

Article

Slip-Ratio-Aware Energy Management of a Hybrid Tractor Under Variable Plowing Loads Using a DP-Calibrated ECMS

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Abstract

To enhance the fuel economy and operational adaptability of hybrid tractors under variable plowing loads, this paper proposes a slip-ratio-aware equivalent consumption minimization strategy (ECMS) calibrated via dynamic programming (DP). A resistance–slip ratio prediction model was first identified using plowing resistance and slip ratio data collected from soil-bin tests. The predicted slip ratio was integrated into the demand power model to quantify slip-induced traction losses. Offline DP was subsequently applied to generate globally optimized power split trajectories and establish a baseline equivalence-factor map indexed by plowing resistance level and battery state of charge (SOC). For real-time operation, the equivalence factor is dynamically adjusted via SOC feedback and normalized slip ratio deviation, enabling coordinated power distribution among the engine, MG1, and MG2. Powertrain bench tests were conducted by reproducing variable plowing loads using a dynamometer. The equivalent plowing resistance was calculated from measured load torque, and the corresponding slip ratio was estimated using the identified prediction model. Compared with A-ECMS, the proposed strategy reduced equivalent fuel consumption by 14.02% in simulation and 7.33% in bench tests. The proportion of engine operation in the high-efficiency region increased from 61% to 80% in simulation and from 65% to 77% in the bench test, while the corresponding proportion for the electric motors increased from 87% to 92% and from 88% to 90%, respectively. The SOC deviation decreased from 3.03% to 2.26% in simulation and from 3.07% to 2.43% in the bench test. These results demonstrate that the proposed strategy improves fuel economy, SOC regulation, and component operating efficiency under variable plowing loads.

Keywords: hybrid electric tractor; energy management; slip ratio; equivalent consumption minimization strategy; dynamic programming; fuel economy



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1. Introduction

Hybrid electric tractors integrate the high energy density of diesel engines with the rapid torque response and flexible power regulation of electric machines, offering a practical solution to improve fuel economy and operational adaptability in heavy-duty agricultural scenarios. Extensive research has been conducted on hybrid powertrain configurations, energy management strategies, and intelligent control techniques; however, achieving coordinated energy allocation under highly variable field loads remains a critical challenge [1,2].

Powertrain configuration and energy management strategies collectively determine the energy-saving performance of hybrid tractors. Coupled-split and distributed hybrid

architectures have been developed to enhance power flow coordination and traction performance [3,4], and systematic configuration design methodologies have also been explored [5]. Optimization-based strategies, such as those built on Pontryagin's minimum principle and model predictive control (MPC), can effectively improve power allocation accuracy and SOC regulation capability [6,7]. Load prediction and dynamic programming have further been introduced to enhance strategy adaptability and provide globally optimized benchmarks [8,9], while DP-MPC and fast DP methods improve the transferability and computational efficiency of global optimization results [10,11].

For real-time control applications, the equivalent consumption minimization strategy (ECMS) has been widely adopted because of its relatively low computational burden. Its performance, however, is strongly influenced by the selection of the equivalence factor. Fuzzy PI control and adaptive updating methods have therefore been introduced to adjust the equivalence factor according to SOC and operating conditions [12,13]. Supervisory control frameworks and operating-state constraints have also been incorporated into energy management to improve real-time adaptability [14,15]. For hybrid tractors, working-condition adaptation and global optimization of the equivalence factor have been shown to improve fuel economy and SOC regulation [16,17], while ECMS-based hybrid powertrain applications have further demonstrated the engineering potential of this type of strategy [18]. These studies provide an effective basis for real-time power allocation, but the optimization is mainly performed within the powertrain, with the traction demand generally treated as an external input.

Traction conditions during plowing provide another important source of information for tractor control. Radrizzani et al. [19] coordinated energy management with vehicle-speed control and demonstrated the benefit of considering the interaction between powertrain operation and tractor motion. At the wheel-control level, de Melo et al. [20] applied wheel-slip control to improve tractive efficiency and reduce energy consumption. Wang et al. [21] further developed a switching control method based on vehicle speed and slip ratio for plowing operation, while Baek et al. [22] investigated the relationship between slip and tractive efficiency for an electric tractor with independently driven wheels. These studies confirm the importance of traction state and slip ratio to tractor energy efficiency. However, traction information is primarily used for speed regulation, wheel-torque control, or slip control, whereas its role in the upper-level power-split decision of a hybrid powertrain has received comparatively less attention.

Against this background, the contribution of the present study does not lie in the individual use of DP, ECMS, or SOC-based equivalence-factor adaptation. Instead, a traction-state representation is incorporated into the upper-level energy management process of a series-parallel hybrid tractor under variable plowing loads. First, a resistance-slip ratio relationship identified from soil-bin measurements is used to estimate the traction state, and the associated traction loss is incorporated into the demand-power formulation. Second, offline DP is used to establish a resistance-level-SOC baseline equivalence-factor map, thereby introducing load-dependent information into the baseline calibration. Third, during online operation, the estimated slip state provides an additional correction to the baseline equivalence factor, while SOC feedback maintains battery charge balance. In this way, the DP-calibrated baseline and the slip-state correction perform distinct functions within the same ECMS framework, linking traction-state information with upper-level power-split optimization.

2. Materials and Methods

2.1. Hybrid Tractor System Configuration

The transmission system of the studied hybrid tractor consists of a front planetary gear set (K1), a rear planetary gear set (K2), a high-low range gearbox, a final drive gear set,

a differential, and wheel-end reduction gears. The ring gear of K1 is fixed, so K1 operates as a fixed-axis planetary gear train, while K2 serves as the primary power-coupling planetary gear set. The powertrain comprises three power sources: a diesel engine, electric machine MG1, and traction motor MG2. MG1 typically operates in idle or generating mode; under specific operating conditions or when engine output alone cannot meet load demand, MG1 can switch to motoring mode to provide auxiliary propulsion power [23].

During operation, the engine and MG1 are coaxially coupled, and their combined power is transmitted to the sun gear of K2. The power output by MG2 is delivered to the sun gear of K1, then transmitted from the carrier of K1 to the ring gear of K2. The two power paths are coupled within K2 and subsequently transferred to the output shaft. This configuration enables both power splitting and power merging. Furthermore, owing to the two-degree-of-freedom characteristic of K2, MG2 can regulate engine speed independently of tractor travel speed, thereby realizing electric continuously variable transmission (ECVT) functionality.

The transmission system incorporates four clutches and two brakes: engine clutch C1, power take-off clutch C2, low-range clutch C3, high-range clutch C4, and brakes B1 and B2. Clutches C3 and C4 are used to select and maintain the low- and high-range transmission modes, while B1 and B2 constrain the corresponding planetary gear members to enable different powertrain operating modes. The powertrain configuration is illustrated in Figure 1. The key specifications of the powertrain components are listed in Table 1.

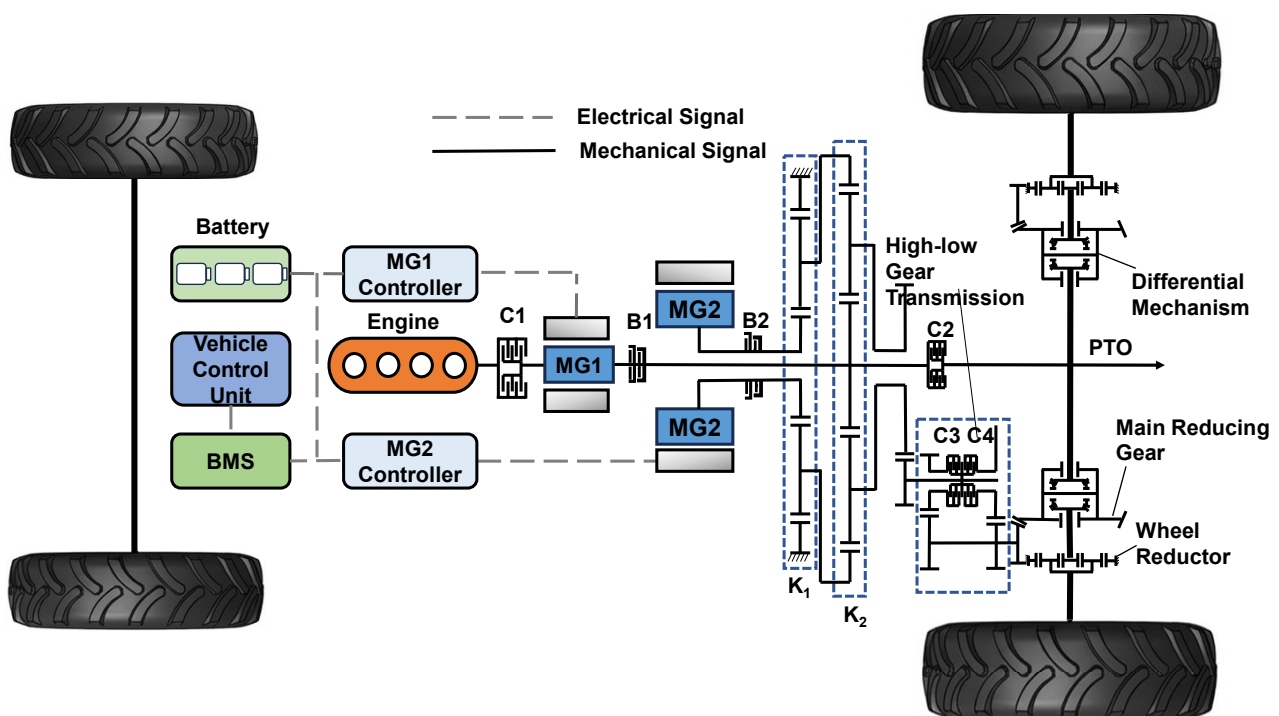


Figure 1. System configuration of the hybrid electric tractor.

Table 1. Main specifications of the hybrid tractor powertrain.

Component	Parameter	Value
Diesel Engine	Rated Power	90 kW
	Rated Speed	2200 r·min ^{−1}
	Maximum Torque	520 N·m

Table 1. Cont.

Component	Parameter	Value
MG1	Rated Power	55 kW
	Rated Speed	4000 r·min ^{−1}
	Maximum Torque	131 N·m
MG2	Rated Power	70 kW
	Rated Speed	2400 r·min ^{−1}
	Maximum Torque	280 N·m

2.2. Powertrain Component Modelling

2.2.1. Diesel Engine Model

Given that this study focuses on power allocation at the powertrain level, the detailed combustion and heat transfer processes of the diesel engine are simplified. A quasi-static lookup table model is established based on engine bench test data [24], which describes the relationship among engine speed, engine torque, and brake-specific fuel consumption (BSFC) and enables rapid fuel consumption calculation during energy management optimization. The BSFC is expressed as a function of engine speed and torque:

$$b_{eng}(t) = f(n_{eng}(t), T_{eng}(t)) \quad (1)$$

Here, $b_{eng}(t)$ denotes the engine fuel consumption rate at time t , measured in g/kw·h; $n_{eng}(t)$ represents the engine output speed at time t , measured in r/min; $T_{eng}(t)$ is the engine output torque at time t , measured in N·m; and $f(\cdot)$ denotes the lookup-table mapping between engine speed, engine torque, and brake-specific fuel consumption.

The relationship between engine output power and rotational speed/torque satisfies:

$$P_{eng}(t) = \frac{n_{eng}(t) \cdot T_{eng}(t)}{9550} \quad (2)$$

The engine performance map established via the lookup table method is shown in Figure 2.

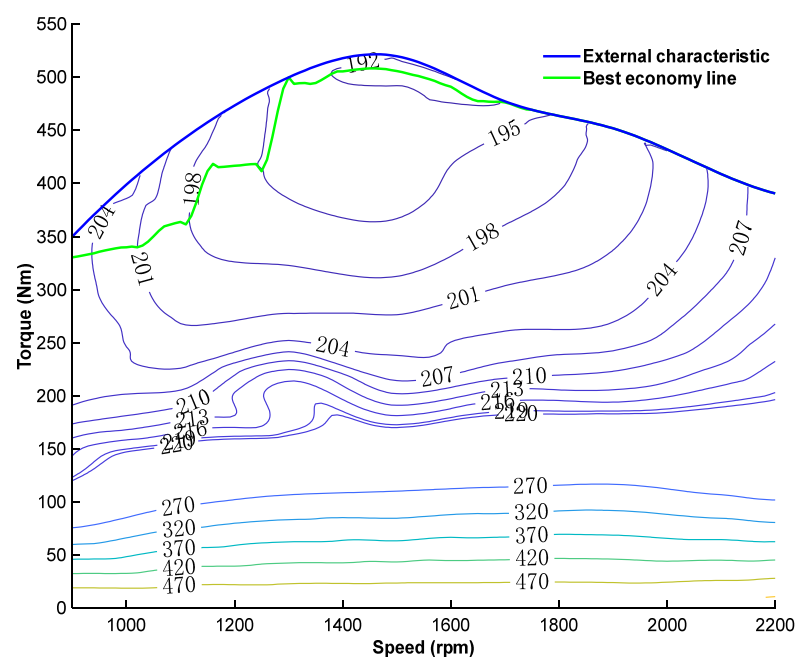


Figure 2. Map of engine.

2.2.2. Electric Motor Model

For motor modelling, complex internal electromagnetic coupling processes, such as stator excitation and rotor electromagnetic induction, are simplified. The modelling focus is placed on describing the external characteristic relationships among rotational speed, torque, and efficiency [25]. Using motor bench test data, an interpolation modelling approach is adopted to derive the relationship between motor efficiency, rotational speed, and torque. This approach ensures model accuracy while reducing computational complexity. The motor efficiency characteristic maps are presented in Figure 3.

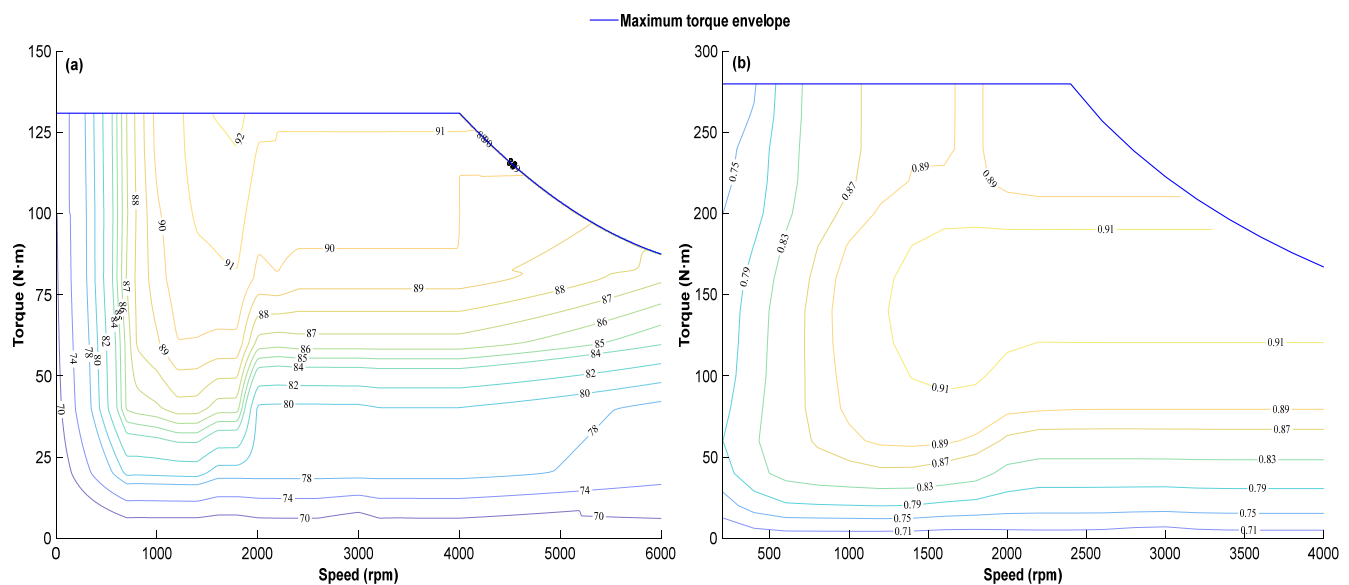


Figure 3. Map of Motor: (a) map of MG1; (b) map of MG2.

The relationship between motor efficiency and rotational speed–torque is expressed as:

$$\eta_{mot} = f(n_{mot}, T_{mot}) \quad (3)$$

Here, η_{mot} represents the motor overall efficiency, measured in %; n_{mot} is the actual motor rotational speed, measured in r/min; T_{mot} denotes the motor output torque, measured in N·m.

Motor output power is a coupled function of rotational speed and torque, calculated as:

$$P_{mot} = \frac{n_{mot} T_{mot}}{9550} \quad (4)$$

Here, P_{mot} denotes the effective motor output power, measured in kW.

To unify bidirectional power symbols for motors, it is stipulated that mechanical power at the motor shaft end $P_{MG_i} > 0$ indicates motor driving (outputting mechanical power to the transmission system), while $P_{MG_i} < 0$ indicates motor generating (absorbing mechanical power from the transmission system).

Concurrently, to characterize bidirectional electromechanical energy conversion and facilitate battery power calculations, the shaft-end mechanical power P_{MG_i} must be converted to electrical power $P_{el,i}$ on the DC bus side. Let $\eta_{MG_i} \in (0, 1)$ denote the efficiency of the i -th motor at its current operating point. The electrical power is then defined as

$$P_{el,i}(k) = \begin{cases} \frac{P_{MG_i}(k)}{\eta_{MG_i}(k)}, & P_{MG_i}(k) \geq 0 \\ P_{MG_i}(k) \cdot \eta_{MG_i}(k), & P_{MG_i}(k) \leq 0 \end{cases} \quad (5)$$

Here, k denotes the discrete sampling time step, $P_{el,i}$ represents the electrical power of motor i , measured in kW; P_{MGi} is the mechanical power at the shaft end of motor i , measured in kW; η_{MGi} denotes the efficiency of motor i at the current operating point.

The combined electrical power of both motors is:

$$P_{el}(k) = P_{el,1}(k) + P_{el,2}(k) \quad (6)$$

The combined electrical power P_{el} characterizes the direction and magnitude of energy flow at the motor side. Within the power battery model, it is further converted into battery-end power by incorporating charge/discharge efficiency to update the state of charge (SOC).

2.2.3. Power Battery Model

The core of the power battery model is to quantify dynamic changes in SOC and power output boundaries, to support power allocation decisions in the energy management strategy. This study adopts a first-order equivalent internal resistance model, which represents the power battery as an ideal voltage source connected in series with an internal resistor [26]. A schematic of the equivalent internal resistance model is shown in Figure 4.

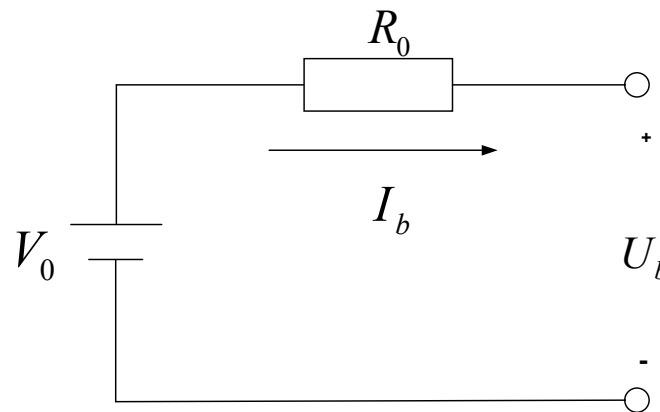


Figure 4. Equivalent internal resistance model of the power battery.

SOC updates are based on Coulomb's law, comprehensively considering charge/discharge current and Coulombic efficiency η_c . The calculation formula is:

$$\text{SOC}(t + \Delta t) = \text{SOC}(t) - \frac{\eta_c \cdot I_b(t) \cdot \Delta t}{3600 \cdot C_{bat}} \quad (7)$$

Here, $\text{SOC}(t)$ represents the SOC value at time t ; $\text{SOC}(t + \Delta t)$ is the SOC value at time $t + \Delta t$; $I_b(t)$ is the charge/discharge current, A; η_c is the coulombic efficiency; Δt represents the sampling interval; and C_{bat} is the rated capacity of the battery, Ah.

In this study, the voltage characteristics of the power battery are determined based on Ohm's law. The maximum output power $P_{b,max}$ of the power battery can be derived from the product of output voltage and current:

$$P_{b,max} = \frac{U_b I_b}{1000} = \frac{(V_0 - I_b R_0) I_b}{1000} \quad (8)$$

The power boundary satisfies:

$$P_{b,min} \leq P_{bat}(t) \leq P_{bat,max} \quad (9)$$

Here, U_b represents the power battery output voltage, measured in V; V_0 is the power battery terminal voltage, measured in V; R_0 is the power battery internal resistance, measured in Ω ; and $P_{b,\max}$ is the maximum discharge power, measured in kW.

2.3. Transmission System Kinematic Model

The ECVT coupling unit of the hybrid-parallel tractor described herein comprises a front planetary train K1 and a rear planetary train K2 arranged in series. The drive motor MG2 inputs to the sun gear of K1, with K1's ring gear fixed in position; the K1 carrier is rigidly connected to the K2 ring gear. The engine is coaxially coupled with MG1 and drives the sun gear of K2. The K2 planet carrier functions as the transmission mechanism driving the output shaft. This configuration enables decoupled power splitting and merging between engine speed and vehicle speed.

The rotational speed constraints for the i -th planetary gear train ($i = 1$ denotes K1, $i = 2$ denotes K2) within the dual planetary gear trains can be uniformly expressed by the Willis equation:

$$n_{ri} + k_i n_{si} = (1 + k_i) n_{ci} \quad (10)$$

Here, n_{si} represents the sun gear rotational speed of the i -th planetary train, measured in r/min; n_{ri} is the ring gear rotational speed of the i -th planetary train, measured in r/min; n_{ci} is the carrier rotational speed of the i -th planetary train, measured in r/min; and k_i is the characteristic parameter of the i -th planetary train.

Combining the structural connection constraints (fixed K1 ring gear, rigid connection between K1 carrier and K2 ring gear, MG2 $\rightarrow$ K1 sun gear, engine/MG1 $\rightarrow$ K2 sun gear, K2 carrier $\rightarrow$ output shaft), the intermediate shaft speed can be eliminated to derive the relationship between the equivalent transmission ratio of the dual planetary gear train and the output shaft speed:

$$\begin{cases} n_{drv} = \frac{(1+k_1)n_{eng} + k_2 n_{MG2}}{(1+k_1)(1+k_2)} \\ i_{pg} = \frac{n_{eng}}{n_{drv}} = \frac{(1+k_1)(1+k_2)n_{eng}}{(1+k_1)n_{eng} + k_2 n_{MG2}} \end{cases} \quad (11)$$

Here, n_{eng} represents the engine output speed, r/min; n_{drv} is the transmission mechanism drive output shaft speed, r/min; n_{MG2} is the drive motor 2 output speed, r/min; and k_1 and k_2 are the characteristic parameters of the two planetary gear trains.

For an ideal planetary train, neglecting inertia and tooth flank friction effects, its internal meshing forces satisfy torque equilibrium and geometric constraints. The corresponding torque distribution relationship can be expressed as:

$$T_{si} : T_{ri} : T_{ci} = 1 : k_i : -(1 + k_i) \quad (i = 1, 2) \quad (12)$$

Here, T_{si} represents the sun gear torque, measured in N·m; T_{ri} is the ring gear torque, measured in N·m; and T_{ci} denotes the carrier torque, measured in N·m.

For the coupled split configuration of this dual planetary gearset, the torque transmission and coupling relationships for key shaft systems are derived as follows (all shaft speeds and torque directions are defined as positive in the output shaft drive direction). When the ring gear of K1 is fixed, the torque T_{MG2} applied by MG2 to the K1 sun gear is amplified at the carrier end via the planetary gear train and serves as the input torque T_{r2} to the K2 ring gear (accounting for planetary gear train transmission efficiency η_{gb}):

$$T_{r2} = \eta_{pg}(1 + k_2)T_{MG2} \quad (13)$$

Here, T_{r2} represents the input torque to rear planetary train ring gear K2, measured in N·m; T_{MG2} is the output torque of drive motor 2, measured in N·m; and η_{pg} denotes the planetary gear train torque transmission efficiency.

The engine is coaxially coupled to the input of sun gear K2, with its equivalent sun gear input torque being $T_{eng} + T_{MG1}$. From Equation (13) for K2 ($i = 2$), the drive torque of the output shaft (planetary carrier) is obtained as:

$$T_{drv} = (1 + k_1)(T_{eng} + T_{MG1}) \quad (14)$$

Here, T_{drv} represents the transmission mechanism drive output shaft torque, measured in N·m; T_{eng} is the engine output torque, measured in N·m; and T_{MG1} denotes the motor 1 output torque, measured in N·m.

The ring gear input torque of K2 simultaneously satisfies, on one hand, the input from K1 via Equation (15); on the other hand, the internal torque distribution within K2 (as given by $T_{r2} = k_1(T_{eng} + T_{MG1})$) for $i = 2$ in Equation (13)). This yields the torque matching constraint under dual planetary gearset coupling:

$$k_1(T_{eng} + T_{MG1}) = \eta_{gb}(1 + k_2)T_{MG2} \quad (15)$$

Equation (15) explicitly defines the coupling relationship between MG2 torque and the combined engine/MG1 torque that must be satisfied within the dual planetary gear ECVT. Substituting (15) into (14) yields the equivalent expression for output shaft torque in terms of MG2:

$$T_{drv} = \frac{1 + k_1}{k_1} \eta_{gb}(1 + k_2)T_{MG2} \quad (16)$$

Equations (13)–(16) collectively constitute the core torque relationships of the dual-planetary ECVT: K1 amplifies MG2 torque via the planetary carrier before transmitting it to the K2 ring gear. K2 then couples the torque from the sun gear side (engine/MG1) with that from the ring gear side (originating from K1) according to their characteristic parameters and outputs the combined torque to the planetary carrier. This architecture achieves power splitting and continuously variable speed regulation.

2.4. Plowing Operation Dynamics and Slip Modelling

2.4.1. Plowing Resistance Model

During plowing operations, the driving force output by the tractor's drive wheels must balance the overall travel resistance and plowing resistance. The force equilibrium relationship in longitudinal dynamics may be described as:

$$F_{total} = F_p + F_r + F_s + F_a + F_c \quad (17)$$

Here, F_p represents the plowing resistance, measured in N; F_r is the rolling resistance, measured in N; F_s denotes the grade resistance, measured in N; F_a denotes the air resistance, measured in N; and F_c is the acceleration resistance, measured in N.

The magnitude of plowing resistance is jointly determined by plough configuration and soil properties. Considering the number of ploughshares, the working width per ploughshare, actual plowing depth, and soil specific resistance, the calculation relationship is:

$$F_p = Z \cdot b_l \cdot h_l \cdot k \quad (18)$$

Here, Z represents the number of ploughshares fitted to the plowing unit, measured in units; b_l is the working width per ploughshare, measured in cm; h_l is the actual working depth, measured in cm; and k is the soil specific resistance, measured in N/cm².

2.4.2. Soil-Bin Test Bench and Data Acquisition

The soil-bin tests used to acquire the plowing-resistance and slip-ratio data were conducted in 2025 using an indoor soil-bin test rig at the College of Engineering, Nanjing Agricultural University (Nanjing, Jiangsu, China). To accurately characterize energy losses due to slippage during plowing operations at the energy management level, this study conducted real-time data acquisition tests under plowing conditions using an indoor soil trench test rig system. The test rig setup and measurement interface are shown in Figure 5.

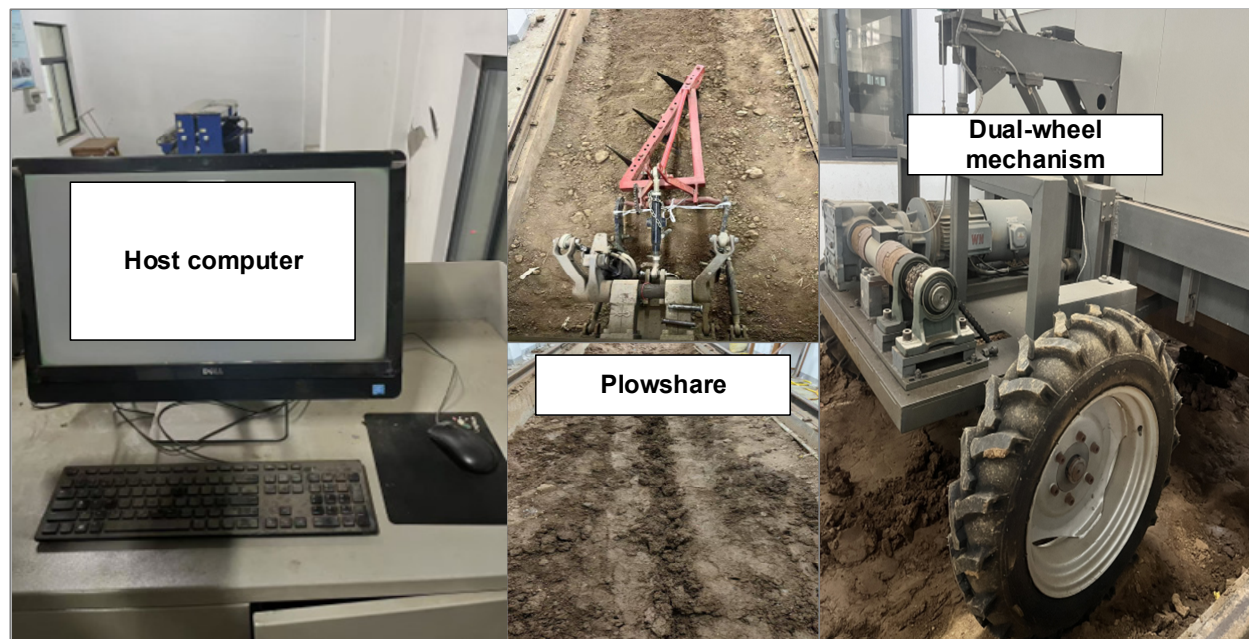


Figure 5. Soil-bin test bench device.

Before each test, the vertical load applied to the dual-wheel drive unit was adjusted to 12–15 kN using the loading mechanism. This ensured sufficient tire deformation and stable tire–soil contact, thereby improving the reliability of slip-ratio measurements. The plowing depth was set to 15 cm for all tests.

During the tests, the drive motor of the dual-wheel unit rotated the tires, while multiple operating signals were acquired synchronously through the measurement system. An OES-II optical velocity sensor was mounted on the test-frame structure, with its probe positioned 500 mm above the soil surface, to measure the actual ground speed v . A ZH07 torque–speed sensor installed on the drive half-shaft measured the rotational speed of the driving wheels. The longitudinal traction resistance was recorded using a tension–compression load cell installed in the traction mechanism.

All signals were synchronously sampled at intervals of 0.1 s. The tests were performed at travel speeds ranging from 4 to 10 km/h, and the automatic constant-speed mode of the soil-bin trolley was used to maintain stable operation. Each operating condition was continuously recorded for 80 s and repeated three times to reduce the influence of random disturbances.

Figure 6 shows the measured variations in travel speed and plowing resistance, and Figure 7 shows the corresponding slip-ratio trajectory.

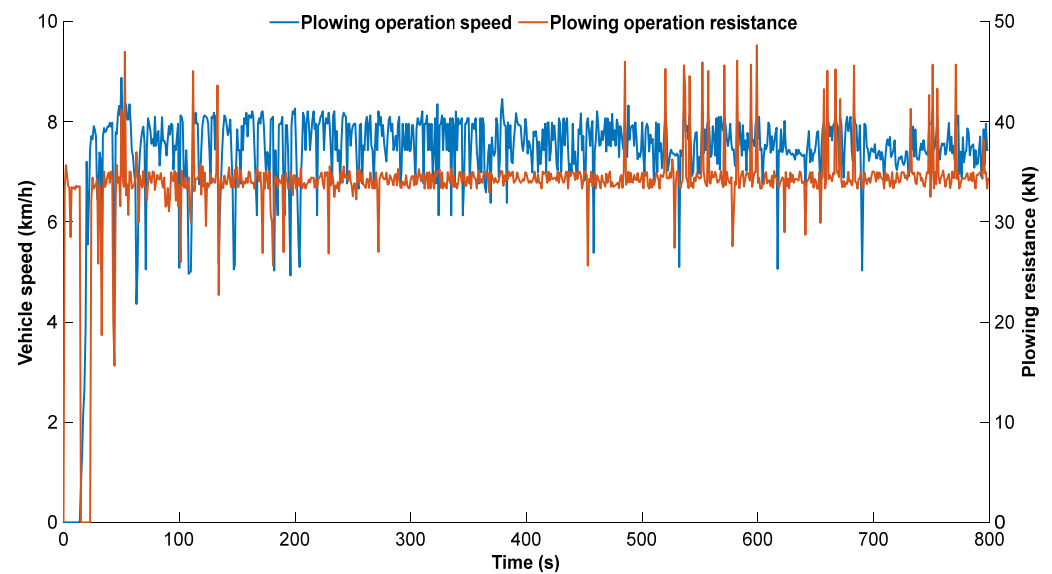


Figure 6. Variation curves of plowing speed and resistance.

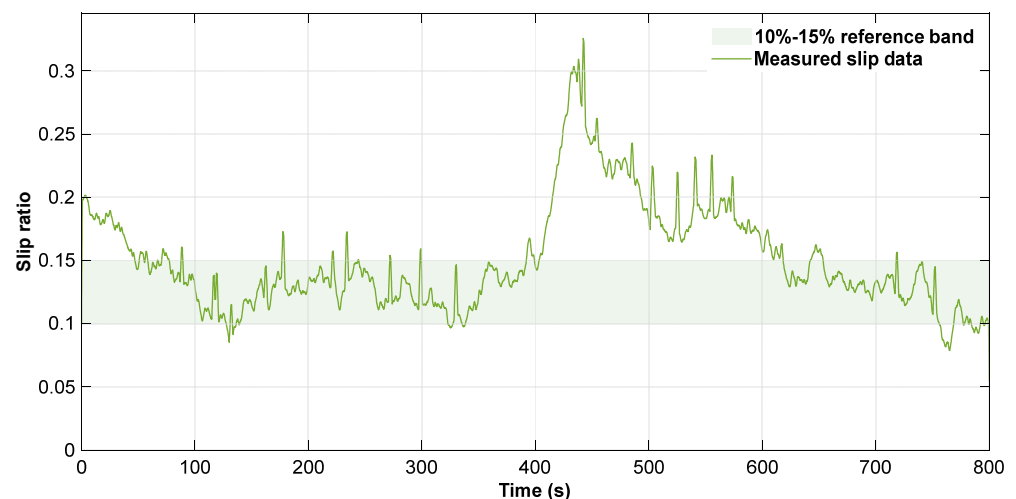


Figure 7. Slip-ratio curve as a function of time.

2.4.3. Plowing Resistance Level Classification

Plowing resistance reflects variations in soil properties, working depth, operating speed, and implement load and is therefore used as the operating-condition input for equivalence-factor calibration. Previous studies have shown that tillage draft varies markedly with soil mechanical properties, tillage depth, travel speed, and implement configuration [27,28]. Therefore, no universal numerical boundaries can be assigned to low-, medium-, and high-resistance plowing conditions. The resistance levels defined in this study are control-oriented, data-driven categories specific to the tested tractor–plow configuration and measured plowing cycle.

Before clustering, the raw resistance data were smoothed using a moving-average filter, abnormal samples were removed using the 3σ criterion, and the retained data were standardized using the Z-score method. K-means clustering was then performed using Euclidean distance. To reduce the influence of random initialization, each clustering scheme was repeated 30 times, and the solution with the minimum within-cluster sum of squares was retained. The number of clusters was evaluated over $K = 2\text{--}6$ using the mean silhouette coefficient. $K = 3$ provided the best balance between cluster separation and control-oriented interpretability, allowing the measured resistance distribution to be

represented by low-, medium-, and high-resistance states without unnecessarily increasing the size of the subsequent resistance-level-SOC calibration map.

The three cluster centers were 31.923, 34.189, and 36.528 kN. The midpoints between adjacent cluster centers were used as the classification thresholds, giving $T_1 = 33.06$ kN and $T_2 = 35.36$ kN. Accordingly, the low-, medium-, and high-resistance states were defined as $F_p \leq 33.06$ kN, $33.06 < F_p < 35.36$ kN, and $F_p \geq 35.36$ kN, respectively. These thresholds are not intended as universal agronomic limits; rather, they provide a compact discretization of the measured load distribution for resistance-level-SOC equivalence-factor calibration. The resulting classification is shown in Figure 8.

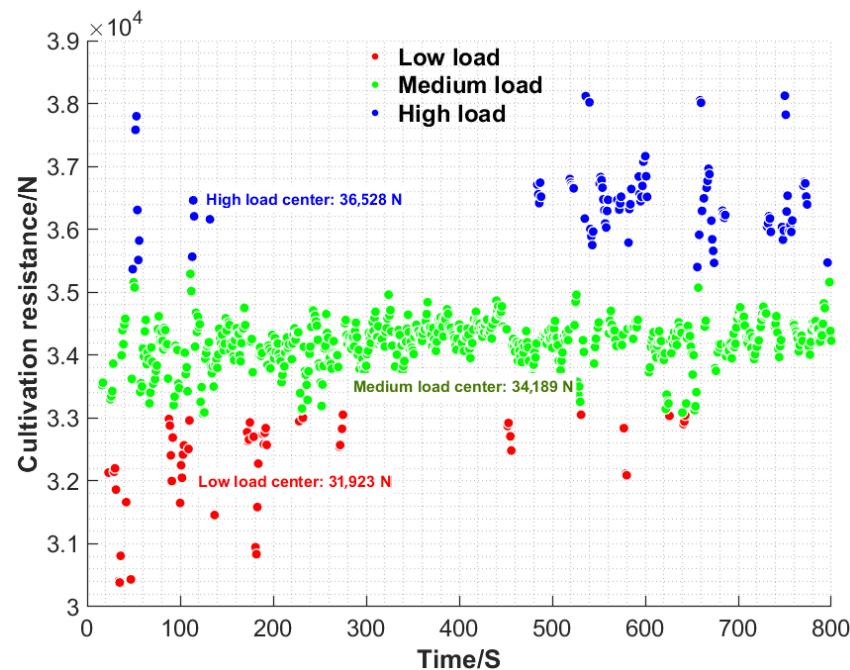


Figure 8. Plowing resistance level division based on K-means clustering.

The purpose of the resistance classification is to convert continuously varying load data into discrete condition indices that can be used by the energy management strategy. These condition indices are combined with SOC to construct a two-dimensional resistance-level-SOC equivalence-factor table during offline calibration. During online operation, the current resistance level is identified in real time, and the corresponding baseline equivalence factor is obtained from the table.

2.4.4. Slip-Ratio Prediction and Traction Loss Model

To describe energy dissipation caused by tire–soil interaction at the energy management level, a resistance-based slip-ratio prediction model is established. Rather than using slip ratio solely as an independently measured kinematic signal, the proposed model identifies the steady-state relationship between traction resistance and slip ratio. The predicted slip ratio is then used to estimate traction efficiency and correct the power demand of the tractor.

Based on 800 sets of ‘traction resistance–slip ratio’ sample data collected from soil trench trolley tests, this paper employs an exponential semi-empirical model [29] to describe traction mechanics:

$$F_{total} = F_{max}(1 - e^{-A\lambda}) \quad (19)$$

Here, F_{total} represents the plowing traction resistance, kN; F_{max} is the maximum adhesion force, kN; and A denotes the soil shear modulus coefficient.

Nonlinear least squares were employed for parameter identification of the experimental data, with the fitting results shown in Figure 9.

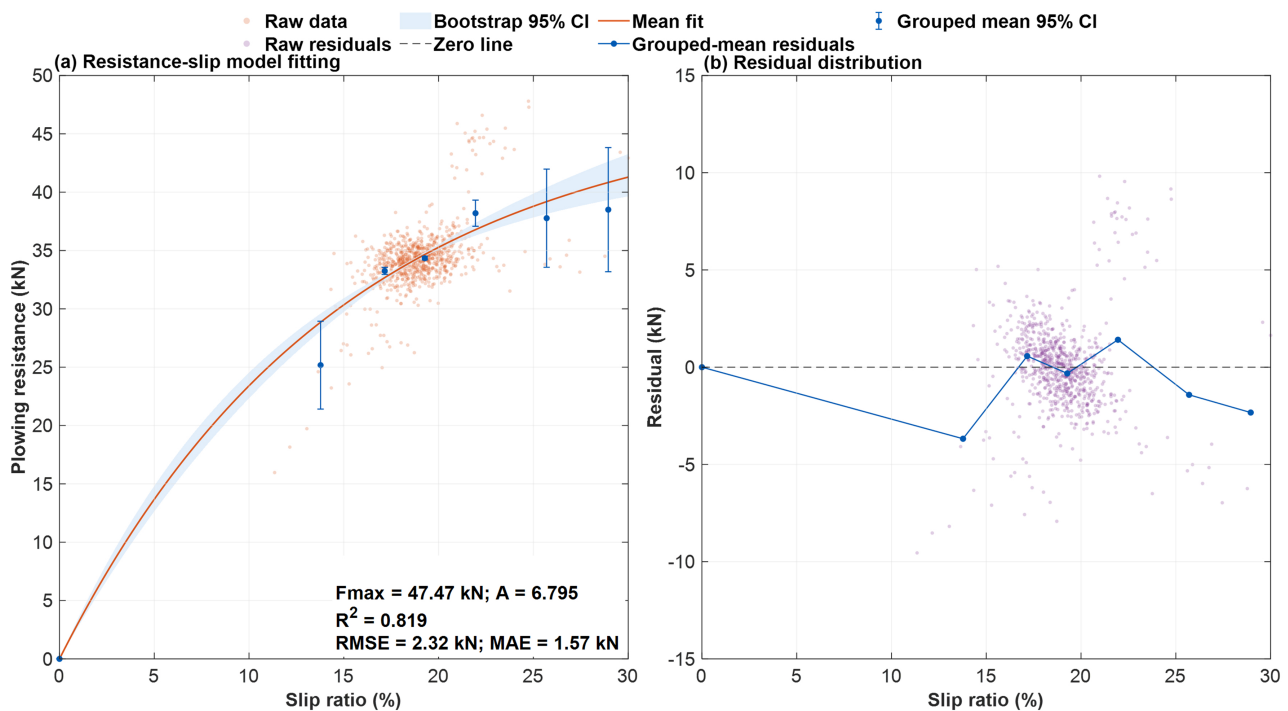


Figure 9. Resistance–slip model validation: (a) resistance–slip relationship; (b) residual analysis.

The exponential relationship was identified using all 800 paired resistance–slip measurements obtained from the soil-bin tests. The fitted parameters were $F_{max} = 47.47$ kN and $A = 6.795$, with $R^2 = 0.819$, an RMSE of 2.32 kN, and an MAE of 1.57 kN. As shown in Figure 9, some dispersion remains in the individual measurements, particularly at higher slip ratios, while the residuals are generally distributed around zero. These results indicate that the model captures the overall steady-state resistance–slip relationship under the tested conditions and is therefore used to provide a load-dependent slip-state estimate for the subsequent energy management calculations. Based on these identified parameters, the slip-ratio prediction model is formulated as follows:

$$\lambda_{pre}(k) = -\frac{1}{6.795} \ln\left(1 - \frac{F_{total}(k)}{47.47}\right) \quad (20)$$

Here, $\lambda_{pre}(k)$ denotes the predicted slip ratio in dimensionless form; percentage values shown in the figures correspond to $100\lambda_{pre}$.

This model rapidly derives the corresponding steady-state slip ratio from real-time resistance level inputs, providing prior state inputs for subsequent power flow calculations.

Traction efficiency $\eta_{trac}(\lambda)$ is defined as the ratio of effective traction power to mechanical power input at the wheel end. Incorporating the predicted slip ratio from Section 2.4.4, the traction efficiency model can be expressed as:

$$\eta_{trac}(\lambda) = (1 - \lambda_{pre})\left(1 - \frac{F_r}{F_{total}(k)}\right) \quad (21)$$

Accordingly, traction power loss due to slip and rolling resistance can be quantified as:

$$P_{loss,trac}(k) = P_{draw}(k)\left(\frac{1}{\eta_{trac}(\lambda)} - 1\right) \quad (22)$$

Here, $P_{draw}(k)$ represents the effective traction power, measured in kW

To address power allocation deviations in conventional energy management strategies arising from neglecting slip losses, this paper employs the predicted slip ratio to correct the overall machine demand power. The modified powertrain demand power model is:

$$P_{req}(k) = \frac{F_{total}(k)v}{\eta_{total} \cdot \eta_{trac}(\lambda)} \quad (23)$$

Here, $\eta_{trac}(\lambda)$ represents the traction efficiency, measured in %; η_{total} is the overall transmission system efficiency, measured in %; and V is the travel speed of the tractor, measured in km/h.

By incorporating the traction-efficiency term, the demand-power model accounts for the additional energy dissipation associated with tire–soil slip. When the estimated slip ratio increases, the corresponding reduction in traction efficiency leads to a higher calculated power demand. Compared with a conventional demand-power formulation that neglects slip-related losses, the modified model therefore avoids underestimating the power required under high-resistance and high-slip conditions and provides a more representative demand-power input for subsequent energy management optimization. The key parameter values for the above formulas are listed in Table 2.

Table 2. Summary table of key parameters of the tractor.

Symbol	Physical Meaning	Unit	Value
m	Tractor Total Mass	kg	8530
g	Gravitational Acceleration	m/s ²	9.8
f	Rolling Resistance Coefficient	-	0.07
ρ	Air Density	kg/m ³	1.0
C_D	Aerodynamic Drag Coefficient	-	0.15
A	Frontal Area	m ²	6.5
η_{fd}	Reduction Gear Efficiency	-	0.95
η_{gb}	Planetary Gear Torque Transmission Efficiency	-	0.98
η_{total}	Overall Transmission System Efficiency	-	0.931

2.5. Offline Equivalence-Factor Calibration via Dynamic Programming

Data preprocessing, K-means clustering, nonlinear least-squares parameter identification, DP-based offline optimization, and energy-management simulations were performed using MATLAB R2024a (The MathWorks, Inc., Natick, MA, USA). The slip-ratio and traction-loss models described above correct the tractor power demand and quantify the influence of tire–soil interaction on the energy balance. On this basis, the equivalence factor, which is the key calibration parameter of ECMS, must be determined appropriately to coordinate engine fuel consumption and battery-energy use.

Because plowing resistance varies substantially during operation, a single fixed equivalence factor cannot provide satisfactory fuel economy and SOC regulation throughout the complete cycle. Therefore, dynamic programming is used offline to obtain globally optimized control trajectories under representative combinations of resistance level and SOC. The resulting optimal trajectories are subsequently used to derive reference equivalence factors for online ECMS implementation.

It should be emphasized that the complete DP procedure is used only for offline calibration and is not executed by the online controller. The online strategy uses the pre-calibrated equivalence-factor table, SOC feedback, slip-ratio correction, and one-dimensional instantaneous optimization.

2.5.1. DP Problem Formulation

The plowing operation is discretized into $k = 0, 1, \dots, N - 1$ time steps with sampling interval Δt . At time step k , the power demand of the dynamic system is $P_{req}(k)$, and the engine output power is $P_e(k)$.

The state variable is selected as the battery state of charge 'SOC'(k), while the engine power serves as the control variable:

$$x(k) = \text{SOC}(k) \quad (24)$$

$$u(k) = P_e(k) \quad (25)$$

The coupled point power balance relation is:

$$P_{req}(k) = P_e(k) + P_{Motor}(k) \quad (26)$$

where $P_{Motor}(k)$ is defined as the algebraic sum of the mechanical shaft-end power of both motors $P_{Motor}(k) = P_{MG1}(k) + P_{MG2}(k)$.

The constraints are unified as

$$\begin{cases} \text{SOC}_{\min} \leq \text{SOC}(k) \leq \text{SOC}_{\max} \\ P_{e,\min} \leq P_e(k) \leq P_{e,\max} \\ P_{MGi,\min} \leq P_{MGi}(k) \leq P_{MGi,\max}, i = 1, 2 \\ P_{bat,\min} \leq P_{bat}(k) \leq P_{bat,\max} \end{cases} \quad (27)$$

The feasible domain $\Omega(k)$ for the control variable $P_e(k)$ can be determined from the power-balance relation and constraints, enabling DP to be implemented via a one-dimensional discrete traversal of $P_e(k)$.

2.5.2. Cost Function Construction

To reflect traction energy waste caused by slip, an equivalent fuel term representing traction loss power is introduced into the stage cost.

The traction power loss is converted to an equivalent fuel mass flow rate using the lower heating value of diesel q :

$$\dot{m}_{trac}(k) = \frac{P_{loss,trac}(k)}{q}, \quad q = 42,705 \text{ kJ/kg} \quad (28)$$

The stage cost at time k is defined as:

$$\dot{g}(k) = \dot{m}_{fuel}(P_e(k)) + S(k) \cdot \dot{m}_{equal}(k) + \dot{m}_{trac}(k) \quad (29)$$

An SOC penalty terminal cost is set:

$$\phi(\text{SOC}(N)) = \beta (\text{SOC}(N) - \text{SOC}_{ref})^2 \quad (30)$$

The total cost function over the entire cycle is then:

$$J = \sum_{k=0}^{N-1} \dot{g}(k) \Delta t + \phi(\text{SOC}(N)) \quad (31)$$

DP minimizes J under constraints to obtain the optimal engine power trajectory $P_e^*(k)$ and SOC trajectory $\text{SOC}^*(k)$.

2.5.3. Optimal Trajectory Solution via DP Recursion

Define the value function $V(k, \text{SOC})$ as the minimum residual cost from time k to the terminal. Terminal conditions are:

$$V(N, \text{SOC}(N)) = \phi(\text{SOC}(N)) \quad (32)$$

The Bellman recurrence relation is:

$$V(k, \text{SOC}) = \min_{P_e \in \Omega(k)} [\dot{g}(k)\Delta t + V(k+1, \text{SOC}(k+1))] \quad (33)$$

Backward recursion yields the optimal control sequence $P_e^*(k)$.

2.5.4. Equivalence Factor Extraction from DP Results

DP can obtain globally optimal trajectories offline but is not suitable for real-time online operation [30]. To transfer the optimal DP information to the online ECMS, this paper retroactively derives the equivalence factor $S(k)$ for each time step, such that the instantaneous optimal decision of ECMS at that moment can reproduce the optimal decision of DP. Let $P_e^*(k)$ denote the optimal engine power from DP at time step k . Based on whether the optimal point triggers boundary constraints, two categories are distinguished for retroactive derivation.

(1) Inner-point solution

When the optimal solution lies within the feasible region (not touching the feasible region boundary), it satisfies the first-order necessary condition:

$$\frac{\partial \dot{m}_{equal}(k)}{\partial P_e} = 0 \quad (34)$$

Rearranging yields:

$$S(k) = \left. \frac{-q \cdot \frac{d\dot{m}_{fuel}}{dP_e} + q \cdot \frac{dP_{loss, trac}}{dP_e}}{\frac{dP_{bat}}{dP_e}} \right|_{P_e = P_e^*(k)} \quad (35)$$

where ' $|^*$ ' denotes evaluation at $P_e = P_e^*(k)$. Assuming $\eta_{trac}(k)$ is determined by slip ratio and does not vary rapidly with P_e over short time scales, we may approximate $\frac{dP_{loss, trac}}{dP_e} \approx 0$. Derivatives are approximated using finite differences. Central differences are employed for interior points.

(2) Boundary Solving

During plowing operations, the optimal DP solution may approach boundaries (where feasible regions contract due to engine/motor/battery power limitations or SOC constraints). At such points, the optimum no longer satisfies the 'zero derivative' condition. To obtain stable and usable back-propagation results, single-sided differentials are applied at boundary points.

If $P_e^*(k) = P_{e, \min}(k)$, take the forward difference:

$$S(k) = \frac{-q \cdot \frac{\dot{m}_{fuel}(P_e^* + \Delta P) - \dot{m}_{fuel}(P_e^*)}{\Delta P}}{\frac{P_{bat}(P_e^* + \Delta P) - P_{bat}(P_e^*)}{\Delta P}} + q \cdot \frac{P_{loss, trac}(P_e^* + \Delta P) - P_{loss, trac}(P_e^*)}{\Delta P} \quad (36)$$

If $P_e^*(k) = P_{e, \max}(k)$, take the backward difference:

$$S(k) = \frac{-q \cdot \frac{\dot{m}_{fuel}(P_e^*) - \dot{m}_{fuel}(P_e^* - \Delta P)}{\Delta P}}{\frac{P_{bat}(P_e^*) - P_{bat}(P_e^* - \Delta P)}{\Delta P}} + q \cdot \frac{P_{loss, trac}(P_e^*) - P_{loss, trac}(P_e^* - \Delta P)}{\Delta P} \quad (37)$$

2.5.5. Baseline Equivalence-Factor Map

Plowing resistance is categorized into three levels as previously defined: $L_k \in \{\text{low, medium, high}\}$. State of charge (SOC) is discretized into six states: $SOC_k \Rightarrow SOC_{\text{bin}}(k)$. For each combination (L_i, SOC_j) , the average value is calculated. The resulting baseline table is shown in Table 3.

Table 3. Baseline table of equivalence factors.

Plowing Resistance/SOC	20–30%	30–40%	40–50%	50–60%	60–70%	70–80%
Low Plowing Resistance (≤ 33.06 KN)	1.95	1.92	1.89	1.86	1.83	1.75
Medium Plowing Resistance (33.06–35.36 KN)	2.28	2.24	2.20	2.13	2.02	1.92
High Plowing Resistance (≥ 35.36 KN)	2.50	2.46	2.43	2.44	2.41	2.31

The basic equivalence-factor table extracted via offline DP reveals that, in the resistance dimension, as plowing resistance levels increase, the engine tends toward higher load operation with reduced opportunities for energy replenishment. Consequently, the equivalence factor S exhibits an overall upward trend, reflecting the strategy of preserving power under heavy loads. On the SOC dimension, S values generally decrease as SOC increases. At low SOC levels, S is set higher to suppress excessive discharge and preserve battery capacity. At higher SOC levels, S is reduced to encourage electric motor assistance for driving, thereby releasing excess energy. This monotonic characteristic ensures the SOC adaptive stability of the online ECMS strategy.

2.6. Slip-Ratio-Aware Adaptive ECMS Strategy

The proposed DP-ECMS retains SOC feedback as the basic adaptive mechanism of conventional A-ECMS, while introducing two additional state-dependent functions. First, the DP-calibrated resistance-level–SOC map determines the baseline equivalence factor according to the current load state and SOC. Second, the estimated slip-state correction term provides an additional online adjustment to this baseline according to the current traction-state estimate. Therefore, DP calibration and slip-state correction act at different stages of the equivalence-factor adaptation: the former determines the load-dependent baseline, whereas the latter performs traction-state-dependent online correction.

2.6.1. Baseline Equivalence-Factor Lookup and Interpolation

Offline DP calibration yields a two-dimensional calibration table of equivalence factors for ‘resistance level–SOC state.’ During online operation, the current operating condition index is used to look up the table and read the corresponding reference equivalence factor:

$$S_{\text{base}}(k) = S_0(L_k, SOC_{\text{bin}}(k)) \quad (38)$$

To avoid discontinuities when SOC crosses the boundary between adjacent intervals, linear interpolation is applied between the neighboring table values. This produces a continuous reference equivalence factor and reduces abrupt changes in the power allocation.

2.6.2. Slip-State-Based Equivalence-Factor Correction

During plowing, excessive deviation of the slip ratio from the reference range of 10–15% indicates deterioration of the traction state and increases non-productive energy dissipation [31]. To actively suppress such energy waste, this study introduces the slip ratio as a pivotal state-fusion variable into the energy management layer. By dynamically adjusting the equivalence factor, the strategy achieves closed-loop feedback optimization of the powertrain output.

In situ plowing environments are characterized by soil non-homogeneity and tire sinkage, which can cause stochastic spikes in the measured slip ratio. Directly incorporating these anomalies into the correction law would lead to excessive transitions in the equivalence factor, triggering undesirable power-split oscillations and system chattering. Consequently, prior to the correction procedure, the fused slip ratio undergoes robust limiting to define the effective slip ratio λ_{eff} :

$$\lambda_{eff}(k) = \min\{\max[\lambda(k), \lambda_{\min}], \lambda_{\max}\} \quad (39)$$

Here, $\lambda_{\min}$ is set to 0, and $\lambda_{\max}$ is set to 0.30 as the upper reference bound of the correction law, determined based on terramechanics theory and plowing operation experience. It should be emphasized that this clipping is not a hard constraint on the actual slip ratio but rather a robustification of the control state to ensure numerical stability and repeatability of the online updates.

Based on the traction efficiency characteristic—where efficiency peaks within the 10–15% range and degrades significantly beyond this range—a dual-sided normalized slip deviation with a dead zone is constructed:

$$e_{\lambda}(k) = \begin{cases} \frac{\lambda_{eff}(k)-0.15}{0.35-0.15}, & \lambda_{eff}(k) > 0.15 \\ 0, & 0.10 \leq \lambda_{eff}(k) \leq 0.15 \\ -\frac{0.10-\lambda_{eff}(k)}{0.10}, & \lambda_{eff}(k) < 0.10 \end{cases} \quad (40)$$

When $\lambda_{eff}(k)$ falls within $[\lambda_L, \lambda_H]$, the deviation is zero (dead zone), preventing frequent fluctuations in the equivalence factor caused by slip ratios within the reasonable range. When slip ratio is excessively high, $e_{\lambda}(k) > 0$ and approaches 1 as slip increases; when slip ratio is excessively low, $e_{\lambda}(k) < 0$ and approaches -1 as slip decreases, thereby achieving a unified description of deviations on both sides.

To map slip deviation into equivalence-factor correction, define the bilateral gain correction law:

$$\Delta S_{\lambda}(k) = \begin{cases} -K_H \cdot e_{\lambda}(k), & e_{\lambda}(k) > 0 \\ -K_L \cdot e_{\lambda}(k), & e_{\lambda}(k) < 0 \\ 0, & e_{\lambda}(k) = 0 \end{cases} \quad (41)$$

In Equation (41), $K_H > 0$ and $K_L > 0$ represent the correction gains for the high-slip and low-slip sides, respectively.

When the slip ratio is excessively high ($e_{\lambda} > 0$), $\Delta S_{\lambda}(k) < 0$, causing the equivalence factor to decrease. This reduces the weight of the equivalent fuel cost of electrical energy in the objective function, making energy management more inclined to utilize the electric motor to share instantaneous power demands. Consequently, it minimizes the engine's inefficient energy output during high-dissipation operating conditions. When the slip ratio is too low ($e_{\lambda} < 0$), $\Delta S_{\lambda}(k) > 0$, the equivalence factor increases, raising the equivalent cost of electrical energy. This suppresses prolonged reliance on the electric motor that could lead to insufficient traction establishment, thereby adjusting the power-split preference toward an operating condition associated with lower traction-energy loss. Parameters were tuned via offline simulation grid search, balancing equivalent fuel consumption, SOC variation, and smoothing of equivalence-factor updates. Final values $K_H = 0.8$ and $K_L = 0.35$ achieve 'strong suppression at high slip ratios and weak correction at low slip ratios,' preventing control objectives from degenerating into unilateral constraints.

With SOC closed-loop feedback superimposed, the online equivalence-factor calculation formula is:

$$S(k) = S_{base}(k) + K_{SOC}(\text{SOC}_{ref} - \text{SOC}_k) + \Delta S_{\lambda}(k) \quad (42)$$

Integrating the baseline S_{base} —calibrated according to resistance levels and SOC states—with the slip-ratio suppression term ΔS_λ and SOC closed-loop feedback ΔS_{SOC} yields the final online dynamic equivalence factor $S(k)$. The resulting control manifold is illustrated in the 3D map in Figure 10.

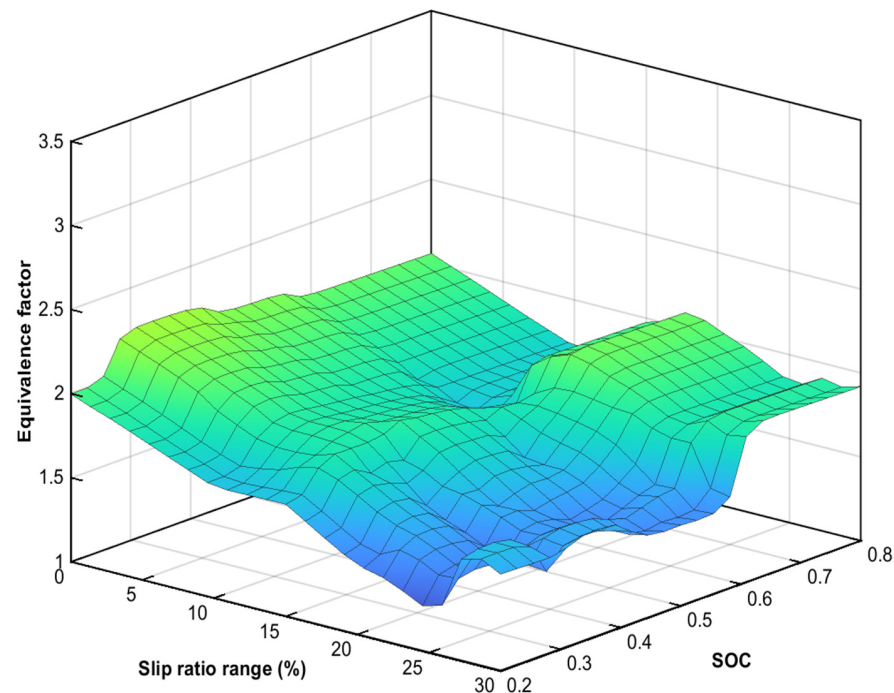


Figure 10. Map of equivalence factor.

2.6.3. Instantaneous Power Allocation Optimization

The online ECMS optimizes engine power $P_e(k)$ at each sampling instant. Considering fuel consumption, electrical energy conversion, and traction loss penalties, the instantaneous equivalent fuel consumption rate [32,33] is defined as:

$$\dot{m}_{equal}(k) = \dot{m}_{fuel}(k) + S(k) \frac{P_{bat}(k)}{q} \quad (43)$$

Here, $\dot{m}_{equal}(k)$ represents the engine fuel consumption rate; $S(k)$ is the dynamic equivalence factor.

Given $P_{Motor}(k)$, the power allocation $P_{MG1}(k)$ and $P_{MG2}(k)$ for the two motors must be determined. To avoid introducing additional decision dimensions in the outer-layer ECMS, this paper adopts an ‘inner-layer one-dimensional allocation’ approach; let

$$P_{MG2}(k) = P_{Motor}(k) - P_{MG1}(k) \quad (44)$$

and select the allocation scheme that minimizes the composite electric power while satisfying the power boundary constraints of both motors. That is:

$$P_{MG1}^*(k) = \underset{P_{MG1} \in D(k)}{\operatorname{argmin}} \left\{ \begin{array}{l} P_{el,1}(P_{MG1}(k)) + \\ P_{el,2}(P_{Motor}(k) - P_{MG1}(k)) \end{array} \right\} \quad (45)$$

The feasible set $D(k)$ is jointly determined by the upper and lower power limits of both motors:

$$D(k) = \left\{ \begin{array}{l} P_{MG1,\min} \leq P_{MG1} \leq P_{MG1,\max} \\ P_{MG2,\min} \leq P_{Motor} - P_{MG1} \leq P_{MG2,\max} \end{array} \right. \quad (46)$$

Hence:

$$P_{MG2}^*(k) = P_{Motor}(k) - P_{MG1}^*(k) \quad (47)$$

Substituting the allocation result $P_{bat}^*(k)$ into (46), the outer-layer instantaneous optimization in the online ECMS is formulated as follows: For any candidate engine power $P_e(k) \in \Omega_k$, first, the total motor power $P_{Motor}(k) = P_{req}(k) - P_e(k)$ is obtained from the power balance. Then, within the feasible set $D(k)$, the inner-layer one-dimensional allocation is performed to obtain the corresponding battery power $P_{bat}^*(P_e)$. Substituting this $P_{bat}^*(P_e)$ as a function of $P_e(k)$ into Equation (44) yields the outer-layer instantaneous optimization for online ECMS:

$$P_e^*(k) = \underset{P_e \in \Omega(k)}{\operatorname{argmin}} \left\{ \dot{m}_{fuel}(P_e) + S(k) \frac{P_{bat}^*(P_e)}{q} \right\} \quad (48)$$

Here, $P_{MG1}^*(k)$ represents the optimal power of motor 1, measured in kW; $P_{MG2}^*(k)$ is the optimal power of motor 2, measured in kW; $P_e^*(k)$ denotes the optimal power of the engine, measured in kW.

Within the feasible region Ω_k , ECMS can determine $P_{eng,k}^*$ that minimizes the objective function J_k through one-dimensional search [34], then automatically allocate $P_{mot,k}^*$ via power balancing, thereby achieving real-time coordinated output between the engine and motors.

The overall control framework of the strategy is shown in Figure 11.

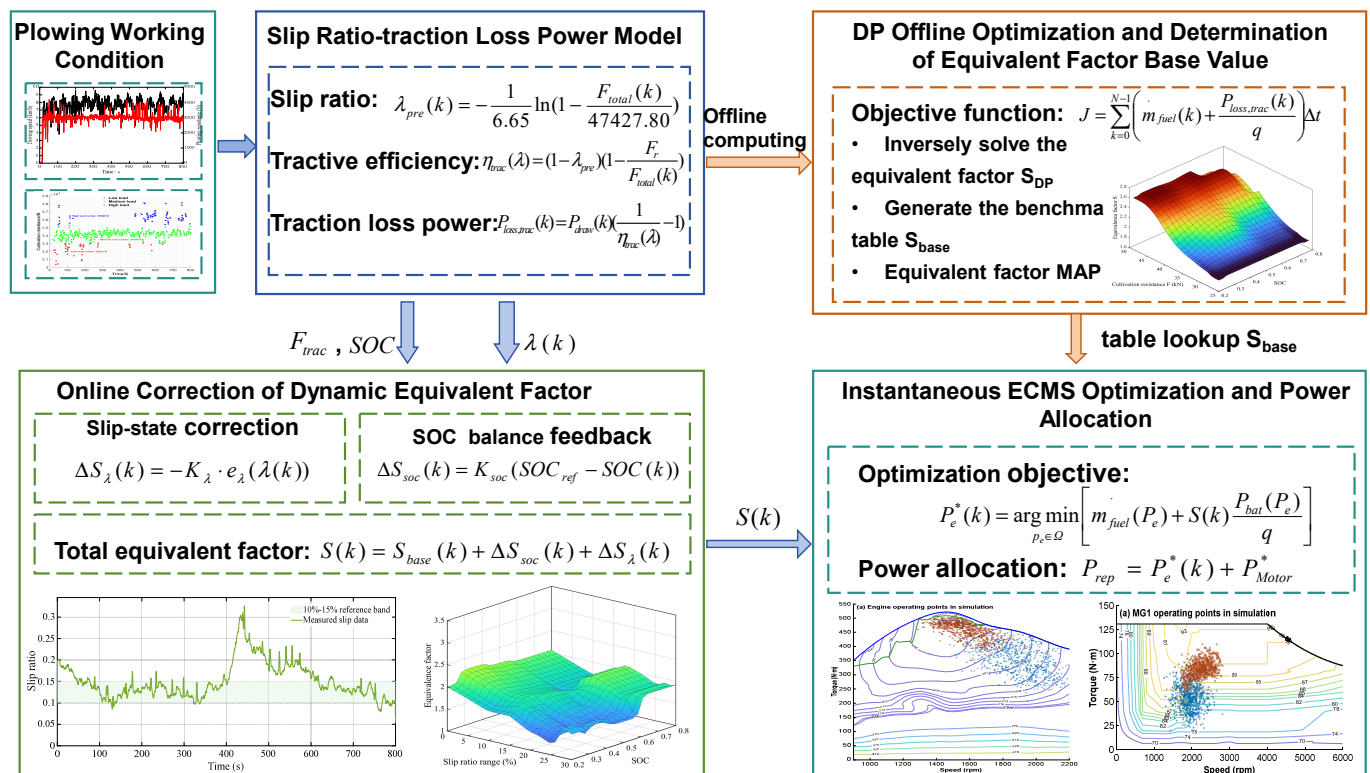


Figure 11. Block diagram of the energy management strategy based on DP-ECMS.

3. Experimental Validation and Results

In January 2026, experimental validation and data acquisition were conducted on a hybrid tractor powertrain test bench. To evaluate the proposed strategy under measured component characteristics and variable-load conditions, a hybrid tractor powertrain test bench was established. During the tests, the target dynamometer torque was prescribed

according to the plowing-resistance profile to reproduce the transitions and dynamic variations among low-, medium-, and high-resistance conditions. The speeds and torques of the engine, MG1, and MG2, together with the DC bus voltage and current, dynamometer speed, and load torque, were recorded synchronously.

The plowing-resistance and slip-ratio data collected from the soil-bin tests were used for parameter identification of the resistance–slip-ratio prediction model. During the bench tests, the equivalent plowing resistance was calculated from the measured dynamometer load torque and the power-transmission relationship. The identified model was then used to estimate the corresponding slip ratio at each sampling instant. The measured bench data were used to evaluate power allocation, equivalent fuel consumption, SOC variation, and component operating efficiency, while the model-estimated slip ratio was used to analyze the response of the energy management strategy to slip-state variations under variable loads.

3.1. Test Bench Setup

The modular test bench consists of four main subsystems: the power-source subsystem, transmission subsystem, load-simulation subsystem, and measurement-and-control subsystem. It supports series hybrid, pure-electric, diesel–electric coupled, and diesel-only operating modes, as well as independent testing of the main power components.

The power-source subsystem includes a diesel engine and two permanent-magnet synchronous machines. The transmission subsystem is centered on a dual-planetary ECVT power-coupling mechanism. Mode switching is achieved using electromagnetic clutches and brakes, and a 1:1 reversing gearbox is used to accommodate the spatial arrangement of the test bench.

The load-simulation subsystem uses an eddy-current dynamometer to reproduce the time-varying resistance encountered during plowing. The dynamometer excitation current is regulated to generate the required load torque.

The measurement-and-control subsystem adopts a hierarchical control architecture. An industrial computer running LabVIEW is used for human–machine interaction, parameter setting, monitoring, and data acquisition. A PLC and variable-frequency drive system perform low-level control and safety protection. A multi-channel data-acquisition unit and multiple sensors are used to record the operating states of the complete powertrain synchronously. The test-bench configuration is shown in Figure 12.

The target load was generated from the resistance data measured during the soil-bin tests. The eddy-current dynamometer had a torque range of 0–1000 N·m. A stepwise load profile with superimposed random fluctuations was used to reproduce transitions and abrupt variations among the low-, medium-, and high-resistance levels.

The sampling frequency was set to 10 Hz. The acquired signals included engine speed and torque, MG1 and MG2 speeds and torques, DC bus voltage and current, and dynamometer speed and load torque. The cooling system was operated continuously to maintain stable component temperatures. Each test condition was repeated three times. Outliers were removed using the 3σ criterion, and the mean of the valid measurements was used for the subsequent analysis.

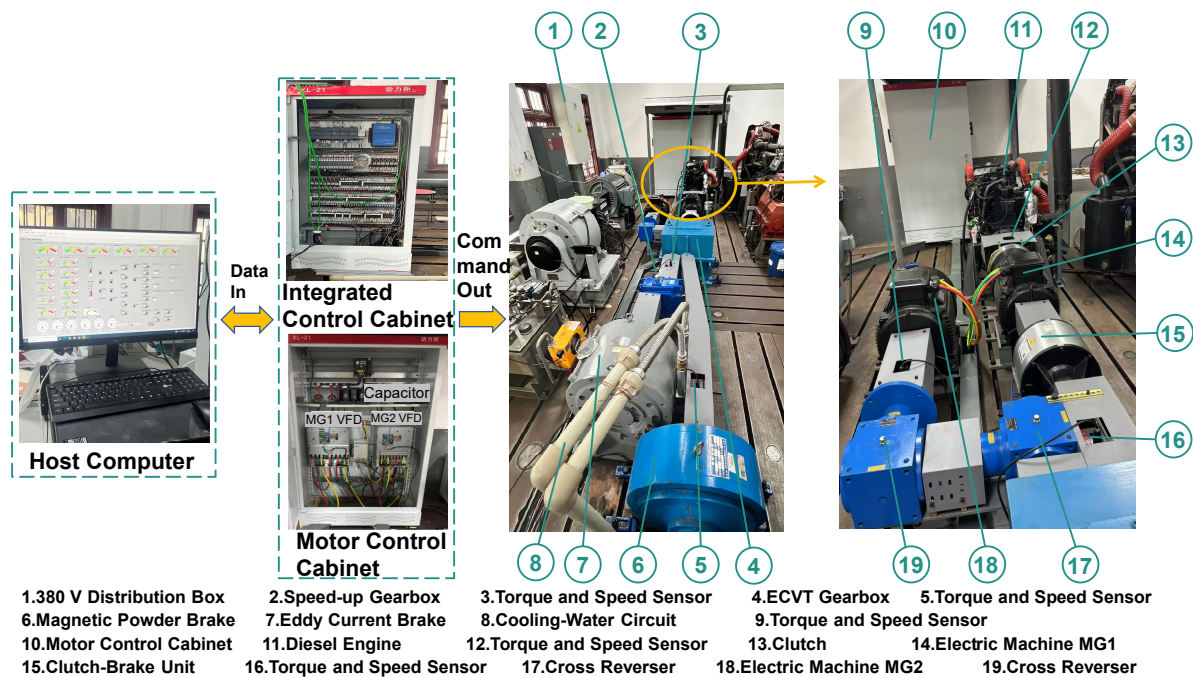


Figure 12. Hybrid Tractor Test Bench.

3.2. Performance Evaluation Metrics

To quantitatively evaluate the performance of the proposed DP-ECMS strategy under bench-measured data conditions, equivalent fuel consumption, SOC variation, and the proportion of operation in high-efficiency regions of power components were selected as the evaluation metrics.

(1) Equivalent Fuel Consumption

To uniformly measure fuel consumption and electrical energy usage costs, equivalent fuel consumption V_{eq} serves as the core economic evaluation metric:

$$V_{eq} = \int_0^T (\dot{m}_{fuel} + s \cdot \frac{P_{bat}}{q}) dt \quad (49)$$

(2) SOC Maintenance

To evaluate the strategy's ability to maintain electrical energy, the absolute deviation ΔSOC between the final and initial SOC values is defined:

$$SOC = |SOC_{end} - SOC_{init}| \quad (50)$$

Here, SOC_{end} represents the final SOC value at the end of the cycle; SOC_{init} is the initial SOC value at the start of the cycle.

A smaller value indicates stronger electrical energy balance control capability and enhances the comparability of fuel economy calculation results.

(3) Proportion of Operation in High-Efficiency Zones

To validate the strategy's optimization of power component operating points, define γ_{eff} as the proportion of operating time for the engine in the low specific fuel consumption zone ($b_e \leq 210 \text{ g/kW}\cdot\text{h}$) and the motor in the high-efficiency zone ($\eta_{mot} \geq 85\%$):

$$r_{eff} = \frac{T_{high}}{T_{total}} \times 100\% \quad (51)$$

Here, T_{high} represents the cumulative operating time of the component in the high-efficiency zone.

3.3. Experimental Results

To evaluate the proposed strategy, the simulation and bench-test results of A-ECMS and DP-ECMS were compared under the same plowing-cycle framework. A-ECMS was used as the benchmark strategy, whereas DP-ECMS was used as the proposed strategy. The comparison focuses on equivalent fuel consumption, SOC variation, power allocation, and the operating characteristics of the engine and motors.

Figure 13 compares the cumulative equivalent fuel consumption obtained from simulation and bench tests for the two energy management strategies. In the simulation results, DP-ECMS reduced the final equivalent fuel consumption from 3780 g to 3250 g compared with A-ECMS, corresponding to a fuel-saving rate of 14.02%. In the bench-test results, after normalization to the same output-energy basis, the equivalent fuel consumption decreased from 2005 g under A-ECMS to 1858 g under DP-ECMS, giving a fuel-saving rate of 7.33%. Although the reduction observed in the bench test is smaller than that in simulation, both results show the same trend, confirming that DP-ECMS can reduce equivalent fuel consumption relative to A-ECMS.

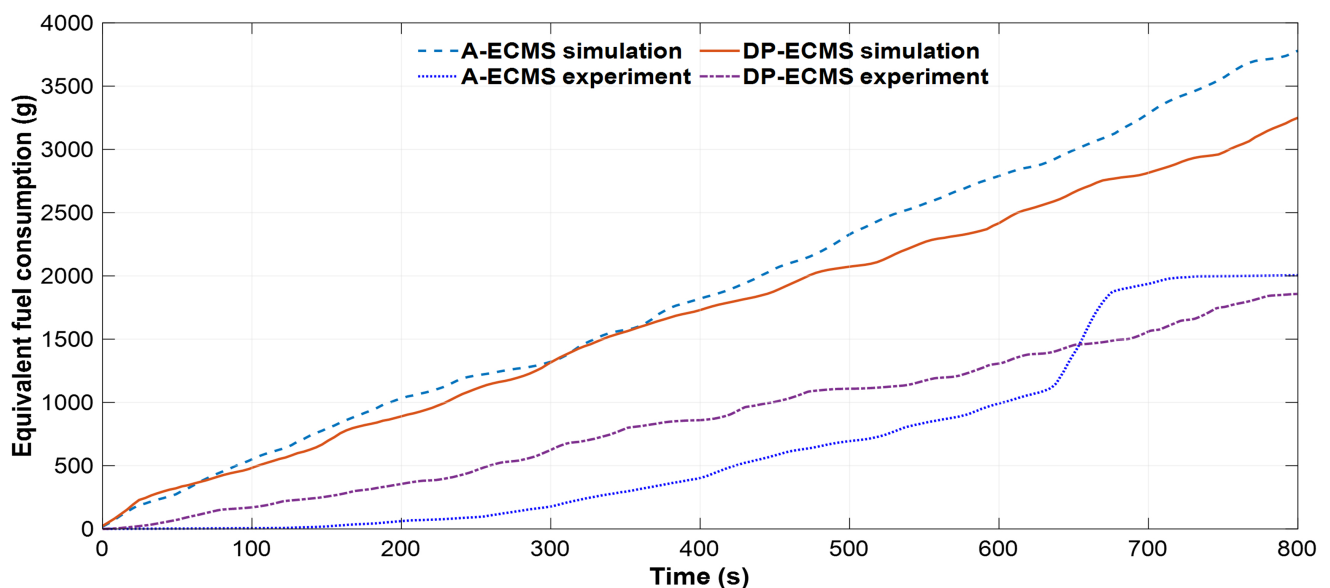


Figure 13. Variation curve of equivalent fuel consumption.

Figures 14 and 15 show the engine operating-point distributions and engine-efficiency trajectories, respectively.

Compared with A-ECMS, DP-ECMS shifted more engine operating points toward the best economy line and the low-BSFC region. This trend was observed in both simulation and bench-test results, indicating that the DP-calibrated equivalence factor improved the engine operating state under variable plowing loads. The average engine efficiency increased from 39.80% to 40.60% in simulation and from 39.90% to 40.40% in the bench test. Meanwhile, the proportion of engine operation in the high-efficiency region increased from 61% to 80% in simulation and from 65% to 77% in the bench test.

Figures 16 and 17 show the operating-point distributions and efficiency trajectories of MG1 and MG2.

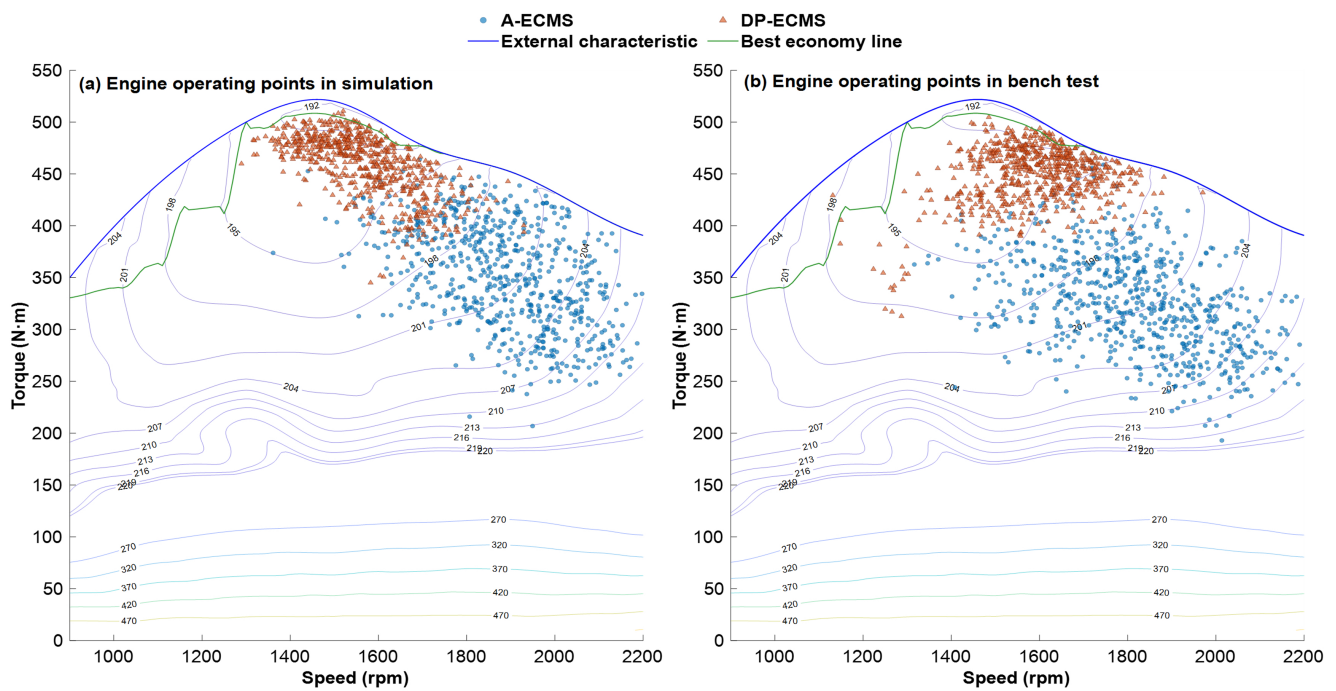


Figure 14. Engine operating-point maps under A-ECMS and DP-ECMS.

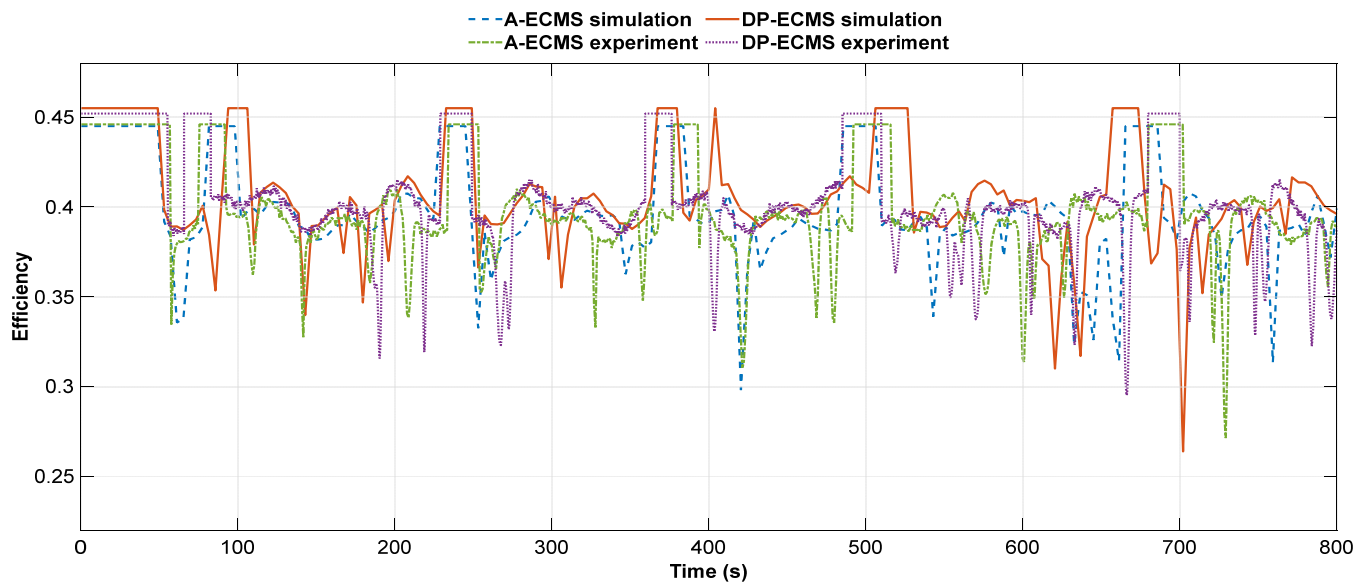


Figure 15. Engine efficiency.

Under DP-ECMS, more motor operating points were concentrated in the high-efficiency regions of the motor maps, whereas A-ECMS showed a relatively wider distribution. For MG1, the average efficiency increased from 93.00% to 94.59% in simulation and from 93.40% to 94.00% in the bench test. For MG2, the average efficiency increased from 90.00% to 91.50% in simulation and from 90.30% to 91.00% in the bench test. The overall motor high-efficiency zone ratio increased from 87% to 92% in simulation and from 88% to 90% in the bench test, demonstrating that DP-ECMS also improved the operating efficiency of the electric drive system.

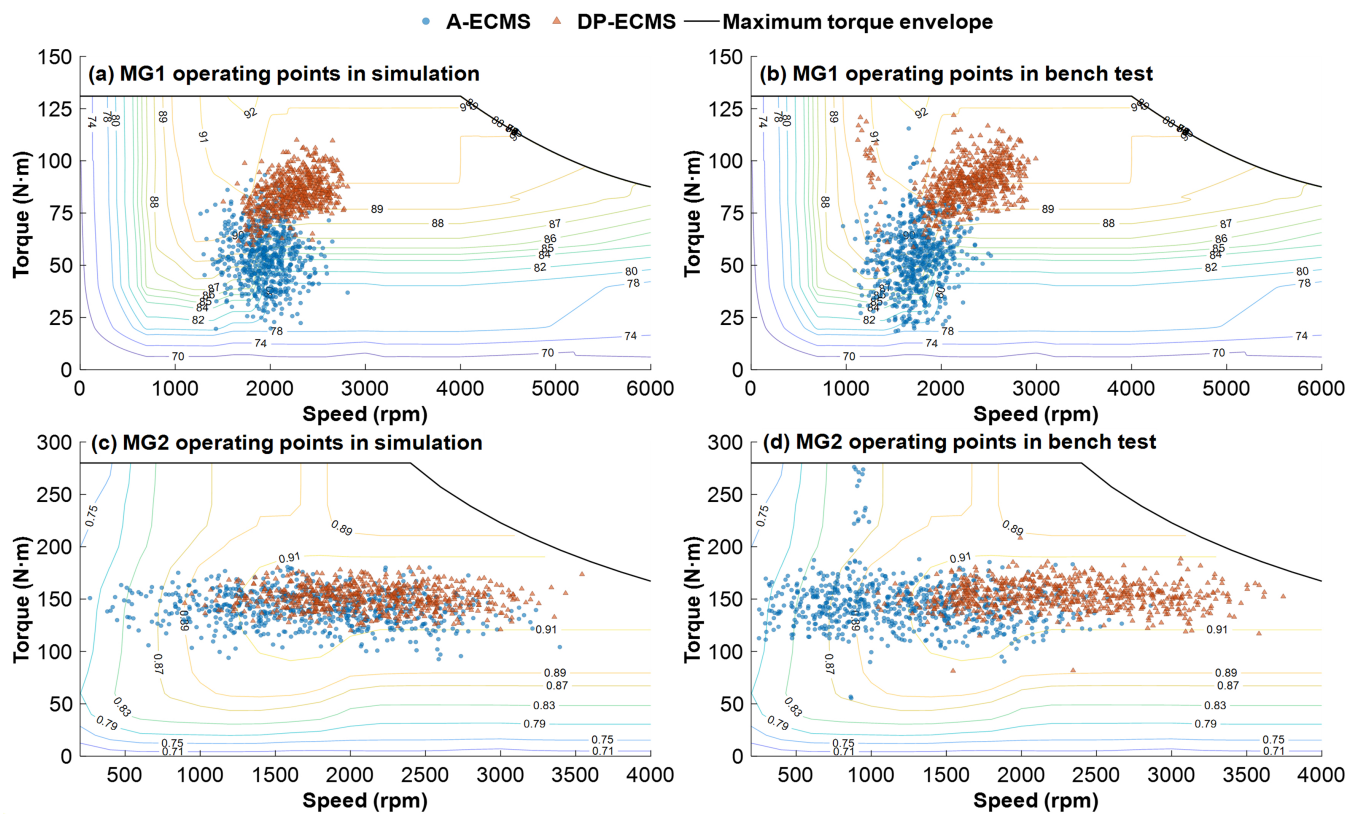


Figure 16. Motor operating-point maps under A-ECMS and DP-ECMS.

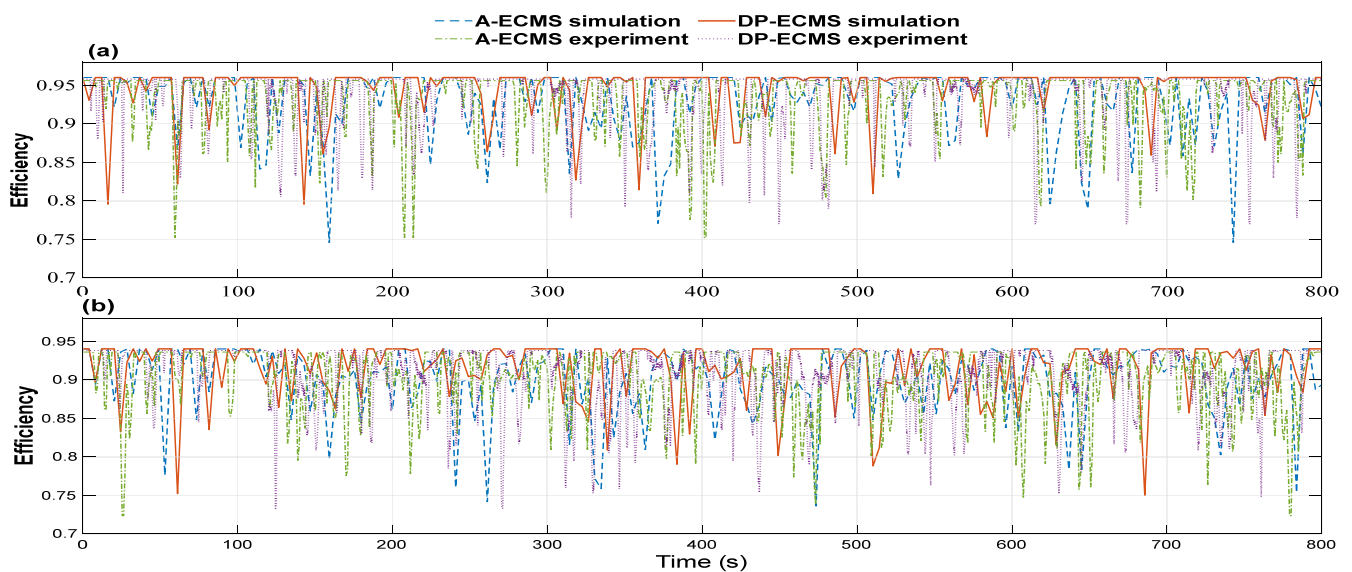


Figure 17. Motor efficiency: (a) MG1 efficiency; (b) MG2 efficiency.

Figure 18 shows the SOC trajectories of A-ECMS and DP-ECMS. The initial SOC was set to 0.80 for both strategies. In simulation, the final SOC values of A-ECMS and DP-ECMS were 0.7697 and 0.7774, corresponding to SOC deviations of 3.03% and 2.26%, respectively. In the bench test, the final SOC values were 0.7693 and 0.7757, with SOC deviations of 3.07% and 2.43%, respectively. These results indicate that DP-ECMS reduced battery depletion while maintaining charge-sustaining operation.

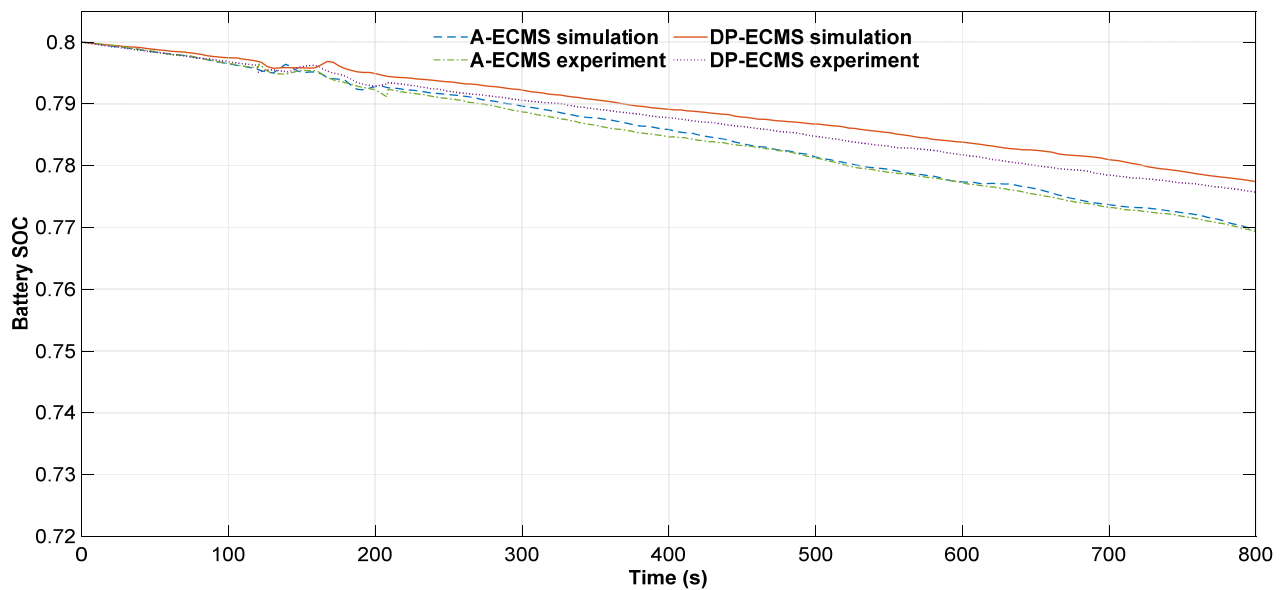


Figure 18. SOC variation curve.

Figure 19 presents the time-domain power allocation of DP-ECMS over a representative variable-load segment. The engine provides the main power contribution, while MG1 and MG2 dynamically adjust their outputs in response to changes in the power demand. When the load increases, the electrical machines provide additional power to complement the engine output; when the demand decreases, their contributions are reduced accordingly. Throughout the selected interval, the combined power of the engine, MG1, and MG2 closely matches the required power, confirming the instantaneous power balance of the proposed strategy. This result directly illustrates how variations in the plowing load are translated into coordinated power-split actions among the three power sources.

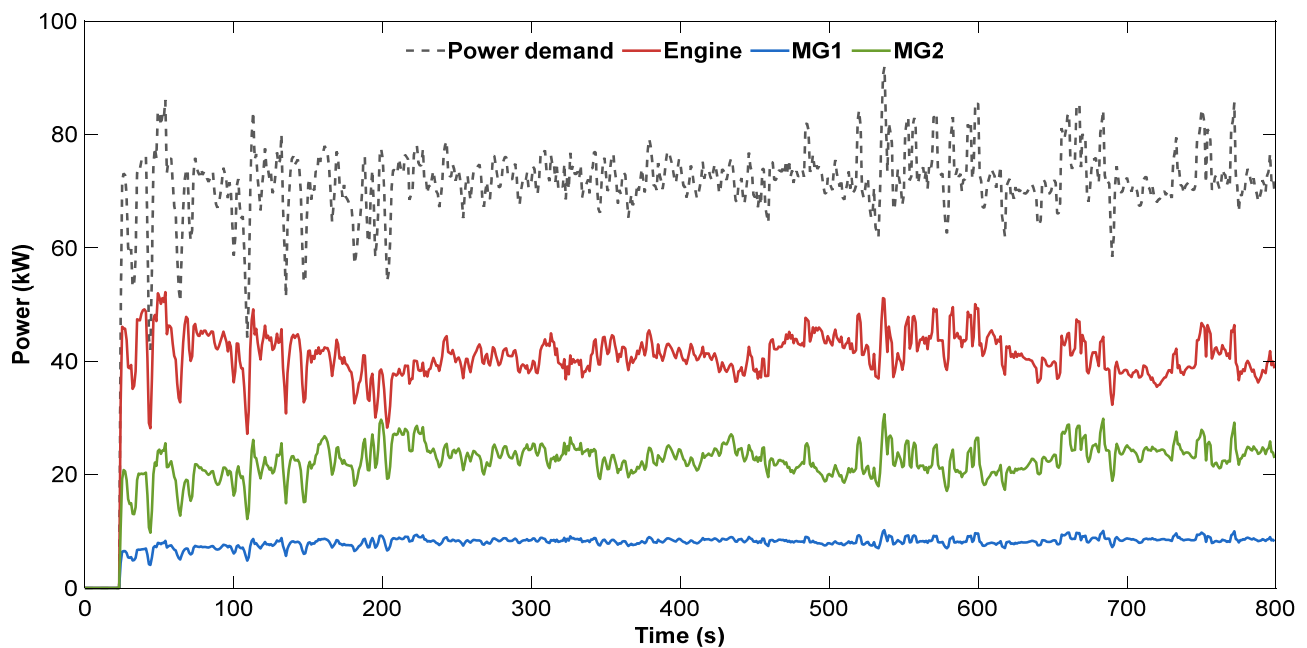


Figure 19. Power allocation under DP-ECMS.

The overall performance of the different strategies is summarized in Table 4.

Table 4. Comparison of performance indicators between two strategies.

Evaluation Index	A-ECMS Simulation	A-ECMS Experiment	DP-ECMS Simulation	DP-ECMS Experiment
Equivalent fuel consumption (g)	3780	2005	3250	1858
SOC deviation (%)	3.03%	3.07%	2.26%	2.43%
Engine high-efficiency zone ratio (%)	61%	65%	80%	77%
Motor high-efficiency zone ratio (%)	87%	88%	92%	90%
Fuel-saving rate (%)	—	—	14.02%	7.33%

The online execution time was also evaluated using the same controller implementation. The mean and maximum computation times were 2.45 and 4.47 ms for A-ECMS and 5.54 and 17.34 ms for DP-ECMS, respectively. Although the proposed strategy requires additional computation, its maximum execution time remains well below the 100 ms control interval used in the present implementation.

3.4. Functional Analysis of the Equivalence-Factor Adaptation Mechanism

To clarify the respective roles of the additional mechanisms introduced in DP-ECMS, the effects of DP calibration and slip-state correction on equivalence-factor adaptation were examined separately. DP calibration determines the load-dependent baseline equivalence factor according to resistance level and SOC, whereas the slip-state correction provides an additional online adjustment according to the estimated traction state. Figure 20 illustrates these two complementary functions.

As shown in Figure 20a, the DP-calibrated term varies systematically with resistance level over the SOC range. At the same SOC, low-resistance conditions produce a negative load-dependent adjustment, whereas high-resistance conditions produce a positive adjustment. This indicates that DP calibration introduces an additional load-dependent dimension into the baseline equivalence factor. Figure 20b shows that the slip-state correction term provides a separate online correction. No correction is applied within the 10–15% dead zone, while deviations outside this range lead to directional adjustment of the equivalence factor. Therefore, DP calibration and slip-state correction perform distinct but complementary functions: the former provides load-dependent baseline adaptation, whereas the latter provides traction-state-dependent online correction. Their roles are therefore functionally distinct but complementary within the proposed energy management strategy.

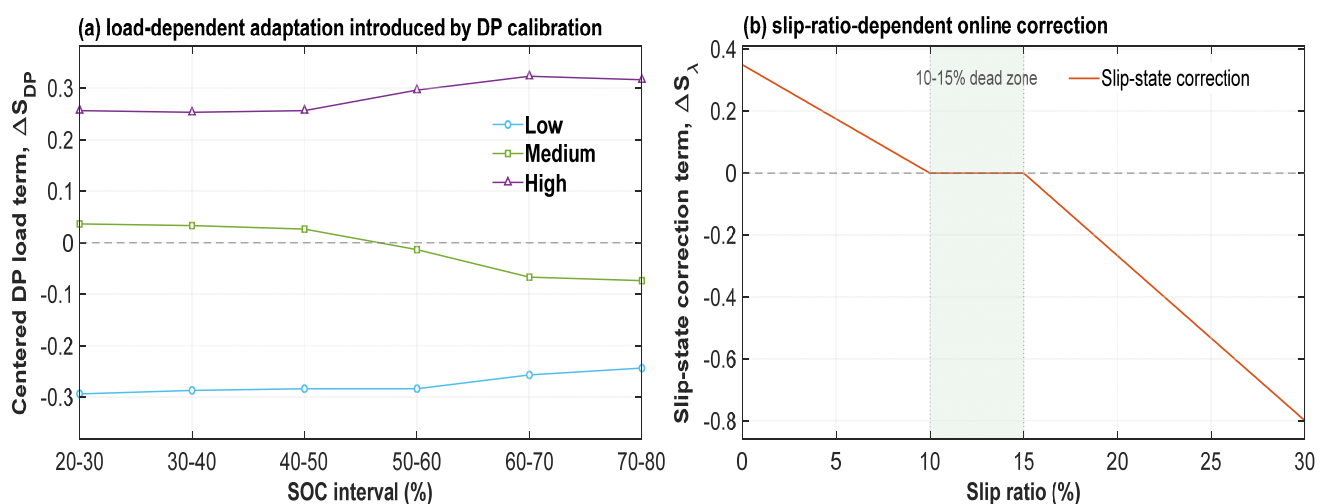


Figure 20. Functional roles of the two additional equivalence-factor adaptation mechanisms in DP-ECMS.

4. Discussion

4.1. Mechanisms of Performance Improvement

The experimental results demonstrate that the proposed slip-ratio-aware DP-ECMS improves fuel economy, SOC regulation, and component operating efficiency compared with A-ECMS. These improvements can be attributed to three complementary mechanisms.

First, offline DP calibration provides a resistance-level–SOC baseline equivalence-factor map. Compared with conventional A-ECMS, which mainly adjusts the equivalence factor according to SOC, the DP-calibrated map introduces load-dependent information into the baseline adaptation, enabling more appropriate power allocation under variable plowing loads and contributing to the observed shift of engine and motor operating points toward higher-efficiency regions.

Second, incorporating the traction-efficiency term into the demand-power model accounts for the additional energy dissipation associated with tire–soil slip. As the estimated slip ratio increases and traction efficiency decreases, the calculated power demand correspondingly increases. This reduces the possibility of underestimating the required power under high-resistance and high-slip conditions and provides a more representative demand-power input for subsequent energy management optimization.

Third, the online slip-state correction mechanism further adjusts the equivalence factor according to the estimated traction state. When the estimated slip state indicates excessive slip, the equivalence factor is reduced to increase the contribution of the electric machines and reduce inefficient engine operation under high-dissipation conditions. This correction therefore modifies the upper-level power-split preference according to traction-state variation.

The smaller fuel-saving rate observed in the bench test than in simulation is mainly attributed to deviations between actual and modeled component efficiencies, dynamometer load-tracking errors, and measurement noise. Nevertheless, the consistent improvement trends observed in both simulation and bench tests support the effectiveness of the proposed strategy.

4.2. Comparison with Existing Studies

Existing traction-aware studies have addressed the interaction between powertrain energy consumption and tractor traction performance at different control levels. Wang et al. [4] considered equivalent fuel consumption and traction efficiency in the power allocation of a distributed hybrid tractor, while Radrizzani et al. [19] coordinated energy management with vehicle-speed control. Wheel-slip control and slip-based switching strategies [20,21] mainly regulate traction behavior at the vehicle or wheel-control level, and the relationship between slip and tractive efficiency has also been investigated for independently driven electric tractors [22].

The present study differs in the manner in which traction information is incorporated into the upper-level energy management problem. A resistance-derived slip-state estimate is used both to account for slip-related traction losses in the demand-power formulation and to modify the online equivalence factor around a DP-calibrated resistance–SOC baseline. Therefore, the proposed method does not treat slip as a direct lower-level control target but as a traction-state indicator that influences the upper-level power-split decision.

Under the same bench load profile, the proposed DP-ECMS reduced equivalent fuel consumption by 7.33% relative to A-ECMS while improving SOC regulation and the operating efficiency of the main power components. Because the bench setup does not reproduce physical tire–soil interaction, these results should be interpreted as verification of traction-state-aware energy management adaptation rather than direct experimental verification of wheel-slip regulation.

4.3. Limitations and Future Work

This study has certain limitations that should be acknowledged. The powertrain test bench can reproduce the time-varying load demand obtained from the soil-bin experiments and can therefore evaluate the response of the engine, electric machines, battery, and energy management controller under measured component characteristics. However, it does not reproduce the physical tire–soil interaction of a complete tractor. In particular, spatial soil heterogeneity, tire sinkage, transient wheel slip, terrain variation, and implement disturbances are not physically generated on the bench. The slip ratio used in the bench analysis is instead estimated from the measured equivalent resistance using the identified resistance–slip relationship. Therefore, the bench results should be interpreted as validation of powertrain-level energy management performance under soil-bin-derived variable-load profiles rather than as direct validation of field traction or wheel-slip control. Second, the slip ratio prediction model was identified based on specific soil conditions and a single plowing depth; its generalization to different soil types and working parameters requires further verification. Third, the current strategy uses a steady-state slip ratio prediction model and does not consider the dynamic response process of slip during transient load changes.

Future work will focus on three aspects: (1) conducting full-scale field vehicle tests under different soil textures, plowing depths, and tire configurations to verify and optimize the strategy under real working conditions; (2) introducing load prediction and machine learning methods to develop a predictive adaptive energy management framework, further improving the adaptability to complex and variable field conditions; (3) combining upper-level energy management with lower-level slip control to achieve multi-layer coordinated optimization of traction efficiency and powertrain efficiency.

5. Conclusions

This study developed a slip-ratio-aware energy management framework for a series-parallel hybrid tractor under plowing conditions. Unlike conventional strategies that treat slip mainly as a lower-layer control target, the proposed method embeds slip-related traction loss into the demand power formulation and the online equivalence-factor adaptation, thereby linking tire–soil interaction with upper-level energy management decision-making.

Based on soil-bin test data, plowing draft resistance was discretized into operating state levels and used together with SOC to construct a two-dimensional baseline map of the equivalence factor via offline DP optimization. During online operation, a dynamic correction law combining SOC feedback and slip-ratio deviation was introduced to adapt the equivalence factor in real time, enabling more efficient power split between the engine and electric machines under highly variable plowing loads.

Under identical initial SOC and plowing conditions, the proposed strategy reduced equivalent fuel consumption by 14.02% in simulation and by 7.33% in the bench experiments relative to A-ECMS. The proportion of engine operation in the high-efficiency region increased from 61% to 80% in simulation and from 65% to 77% in the bench test, while the corresponding proportion for the electric motors increased from 87% to 92% and from 88% to 90%, respectively. The SOC deviation decreased from 3.03% to 2.26% in simulation and from 3.07% to 2.43% in the bench test. These results demonstrate that incorporating traction-state information into the upper-level energy management strategy can improve fuel economy, SOC regulation, and component operating efficiency under variable plowing loads.

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