and discharging power is 4.56, 7.62, 5.09 kWh, while the battery charging power of the vehicle test is 2.25, 1.50, 4.80 kWh and discharging power is 2.85, 0.90, 3.15 kWh. In this paper, the PEM algorithm plans the vehicle speed according to the future road slope change, then performs reasonable energy distribution on this basis. Compared with the rule-based energy management strategy under the driver's manual control of the vehicle speed, the vehicle fuel saving rate can be greatly improved. After converting the battery SOC changes before and after the working conditions into engine fuel consumption, the fuel saving rates compared to the vehicle test in three road sections are respectively 20.26%, 3.45%, 74.96%. Assuming 200000 km of annual odometer is added to the vehicle, there will be 2240 liters of diesel saved accroding to the fuel consumption results with the lowest fuel saving rate in road section 2. 17225.6 CNY is saved annually given that the diesel is 7.69 CNY per liter, which is estimately 5% of vehicle intial purchase cost.

Conclusion

This paper takes FAW Jiefang JH6 hybrid vehicle as the target model, performs speed planning based on the predictive cruise control algorithm, then uses the dynamic programming algorithm to determine energy distribution between the engine and motor according to previous speed planning results. The effectiveness and rationality of the algorithm is validated by comparing simulation calculation results to real vehicle test results, and conclusions are as follows.

1. The proposed predictive cruise speed planning algorithm based on ADAS map can reasonably plan the future vehicle speed, minimizing energy consumption of the vehicle while assuring transportation timeliness.
2. The proposed predictive energy management strategy combines vehicle speed planning and energy distribution, which can significantly improve the fuel saving rate of hybrid vehicles under high-speed driving conditions.

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Definitions/Abbreviations

ADAS - Advanced driver assist system
DNN - Deep neural network
DOIP - Dual-loop online intelligent programming
FAW - First automotive works
GIS - Geographic information systems
GPS - Global positioning system
PEM - Predictive energy anagement
SOC - State of charge
V2X - Vehicle to everything

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