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Optimization of Power-System Parameters and Energy-Management Strategy Research on Hybrid Heavy-Duty Trucks

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Abstract: Hybrid heavy-duty trucks have attracted wide attention due to their excellent fuel economy and high mileage. For power-split hybrid heavy-duty trucks, the optimization of powertrain parameters is closely related to the control strategies of hybrid vehicles. In particular, the parameters of the powertrain system will directly affect the control of the vehicles’ power performance and economy. However, currently, research on hybrid heavy-duty trucks employing power-split configurations is lacking. Furthermore, few studies consider both the optimization of powertrain parameters and the control strategy at the same time to carry out comprehensive optimization research. In order to address these issues, this paper focuses on the fuel economy of hybrid heavy-duty trucks with power-split configurations. Improved particle swarm optimization (IPSO) and dynamic programming (DP) algorithms are introduced to optimize powertrain parameters. With these methods being applied, hybrid heavy-duty trucks show a 2.15% improvement in fuel consumption compared to that of the previous optimization. Moreover, based on the optimal powertrain parameters, a DP-based rule-control strategy (DP-RCS) and optimal DP-RCS scheme are presented and used in this paper to conduct our research. Simulation results show that the optimal DP-RCS reduces fuel consumption per hundred kilometers by 11.35% compared to the rule-based control strategy (RCS), demonstrating that the combination of powertrain parameter optimization and DP-RCS effectively improves the fuel economy of hybrid heavy-duty trucks.

Keywords: power-split hybrid heavy-duty trucks; energy management; powertrain parameters; dynamic programming; improved particle swarm optimization; optimal DP-RCS

1. Introduction

With growing problems of energy consumption and environmental pollution, the energy crisis and climate change have attracted more and more attention from all over the world. The large consumption of fuel and emission of exhaust gas have a seriously negative impact on these issues. Consequently, there is an urgent need for countries to develop energy-efficient vehicles to cope with the global energy crisis and climate change [1]. Hybrid electric vehicles (HEVs), with their low energy consumption and extended driving range, are widely recognized as a public transportation solution with significant potential for further development [2,3]. HEVs, as distinguished from conventional vehicles, are equipped with new types of energy storage devices such as batteries or supercapacitors. As sustainable energy storage technologies, they possess advantages such as long cycle life and less pollution [4].

HEVs can be classified into series, parallel, and series–parallel types based on system configuration. However, the most representative series–parallel configuration is the power-split configuration. Power-split hybrid electric vehicles (PSHEVs) have received
widespread attention and application due to their excellent fuel economy [5]. Numerous automobile manufacturers worldwide are actively investing in the development of HEVs, and currently, PSHEVs have taken a dominant position in the market [6,7]. However, the complexity of the structure of power-split hybrid heavy-duty trucks leads to two important issues that must be considered during the study of their fuel consumption. Firstly, the impact of key parameters of the power system on vehicle fuel consumption must be considered, as their rational optimization can improve the vehicle’s fuel economy. Secondly, the development of efficient energy-management control strategies can further enhance the fuel economy of the vehicle. The focus of this paper is a hybrid heavy-duty truck, specifically a heavy-duty dump truck. Compared to general vehicles, heavy-duty dump trucks face more complex and variable operating conditions. Therefore, when facing such complex conditions, it is crucial to optimize key parameters of the powertrain system or control strategies for hybrid heavy-duty dump trucks in order to reduce fuel consumption.

1.1. Optimization of Key Parameters

To improve fuel economy, the optimization of key parameters of the power system in hybrid heavy-duty trucks has become research focus. Common optimization algorithms include simulated annealing (SA) [8], particle swarm optimization (PSO) [9–11], and the genetic algorithm (GA) [12]. Yang et al. combined PSO and rapid dynamic programming (rapid-DP) to optimize the key parameters of the power system of power-split hybrid vehicles. Simulation analysis indicates that the fuel consumption of the vehicle was reduced by 6.56% and 3.15% under FTP72 and HWFET cycle conditions, respectively [13]. Chu et al. conducted a parallel hybrid powertrain parameter optimization study and performed simulation analysis under urban driving cycle conditions in China; they achieved a higher fuel economy with the same state of charge (SOC) before and after optimization [14]. Sheng et al. used the GA to optimize the gear ratio of a two-speed AMT in a pure electric vehicle. Simulation verification under the NEDC cycle showed that the driving range increased by 5.85% after optimization [15]. Hao et al. optimized the key parameters of the energy-management strategy for parallel hybrid electric vehicles using the DIRECT algorithm. Seven key parameters, including engine torque and battery state of charge (SOC), were identified for optimization, and the effectiveness of the DIRECT algorithm was validated [16]. Fu et al. conducted powertrain system parameter-matching optimization for parallel hybrid electric vehicles, with parameters including motor maximum torque and engine maximum torque. Their proposed parameter-matching optimization methods for hybrid electric vehicles significantly reduce fuel consumption compared to that of traditional methods [17].

1.2. Optimization of Energy-Management Strategies

The energy-management control strategies are mainly divided into rule-based control strategies, optimization-based control strategies, and based-on-learning control strategies. Based-on-learning strategies for HEVs and other control problems have been investigated. For example, Nuchkrua et al. explored the application of pneumatic artificial muscle (PAM) based on metal hydride (MH) as a compact compliant actuator and applied a learning-based adaptive robust control to solve the problem of PAM actuator compliance control [18]. Ma et al. conducted research on short-term household load forecasting in the context of home energy-management systems (HEMS). Firstly, they presented the application of deep-learning algorithms such as recurrent neural networks (RNN), long short-term memory (LSTM), and convolutional neural networks (CNN) in short-term household load forecasting. Meanwhile, they proposed that combining forecasts using multiple deep-learning methods can effectively improve model generalization [19]. Learning-based control strategies such as deep learning are helpful for the research of fuel economy in hybrid heavy-duty trucks. However, based-on-learning strategies usually require heavy computational resources, which leads to difficult implementation in real-time applications.
with automobiles. The advantages of rule-based control strategies (RCSs) include low computation burden, good stability, and reliability. In engineering practice, in order to consider the implementation ability of energy-management strategies, engineers often adopt energy-management strategies based on logical threshold rules [20,21]. However, the formulation of traditional strategies based on logic-threshold rules relies on expert experience, so it is difficult to guarantee the optimality of fuel consumption. Optimization-based control strategies are mainly divided into global optimization and real-time optimization [22]. A typical representative of global optimization methods is dynamic programming (DP) [23–26]. DP has the drawback of complex computation and is unsuitable for real-time control of real vehicles, but it has been recognized as the standard for energy optimization of HEVs due to its ability to obtain globally optimal solutions [27]. More importantly, DP can use its optimal solution to extract the optimal control strategy based on RCSs, which can further improve the fuel economy of conventional RCSs.

The DP-based rule-control strategy (DP-RCS) has been increasingly attracting researchers’ attention due to its outstanding fuel economy and online applicability. Riccardo et al. designed an energy-management strategy for medium-sized parallel hybrid trucks by extracting rules from the DP algorithm [28]. Domenico et al. extracted rules from the global optimal results of the DP and proposed a feasible RCS for series/parallel hybrid vehicles [29]. Peng et al. proposed a recalibration method to improve the performance of the RCS by using the results calculated by the DP [30]. Fan et al. proposed an offline parameter extraction method with the DP algorithm for plug-in P2 hybrid electric buses, aiming to improve driving performance. In this method, three typical driving cycles were considered and applied to extract the boundary conditions for engine start/stop state switching and gear shifting. Finally, it was concluded that these boundary conditions have a significant effect on driving performance [31]. After determining the energy-management strategy for a hybrid heavy-duty truck, powertrain parameters and the selected control strategy interact with each other and collectively determine the fuel economy of a hybrid vehicle [32].

However, in the aforementioned studies, it is evident that there is lack of attention towards the following topics. Firstly, the selection of the vehicle configuration has been studied for parallel configurations, with limited focus on complex configurations such as power-split configuration. Furthermore, the research on hybrid vehicles has paid less attention to powertrain parameters (e.g., final drive ratio, transmission gear ratio) optimization and has mainly focused on optimizing threshold parameters of certain components in the strategy. Finally, few studies consider both the optimization of powertrain parameters and control strategy at the same time. Therefore, the objective of this study is to investigate the fuel economy of hybrid heavy-duty trucks employing power-split configurations. Special attention is given to the optimization of powertrain parameters for hybrid heavy-duty trucks, in conjunction with the DP-RCS, to provide an effective optimization approach to enhance the fuel efficiency of hybrid heavy-duty trucks.

The contributions of this paper mainly include the following two aspects: (1) Using the improved particle swarm optimization (IPSO) algorithm and the DP algorithm to optimize powertrain parameters of hybrid heavy-duty trucks. (2) Designing the DP-RCS and obtaining the optimal DP-RCS scheme to further improve the fuel economy of hybrid heavy-duty trucks based on optimal powertrain parameters.

The rest of this paper is organized as follows: Section 2 introduces the model of a hybrid heavy-duty truck and the modeling of the whole-vehicle components. Section 3 introduces the IPSO and DP algorithms and presents the optimization simulation of powertrain parameters. Section 4 first introduces the RCS and DP-RCS, and then designs the optimal DP-RCS. Section 5 describes some results and analyses. Conclusions are drawn in Section 6.
2. Modeling of the Power System

The subject of this study is a hybrid heavy-duty truck, and the structure of its powertrain is shown in Figure 1. The power system mainly consists of an engine (ICE), a generator (MG1), a drive motor (MG2), a battery pack, and a coupling mechanism planetary gear (PG1). The ICE, MG1, MG2 serve as the main power sources of the vehicle. The function of the battery pack is to provide electricity to MG1 and MG2, and the electricity generated by MG1 can also be stored in the battery pack to maintain the balance of the vehicle’s electricity. PG1 serves as a power-split mechanism, where engine power can be converted into electrical and mechanical power. The relevant parameters of the hybrid heavy-duty truck are shown in Table 1. The ICE is connected to the planetary carrier of PG1, and the connection and disconnection of the engine are controlled by the clutch. The MG1 is connected to the sun gear of the PG1, the MG2 is connected to the ring gear of the PG1 through a reduction gear, and the power is transmitted to the automatic manual transmission (AMT) through the ring gear, and then to the wheels through the main reduction gear.

![Figure 1. Powertrain system configuration.](image)

Table 1. Main parameters of the hybrid heavy-duty truck.

<table>
<thead>
<tr>
<th>Component</th>
<th>Parameter (Unit)</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle</td>
<td>Vehicle curb mass (kg)</td>
<td>31,000</td>
</tr>
<tr>
<td></td>
<td>Wheel radius (m)</td>
<td>0.528</td>
</tr>
<tr>
<td></td>
<td>Frontal area (m²)</td>
<td>8.28</td>
</tr>
<tr>
<td></td>
<td>Wind resistance coeff.</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td>Rolling resistance coeff.</td>
<td>0.0041 + 0.000025 v</td>
</tr>
<tr>
<td>ICE</td>
<td>Maximum power (kW)</td>
<td>243</td>
</tr>
<tr>
<td></td>
<td>Maximum torque (Nm)</td>
<td>1400</td>
</tr>
<tr>
<td></td>
<td>Maximum speed (rpm)</td>
<td>2200</td>
</tr>
<tr>
<td>MG1/MG2</td>
<td>Maximum power (kW)</td>
<td>110/196</td>
</tr>
<tr>
<td></td>
<td>Maximum torque (Nm)</td>
<td>700/375</td>
</tr>
<tr>
<td></td>
<td>Maximum speed (rpm)</td>
<td>8500/15,000</td>
</tr>
<tr>
<td>Transmission</td>
<td>Transmission ratio of PG1</td>
<td>4.4</td>
</tr>
<tr>
<td></td>
<td>AMT gear ratio</td>
<td>6.3/2.1/1/0.86</td>
</tr>
<tr>
<td></td>
<td>Final drive ratio</td>
<td>5.1</td>
</tr>
<tr>
<td>Battery</td>
<td>Capacity (Ah)</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>Voltage (V)</td>
<td>576</td>
</tr>
</tbody>
</table>

2.1. Power-Split Model

The power distribution of the hybrid heavy-duty truck system is shown in Figure 2. In the power-split hybrid heavy-duty truck, the PG1 is used as the power-split mechanism, and the output power of the engine is split by it. Part of the engine’s output power...
is converted into electrical power by the MG1 and then converted into mechanical power by the MG2 and transmitted to the output shaft through the reduction gear. Another part is directly transmitted to the output shaft through the ring gear at PG1 in the form of mechanical power. Therefore, it is possible to achieve dual decoupling of engine speed and torque from the wheels and allow the engine to always work at high efficiency [33].

Figure 2. Power-split block diagram.

The corresponding speed and torque relationships of power-split system are as follows [34]:

\[
\begin{align*}
    n_{\text{MG1}} &= (1 + k_1)n_{\text{ICE}} - k_1 n_{\text{out}} \quad (1) \\
    n_{\text{MG2}} &= k_2 n_{\text{out}} \quad (2) \\
    T_{\text{MG1}} &= -\frac{T_{\text{ICE}}}{1 + k_1} \quad (3) \\
    T_{\text{out}} &= \frac{k_1 T_{\text{ICE}}}{1 + k_1} + k_2 T_{\text{MG2}} \quad (4)
\end{align*}
\]

where \(T\) and \(n\) denote torque and speed, respectively, and out denotes the output shaft of the power-split system. \(n_{\text{MG1}}, n_{\text{MG2}}, \) and \(n_{\text{ICE}}\) donate the speed of MG1, MG2, and ICE, respectively; \(T_{\text{MG1}}, T_{\text{MG2}}, \) and \(T_{\text{ICE}}\) denote the torque of MG1, MG2, and ICE, respectively; \(n_{\text{out}}\) and \(T_{\text{out}}\) denote the output speed and output torque of the power-split system, respectively. \(k_1\) is the transmission ratio of the PG1, and \(k_2\) is the gear ratio of the MG2.

Correspondingly, the relationship between the torque of the power-split output shaft and the vehicle driving force can be obtained as follows:

\[
T_{\text{out}} = \frac{F_R}{i_s i_0} \quad (5)
\]

where \(F_r\) denotes the driving force of the vehicle, \(R\) denotes the wheel radius, \(i_s\) denotes the gear ratio, and \(i_0\) denotes the main reduction ratio.

2.2. Vehicle Longitudinal Dynamics Model

In the modeling process, the effects of lateral and vertical dynamics are ignored. The resistance of the vehicle is determined by rolling resistance, air resistance, slope resistance, and acceleration resistance. Based on the longitudinal dynamics of the vehicle, the vehicle dynamics equation is as follows [35]:

\[
F_r = m g f \cos \varphi + m g \sin \varphi + \frac{1}{2} \rho C_d A v^2 + \sigma m \dot{v} \quad (6)
\]
where \( F_d \) denotes the required driving force of the vehicle, \( m \) denotes the total vehicle mass, \( g \) denotes the gravitational acceleration, \( f \) denotes the rolling resistance coefficient, \( \varphi \) denotes the road slope angle, \( \rho \) denotes the air density, \( C_D \) denotes the air drag coefficient, \( A \) denotes the windward area, \( v \) denotes the vehicle speed, \( \sigma \) denotes the rotational mass conversion coefficient, and \( \ddot{v} \) denotes the acceleration.

2.3. ICE Model

There are numerous methods for engine modeling, including both theoretical modeling and experimental modeling. In theoretical modeling, due to the complexity of the model and the lengthy computation time, it is challenging to apply the model to practical optimization algorithms [36]. Therefore, only a quasi-static simulation model based on the corresponding bench-test data is established in this paper. Furthermore, in this paper, the operating points of the engine are preferentially selected based on the universal characteristics of the engine, and each operating point corresponding to the torque point with the lowest fuel consumption is connected one by one to extract the optimal operating curve of the engine, as shown in Figure 3.

2.4. Motor Model

The type of motor selected in this study is a permanent magnet synchronous motor, which acts as a traction motor during the driving process and as a generator during the braking process. Finally, similar to engine modeling, this paper establishes a quasi-static simulation model for motors based on bench-test data.

The power when the motor is operating in the driving state is:

\[
\eta = \frac{P_{\text{motor, req}}}{\frac{T_w}{\omega_w} / \eta_m}
\]

where the \( P_{\text{motor, req}} \), \( T_w \), \( \omega_w \), and \( \eta_m \) denote the required power, torque, angular speed, and efficiency of the drive motor, respectively.

The power when the motor is operating in the generating state is:

\[
P_{\text{gen, req}} = \frac{T_g}{\omega_g} \eta_g
\]

where the \( P_{\text{gen, req}} \), \( T_g \), \( \omega_g \), and \( \eta_g \) denote the required power, torque, angular speed, and efficiency of the generator, respectively. The motor efficiency \( \eta_j (j \in \{m, g\}) \) is a function of the angular speed \( \omega_j \) and torque \( T_j \), as shown in Figure 4.

\[
\eta_j = f(\omega_j, T_j)
\]
2.5. Battery Model

In this paper, the effect of temperature on the power battery is neglected in the process of modeling the battery. The battery is modeled with a common equivalent circuit, as shown in Figure 5. The voltage characteristic curve of the battery is shown in Figure 6, and as can be seen in Figure 6, the open-circuit voltage depends on the state of charge (SOC) of the battery. The relevant equations for battery power, current, and SOC are as follows:

\[
P_{\text{batt}} = U_{\text{oc}} I_{\text{batt}} - I_{\text{batt}}^2 R_{\text{batt}}
\]  \hspace{1cm} (10)

\[
I_{\text{batt}} = \frac{U_{\text{oc}} - \sqrt{U_{\text{oc}}^2 - 4R_{\text{batt}} P_{\text{batt}}}}{2R_{\text{batt}}}
\]  \hspace{1cm} (11)

\[
\text{SOC} = \text{SOC}_0 - \frac{1}{Q_{\text{batt}}} \int_0^T I_{\text{batt}}(t)dt
\]  \hspace{1cm} (12)

where \( P_{\text{batt}} \), \( U_{\text{oc}} \), \( I_{\text{batt}} \), and \( R_{\text{batt}} \) denote the power, open-circuit voltage, current, and internal resistance of the battery, respectively. \( \text{SOC}_0 \) and \( Q_{\text{batt}} \) denote the initial SOC and battery capacity, respectively.
3. Verification of Local Optimization of Powertrain Parameters Based on DP and IPSO

3.1. DP Algorithm

Dynamic programming (DP) is an optimization method first proposed by Bellman [37] to solve multi-stage decision problems. Based on Bellman’s optimality principle, DP transforms multi-stage decision problems into a series of single-stage problems, thereby simplifying the problem-solving form. DP has a solid application foundation in the optimization problem of energy-management strategies for hybrid power systems. The dynamic programming algorithm is divided into two processes to solve the problem: The first process is a reverse direction solution, using recursive equations starting from the last stage to find the optimal performance indicators and optimal control variable parameters for each state. The second process is a forward recursive process for finding the optimal control sequence and the optimal trajectory, and for finding the corresponding optimal control from the given initial state.

In this paper, the dynamic programming algorithm is used, and the simulation is carried out under the CHTC-D test conditions, as shown in Figure 7.

DP adopts a discrete time form, taking the battery SOC as the state variable and the engine power and gear ratio as the control variables. The corresponding state variables, control variables, and transition functions can be expressed as [38]:

\[ x(k) = [\text{SOC}(k)] \]  \hspace{1cm} (13)

\[ u(k) = [P_{\text{ICE}}(k), i_e(k)], g = 1, 2, 3, 4 \]  \hspace{1cm} (14)

\[ x(k+1) = f[x(k), u(k)], k = 0, 1, \ldots, N-1 \]  \hspace{1cm} (15)
where $x(k)$ denotes the state variables in stage $k$ and $x(k+1)$ denotes the state variables in stage $k+1$. $u(k)$ denotes the control variables in stage $k$, and $k$ denotes the discrete sampling time. $SOC(k)$ denotes the battery SOC in stage $k$; $P_{ICE}(k)$ and $i_g(k)$ denote engine power and transmission gear ratio in stage $k$, respectively. $g$ denotes the number of the transmission gear ratio. In the hybrid system, the battery SOC can reflect the current state of the system, and the corresponding state transition equation is as follows:

$$SOC(k+1) = SOC(k) - \frac{I_{batt}(k) \cdot \Delta t}{Q_{batt}}$$

(16)

where $\Delta t$ denotes the time step. $SOC(k+1)$ denotes the battery SOC in stage $k+1$.

The related constraints should be met during the optimization process to ensure the operability of key powertrain components. The global optimization problem of DP can be formulated as follows:

$$\min_{u(t)} J(u(t))$$

s.t. $SOC_{\min} < SOC(t) < SOC_{\max}$

$$P_{ICE_{\min}} < P_{ICE}(t) < P_{ICE_{\max}}$$

$$P_{MG1_{\min}} < P_{MG1}(t) < P_{MG1_{\max}}$$

$$P_{MG2_{\min}} < P_{MG2}(t) < P_{MG2_{\max}}$$

$$i_g(k) \in [6.3, 2.1, 1, 0.86]$$

(17)

where the subscripts ICE, MG1, and MG2 denote the engine, generator, and motor, respectively. $P_{ICE_{\min}}$ and $P_{ICE_{\max}}$ denote the bound range of engine power. $P_{MG1_{\min}}$ and $P_{MG1_{\max}}$ denote the bound range of generator power. $P_{MG2_{\min}}$ and $P_{MG2_{\max}}$ denote the bound range of drive motor power. $SOC_{\min}$ and $SOC_{\max}$ denote the bound range of battery SOC. $J(u(t))$ denotes the cost function of fuel consumption of the hybrid heavy-duty truck system. The studied vehicle is a hybrid electric vehicle rather than a plug-in hybrid electric vehicle or electric vehicle, so we cannot charge the battery through an external power source. Thus, the SOC penalty function is introduced to maintain the battery SOC within a certain range. The corresponding expression is:

$$J(u(t)) = \alpha [SOC(t) - SOC_f]^2 + \int_0^{t_f} m_{fuel}(x(t), u(t), t) dt$$

(18)

where $m_{fuel}(x(t), u(t), t)$ denotes the instantaneous cost function. $\alpha [SOC(t) - SOC_f]^2$ denotes the penalty function of the final SOC value, and $\alpha$ denotes the penalty factor.

### 3.2. IPSO + DP Algorithm

This section first introduces the PSO algorithm and its corresponding optimization process, and then proposes an improved particle swarm optimization (IPSO) algorithm. Subsequently, the DP is combined with the IPSO algorithm to jointly optimize powertrain parameters of the hybrid heavy-duty truck to further improve the fuel economy of the vehicle. The PSO and its corresponding search process are introduced below [39].

The PSO algorithm was first proposed by Kennedy and Eberhart [40] and has been widely used for optimization in engineering. The characteristics of particle swarm optimization are fast search speed and easy implementation, but there is also a problem of premature convergence. Therefore, PSO uses inertia weights and acceleration factors to improve the algorithm’s ability to solve the global optimal solution. In the search for multidimensional space, PSO uses two main parameters, particle position $x_i$ and particle
speed \( v \). The positions and speeds of all particles \([41,42]\) are updated according to the following formula:

\[
v_{i}^{k+1} = \alpha v_{i}^{k} + c_{1}r_{1}\cdot(p_{i}\text{Best} - x_{i}^{k}) + c_{2}r_{2}\cdot(g_{i}\text{Best} - x_{i}^{k}) \tag{19}\]

\[
x_{i}^{k+1} = x_{i}^{k} + v_{i}^{k+1} \tag{20}\]

where \( x_{i}^{k} \) and \( v_{i}^{k} \) denote the position and velocity of the \( i \)-th particle evolved to the \( k \)-th generation, respectively; \( p_{i}\text{Best} \) denotes the individual optimal position of the \( i \)-th particle; \( g_{i}\text{Best} \) denotes the optimal position in the population; \( c_{1} \) and \( c_{2} \) denote acceleration factors; \( r_{1} \) and \( r_{2} \) are random numbers distributed in \([0, 1]\); and \( \alpha \) denotes the inertia weight.

In the general PSO, the larger the inertia weight \( \alpha \) is, the faster the particle’s flight speed is, and the particle will perform a global search with a larger step. However, if \( \alpha \) is excessively large, it can lead to issues such as “premature convergence” and oscillations in the vicinity of the global optimal solution. The smaller the value of \( \alpha \), the finer the particle’s step towards a localized search. However, if \( \alpha \) is excessively small, it will significantly increase the final convergence time of the particle.

Therefore, this paper proposes an IPSO algorithm, where the inertia weight is designed as an adaptive inertia weight \((w)\). As the objective values of the particles tend to be consistent or tend to be locally optimal, IPSO will adjust by increasing the inertia weight. Conversely, when the objective values of the particles are relatively dispersed, the IPSO will decrease the inertia weight. Simultaneously, particles outperforming the average objective value possess a lower associated inertia weight, allowing IPSO to retain these particles. Conversely, for particles whose objective function value is worse than the average objective value, IPSO boosts their inertia weight, nudging them towards more promising search zones. The corresponding adaptive inertia weight \( w \) is expressed as follows:

\[
w = w_{\text{min}} - \frac{(w_{\text{max}} - w_{\text{min}}) \times (f - f_{\text{min}})}{f_{\text{avg}} - f_{\text{min}}}, f \leq f_{\text{avg}} \tag{21}\]

\[
w = w_{\text{max}}, f > f_{\text{avg}} \tag{22}\]

where \( f \) denotes the current objective function value of the particle. \( f_{\text{min}} \) and \( f_{\text{max}} \) denote the bound range of the current objective function value, respectively. \( f_{\text{avg}} \) denotes the average value of the objective function. \( w_{\text{min}} \) and \( w_{\text{max}} \) denote the bound range of the adaptive inertia weight.

In the improved particle swarm algorithm, powertrain parameters that need to be optimized constitute a particle. This particle includes the characteristic coefficient \( k_{1} \) of PG1, the reduction ratio \( k_{2} \) of MG2, the main reduction ratio \( i_{0} \), the transmission gears \((i_{1}, i_{2}, i_{4})\), and the wheel radius \( R \). Within the transmission gears, the third gear functions as the direct gear with a gear ratio of 1, and thus is not considered for optimization in this study. In the particle swarm optimization process, the total particle count is set to 10, and the fuel consumption of the whole vehicle over 100 km is selected as the objective function value. The flow block diagram of the joint optimization of IPSO and DP is shown in Figure 8.

The corresponding joint optimization process can be described as Algorithm 1:
Algorithm 1: IPSO-DP
Joint Optimization Process

Input: population size $N$, number of iterations $T$, problem dimension $D$, constraint range of particles
Output: global optimal position vector $x_{best}(t)$

1. Initialize the particle swarm position vector: $x_i^0 = x_{min} + (x_{max} - x_{min}) * \text{rand}(1,N)$
2. Initialize the particle swarm velocity vector: $v_i^0 = v_{min} + (v_{max} - v_{min}) * \text{rand}(1,N)$
3. while $(f(x_{best}(t)) \leq \epsilon \lor (t < T))$ calculate
4. $f(x_i(t)) \leftarrow$ Combine IPSO with DP to calculate the fitness function for each particle.
5. Determine the contemporary $p_{Best}$ and $g_{Best}$ according to the minimum fuel consumption.
6. Update the particle velocity vector $V_i(t)$ and the position vector $X_i(t)$:
   \[
   v_i^{k+1} = \omega v_i^k + c_1 r_1 \cdot (p_{Best} - x_i^k) + c_2 r_2 \cdot (g_{Best} - x_i^k) \\
   x_i^{k+1} = x_i^k + v_i^{k+1}
   \]
7. If the convergence condition is met, stop the iteration, otherwise, perform step 4.
8. Return $x_{best}(t)$.
9. End.

Figure 8. Flowchart of the joint optimization method.

3.3. Simulation Verification

Powertrain parameters for the hybrid heavy-duty truck are jointly optimized using DP and IPSO, validating the impact of these key parameters on the fuel economy of hybrid heavy-duty trucks. According to references [43,44], the boundaries of the key parameters to be optimized are listed in Table 2. Subsequently, simulation verification is carried out under the CHTC-D test cycle conditions, and the iterative results of the joint optimization are presented in Figure 9. As evident in Figure 9, the proposed optimization parameters and objective function demonstrate convergence within the iteration range, contributing to the enhancement of fuel economy. Meanwhile, the optimization outcomes of powertrain parameters for the hybrid heavy-duty truck are shown in Table 3, alongside the corresponding fuel consumption performance in Table 4. As can be seen from Table 4, under
the CHTC-D test cycle conditions, the fuel consumption of the optimized DP is 22.63 L/100 km, which is 2.15% lower than that of the original DP. Thus, the proposed optimization method for the powertrain parameters of the hybrid heavy-duty truck is effective.
Figure 9. Optimization process under the CHTC-D cycle: (a) Results for $k_1$; (b) Results for $k_2$; (c) Results for $i_0$; (d) Results for $i_1$; (e) Results for $i_2$; (f) Results for $i_4$; (g) Results for R; (h) Results for fuel consumption.

Table 2. Bounds of parameters to be optimized in hybrid heavy-duty trucks.

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<thead>
<tr>
<th>Parameter</th>
<th>$k_1$</th>
<th>$k_2$</th>
<th>$i_0$</th>
<th>$i_1$</th>
<th>$i_2$</th>
<th>$i_4$</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value range</td>
<td>3.8–4.8</td>
<td>4.4–7.4</td>
<td>4.5–6.5</td>
<td>5.4–7.4</td>
<td>1.5–2.5</td>
<td>0.4–1.0</td>
<td>0.5–0.55</td>
</tr>
</tbody>
</table>

Table 3. Optimized parameters under CHTC-D driving cycles.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$k_1$</th>
<th>$k_2$</th>
<th>$i_0$</th>
<th>$i_1$</th>
<th>$i_2$</th>
<th>$i_4$</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>4.4</td>
<td>6.7</td>
<td>5.1</td>
<td>6.3</td>
<td>2.1</td>
<td>0.86</td>
<td>0.528</td>
</tr>
<tr>
<td>Optimal</td>
<td>3.86</td>
<td>4.5</td>
<td>6.34</td>
<td>7.3</td>
<td>1.8</td>
<td>0.83</td>
<td>0.537</td>
</tr>
</tbody>
</table>

Table 4. Fuel consumption and its improvement was caused by parameters optimization.

<table>
<thead>
<tr>
<th>CHTC-D (L/100 km)</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP</td>
<td>23.2</td>
</tr>
<tr>
<td>Optimal DP</td>
<td>22.63</td>
</tr>
</tbody>
</table>

4. Design of a Control Strategy Algorithm

4.1. Design of a Rule-Based Strategy

This paper presents a study on a rule-based strategy (RCS) for a hybrid heavy-duty truck and designs multiple operating modes for these vehicles. The operating states of each component under different modes are depicted in Table 5. The operating modes of the hybrid heavy-duty truck are divided into the following six modes:

- **Pure Electric Mode (OpMode = 1):** When SOC > 80% or $P_{req} < 35$ kW, the vehicle can use the battery to power the MG2 drive. This mode is suitable for situations when the vehicle has just started or when the vehicle speed is low and the battery is sufficiently charged.

- **Engine Drive Charging Mode (OpMode = 2):** When SOC < 30%, the engine starts and the vehicle is driven by the engine only. The engine operates at its optimal operating curve as a reference and works on the optimal operating curve as much as possible. At the same time, the engine drives MG1 to generate electricity to charge the power battery.

- **Hybrid Drive Mode (OpMode = 3):** When 30% < SOC < 80% or $P_{req} > 35$ kW, the vehicle requires a large amount of power, and MG2’s power is insufficient to meet the overall power demand of the vehicle. In this case, the engine works together with the MG2 to drive the vehicle, and the operating point of the engine is along the optimal operating curve as much as possible.

- **Brake Energy Regeneration Mode (OpMode = 4):** When SOC < 80% or $P_{req} < 0$ kW, the vehicle is in a braking or decelerating state. In this mode, the MG2 (which acts as a generator) is used to generate negative torque to recover energy from braking and charge the power pack to reduce overall vehicle fuel consumption.

- **Mechanical Braking Mode (OpMode = 5):** When the battery SOC is high, the vehicle relies only on the mechanical braking system to decelerate the vehicle in order to avoid overcharging the power battery pack due to brake energy regeneration.

- **Mechanical Braking + Brake Energy Regeneration Mode (OpMode = 6):** When SOC < 80% and MG2 (which acts as a generator in this case) cannot provide enough negative torque, mechanical braking is required to decelerate the vehicle.
All rules are drawn on a tree diagram, as shown in Figure 10. \( P_{\text{req}} \), \( P_{\text{ev}} \), \( P_{\text{h}} \), and \( P_{\text{BE}} \) donate the vehicle power demand, the threshold for power demand in pure electric mode, the threshold for power demand in hybrid mode, and the threshold for power demand in regenerative braking mode, respectively. \( \text{SOC}_L \) and \( \text{SOC}_H \) donate the minimum and maximum thresholds for battery SOC.

![Figure 10. Logical rules.](image)

<table>
<thead>
<tr>
<th>OpMode</th>
<th>Engine</th>
<th>MG1</th>
<th>MG2</th>
<th>Battery</th>
<th>Mechanical Brake</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Off</td>
<td>Off</td>
<td>Motor</td>
<td>Discharge</td>
<td>Off</td>
</tr>
<tr>
<td>2</td>
<td>On</td>
<td>Generator (^1)</td>
<td>Off</td>
<td>Charge</td>
<td>Off</td>
</tr>
<tr>
<td>3</td>
<td>On</td>
<td>Generator</td>
<td>Motor (^2)</td>
<td>Discharge</td>
<td>Off</td>
</tr>
<tr>
<td>4</td>
<td>Off</td>
<td>Off</td>
<td>Generator</td>
<td>Charge</td>
<td>Off</td>
</tr>
<tr>
<td>5</td>
<td>Off</td>
<td>Off</td>
<td>Off</td>
<td>Discharge</td>
<td>On</td>
</tr>
<tr>
<td>6</td>
<td>Off</td>
<td>Off</td>
<td>Generator</td>
<td>Charge</td>
<td>On</td>
</tr>
</tbody>
</table>

\(^1\) Generator indicates motor as generator; \(^2\) Motor indicates motor as drive motor.

### 4.2. Design Method Based on DP Optimal Control Rules

The general rule-based strategy cannot take full advantage of the fuel savings of the hybrid heavy-duty truck. However, the DP algorithm can obtain the least costly power allocation strategy and effectively handle the constraints and nonlinearities of the problem to find the global optimal solution. Additionally, some studies have shown that optimizing the rule-based control strategy based on the control rules extracted by DP can achieve better control results. Therefore, in this paper, an offline DP method is introduced to extract the boundary of mode switching, and the extracted control rules are further optimized for the rule-based strategy, resulting in DP-RCS. The operating points of the hybrid heavy-duty truck corresponding to different modes following DP optimization are shown in Figure 11a, where blue points represent the pure electric mode and red points represent...
the hybrid mode. As can be seen from Figure 11a, the pure electric mode is mostly distributed in the low-speed and smaller-demand torque interval, and the hybrid mode is distributed in the higher-speed and larger-demand torque interval. The solid line in Figure 11a represents the switching boundary between these two modes.

Figure 11. (a) Operating points of different modes based on DP; (b) The relationship between the power demand and the ICE power.

The power distribution between the engine and the battery in the power-split hybrid heavy-duty truck is a key point of the energy-management control strategy. The energy flow of the whole vehicle can be controlled by the engine power, thereby achieving the purpose of controlling the power distribution between different energy sources. Under the CHTC-D test cycle conditions, the relationship between the power demand of the whole vehicle and the engine power based on the DP strategy is shown in Figure 11b. From Figure 11b, it can be seen that the engine power increases with an increase in the power demanded by the whole vehicle. After fitting the data, there is a reference line between the engine power and the whole vehicle’s power demand. Therefore, under the hybrid power mode, the engine power distribution based on the rule-based energy-management strategy can refer to this line, which can achieve the effect of optimizing the fuel consumption of the whole vehicle.

4.3. Design of an Optimal DP-RCS Based on Optimal Powertrain Parameters

This section will further explore the impact of the combination of powertrain parameter optimization and DP-RCS on the fuel economy of a hybrid heavy-duty truck. The related optimization process is shown in Figure 12. As can be seen from Figure 12, under the CHTC-D test cycle conditions, this paper first describes the local optimization of key powertrain parameters. Based on the optimal powertrain parameters, designing the DP-RCS and obtaining the optimal DP-RCS scheme can be performed to further improve the fuel economy of the hybrid heavy-duty truck.
5. Results and Discussion

In this section, in order to verify the effectiveness of the optimal DP-RCS, simulation analysis is performed under CHTC-D test cycle conditions, and the simulation results are compared with the RCS results for verification. Meanwhile, before the simulation, the initial SOC of the battery is set to 0.6. The vehicle speed following the optimal DP-RCS is shown in Figure 13. As can be seen from Figure 13, the actual speed and target speed curves basically overlap, indicating that the vehicle speed followed the program well.
The engine power of the RCS operates mainly in the 120 kW region, as shown in Figure 14a. However, the engine power of the DP-based strategy fluctuates greatly because the DP-based strategy optimizes the engine operating points by global planning for the purpose of maximizing the fuel economy of the hybrid heavy-duty truck system, as shown in Figure 14b. Furthermore, it can be found from Figure 14b that the DP-based energy-management strategy tends to use less engine power during the first 500 s of the CHTC-D test cycle condition at low-speed drive conditions. Finally, in the optimal DP-RCS, referring to the engine power allocation of the DP strategy, the engine power is rarely used for low-speed driving but follows the higher power demand of the vehicle for high-speed driving conditions, as shown in Figure 14a. Moreover, the average engine power of the optimal DP-RCS is higher than that of the RCS, so the engine can operate in a more efficient area and the excess power can be used to charge the power battery, as shown in Figure 14c.

![Figure 14](image)

**Figure 14.** Simulation results under the CHTC-D cycle: (a) ICE power; (b) ICE power based on the DP EMS; (c) Battery power.

The trend of SOC is shown in Figure 15a. The type of hybrid heavy-duty truck studied in this paper is not a plug-in type, so the corresponding energy-management strategy
needs to have SOC maintenance capability. Simulation analysis was performed under CHTC-D test cycle conditions, and it was found that the SOC of all three energy-management strategies returned to their initial values. In addition, the SOC trend of the optimal DP-RCS was closer to that of the DP-based energy-management strategy with less fluctuation in the SOC. In summary, the proposed optimal DP-RCS can achieve better SOC maintenance for hybrid heavy-duty trucks.

The comparison of fuel consumption between the optimal DP-RCS, the RCS, and DP-based strategy is shown in Figure 15b. It can be seen that the fuel consumption of the optimal DP-RCS is lower than that of the RCS, while the fuel consumption of the DP-based strategy is the lowest. Under a single CHTC-D driving cycle, the fuel consumption is 2.136 L for the optimal DP-RCS, 2.409 L for the RCS, and 1.894 L for the DP-based strategy.

![Figure 15. (a) The trend of SOC changes corresponding to three energy-management strategies; (b) The fuel consumption.](Image)

The distribution of engine operating points corresponding to the RCS, the DP-based strategy, and the optimal DP-RCS are shown in Figure 16a–c, respectively. The blue bars represent the percentage distribution of engine operating points, while the red curve represents the optimal operating curve (BSFC) for each engine’s power. The engine power distribution for the RCS is mainly concentrated on 110 and 120 kW, which corresponds to the lowest points on the engine’s BSFC curve, as shown in Figure 16a. In contrast, the engine power distribution for the DP strategy is wider, mainly between 40 and 160 kW, as shown in Figure 16b. The engine power distribution for the optimal DP-RCS is similar to that for the DP-based strategy, mainly distributed between 40 and 120 kW, as shown in Figure 16c. Compared with the RCS and the optimal DP-RCS, the DP-based strategy increases the proportion of the engine power distribution in the region of 120 to 160 kW. From Figure 16b, it can be observed that the RCS has higher fuel consumption than the DP strategy and optimal DP-RCS for a single CHTC-D driving cycle, with the DP strategy having the lowest fuel consumption. Therefore, there is room for improvement in the fuel economy of hybrid heavy-duty trucks by optimizing the engine power distribution in the range of 120 to 160 kW, corresponding to the lowest point on the optimal operating curve (BSFC), as shown in the graph.
Figure 16. Power distribution at the ICE operating point: (a) RCS EMS; (b) DP EMS; (c) optimal DP-RCS EMS.

The fuel consumption per 100 km is an important indicator for evaluating the performance of energy-management strategies for hybrid heavy-duty trucks. The fuel consumption per 100 km for the RCS, optimal DP-RCS, and DP strategy are shown in Figure 17. Meanwhile, according to Table 6, under the CHTC-D driving cycle for Chinese heavy-duty trucks, the fuel consumption for the RCS is 28.79 L/100 km, the fuel consumption for the optimal DP-RCS is 25.52 L/100 km, and the fuel consumption for the DP strategy is 22.63 L/100 km. The optimal DP-RCS achieves an 11.35% reduction in fuel consumption compared to that of the RCS, reaching 88.67% of the fuel consumption of the DP-based strategy and demonstrating a large improvement.

Figure 17. Fuel consumption to three energy-management strategies.
Table 6. Fuel consumption and its improvement caused by parameter optimization and strategy optimization.

<table>
<thead>
<tr>
<th></th>
<th>CHTC-D (L/100 km)</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP</td>
<td>23.2</td>
<td>–</td>
</tr>
<tr>
<td>RCS</td>
<td>28.79</td>
<td>–</td>
</tr>
<tr>
<td>Optimal DP-RCS</td>
<td>25.52</td>
<td>11.35%</td>
</tr>
</tbody>
</table>

6. Conclusions

This study aims to explore the impact of the combination of powertrain parameters optimization and DP-RCS on the fuel economy of power-split hybrid heavy-duty trucks. Firstly, an IPSO algorithm and DP algorithm are introduced to optimize powertrain parameters, resulting in the optimal parameters of the power system. Then, based on optimal powertrain parameters, the optimal DP-RCS is proposed to minimize the total fuel consumption of the vehicle. The following conclusions are drawn from the simulation verification:

- For powertrain parameters that significantly affect the overall economy of the vehicle, the IPSO algorithm is used to search for the optimal parameters within a controllable range, resulting in locally optimal powertrain parameters. The DP fuel consumption optimization result is 2.15% lower than that of the prototype vehicle.
- Based on optimal powertrain parameters, designing the DP-RCS and obtaining the optimal DP-RCS scheme further improve the fuel economy of hybrid heavy-duty truck. The simulation results demonstrate that the optimal DP-RCS is closer to the DP-based energy-management strategy, in terms of both engine operating points and SOC variation curves. The fuel economy of the optimal DP-RCS is 11.35% higher than that of the RCS, demonstrating that the combination of powertrain parameter optimization and DP-RCS effectively improves the fuel economy of hybrid heavy-duty trucks.

In our future research, we can expand our work in two aspects. Firstly, based on existing research, artificial intelligence algorithms can be added to conduct research on hybrid heavy-duty trucks further exploring the effectiveness of improving the fuel economy of hybrid heavy-duty trucks. Secondly, currently, we primarily utilize existing computer configurations for offline simulation of the algorithms, without conducting hardware-in-the-loop testing or embedding the algorithms into vehicle microprocessors for real-time simulations. In future work, if feasible, we can utilize popular microprocessors to evaluate the real-time application effectiveness of optimization algorithms such as IPSO and DP-RCS on vehicles.

Author Contributions: Conceptualization, Y.Z. and W.H.; methodology, Y.Z. and R.Y.; software, Y.Z.; validation, Y.Z., S.Z. and W.H.; formal analysis, Y.Z. and K.L.; investigation, K.L.; resources, S.Z.; data curation, Y.Z.; writing—original draft preparation, Y.Z.; writing—review and editing, R.Y. and W.H.; visualization, Y.Z. and K.L.; supervision, W.H.; project administration, W.H.; funding acquisition, W.H. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: Song Zhang is an employee of Guangxi Yuchai Machinery Company Limited. The paper reflects the views of the scientists, not the company.
References


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