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MULTI-OBJECTIVE OPTIMIZATION METHOD WITH MULTI CONTROL VARIABLES AND ITS APPLICATION IN CONFIGURATION COMPARISON OF COMBINATION HEV

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ABSTRACT−Combination hybrid electric vehicle (HEV) mainly includes two configurations: series-parallel and power-split. It is necessary to consider a variety of metrics to comprehensively evaluate the configuration performance of HEV and compare the two configurations. In order to fully evaluate the HEVs' potential in energy management, a practical and effective multi-objective method that can solve the global optimization-based energy management problem is needed. Based on the idea of dynamic programming (DP) and non-dominated sorting method, this paper proposes a global multi-objective optimization method of non-dominated sorting dynamic programming (NSDP) with multi-control variables. This algorithm can calculate a set of uniformly distributed Pareto solutions for the conflicting or coupling optimization objectives, and the performance of the solution set is improved due to the increase in the dimension of the control variables, which increases the strategy search space. NSDP is applied to two different configurations to fully evaluate the performance of fuel consumption and battery lifespan. The parameters of the configurations are optimized and comprehensively compared based on the implementation of NSDP. The above process can provide theoretical analysis for hybrid power system developers.

KEY WORDS : Hybrid electric vehicle (HEV), Multi-objective optimization, Multi control variables, Non-dominated sorting dynamic programming, Configuration comparison

NOMENCLATURE

A	: frontal area, m^2
b_e	: fuel consumption rate of engine, g/kWh
T_e	: output torque of engine, N·m
T_{e_max}	: maximum output torque of the engine, N·m
T_{e_min}	: minimum output torque of the engine, N·m
n_e	: output speed of the engine, rad/s
n_{e_max}	: maximum output speed of the engine, rad/s
$n_{e\ min}$	: minimum output speed of the engine, rad/s
SOC	: state of charge of the battery
P_{bat}	: output power of the power battery, kW
U_{oc}	: open circuit voltage of the power battery, V
Q_{nom}	: nominal capacity of the power battery, As
R_{int}	: internal resistance of the power battery, Ω
η_t	: transmission working efficiency
u_a	: vehicle speed, m/s
r_v	: tire radius, m
T_d	: required torque at wheel end, N·m
α	: planetary gear characteristic parameter
i_0	: gear ratio of main reducer
i_1	: gear ratio from Motor2 to main reducer
T_{MG1}	: output torque of the Motor1, N·m
T_{MG1_min}	: minimum output torque of the Motor1, N·m
T_{MG1_max}	: maximum output torque of the Motor1, N·m
n_{MG1}	: output speed of the Motor1, rad/s
n_{MG1_min}	: minimum output speed of the Motor1, rad/s
n_{MG1_max}	: maximum output speed of the Motor1, rad/s
T_{MG2}	: output torque of the Motor2, N·m
T_{MG2_min}	: minimum output torque of the Motor2, N·m
T_{MG2_max}	: maximum output torque of the Motor2, N·m
n_{MG2}	: output speed of the Motor2, rad/s
n_{MG2_min}	: minimum output speed of the Motor2, rad/s
n_{MG2_max}	: maximum output speed of the Motor2, rad/s
T_m	: output torque of the driving motor, N·m
n_m	: output speed of the driving motor, rad/s
m	: curb weight of vehicle, kg
g	: gravity constant, m/s^2
f	: rolling resistance coefficient
i_s	: slope of the road
C_D	: air resistance coefficient
δ	: rotational inertial coefficient
Ah	: accumulated Ah-throughput
SOC_{max}	: maximum allowable SOC values of the battery
SOC_{min}	: minimum allowable SOC values of the battery
P_{bat_min}	: minimum output power of the battery, kW
P_{bat_max}	: maximum output power of the battery, kW

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1. INTRODUCTION

Road transportation plays a significant role in air pollutants and greenhouse gases emissions (Mavrin *et al.*, 2020). In order to satisfy the increasingly stringent emission regulations, the market share of hybrid electric vehicles (HEVs) and pure electric vehicles has increased rapidly in recent years (İnci *et al.*, 2021). Pure electric vehicles have shortages of low battery energy density, short range, and inconvenient charging, which make it difficult to travel a long distance. HEVs can give full play to the advantages of each power source through reasonable power combination and control strategy to reduce energy consumption and waste, which are the good solution for the emission reduction and long travel challenges (Hannan *et al.*, 2014). According to the components and configurations of the powertrain, HEVs are generally classified as three types: series HEV, parallel HEV and combination HEV (Xue *et al.*, 2020). Combination HEVs mainly include power-split configuration and series-parallel hybrid configuration, and exist two different pathways of power delivered to the wheels (Krithika and Subramani, 2018).

The powertrain structure of power-split with a planetary gear mechanism is depicted in Figure 1 (a), which has two degrees of freedom and can divide the power output of the engine into two paths: mechanical and electrical. The motor can realize the stepless speed regulation function of the vehicle, reducing the energy loss caused by the gear change mechanism and decoupling vehicle speed and engine speed. The powertrain structure of series-parallel is depicted in Figure 1 (b). The switching between series and parallel drive modes of the series-parallel configuration can be controlled by the clutch, and a gear mechanism is used as the torque coupling device. Series-parallel and power-split HEVs are popular among automobile manufacturers because of their flexibility of the drive train and diversity of available functions.

Since more components increase the powertrain complexity of the combination HEVs, an appropriate energy management strategy is needed to give full play to the advantages of each power source and make up for its disadvantages. Most of energy management control methods can be grouped as three approaches, which include rule-base, optimization-based and learning-based (İnci *et al.*, 2021; Tie and Tan, 2013). There are some advantages and limitations for these strategies in optimality, computational efficiency, and physical causality (Yang *et al.*, 2019). Although it is difficult to perform in real time because of high computing consumption and the weakness that all the information of driving condition needed to be known in advance, global optimization-based energy management strategy can provide high accuracy theoretical optimal control and can be used as a benchmark for other energy management strategies. In addition, the decision-making process of energy management strategy based on global optimization is not affected by configuration parameters, and the global optimal energy allocation scheme under different configuration parameters can be obtained, which fully reflects the fuel saving and emission reduction potential of the hybrid configuration.

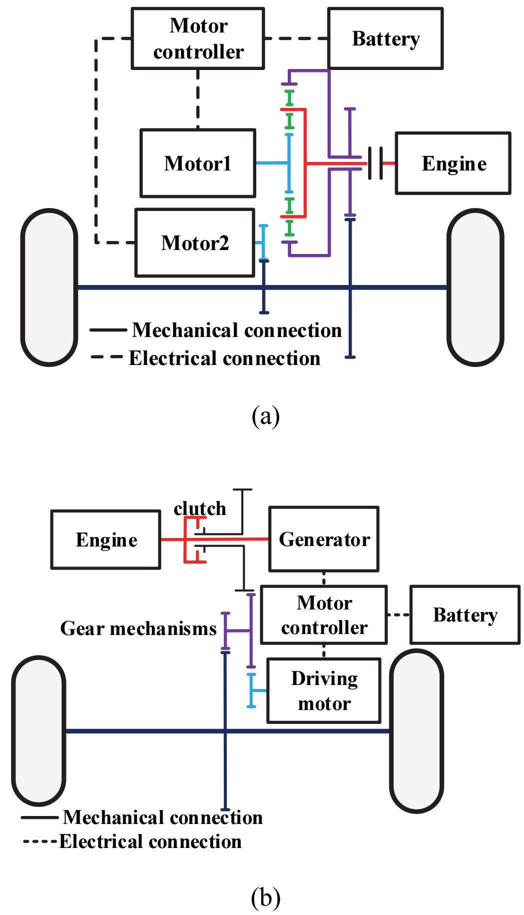


Figure 1. Powertrain structure of HEV: (a) Power-split; (b) Series-parallel.

Some researchers (Ju *et al.*, 2020) have considered using DP to evaluate the energy efficiency of different configurations of four-wheel-drive (4WD) hybrid powertrain, and have made detailed comparisons of fuel economy and power performance indicators for different configurations of 4-wheel drive HEVs. In the literature (Wei *et al.*, 2021), two hybrid powertrain systems are detailed studied and compared by using DP, whose optimization objective is sum of weighted fuel consumption and SOC. Some scholars also use DP to evaluate the economic performance of series hybrid transmissions and series-parallel hybrid transmissions (Xu *et al.*, 2022). Although global energy management optimization methods are adopted in most comparative studies on structure, it is usually considering single objective.

Single objective global optimization methods are hard to handle problems about conflicting objectives, which may cause performance degradation of other objectives when optimizing one objective. Hence, multi-objective global optimization algorithm is needed to meet the practical development requirements. Some multi-objective optimization is to convert the multi-objectives into a single comprehensive objective through some mathematical method, such as the weighted sum method (Fu *et al.*, 2019; Anselma *et al.*, 2020b), which cannot embody the coupling relationship between objectives (Deng *et al.*, 2019). Some researchers also use particle swarm optimization (PSO) (Du *et al.*, 2021) algorithm, ant colony optimization (ACO) (Zhang *et al.*, 2020) algorithm to find optimal parameters and apply non-dominated sorting genetic algorithm (NSGA-II) (Song *et al.*, 2020; Tang *et al.*, 2022a) to solve the non-dominated solution set under multi-objective. The above hybrid optimization multi-objective optimization problem is mainly to optimize the relevant parameters of the HEV under a certain energy management strategy or use a multi-objective optimization method to optimize the relevant parameters of the control strategy. Few studies can consider implementing multi- objective global optimization from the decision-making of energy management. In addition, in the multi-objective optimization, multi degrees of freedom control is often transformed into single degree of control through constraints, which cannot fully exploit the potential of hybrid configurations. Increasing the dimension of control variables can expand the range of action space, and its simulation results are more authentic and reliable.

The contributes of this paper can be listed as follow: (1) A multi-objective global optimization method of Non-dominated sorting dynamic programming (NSDP) is developed to evaluate the economic and battery lifespan performance. The increase of the control variable dimension can increase the search space and improve the performance of the solution; (2) From the perspective of energy management global optimization, the NSDP method is applied to comprehensively evaluate the performance and potential of power-split and series-parallel configurations in terms of fuel consumption and battery lifespan; (3) A complete configuration comparison process based on NSDP is established to provide a comprehensive and reliable evaluation basis for configuration comparison analysis. In addition, the proposed method can also theoretically provide inspiration for solving multi-objective multi-stage decision making problems similar to energy management optimization.

The major content of the rest of the paper is as follows. First, modeling for power-split and series-parallel HEV and next NSDP algorithm and its implementation process is introduced. Then, results of algorithm implementation and optimization in power-split and series-parallel HEV are analyzed. Finally, the two configurations of HEV are comprehensively compared.

2. MODEL OF COMBINATION HEVS

Many studies have been done on battery and motor models, and this paper will refer to one of them (Chen *et al.*, 2018), and the key parameters of the vehicle of the combination HEV are listed in Table 1.

2.1. Engine and Motor Model

The engine and motor model of HEV are built as follow. The engine fuel consumption rate can be donated as $b_e = f(T_e, n_e)$ (Hu and Zhang, 2022), where b_e, T_e, n_e are the fuel consumption rate of engine (g/kWh), engine torque (N·m), engine speed (rad/s). The external characteristic curve of engine is showed in Figure 2 (b). The efficiency of Motor can be donated as $\eta = f(T, n)$ (Hu and Zhang, 2022), where η, T, n are motor efficiency, motor torque (N·m) and motor speed (rad/s). Motor cloud map is shown in Figure 2 (c). Modeling of motors and engines in both configurations are similar except that the parameters are different.

2.2. Battery Model

The power battery parameters and models of two configurations are the same to increase the reliability of comparison. The discrete battery state of charge (SOC) with time can be expressed as (Chen *et al.*, 2018)

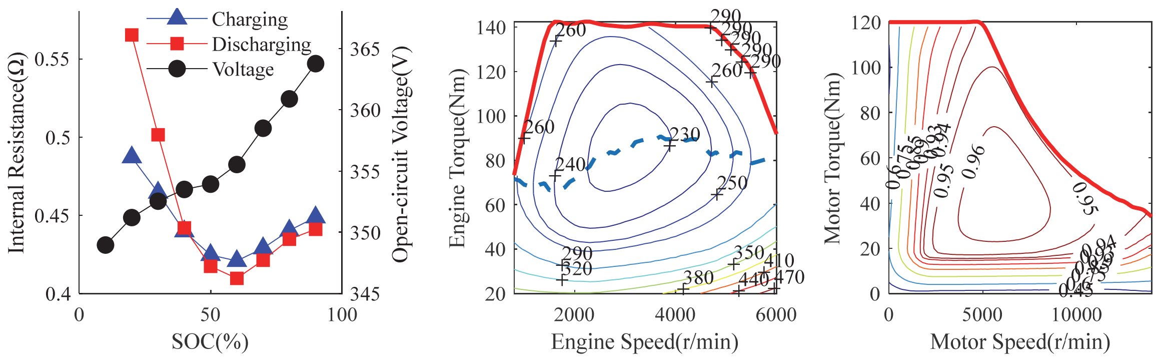
$$\frac{SOC(t_{n+1}) - SOC(t_n)}{t_{n+1} - t_n} = -\frac{U_{oc} - \sqrt{U_{oc}^2 - 4P_{bat}R_{\text{int}}}}{2Q_{nom}R_{\text{int}}} \tag{1}$$

Where U_{oc} is the circuit voltage of the power battery (V), P_{bat} is the output power of the power battery (kW), Q_{nom} is the nominal capacity of the power battery (As), R_{int} is the internal resistance of the power battery (Ω). The relationship of battery parameters is shown in Figure 2 (a).

The concept of accumulated Ah-throughput can be used to measure the battery aging. Accumulated Ah-throughput is the total amount of electrical charge (in both charge and discharge) that can flow to and from the battery before this reaches the end of life. The larger the Ah-throughput, the greater the battery degradation. In order to simplify the calculation, the influence of temperature is ignored.

Table 1. Main parameters of the combination hybrid electric vehicle.

Parameter	Values
Curb weight (kg)	1710
Wheel radius (m)	0.317
Efficiency of transmission system	0.965
Frontal area (m^2)	2.6
Air resistance coefficient	0.32
Rated battery capacity (kWh)	13



(a) (b) (c)

Figure 2 Characteristic curve of power components: (a) Relationship between open circuit voltage and resistance and SOC; (b) Fuel consumption rate of engine; (c) Cloud map of Motor efficiency.

Accumulated Ah-throughput can be simplified and expressed as (Tang *et al.*, 2022b; Serrao *et al.*, 2011):

$$\begin{cases} Ah(t) = \int_{t_0}^{t} \sigma(\tau)\left|I(\tau)\right|d\tau \\ \sigma(\tau) = \dfrac{1.6}{625} I_c^2(\tau) + 1 \\ I_c = \dfrac{I(\tau)}{Q_{nom}} \end{cases} \tag{2}$$

Where *Ah* is accumulated *Ah*-throughput, $\sigma(\tau)$ represents the working strength of the battery related to the charge-discharge rate.

2.3. Transmission System Model

For power-split configuration, the speed and torque relationship between components are shown as (Wu *et al.*, 2018):

$$\begin{cases} T_{MG1} : T_e = 1 : -(1+\alpha) \\ \eta_t i_0 \cdot \left(i_1 T_{MG2} + \dfrac{\alpha}{(1+\alpha)} T_e \right) = T_d \\ n_{MG1} + \alpha \cdot \dfrac{n_{MG2}}{i_1} = (1+\alpha) n_e \\ \dfrac{n_{MG2}}{i_0 i_1} = \dfrac{u_a}{r_v} \end{cases} \tag{3}$$

In the Equation (3), η_t is transmission working efficiency, u_a is vehicle speed, r_v is tire radius, T_d is required torque at wheel end, α is planetary gear characteristic parameter. i_0, i_1 are gear ratio of main reducer and gear ratio between Motor2 and main reducer. T_{MG1}, n_{MG1}, T_{MG2}, n_{MG2} represent the torque and speed of Motor1 and Motor2.

For series-parallel configuration, the speed and relationship between components are shown as (Anselma *et al.*, 2020a):

$$\begin{cases} n_m = \dfrac{i_m \cdot u_a}{r_v} \\ n_e = \dfrac{i_e \cdot u_a}{r_v} \\ T_e \cdot i_e + T_m \cdot i_m = \dfrac{T_d}{\eta_t} \end{cases} \tag{4}$$

The meaning of η_t, u_a, r_v, T_e, n_e, T_d are the same with power-split configuration. T_m and n_m represent the driving motor torque and speed. i_m and i_e represent the gear ratio of motor and engine to wheel end. When the vehicle work in pure electric mode and series mode, torque at wheel end provided by drive model, where $T_e = 0$, $n_e = 0$. When the vehicle work in parallel mode, $T_m = 0$, $n_m = 0$.

2.4. Longitudinal Dynamic Model of HEVs

The longitudinal dynamics model calculates the driving resistance model to obtain the energy requirements of the vehicle. The required torque at wheel end can be calculated by (Anselma *et al*., 2020a):

$$\begin{aligned} T_d = (&mgf\cos(\arctan(i_s)) + mg\sin(\arctan(i_s)) \\ &+ \frac{C_D A}{21.15} u_a^2 + \delta m \frac{du_a}{dt}) r_v \end{aligned} \tag{5}$$

Where m is the curb weight of vehicle (kg), g is the gravity constant (m/s^2), f is the rolling resistance coefficient, i_s is the slope of the road, C_D is the air resistance coefficient; A is the frontal area of the vehicle (m^2), δ is the rotational inertial coefficient.

3. ALGORITHM PROCESS

3.1. Establishment of NSDP Problem

The NSDP method proposed in this paper has multiple objectives and control variables, which is different from traditional DP method. The number of control variables are generally equal to the number of control degrees of freedom of the whole system, so that the action space can be enlarged and the location of the states can be adequately searched. According to the solution idea of DP, the multi-objective multi-stage decision problem can be divided into N sub-stages in time or space, and there are state variables and control variables in each current sub-stage. Therefore, multi-objective DP problem with multi-variable can be described as follows:

$$\begin{aligned}
\min\ F &= \left(f_n^{(1)}, f_n^{(2)}, \ldots, f_n^{(r)}\right)^T \\
f_n^{(r)} &= \sum_{k=1}^{n} J_k^{(r)}\left(x_k, U_k\right) \\
s.t.\quad x_{k+1} &= T_k\left(x_k, U_k\right) \\
p_{1,k} &= \left\{U_1, U_2, \ldots, U_k\right\} \\
U_k &= (u^{(1)}, u^{(2)}, \ldots, u^{(e)})^T \\
k &= 1, 2, \ldots, n
\end{aligned} \tag{6}$$

Where k represents stage k, x_k, U_k, $J_k^{(r)}(x_k, U_k)$ are state variable of stage k, e dimensions vector of each control variable, the r-th instantaneous objective function of optimization objectives. u is one of the components of vector U_k. $p_{1,k}$ is the strategy from initial stage to stage k. $T_k(x_k, U_k)$ is state transfer function of the problem. $f_n^{(r)}$ is optimal objective function value of stage k to final stage.

Pareto optimal theory is widely used in multi-objective optimization. Pareto optimality is an important concept in game theory. It refers to multiple sets of optimal objective solutions. When preference information is not considered, each set of solutions has no advantages or disadvantages, which provides more choices for the initial design. The solution method of NSDP combines the solution method of DP with Pareto mechanism to solve the optimal non-dominated solution set of multiple objectives at each stage of the DP process. The result of the solution is a set of Pareto fronts about the objective function. In this paper, the NSDP solution steps can be shown as follows:

1) The problem is divided into N stages. There are m state variables that donated as x_k^i, $i = 1, 2, \ldots, m$ at stage k, and there are n feasible control variables that donated as $U_{k,i}^j$, $j = 1, 2, \ldots, n$ in each state.
2) At the final stage, the instantaneous function values vector of the feasible control variables and the solution set of the objective function are calculated for each state. The solution set can be donated as $f = (J_{N,i}^{(1)}(x_N^i, U_{N,i}^j), J_{N,i}^{(2)}(x_N^i, U_{N,i}^j), \ldots, J_{N,i}^{(r)}(x_N^i, U_{N,i}^j))$.
3) The optimal objective function is obtained by backward solving. In each state x_k^i, instantaneous objective function values $J_{k,i}(x_k^i, U_{k,i}^j)$ that under the control of vector $U_{k,i}^j$ can be calculated. State value of stage k+1 can be calculated by state transition function $x_{k+1}^* = T_k(x_k^i, U_{k,i}^j)$, and non-dominated solution set of objective function $f_{k+1,i}^*$ added with $J_{k,i}(x_k^i, U_{k,i}^j)$.
4) The result $J_{k,i}(x_k^i, U_{k,i}^j) + f_{k+1,i}^*$ calculated in step 3) is used for non-dominated sorting and crowding distance calculation, which can be donated as

$$f_{k,i}^* = pareto(J_{k,i}(x_k^i, U_{k,i}) + f_{k+1,i}^*) \tag{7}$$

The result $f_{k,i}^*$ is the optimal solution of state x_k^i. Repeat step 3) until all state iterations are completed.
5) Backward solving until k = 1, and the elements of non-dominated solution set for the initial stage and the corresponding control sequence for each stage can be exported.

Table 2. Pseudo code for solving NSD

Algorithm NSDP algorithm

Divide into N stages based on problem characteristics.
Initialize total stage number, state number and feasible control variable number.
Calculate the set of solutions of the objective function for each state at the end stage.
for stage = N, 1 **do**
  for state = 1, m **do**
  Obtain the feasible control set **U** in the determined state from the decision process.
  for control variable = 1, n **do**
  Calculate the instantaneous objective function vector $J_{k,i}(x_k^i, U_{k,i}^j)$.
  Calculate the state of the next stage via the state transfer function $x_{k+1}^* = T_k(x_k^i, U_{k,i}^j)$.
  Calculate $J_{k,i}(x_k^i, U_{k,i}^j) + f_{k+1,i}^*$, and place it into the set Q_k^i.
  end for
  Perform non-dominated sorting and crowding distance calculation on the elements of the set Q_k^i.
  Filter the non-dominated solution set of state i.
  Obtain control variable U^* corresponding to the elements of the set $f_{k,i}$.
  end for
end for
Output the element of non-dominated solution set for the initial stage and the corresponding control sequence for each stage.

3.2. Implementation of NSDP

In this section, detailed implementation process of NSDP algorithm for power-split configuration is described. The implementation process of series-parallel configuration is similar with power-split and will not be detailed.

3.2.1. Discretization of continuous space

In the experiments, WLTC driving cycle is used as the simulation condition, the whole test condition is divided into N stages at an interval of 1 s, and SOC of power battery is taken as the state variable of the problem. There are two control degrees of freedom for power-split HEV, including speed and torque of engine, which are the control variables for the optimization problem donated as $u_{k,i}^{j} = (n_e^j, T_e^j)$, $j = 1, 2, ..., n$. The range of control variables is limited by the external characteristic curve. In particular, when HEV works in pure electric mode, $u_{k,i}^{j} = (n_e^j, T_e^j) = (0, 0)$.

3.2.2. Objective function

The fuel consumption and battery damage of power-split HEV are taken as the optimization objectives. As the speed of the HEV changes frequently during the simulation, it is prone to switch the working mode frequently. This phenomenon has a great impact on the ride comfort of vehicles, and reduces reliability of the simulation. Therefore, mode switching penalty should be added to the instantaneous fuel consumption objective function to reduce the working mode switching.

$$\begin{aligned} &\min f = (f_1, f_2)^T \\ &f_1 = \sum_{k=1}^{N} (B_e(k) + \varphi B_e(k) \cdot \Delta Mode) \\ &f_2 = \sum_{k=1}^{N} Ah(k) \end{aligned} \tag{8}$$

Where, f_1, f_2 are total fuel consumption and accumulated Ah-throughput, $B_e(k)$ is engine fuel consumption in stage k, $Ah(k)$ is Ah-throughput of power battery in stage k. $\Delta Mode$ is flag of mode switching. $\Delta Mode = 1$ if and only if vehicle is in power-split mode at stage k and in pure electric drive mode at stage k+1, otherwise $\Delta Mode = 0$. φ is mode switching coefficient. It is worth noting that if the SOC of the battery is not the same at the beginning and end of the test condition, the difference between the SOC of the battery at the beginning and end of the test condition needs to be converted to fuel consumption additionally, which will affect the solution results. HEV power battery should be set to work in power maintenance mode, which means the SOC of battery at the beginning and end of the test driving cycle are equal.

3.2.3. State equation

According to the Equation (1), the state equation of SOC can be briefly written as

$$SOC(k+1) - SOC(k) = f(U_{oc}(k), R_{\text{int}}(k), Q_{nom}, P_{bat}(k)) \tag{9}$$

Where k and k+1 are the moment k and moment k+1, the meaning of remaining variables above is the same as Equation (1). On the basis of the working principle of power-split HEV, the relationship at moment k between battery power and Motor1 and Motor2 is

$$\begin{aligned} &P_{bat}(k) = P_{MG1}(k) + P_{MG2}(k) \\ &P_x(k) = \frac{T_x(k) \cdot n_x(k)}{\eta_x(T_x(k), n_x(k))} \\ &x = MG1, MG2 \end{aligned} \tag{10}$$

$P_{bat}(k)$, $P_{MG1}(k)$, $P_{MG2}(k)$ are power of power battery, Motor1, Motor2 at stage k (W). When the power is positive, it means that the output power does work to drive the vehicle, and when the power is negative, it means that the input power generates electricity. $T_x(k)$, $n_x(k)$ means torque and speed of Motor1 or Motor2. According to the Equation (3) at the moment k, the speed and torque of Motor1 and Motor2 are related as follows

$$\begin{cases} n_{MG1}(k) = (1+\alpha)n_e(k) - \dfrac{\alpha i_0 u(k)}{r_v} \\ T_{MG1}(k) = -\dfrac{T_e(k)}{1+\alpha} \\ n_{MG2}(k) = \dfrac{i_0 i_1 \cdot u(k)}{r_v} \\ T_{MG2}(k) = \dfrac{T_d(k)}{\eta_t i_0 i_1} - T_e(k) \cdot \dfrac{1}{i_1} \cdot \dfrac{\alpha}{1+\alpha} \end{cases} \tag{11}$$

Where the meaning of variables is the same as Equation (3).

The Equations (10) ~ (11) describe the state of each power source inside the vehicle at moment k. Equation (9) explains the transformation relationship between moment k and moment k+1, and links the two adjacent moments, which is the basis for the reverse solution of NSDP algorithm.

In the solution process, there are physical constraints in all the mechanical and electrical equipment of HEV. Each power component of the HEV needs to meet the following inequalities constraints:

$$\begin{cases} T_{e\_\min} \le T_e(k) \le T_{e\_\max} \\ T_{MG1\_\min} \le T_{MG1}(k) \le T_{MG1\_\max} \\ T_{MG2\_\min} \le T_{MG2}(k) \le T_{MG2\_\max} \\ n_{e\_\min} \le n_e(k) \le n_{e\_\max} \\ n_{MG1\_\min} \le n_{MG1}(k) \le n_{MG1\_\max} \\ n_{MG2\_\min} \le n_{MG2}(k) \le n_{MG2\_\max} \\ SOC_{\min} \le SOC(k) \le SOC_{\max} \\ P_{bat\_\min} \le P_{bat}(k) \le P_{bat\_\max} \end{cases} \tag{12}$$

4. RESULTS OF IMPLEMENTATION

In this scenario, the worldwide light-duty test cycle (WLTC) driving cycle is used for the simulation to obtain the non-dominated solution set about fuel consumption and accumulated Ah-throughput of two configuration hybrids. The implementation results of the algorithm are analyzed in detail.

4.1. Results of Power-split HEV

In the implementation of NSDP process, both the speed and the torque were set as the control variable for power-split configuration. According to the vehicle performance metrics shown in Table 7, the preliminary parameters are obtained and given in Table 3, where $P_{e\_\max}$ is the maximum output power of the engine, $P_{MG1\_\max}$ is the peak power of Motor1, $P_{MG2\_\max}$ is the peak power of Motor2, α is planetary gear characteristic parameter, i_0 the gear ratio of main reducer, i_1 is gear ratio from Motor2 to main reducer.

The solution result of NSDP algorithm is shown in the Figure 3, the SOC change curve corresponding to 200 solutions in the solution set is shown in the Figure 4. The solutions in the two graphs can be corresponded by color scales.

Table 3. Preliminary component parameters of power-split configuration.

Parameters	Values
$P_{e\_\max}$ (kW)	80
$P_{MG1\_\max}$ (kW)	40
$P_{MG2\_\max}$ (kW)	60
α	1.9
i_0	3.078
i_1	2.47

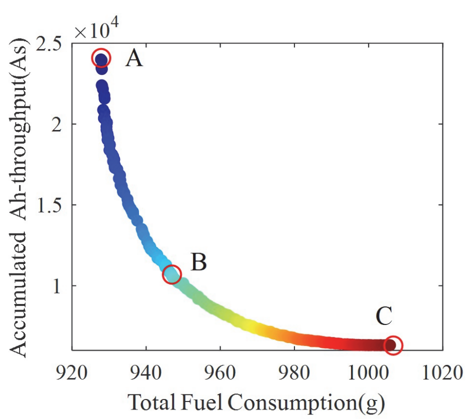


Figure 3. Solution of NSDP optimization algorithm for power-split configuration.

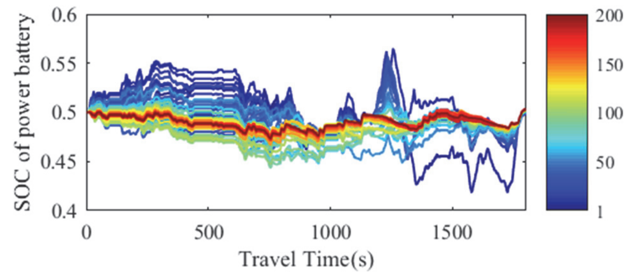
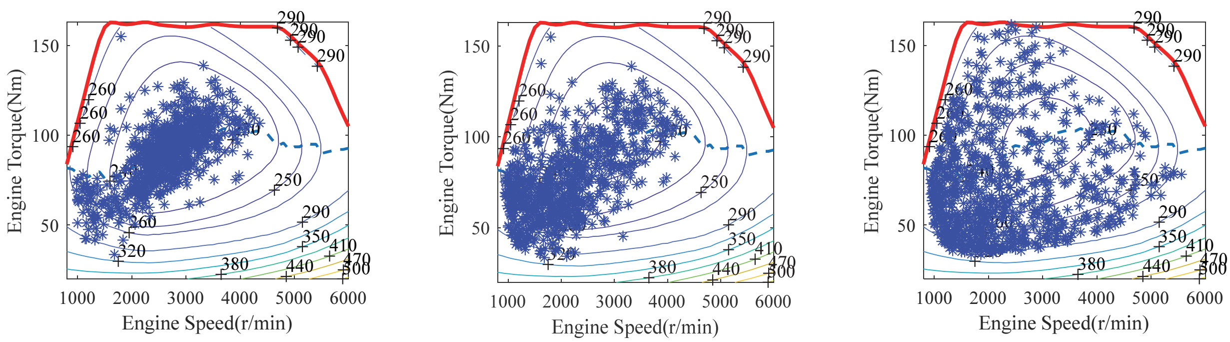


Figure 4. SOC change curve of solution set.

As shown in Figure 3, total fuel consumption and accumulated Ah-throughput are mutually restricted, and the distribution of the non-dominated solution set is relatively uniform. Each solution in the solution set corresponded to a set of control strategies. The strategies corresponding to the left part of the solution set pay more attention to the fuel consumption performance of the HEV, and engine mainly works in the economic region, so the SOC of the power battery changes greatly. The strategies corresponding to the right part of the solution set pay more attention to the battery lifespan of the HEV, and engines output power is mainly used for driving the vehicle rather than transmitting to the battery, so the SOC of the power battery changes relatively smoothly. The solution points A, B and C in the Figure 3 were selected and the calculation result of the performance of the powertrain under the corresponding strategies are shown in Figures 5 ~ 7.

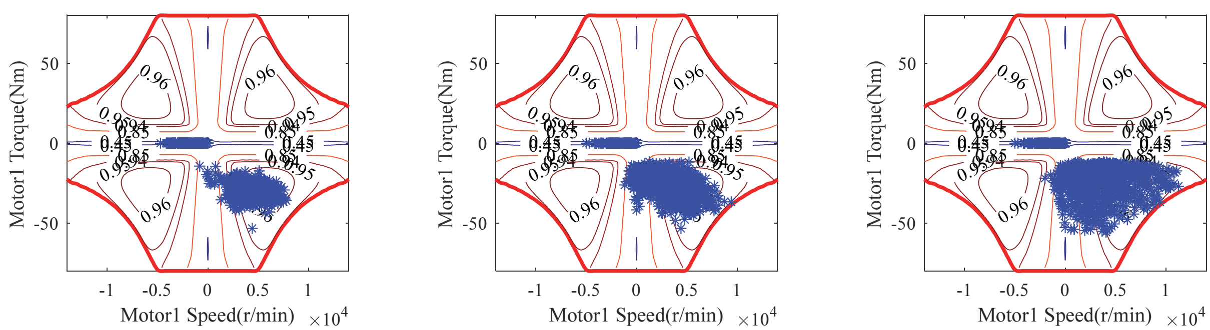
In the case of low vehicle speed and small torque, since the efficiency of the motor is much higher than the working efficiency of the engine, the HEV works in pure electric mode. In the case of high vehicle speed and large torque, power split mode is adopted, because the output power of the powertrain needs to meet the torque and speed demand at the wheel end.

Strategies corresponding to solution point A have the lowest fuel consumption and highest accumulated Ah-throughput. Under these strategies, the operating points of the engine are less affected by the driving condition. They locate in the low fuel consumption area, and the HEV has the high fuel economy. The strategies will increase the use of the HEV pure electric mode and reduce the use of power split mode, which will cause the power battery is charged and discharged at a large rate during the driving process, resulting in a large fluctuation range of SOC throughout the entire test condition, a maximum accumulated Ah-throughput and serious battery degradation. The SOC variation curve of strategies corresponding to solution Point A is shown in Figure 8. In this case, in order to minimize the optimization cost, the operating points of the engine is concentrated in the low fuel consumption area, and the operating points of the motor is concentrated in the efficient working range of the motor. When the power transmitted



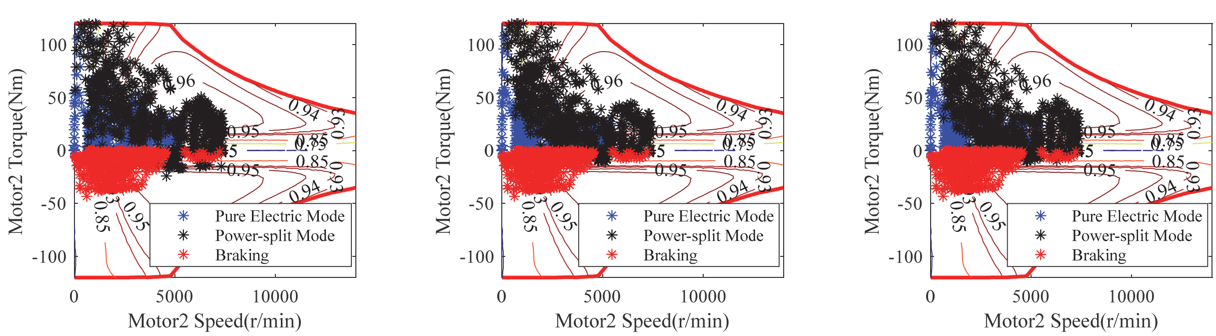
(a) (b) (c)

Figure 5. Engine operating points: (a) Results of point A; (b) Results of point B; (c) Results of point C.



(a) (b) (c)

Figure 6. Motor1 operating points: (a) Results of point A; (b) Results of point B; (c) Results of point C.



(a) (b) (c)

Figure 7. Motor2 operating points: (a) Results of point A; (b) Results of point B; (c) Results of point C.

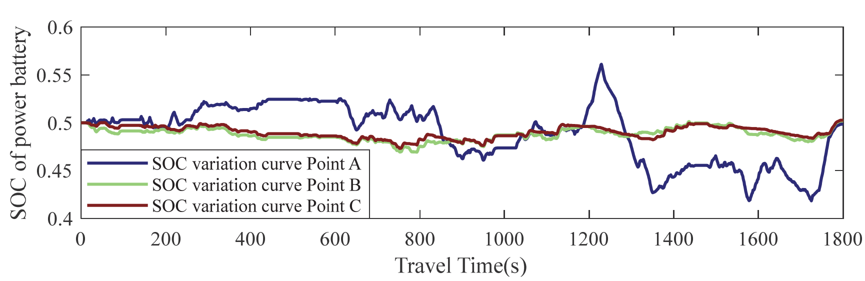


Figure 8. SOC variation curve of point A, B, C during traveling.

from the engine to the wheel end is higher than the driving power demand of the vehicle, the generator (Motor1) charges the power battery. Otherwise, when the power transmitted from the engine to the wheel end is lower than the driving power demand of the vehicle, the power battery provides power to the driving motor (Motor2) to supplement power.

Strategies corresponding to solution point C have the highest fuel consumption and lowest accumulated Ah-throughput. The power battery is charged and discharged at a low rate. It demonstrates strong SOC correction ability, so the SOC changes gently and the battery lifespan decays slowly during driving. The use of power split mode will be increased during HEV actual driving and the use of pure electric mode will be reduced to reduce battery degradation. The SOC variation curve of strategies corresponding to solution Point C is shown in Figure 8. The operating points of the motor move to the high efficiency area, and the power demand of the vehicle is mainly met by the engine. The operating points of engine are scattered, resulting in high fuel consumption and low fuel economy. Strategies corresponding to solution point B have the middle fuel consumption and middle accumulated Ah-throughput, which are the balance of point A and C. Under these strategies, not only should the engine work in the economic area and the motor work in the high efficiency area as much as possible, but also fast charging and discharging of the power battery should be avoided. The fuel consumption and accumulated Ah-throughput change in the whole process should be relatively stable.

It is worth noting that points A, B and C belong to the three representative solutions in the entire non-dominated solution set, and there is no distinction of excellent or bad solutions in the entire non-dominated solution set. Each solution of the non-dominated solution set represents the optimal strategy of each optimization objective under different degrees of attention. Developers can choose appropriate strategies and solutions according to actual needs and optimization objectives, and analyze configuration work characteristics, so as to guide the development of actual energy management and control systems.

Overall, in the changing of the control strategies from Point A to C, it has lower requirement of minimizing fuel consumption and higher requirement of Ah-throughput. The operating points of the engine are becoming more scattered, as shown in Figures 5 (a) to 5 (c). And the working points of the motor shown in Figures 6 (a) to 6 (c) are also becoming more scattered due to the sum of the engine and motor power should remain the similarity in numerical values in the same test condition.

Some researchers reduce the degree of control variable by limiting the engine to work alone the optimal brake specific fuel consumption (BSFC) curve in the power-split configuration (Geng *et al.*, 2020), which can't fully reflect

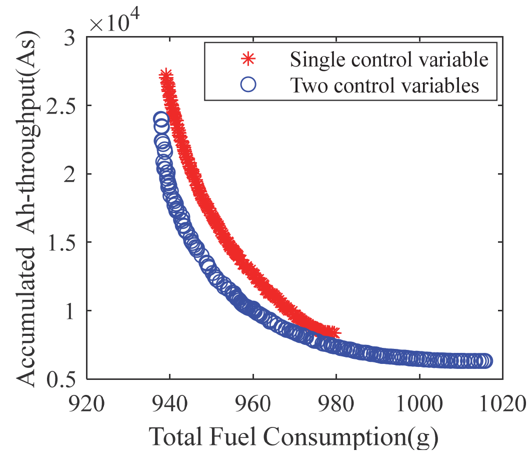


Figure 9. Comparison of results between two control variables and single control variable.

the potential of the configuration. Since the speed and torque of the engine and the motor in the power-split configuration are decoupled, the system control degree of freedom is two-dimensional. Operating the engine on the BSFC curve does not necessarily mean that the sum of its output and the motor's output at a given time is the optimal value.

The minimum fuel consumption achieved by the single control variable scheme and the multi control variables scheme are relatively close. At this time, the engines of both schemes work in the economic region. As shown in Figure 9, compared with the Pareto solution set of the single variable control scheme, the solution set obtained by using engine speed and torque as control variables has a wider range and better performance than the solution set obtained by using only one control variable. This is because the feasible working range of the engine is expanded from the optimal BSFC curve to the whole space of the external characteristics, the working state system is increased, and the operating point for higher battery life can be found. Therefore, NSDP with multi control variables scheme fully exploit the potential of hybrid configuration.

4.2. Results of Series-parallel HEV

The range of powertrain parameters were calculated according dynamic model and vehicle performance metrics shown in Table 7, and preliminary component parameters of series-parallel configuration are calculated and listed in Table 4, where $P_{APU\_\max}$ is maximum output power of engine, $P_{DM\_\max}$ is the peak power of driving motor, $P_{G\_\max}$ is the peak power of generator, i_e gear ratio of engine to wheel end, i_m is gear ratio of driving motor to wheel end.

The energy management optimization problem solving process of series-parallel configuration is similar to power-split configuration. In series-parallel configuration, engine speed and torque are not completely decoupled from

Table 4. Preliminary component parameters of series-parallel configuration.

Parameters	Values
P_{APU_max} (kW)	80
P_{DM_max} (kW)	80
P_{G_max} (kW)	60
i_e	3.339
i_m	7.791

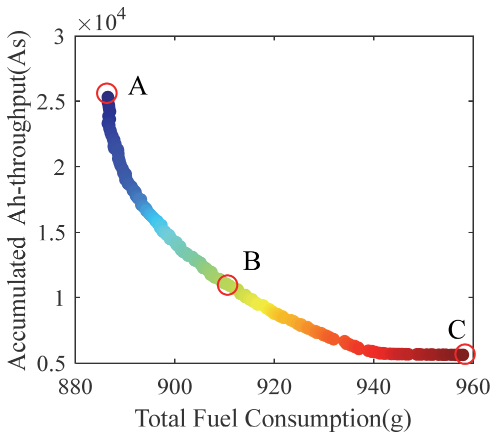


Figure 10. Solution of NSDP optimization algorithm for series-parallel configuration.

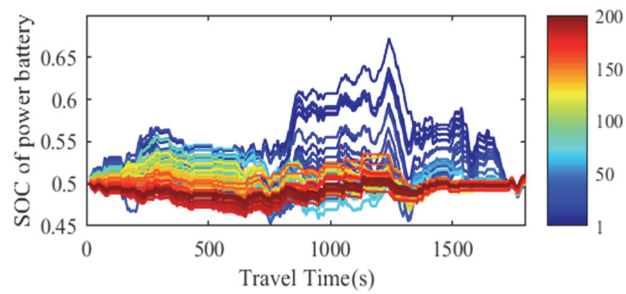


Figure 11. SOC change curve of solution set.

driving conditions, which can't represent all control states and is not suitable for being control variables. Thus, fuel consumption and battery decay were taken as the optimization objectives and considered power distribution coefficient as control variables, where the power distribution the proportion of the power battery output to the required power at the wheel end. The results of the implementation are listed in Figure 10.

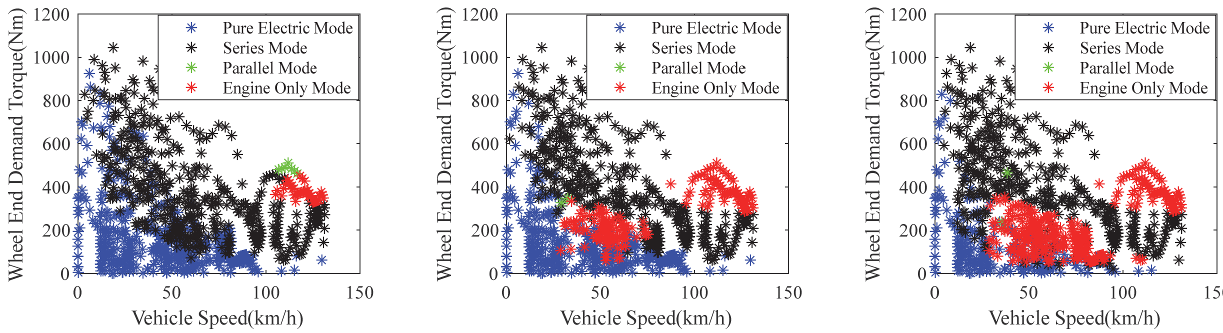
The corresponding solutions at three points A, B and C with minimum total fuel consumption, minimum accumulated Ah-throughput and moderate two optimization objectives are extracted from Figure 10 for analysis. And the results are shown in Figures 12 ~ 15.

According to the figure of operating point for drive mode, vehicle tends to work in pure electric drive mode at low speed or low torque requirements, work in series drive mode under high speed and moderate load, and work in pure engine drive mode and parallel drive mode under heavy load.

Strategies corresponding to solution point A have the lowest fuel consumption and highest accumulated Ah-throughput. In most cases, the required power of the vehicle is supplied directly by the driving motor and the vehicle works in series mode and pure electric mode, which has good fuel efficiency but may lead to significant SOC changes, as shown in the SOC change curve of point A in Figure 16. In the case of high speed and high demand torque, the vehicle works in the pure engine drive mode directly. When the demand torque exceeds supply torque of the engine, the vehicle works in the parallel drive mode to supply part of the power by the driving motor, so that the engine can always work in the economic area.

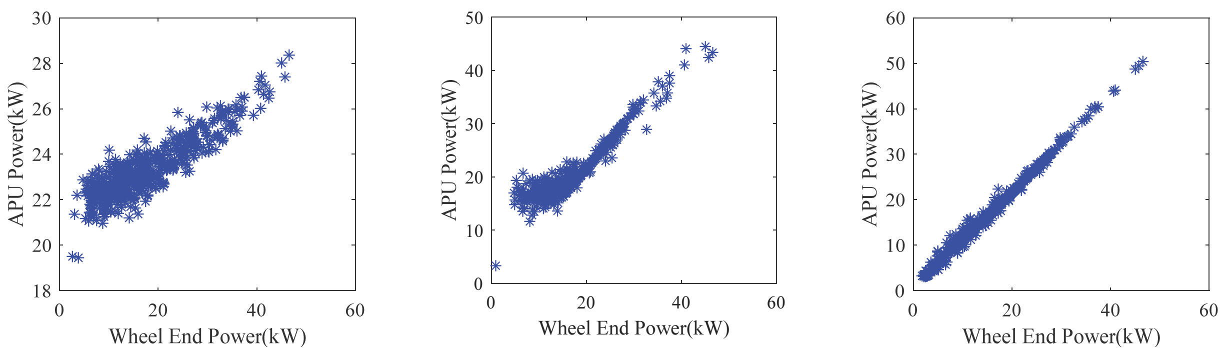
Strategies corresponding to solution point C have the highest fuel consumption and lowest accumulated Ah-throughput. The SOC change range of power battery shown in Figure 16 is much lower than point A, and the battery is charged and discharged in a low rate. In most cases of medium and high speed, the vehicle work in series mode. The output power of APU is basically linearly related to the required power at wheel end, which means the required power at wheel end is basically provided by APU, so as to minimize the charge and discharge of power battery. Besides, the working range of APU is increased. When the vehicle operates in series mode, APU overpower occurs in case of small load at medium and low speed, and APU power shortage occurs in case of high load at high speed Therefore, the pure engine drive mode is mostly used to avoid the power battery from working, so as to reduce the accumulated Ah-throughput. However, the engine working in non-economic areas will lead to fuel consumption increasing.

Strategies corresponding to solution point B have the middle fuel consumption and middle accumulated Ah-throughput, which are the balance of point A and C. In series driving mode, APU output power roughly meets the demand power of the vehicle, and the excess output power of APU charges the power battery at medium and low speed. In general, it can be seen that from control of strategies A to C, the operating conditions of the engine-only mode increase, the engine operating points become more scattered and the magnitude of the SOC variation becomes smaller.



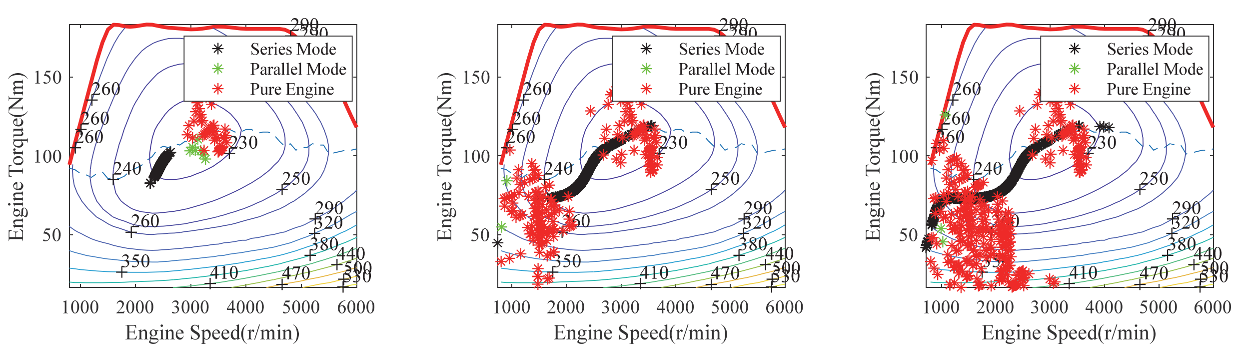
(a) (b) (c)

Figure 12. Driving mode operating points: (a) Results of point A; (b) Results of point B; (c) Results of point C.



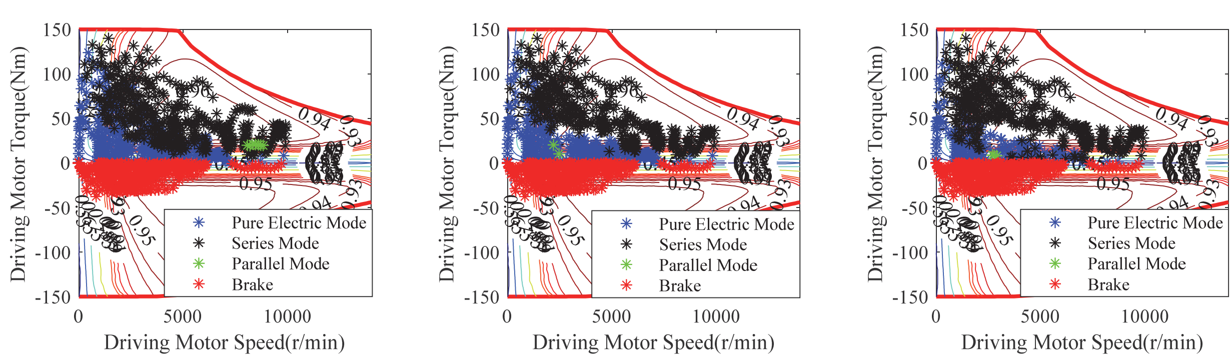
(a) (b) (c)

Figure 13. Power relationship between AUP and wheel end: (a) Results of point A; (b) Results of point B; (c) Results of point C.



(a) (b) (c)

Figure 14. Engine operating points: (a) Results of point A; (b) Results of point B; (c) Results of point C.



(a) (b) (c)

Figure 15. Driving motor operating points: (a) Results of point A; (b) Results of point B; (c) Results of point C.

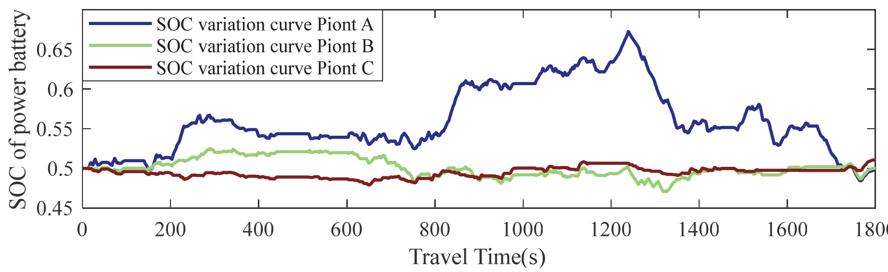


Figure 16. SOC variation curve of point A, B, C during traveling.

Table 5. Optimal component parameters of power-split configuration.

Parameters	Values
$P_{e\_\max}$ (kW)	80
$P_{MG1\_\max}$ (kW)	40
$P_{MG2\_\max}$ (kW)	60
α	2.6
i_0	2.726
i_1	2.47

Table 6. Optimal component parameters of series-parallel configuration.

Parameters	Values
$P_{e\_\max}$ (kW)	80
$P_{DM\_\max}$ (kW)	120
$P_{G\_\max}$ (kW)	50
i_e	3.718
i_m	8.673

5. PARAMETERS OPTIMIZATION AND CONFIGURATION COMPARISON

In this section, a comprehensive comparison of two HEV configurations is performed. Prior to the comparison, the optimal parameter combinations for each configuration are optimized to ensure the fairness of the comparison.

5.1. System Parameters Optimization of Two Configurations

NSDP can solve the fuel economy and battery lifespan performance of hybrid configuration under different strategies, whose results are the excellent reference for system parameter optimization. The working performance of each component should be comprehensively considered in the parameter optimization of hybrid power system. Since the product parameters of optional components are discrete and finite in the actual development process, the orthogonal experiment method can be used to optimize the parameters. Orthogonal experimental is an efficient, fast and economical design method to explore multi-factor and multi-level problems. It can generate orthogonal table based on the principle of orthogonality, compare representative parameter combinations, and determine the main influencing factors and select the best parameter combination efficiently and quickly. The parameters of different configurations will be optimized. In optimization of two configurations, average fuel consumption and average accumulated Ah-throughput of the NSDP solution set are selected as the evaluation metrics.

The parameter optimization results of the power-split configuration are shown in Table 5.

After optimization, fuel consumption and accumulated Ah-throughput have been significantly reduced. In detail, the average fuel consumption decreased by 3.2 % and the average Ah-throughput decreased by 10.0 %.

The parameter optimization results of the series-parallel configuration are shown in Table 6.

After parameter optimization, the total fuel consumption of the series-parallel configuration is significantly reduced, which is more significant than that of the power-split configuration. The optimized average consumption of non-dominated solution set fuel decreases by 6.3 % and the average accumulated Ah-throughput decreases by 12.1 %.

5.2. Configuration Comparison

The configuration of the hybrid system determines the optimal performance and operating characteristics of the HEV. During the development of HEV, factors such as performance and cost of different configurations need to be comprehensively compared and considered. The performance of different configurations is related to HEV parameters and energy control strategies, which are difficult to determine at the beginning of development. Based on NSDP energy management algorithm and orthogonal experimental method, parameters optimization method of hybrid power system has been established in the previous section. This method solves all possible optimal energy management control strategies in each configuration and optimizes parameters using the calculation results of the optimal strategies. In this section, the optimal two different configuration HEVs are comprehensively compared.

In the development of hybrid electric vehicles, configuration comparison analysis is an essential step. The dynamic, economic and system life performance potential of HEV varies with configurations. Researchers need to consider various factors to determine the final system configuration scheme. The dynamic performance metrics of HEV were calculated according to the results of parameter optimization mentioned above, and the calculation results are shown in Table 7.

For the series-parallel configuration, the output torque of the driving motor decreases and can be switched to parallel mode, which can be supplemented by the engine when the HEV driving at high speed. For the power-split configuration, only part of the torque is output to the wheel end and a part of the torque need to be supplied to Motor1 for power generation, when the vehicle working in power-split mode at high speed. Therefore, the power-split configuration is not as dynamic as the series-parallel configuration at high speed under the same dynamic parameters.

Based on the results of parameter optimization for series-parallel configuration and power-split configuration mentioned above, experiments were carried out under WLTC driving cycle, and the results are shown as Figure 17.

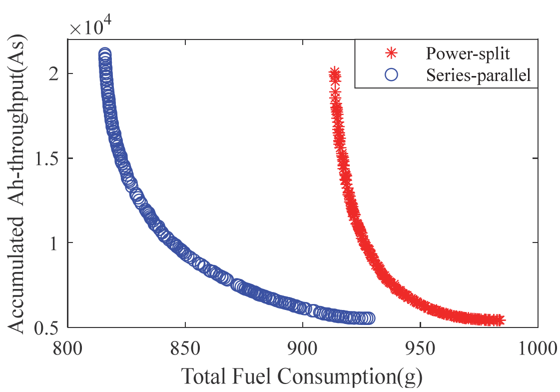
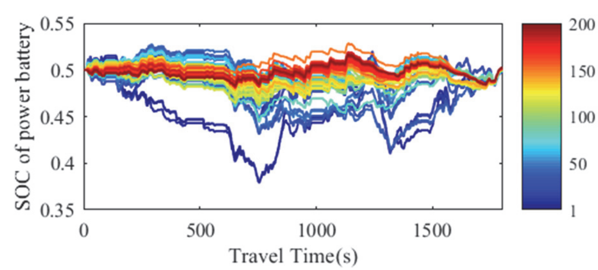


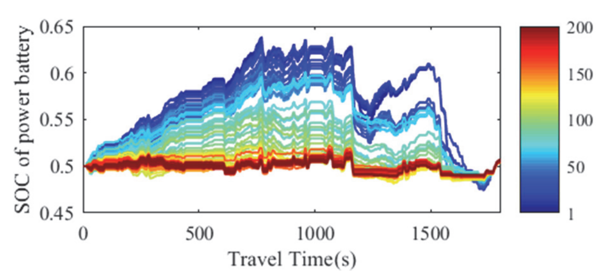
Figure 17. NSDP solution set comparison of two configurations.

In general, the average fuel consumption in series-parallel configuration is 8.9 % lower than that in power-split configuration, and average accumulated Ah-throughput of series-parallel configuration is 9.9 % higher than that of power-split configuration. And the SOC change curves of corresponding strategies for the two configuration solutions sets are shown in Figure 18.

For the right part of the non-dominant solution set which corresponding to the red part in the figures, more attention is paid to the solution of battery life. The trend of SOC change of the two configurations is similar, and power mainly supplied by the engine to minimize the SOC change. For the non-dominant solution left part which pays more attention to fuel economy, the SOC curve of series-parallel configuration shows a trend of rising first and then decreasing. The vehicle is in series mode at low and medium speed, the excess engine power charges the power battery, while the battery energy is consumed at high speed, resulting in a large SOC change of the battery. For



(a)



(b)

Figure 18. SOC change curve of solution set: (a) Power-split configuration; (b) Series-parallel configuration.

Table 7. Dynamic performance parameters of two configurations of HEV.

Vehicle performance items	Required index value	Power-spilt	Series-parallel
Maximum driving speed (km/h)	⩾180	194.3	204.3
0 ~ 100 km/h acceleration time (s)	⩽13	9.3	7.6
Maximum climbing degree (%)	⩾30	30	30
Maximum climbing speed (km/h)	⩾20	28.7	32.3

power-split configurations, HEV works in pure electric drive mode to consume battery power at low speed and works in power-split mode to charge battery at medium and high speed.

Based on the analysis of two configurations, the series-parallel configuration is better than the power-split configuration in power dynamics and fuel economy, while the power-split configuration is better than the series-parallel configuration in battery life. In terms of driving comfort, series-parallel configuration has many operating modes, which need to be switched through clutches for different modes, resulting in frustration and less comfort than power-split configuration. At the same time, the power of generator and driving motor in series-parallel configuration is high, which will increase the cost of the whole vehicle and the difficulty of structure arrangement, and require higher layout space of hybrid power system.

In terms of engine operation, power-split engine operating points are more scattered than those of series-parallel engine, especially those on the right part of the non-dominant solution set, which cover the entire engine external characteristic area. This is because the engine torque and speed are uncoupled under two-dimensional control variables and the engine has more exploration space.

6. CONCLUSION

In this paper, a multi-objective energy management optimization algorithm was established to meet the requirements of configuration comparison analysis in hybrid electric vehicle development. Based on the results of energy management optimization and orthogonal experimental method, the parameters of hybrid power system were optimized, which provides a comprehensive and reliable evaluation basis for configuration comparison analysis. The solution flow of NSDP algorithm is proposed based on the non-dominant sorting and DP methods. With power-split configuration and series-parallel configuration as research objects, the simulation models were respectively constructed. The NSDP algorithm was used to solve the optimal energy management strategy, and the working characteristics of the two configurations under different strategies were analyzed. Parameter orthogonal optimization experiments of two configurations were carried out based on orthogonal experimental method to determine the optimal parameter combination of two configurations, which improve the fuel economy and battery life. The power dynamic performance, fuel economy, battery life and other aspects of the two configurations were analyzed and compared. The comparison results show that the power-split configuration has advantages in battery life, comfort and arrangement cost, while the series parallel configuration performs better in power performance and fuel economy.

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