

# Research on Dynamic Optimization Algorithm of Electric Car Composite Energy Storage System Based on Model Predictive Control

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## **Abstract:**

A strong hybrid vehicle control method may not only fulfill the vehicle's energy requirements, but also saves fuel and reduces pollutants effectively. This article proposes the creation of a hybrid electric vehicle model predictive control. For application of prediction models (MPC) based on the dynamic programming (DP) method, the solution procedure and usage of reference pathways are described. The composite energy storage system of electric vehicle is simulated by the specified operation status. The simulated results demonstrate that the designed algorithm may efficiently minimize energy consumption by appropriately distributing the torque of motors and engines, and check the efficiency of the control method.

**Keywords:** SOC, Model predictive control, DP, Optimization algorithm

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## I. INTRODUCTION

Safe operation, energy conservation and environmental are essential guidelines for automotive development and hot research topics. As manufacturing and ownership of cars increased rapidly, traffic, resources and environment strain were imposed. Electric cars have become the hotspot for the development of the world automotive industry under pressure from resources and the environment in recent years. Hybrid electric vehicles are controlled using a most acceptable combination of engine output and engine power output. In order to ensure demand for vehicle power, vehicle exhaust emissions must be minimized and the energy loss of the system is the smallest.

In the study [1], in order to make the vehicle energy system keep its speed downward by the adaptive model predictive control when the slope of pavement varies, and build mathematical model of vehicle energy control system with braking control constraints. Nevertheless, the the adaptive method convergence is relatively small, and frequently a solution is not optimal, making it difficult to apply in actual engineering applications. Aiming at the fast nonlinear system of electric vehicle, the traditional model predictive control algorithm is improved [2], which improves the operation efficiency of the algorithm on the premise of ensuring the control safety and improving the regenerative braking efficiency. For the regenerative braking process of electric vehicle, a controller based on the improved nonlinear model predictive control algorithm is designed. Under different braking conditions, through simulation and analysis, the optimal interval of weight under different control objectives is established, and the rationality and feasibility of the algorithm are verified. Without real-time tracking control, the control method for this nonlinear system is sluggish and complex, and the nonlinear system still has significant technical control difficulties that are difficult to address. In the dynamic management of sophisticated hybrid systems in vehicles, Ripaccioli described [3] the application of stochastic models predictive control. However, stochastic models are typically issues with optimisation and might be difficult to solve directly under probabilistic restrictions. Tang [4] has proposed a model predictive control technique for the optimum and scalable loading of low complexity electric vehicles. However, in real applications this method is relatively inefficient, and does not fulfill vehicle requirements. Li [5] provided a hybrid bus' method for regenerative braking energy recovery based on a predictive model control which could assure stability of brakes and maximize braking energy recovery. The problem with the method is nevertheless rather hard to apply. New energy electric vehicles are also going towards smart information development, notably with the development of autonomous automobiles and smart cars [6-7]. The ongoing technological upgrade is also particularly important for the progress towards enhanced energy use. Research on energy recovery in future energy vehicles is therefore extremely essential.

In this work, a model prediction algorithm based on dynamic programming optimization [8] is proposed to study the compound energy control strategy of electric vehicle. At the same time, the structure of semi-active composite energy storage system is designed, and its performance is analyzed and compared based on the aforementioned control directions and the current defects. The predictive model control is applied to the dynamical programming algorithm, and referral paths to charge (SOC) are evaluated and examined on the basis of the SOC dynamic programming algorithm and prediction. The algorithm proposed in this study uses the SOC reference track as the system restraint condition, which can control the motor torque in real time and optimize it. In this way, the energy consumption of the whole vehicle system can be reduced as much as possible, and the efficiency and stability of the whole vehicle can be improved [9].

## II. DYNAMIC MODEL OPTIMIZATION CONTROL DESIGN OF ELECTRIC VEHICLE COMPOSITE ENERGY STORAGE SYSTEM

The model of prediction control method aimed at controlling the power system and thus reducing the power consumption of a vehicle is proposed to assure the reasonable distribution of engine and motor torque of electric vehicle composite energy storage system, and improve the effectiveness and rationality of output power. And energy saving and car miles rise. In this paper [10], Markov prediction method is used to forecast the future operation state of hybrid electric vehicle, and a fuzzy logic controller is established according to the predicted results to realize the optimal torque distribution between engine and motor, so as to make the engine work at the optimal working point and keep the battery SOC within the expected range. The predictive models of the operational state of the car are designed and the operating state of the vehicle is forecast in order to provide optimum information for predicting time domain which it can obtain the useful message that controlled by the operation speed and acceleration at the formerly moment in the whole running process, together with current speed and acceleration. Based on the calculated anticipated vehicle status inside the vehicle's future time area and calculating the vehicle demand torque, a particular method is utilized for achieving the system's optimum engine torque sequence within certain restrictions in the time-domain forecasted. The initial value of a predictory control model's Optimum Motor Torque Sequence is added to the vehicle and continues with the acquisition of information such as history of speed and vehicle acceleration, and the following period forecasts the vehicle running state to correct its anticipated moment value. Then repeat the forecast, optimization and correction procedures. If dynamic programming builds up the control strategy of on board composite energy storage system, it has the following index function:

$$J_l = \sum_l^{l+\tau} L(x(t), u(t)) = \sum_l^{l+\tau} f(t) \quad (1)$$

In which,  $x(t)$  is the SOC value at the time  $t$ ,  $u(t)$  is the motive torque input at the time  $t$ ,  $L$  is a objective function at appoint time,  $J_l$  is an indication of the overall function of the indicator and  $l \sim l+\tau$  is the forecast time.  $f(t)$  indicates the vehicle's immediate fuel usage at the time  $t$ .

## III. APPLICATION OF DYNAMIC MODEL PREDICTION ALGORITHM IN COMPOSITE ENERGY STORAGE SYSTEM OF ELECTRIC VEHICLE

Using dynamic programming and MPC algorithm to predict the operation status of electric

vehicle composite energy storage system at the next moment can optimize the motor torque of the multi-objective system, improve the dynamic performance and stability of the system, and further improve the energy-saving effect. By optimizing the multi-objective problem in the operation process, the vehicle performance and energy utilization efficiency can be improved. In order to obtain SOC reference trajectories in optimizing processes, the SOC variability law, developed in dynamic algorithms of programming, must be properly regulated while forecasting the transition status variable. The transition state variables must be controlled by the certain restrictions and the changing law of SOC can be well applied.

### 3.1 MPC Optimization Algorithm

In general, we believe that at time  $l$ , the prediction time domain of the studied nonlinear control system is  $l \sim l + \tau$ . In order to seek the solution of the optimal motor torque and related optimization variables on-board composite energy storage system based on MPC. So it is necessary to solve the optimal values of motor torque power and system objective function in the opposite order each time.

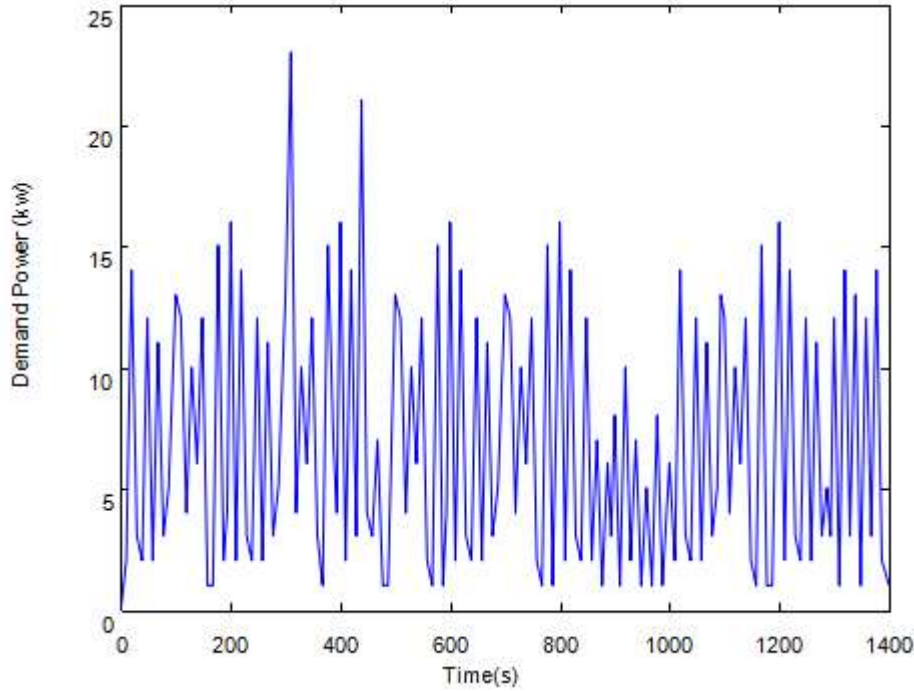
The optimised objective function can be achieved as follows in the specified prediction time domain:

$$J_l^*(SOC(l)) = \min_{u(l)} [L(SOC(l), u(l)) + J_{l+1}^*(SOC(l+1))] \quad (2)$$

In the formula,  $J_l^*(SOC(l))$  is the optimal target value from  $l$  time up to  $l + \tau$  time; in the prevision period,  $u(l)$  is the optimum torque value that matches time  $l$ . Using the proposed algorithm for motor torque analysis, the first optimal sequence value can be obtained to look upon as the motor torque value in the prediction time domain of the system, while other sequences and moments are not considered. In this way, the calculation speed of the system is improved, the running time is reduced, and the efficiency of the program is increased.

### 3.2 SOC Tracking Path Based on Model Prediction Constraints

The SOC tracking path curve can be generated by global optimization of constraint rules when the cycle conditions are established (as illustrated in Figure 1). The SOC is changing from the maximum SOC to the minimum SOC value by increasing the vehicle miles. 2 The SOC is constantly decreasing and fluctuating around a straight line as seen in Figure 2.



**Figure 1. Vehicle demand power curve based on cycle conditions**

If the car's trip duration to its destination is established, the change in SOC essentially declines linearly according to SOC law, the linear decline from the greatest value for the SOC in vehicles to the lowest value in the SOC is characterized as the hypothesized change trajectory for SOC. The theoretical trajectory of the SOC changing path is used as the SOC tracking path, the predictive model monitoring being restricted. Figure 2 shows the SOC reference theory trajectory.

The reference SOC value may be determined at any moment  $k$ .

$$SOC_r(l) = SOC_0 - \frac{l}{d}(SOC_0 - SOC_f) \quad (3)$$

In which,  $SOC_r(l)$  is the SOC tracking path at  $l$  time during the whole operation,  $SOC_0$  the SOC value of the vehicle's starting operating status, which may be determined on its own in accordance with the current circumstances.  $SOC_f$  is the lowest SOC threshold value;  $d$  reflects the overall distance length.

It is the major purpose of the  $SOC$  reference path to restrict the volatility of  $SOC$  inside the  $SOC$  reference path under real operation. Formula (3) calculates the  $SOC$  reference value at all times. Depending on the current circumstances, the original  $SOC$  and the final  $SOC$  will be specified. Usually, a portion of the electricity for the start-up energy should be reserved for the initial  $SOC$  value, therefore it will be reduced by a tiny value 0.01:

$$SOC_0 = SOC_i - 0.01 \quad (4)$$

In which,  $SOC_i$  is the initial battery SOC of the composite energy system.

At each time  $l$  when the car is running, the prediction time domain is  $l \sim l + \tau$ . Generally speaking, the battery SOC is limited to every moment so it can enhance model control accuracy. The system can be used to limit the formula (5) with the quadratic cost function.

$$J_l = \sum_l^{l+\tau} (f(t) + h(SOC(t+1))) \quad (5)$$

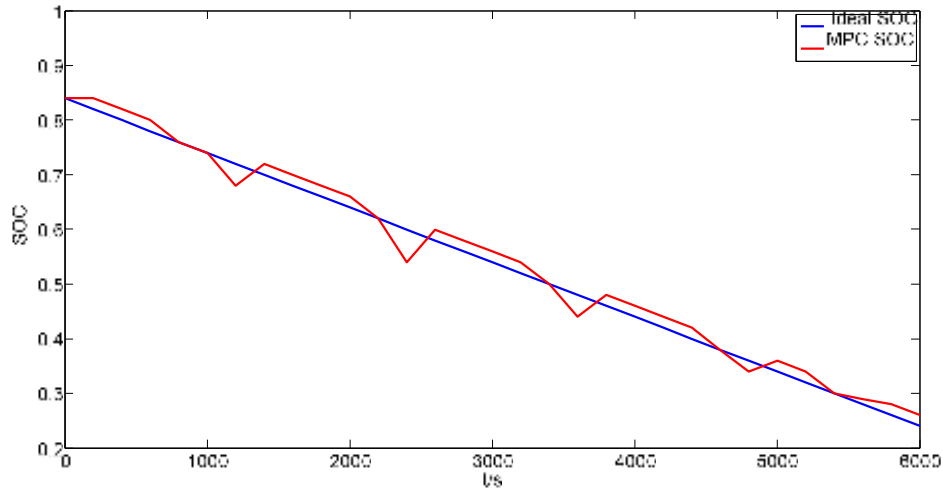
In which,  $h(\cdot)$  expresses the  $SOC$  cost function which can be described as the formula (6).

$$h(SOC(t)) = \begin{cases} 0, & SOC(t) \geq SOC_r(t) \\ \alpha(SOC(t) - SOC_r(t))^2, & SOC(t) < SOC_r(t) \end{cases} \quad (6)$$

In which,  $SOC_r(t)$  represents the  $SOC$  tracking path that it in the  $t$  time;  $\alpha$  is the weight coefficient, it may be  $1 \times 10^{10}$ .  $SOC(t)$  expresses the practical battery  $SOC$ . The cost function is zero and does not affect the exponential function if the real  $SOC$  value is equal or higher than the tracking path. If  $SOC(t) \geq SOC_r(t)$ ,  $h(\cdot)$  will be is 0. If  $SOC(t) < SOC_r(t)$ ,  $h(\cdot)$  value is related to the SOC square difference and the weighting coefficient.

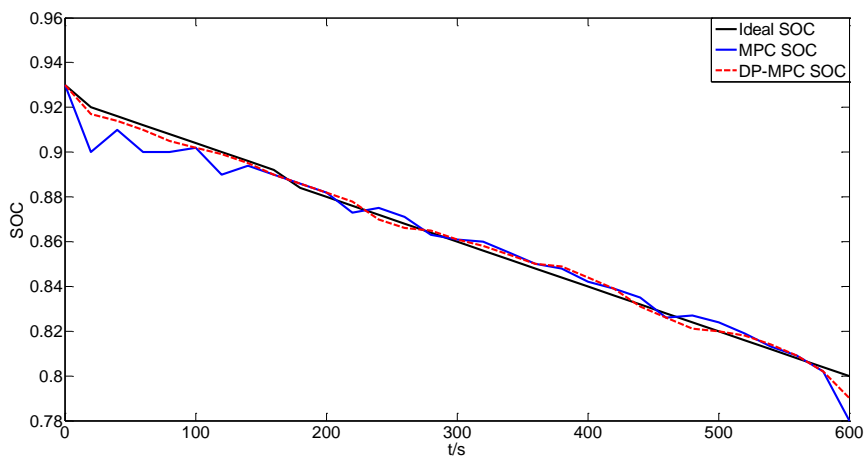
This article includes the prototype of a hybrid vehicle and conducts simulation tests with MATLAB. The car has an engine voltage of 1125 kg, an engine power rater of 5.8 kW and a rating speed of 3000 rpm with an engine capacity of 150 AH. The Urban Dynamometer Driving Schedule (UDDS) is created by the United States Environmental Protection Agency (EPA). In order to analyze the various cyclical performances on urban way. Matlab is used to simulate

and analyze the required power under the cycle condition of the whole vehicle, and the results are shown in the Figure 2.



**Figure 2. Battery SOC curve**

Figure 2 shows that the dynamic predictive control model proposed by this study is well able to optimize the car control system successfully, and the simulation  $SOC$  is near to the prospective outcome and the intended impact is obtained.



**Figure 3. SOC curves of different control strategy**

Figure 3 illustrates the various control strategy  $SOC$  curves. The figure shows that the prospective value of the DP-MPC controlling strategy is extremely closely related to the ideal  $SOC$  value, while the error of the entire process is just 0.01; the MPC control strategy's  $SOC$  value varies significantly, and its final value deviates from the ideal value by 0.02. Thus, the control technique suggested in this work may provide composite power storage control system stability for electric vehicles.

The following table shows that various control methods take various amounts of fuel under the same cycle conditions, with the optimum situation, the DP-MPC control approach consuming least, and the MPC control strategy using the most. Thus, I may infer that the results from the simulation are correct utilizing the control technique. This means that the control approach used in this research can achieve more accurate controls and better results.

**Table I. Energy consumption comparison with different control method (L/km)**

<b>Ideal cycle condition</b>	<b>MPC control strategy</b>	<b>DP-MPC control strategy</b>
35.6	31.5	28.4

#### IV. RESULTS

Here is the application of the control technique for hybrid vehicles to predictive model control. Dynamic programming approaches are recommended for predictive model control. It is mostly utilized for the optimal torque management across the time domain. The practical trajectory is employed and the  $SOC$  reference trajectory and prediction model solution steps at the practical  $SOC$  value are applied. It is shown that the prediction model is built on multiple prediction models, applying the concept of roll optimisation, and has preponderances in linear and non-linear system resilience, good effect and high stability.

There are several weaknesses in this paper at the same time. Although the description of a model and comparison of the simulation were well suited to actual operating circumstances, there were no tests to confirm this, which was also a deficiency of this work. The authors will continue their study in this area to apply it better to real operating cars.

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## **CONFLICT OF INTEREST**

The authors declared that they have no conflicts of interest to this work.

## **REFERENCES**

- [1] Peng X. Research on Constant Velocity Downhill Control of Electric Vehicles Based on Adaptive Model Predictive Control. Nanjing Agricultural University, 2015.
- [2] Zhan Z Q. Research on Model Predictive Control Method for Regenerative Braking Process of Electric Vehicle. Beijing University of Technology, 2014.
- [3] Ripaccioli G, Bernardini D, Cairano S D, et al. A stochastic model predictive control approach for series hybrid electric vehicle power management. American Control Conference. IEEE, pp. 5844-5849, 2010.
- [4] Tang W, Zhang Y. A Model Predictive Control Approach for Low-Complexity Electric Vehicle Charging Scheduling: Optimality and Scalability. IEEE Transactions on Power Systems, no. 99, pp. 1-1, 2016.
- [5] Li L, Zhang Y, Yang C, et al. Model predictive control-based efficient energy recovery control strategy for regenerative braking system of hybrid electric bus. Energy Conversion & Management, vol. 111, pp. 299-314, 2016.
- [6] Godoy J, et al. A driverless vehicle demonstration on motorways and in urban environments. Transport, pp. 253-263, 2015.
- [7] Haber R E, et al. A simple multi-objective optimization based on the cross-entropy method. IEEE Access, no. 99, pp. 1-1, 2017.
- [8] Zeng X, Wang J. A Parallel Hybrid Electric Vehicle Energy Management Strategy Using Stochastic Model Predictive Control With Road Grade Preview. IEEE Transactions on Control Systems Technology, vol. 23, no. 6, pp. 2416-2423, 2015.
- [9] Zhang S, Rui X, Sun F. Model predictive control for power management in a plug-in hybrid electric vehicle with a hybrid energy storage system. Applied Energy, vol. 185, pp. 1654-1662, 2015.
- [10] Wahl H G, Bauer K L, Gauterin F, et al. A real-time capable enhanced dynamic programming approach for predictive optimal cruise control in hybrid electric vehicles. International IEEE Conference on Intelligent Transportation Systems, 2013.