OPTIMAL SPEED TRAJECTORY OF ELECTRIC WHEEL LOADERS AIMING AT EXTENDING BATTERY LIFETIME

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ABSTRACT

The electrification of wheel loaders is considered a leading trend due to its advantage of zero-carbon emissions. However, the inevitable phenomenon of battery degradation has led to increased battery usage and maintenance costs. This study first extends the battery lifetime by optimizing the speed trajectory based on the typical loading cycle of the wheel loader. The optimal control problem is formulated by systematically modelling the wheel loader's powertrain and using a precise semi-empirical battery aging model. To reduce computational costs, the modified optimal control problem includes a weighted penalty on travel time. A combined algorithm of dynamic programming and Brent's method (DP-BM) is introduced to provide a numerical solution to the optimization problem with a reduced computational burden. Simulation results demonstrate that the optimized trajectory can decrease the average power consumption of the battery and reduce the number of full equivalent cycles, resulting in a 4.48% improvement in the average battery lifetime compared to the typical trajectory. Furthermore, the proposed approach significantly reduces computation time compared to the conventional dynamic programming method, with an average reduction of 95%.

Keywords: Speed trajectory optimization, Dynamic programming, Brent's method, Battery lifetime, Electric wheel loader

1. INSTRUCTION

The electric wheel loader has been gradually rolling out in recent years due to its advantage of zero-carbon emission. However, the inevitable battery degradation phenomenon influences the battery lifetime and hinders the widespread application of the electric wheel loader. The high load and high inertia characteristics of the electric wheel loader result in a high average discharge current, exacerbating battery degradation. Additionally, the wheel loader is usually designed for a single application such as loading material, meaning that the driving path is relatively short and fixed. The high repetition of the duty cycle causes the battery to charge and discharge frequently, which further accelerates battery degradation.

Aiming at extending battery lifetime, this paper attempts to find the optimal speed profile of electric wheel loaders in the typical loading cycle. The optimization problem can be defined as follows: given the target route and duration time of the vehicle, calculate the speed at each moment to form a velocity trajectory, aiming at maximizing the battery lifetime.

Currently, there is no work for either wheel loaders or on-road vehicles on extending battery lifetime through speed trajectory optimization. However, some studies around speed optimization focus on minimizing energy consumption, which can provide references to this paper. Mello and Bauer optimize speed trajectories between stops for electric vehicles by considering real-world constraints such as following distance to the next vehicle and jerk [1]. Wu et al. [2] address similar issues and focus on avoiding stops in arterial corridors considering the impact of the presence of intersection queues in both temporal and spatial dimensions for an electric vehicle. In addition, some works focus on the speed profile of trams [3, 4]. The specific operating scenario gives the optimization problem extra constraints such as precise green signal time windows.

Numerical methods in dealing with trajectory optimization problem greatly affect the calculation efficiency and accuracy. Dynamic programming has been widely and extensively used because it can find a global optimum even for nonlinear systems with nonlinear constraints. However, it is difficult to obtain an accurate solution within an acceptable time. Since the operating distance and duration vary for each loading cycle, the optimization problem must be addressed frequently, which puts forward higher requirements on the algorithm's efficiency. The conventional dynamic programming algorithm takes substantial computation time and must be improved.

The contribution of this study is to extend battery lifetime of an electric wheel loader through speed trajectory optimization. To achieve this target, dynamic programming method is employed to give a numerical and optimal speed-versus-time trajectory that satisfies the given constraints. In order to reduce the computational cost, the optimal control problem is modified such that a weighted penalty on travel time is included. Brent's method is first used to calculate the weighted penalty (achieve time constraint in the cost function). The dynamic programming combining Brent's method (DP-BM) proposed in this paper provides a very useful tool that can calculate the global optimal speed trajectory with a reduced computational burden. The significant saving of operation time provides the possibility for the application of trajectory optimization in real working cycles.

2. MATHEMATICAL MODELING OF ELECTRIC WHEEL LOADER

2.1. System Overview

The conventional wheel loader generally uses one internal combustion engine that simultaneously drives the hydraulic pump and the drive shaft. Taking advantage of the electric motor's small size and flexibility in arrangement, the distributed solution with two independent electric motors that separately drive the working hydraulic system and propulsion system is widely used in the electric wheel loader. **Figure 1** shows the powertrain architecture analyzed in this study. The two systems are powered simultaneously by one battery pack, then achieve their respective functions.

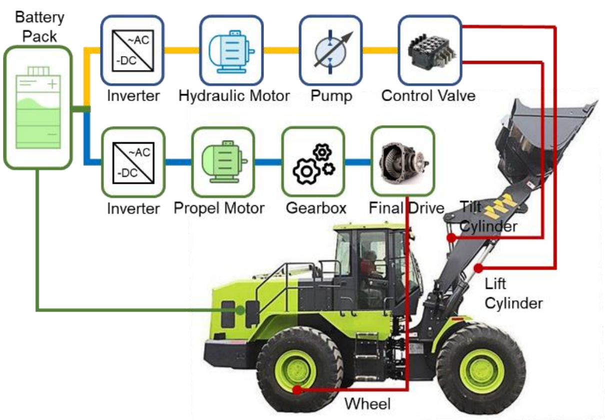


Figure 1: Powertrain of the electric wheel loader

2.2. System Modelling

Drivetrain

The time-based longitudinal dynamics of a wheel loader can be described as:

$$\dot{s} = v$$
$$\dot{v} = \frac{1}{m}\left(F_t + F_b - F_r\right) \tag{1}$$

where m is the operating mass of the wheel loader, v is the wheel loader speed, s is the position of the wheel loader. F_t, F_b and F_r are the motor traction force, electrical braking force and resistance force respectively.
The basic resistance force of an operating wheel loader includes the aerodynamic friction, the rolling friction, and the thrust force, as given by:

$$F_r = \mu mg + \frac{1}{2}\rho v^2 C_d A_v + F_{th} \tag{2}$$

where μ is the rolling friction coefficient, g is the gravitational acceleration, ρ is the air density, C_d is the aerodynamic drag coefficient, A_v is the frontal area of the vehicle body.
The relationship between electric motor torque T_m and the motor traction force F_t is:

$$T_m = \frac{r_w}{\gamma_g \gamma_f} F_t \tag{3}$$

where r_w is the wheel radius, γ_g is the gear ratio of gearbox, and γ_f is the final drive ratio.

Electric motor

The electric motor power in the steady-state condition, P_m, is given by:

$$P_m = T_m \omega_m \eta_m^{-\mathrm{sgn}(T_m)} \tag{4}$$

where ω_m is the motor speed and η_m is the motor efficiency. The motor outputs mechanical power if $T_m > 0$ and generates electric power if $T_m < 0$.

Battery

The battery pack is developed by an equivalent circuit model composed of a voltage source U_{oc} and a resistance R_b accounting for Joule losses. The battery current can be derived as:

$$i_b = \frac{U_{oc} - \sqrt{U_{oc}^{\ 2} - 4R_b P_b}}{2R_b} \tag{5}$$

The battery C-rate is defined as:

$$I_c = \frac{|i_b|}{Q_b} \tag{6}$$

where Q_b is the capacity of battery and $Q_b = Q_{init} - Q_{loss}$. Q_{init} is the battery initial capacity at the manufactory (nominal capacity) and Q_{loss} is the total capacity loss.

The battery SOC accounts for the current battery capacity and its dynamic model is given by:

$$\dot{SOC}_b = -\frac{i_b}{Q_b} \tag{7}$$

The equivalent voltage source has a nonlinear connection with the battery SOC.

3. SPEED TRAJECTORY OPTIMIZATION

3.1. Typical Loading Trajectory

The commonly used movement trajectory for wheel loaders to carry material from material pile to truck is the V-type loading cycle (V-cycle) [5]. The V-cycle consists of six operating phases: bucket filling, backward 1, forward 1, dumping, backward 2, and forward 2. The speed trajectory optimization in this study focuses on the forward/backward phases, where the short moving in bucket filling and dumping phases are not part of the research. In addition, the prerequisite of optimizing the speed trajectory for a wheel loader is to determine a moving route. In this study, the forward/backward routes are taken as known conditions for optimizing the speed trajectory.

3.2. Battery Aging Model

For battery lifetime optimization, the first step is to set up an accurate and useful battery aging model. In this study, an accurate semi-empirical model from Naumann's previous works [6, 7] is adopted. The battery degradation contains cycle aging capacity loss Q_{cyc} and calendar aging capacity loss Q_{cal}:

$$Q_{loss} = Q_{cyc} + Q_{cal} \tag{8}$$

The expressions of Q_{cyc} and Q_{cal} are:

$$\begin{cases} Q_{cyc} = k_c k_{SOC\_cyc} FEC^z \\ Q_{cal} = k_T k_{SOC\_cal} \sqrt{t} \end{cases} \tag{9}$$

where k_c and k_{SOC_cyc} are the C-rate influence factor and the SOC influence factor for cycle aging capacity loss, $k_c = aI_c + b$ and $k_{SOC\_cyc} = c(0.4 - SOC_b)^3 + d$. k_T and k_{SOC_cal} are the temperature influence factor and the battery SOC influence factor for calendar aging capacity loss, $k_T = k_{ref} \cdot \exp\left[k\left(\frac{1}{T} - \frac{1}{T_{ref}}\right)\right]$ and $k_{SOC\_cal} = e\left(SOC_b - 0.5\right)^3 + f$. FEC is the full equivalent cycle and defined as the ratio of accumulated charge throughput to the current battery capacity, k_{ref} and T_{ref} are the reference aging rate and storage temperature, a , b , c , d , e , f , k and z are model based parameters and their specific values are referred to reference [6, 7].

3.3. Problem Formulation

The aim of the optimal control problem formulated and solved in this study is to minimize the loss of battery capacity. The primary step is developing a model that accurately measures battery deterioration and incorporates it into the cost function. The concept of severity factor, defined by Onori [8], is utilized to quantify the relative aging effect with respect to a nominal operating condition. The battery lifetime Γ with respect to a nominal cycle can be characterized by the total full equivalent cycle (total FEC) when the battery reaches its end of life, which is expressed as:

$$\Gamma = \int_0^{EOL} \frac{\left|I_{nom}(t)\right|}{2Q_b} dt \tag{10}$$

where $I_{nom}(t)$ is the current profile under nominal conditions. EOL represents the time when the battery life reaches its end, and at this time the battery capacity has dropped 20% from its initial value. Since one FEC stands for a complete discharge process and a complete charge process, the total FEC is calculated as Ah-throughput divided by two times of battery capacity.

Then, the relative aging effects of any other loading cycle the battery is subject to can be reflected by the severity factor:

$$\sigma(I,T,SOC)=\frac{\Gamma}{\gamma(I,T,SOC)}=\frac{\int_0^{EOL}\left|I_{nom}(t)\right|dt}{\int_0^{EOL}\left|I(t)\right|dt} \tag{11}$$

where $\gamma(I,\theta,SOC)$ is the battery lifetime with specific operating conditions given in terms of current I, temperature T, and SOC. When the battery is undergoing a more severe load cycle, the severity factor is greater than one and a shorter life is expected.

In order to give the effective lifetime depletion due to charge exchange within the battery, an effective battery full equivalent cycle (effective FEC) FEC_{eff} is defined as:

$$FEC_{eff}(t)=\int_0^{t_f}\sigma(I,T,SOC)\cdot\frac{\left|i_b(\tau)\right|}{2Q_b}d\tau \tag{12}$$

where t_f is the operational time. Effective FEC gives the effective lifetime depletion with respect to the nominal lifetime defined by Γ. The battery will reach the end of life when $FEC_{eff}(t)=\Gamma$, and the objective of minimizing battery aging is equivalent to minimizing $FEC_{eff}(t)$. Therefore, the cost function to be minimized is defined by:

$$J_E=\frac{1}{2Q_b}\int_0^{t_f}\sigma(t)\left|i_b\right|dt \tag{13}$$

The optimal control problem is subjected to the longitudinal dynamics of the wheel loader. The state equations in the time-domain give a direct description of the dynamic system, however, it is difficult to represent some distance-dependent parameters, e.g., the speed restriction. In this study, the problem of optimizing a speed profile is formulated in the distance domain to make it robust. The dynamics of the wheel loader in (1) is rewritten as:

$$\begin{aligned}\dot{x}_1&=\frac{1}{x_2}\\ \dot{x}_2&=\left[\frac{F_t}{m}-\left(\mu g+\frac{\rho v^2 C_d A_f}{2m}+\frac{F_{th}}{m}\right)\right]\frac{1}{x_2}\end{aligned} \tag{14}$$

where x_1 is the travel time of the wheel loader, x_2 is the wheel loader speed. Thus, the battery current i_b with respect to the state variables can be expressed by:

$$i_b=\frac{P_b}{U_b}=\frac{x_2 u}{U_b}\eta^{-\mathrm{sgn}(u)} \tag{15}$$

where P_{bat} is the battery power. η is the overall efficiency and $\eta=\eta_{dri}\cdot\eta_m$, where η_{dri} is the overall efficiency of drivetrain.

Finally, the optimal control problem takes the following mathematical form, considering the boundary conditions and the physical constraints for states and control inputs:

$$\min J_E = \frac{1}{2Q_bU_b}\int_0^{s_f}\sigma(s)\left|\frac{x_2u}{U_{oc}}\eta^{-\mathrm{sgn}(u)}\right|\frac{1}{x_2}ds$$
$$s.t.\;\; \dot{x}_1 = \frac{1}{x_2},\, \dot{x}_2 = \left[\frac{F_t}{m} - \left(\mu g + \frac{\rho v^2 C_d A_f}{2m} + \frac{F_{th}}{m}\right)\right]\frac{1}{x_2} \tag{16}$$
$$x_1(0)=0,\, x_1(s_f)=t_f,\, x_2(0)=0,\, x_2(s_f)=0$$
$$x_2 \in [0, v_{\max}],\, F_t \in [F_{t,\min}, F_{t,\max}]$$

where s_f is the distance traveled. t_f and s_f are bounded, meaning that the vehicle stops at time t_f after traveling a given distance, s_f. $v_{\max}$ is the maximum speed of the wheel loader. $F_{t,\min}$ and $F_{t,\max}$ are the braking and driving force limits of the wheel loader.

In order to further reduce the computational cost, the optimal control problem (16) is modified such that a weighted penalty on travel time is included as follows:

$$\min J_E{}' = \int_0^{s_f}\left(\frac{1}{2Q_bU_b}\sigma(s)\left|\frac{x_2u}{U_{oc}}\eta^{-\mathrm{sgn}(u)}\right|\frac{1}{x_2} + \lambda\frac{1}{x_2}\right)ds$$
$$s.t.\;\; \dot{x}_2 = \left[\frac{F_t}{m} - \left(\mu g + \frac{\rho v^2 C_d A_f}{2m} + \frac{F_{th}}{m}\right)\right]\frac{1}{x_2} \tag{17}$$
$$x_2(0)=0,\, x_2(s_f)=0,\, x_2 \in [0, v_{\max}],\, F_t \in [F_{t,\min}, F_{t,\max}]$$

where λ is a weighting factor to penalize a travel time. Apparently, this formulation can effectively eliminate the state variable x_1 from the optimal control problem. The index of each state is changed from time to distance. The desired travel time can be achieved by adjusting the weighting penalty factor λ.

3.4. Combined DP-BM Method

Dynamic Programming is a technique that is applied to the very wide field of optimal control in multi-stage decision problems. It solves complex problems by breaking them down into simpler subproblems [9]. The motivation of using dynamic programming mainly relies on its ability in finding the global optimal solution. In this study, dynamic programming is implemented with the open-source software DynaProg which was developed by Miretti [10].

As for the optimization problem shown in (17), the desired operating time should be achieved by adjusting the weighting factor λ, then finding the best solution by DP. The operating time is negatively correlated with the weighting factor, where a large λ will force the wheel loader to run at a relatively high average speed. Take $t_f = g(\lambda)$ as the actual final time, and define $f(\lambda) = g(\lambda) - t_d$, where t_d is the target operating time. Therefore, the time constraint is transferred to find the single root of $f(\lambda)$.

To find the root of a function, a hybrid approach called Brent's method is applied in the study, where it does just that by applying a speedy open method wherever possible, but reverting to a reliable bracketing method if necessary, thereby is applied in this study, to achieve time constraint in the cost function. Brent's method combines the bisection method, the secant method and IQI, where the bisection method is used for increasing the possibilities of convergence, the secant method is used for faster convergence, and the IQI is applied for solving the parabola-typed equation. Combining dynamic programming and Brent's method (DP-BM), the numerical solution of the optimal control problem can be obtained. Details of the algorithm is shown with pseudo-code.

Pseudo-code of the DP-BM algorithm.

1: Given a stopping tolerance $\delta > 0$

2: Given points a and b such that $f(a)f(b) < 0$, make sure $|f(a)| \geq |f(b)|$ so that b is regarded as the better approximate solution. $f(a)$ and $f(b)$ are calculated by using dynamic programming.

3: A third point c is initialized by setting $c = a$.

4: A flag is initialized by setting flag = Ture.

5: **Repeat until** $f(b) = 0$ or $f(\hat{b}) = 0$ or $|b - \hat{b}| < \delta$

6: **If** $a = c$ **then** $\hat{b}$ is determined by linear (secant) interpolation: $\hat{b} = \dfrac{af(b) - bf(a)}{f(b) - f(a)}$.

7: **Otherwise** a, b, and c are distinct, and $\hat{b}$ is determined using inverse quadratic interpolation:

$$\hat{b} = \frac{af(b)f(c)}{(f(a)-f(b))(f(a)-f(c))} + \frac{bf(a)f(c)}{(f(b)-f(a))(f(b)-f(c))} + \frac{cf(a)f(b)}{(f(c)-f(a))(f(c)-f(b))}$$

8: **If** (condition 1: $\hat{b}$ is not between $\dfrac{3a+b}{4}$ and b) or

(condition 2: flag = True and $|\hat{b} - b| > \frac{1}{2}|b - c|$) or

(condition 3: flag = False $|\hat{b} - b| > \frac{1}{2}|c - d|$) or

(condition 4: flag = True and $|b - c| < \delta$) or

(condition 5: flag = False and $|c - d| < \delta$) **then**

$\hat{b} = \dfrac{a+b}{2}$ and set flag = True. (Bisection method).

9: **Otherwise** set flag = False.

10: Calculate $f(\hat{b})$ using dynamic programming.

11: $d = c$, $c = d$. (d is assigned for the first time here; it won't be used above on the first iteration because the flag is set as True)

12: **If** $f(a)f(\hat{b}) < 0$ **then** $b = \hat{b}$, otherwise $a = \hat{b}$.

13: **If** $|f(a)| < |f(b)|$ **then** swap (a, b).

14: **end repeat**

15: Output the optimal $\lambda = \hat{b}$.

4. SIMULATION STUDIES

4.1. Simulation Parameters

In the simulation, a typical medium wheel loader with an operating weight of 19000 kg is adopted and basic parameters including the drivetrain, the electric motor, the battery, and the working hydraulic system are shown in **Table 1**. The efficiency map of the electric motors is obtained from Advisor 2002. The working hydraulic pump efficiency map comes from Eaton and can be found in previous work [11]. Efficiencies of the other parts of the drivetrain, such as the inverter, gearbox, and final drive, are assumed to be constant.

Table 1: Basic parameters of the wheel loader

Property	Symbol	Value	Unit
Operating weight	m	19000	kg
Radius of tire	r_w	0.789	m
Tire rolling friction coefficient	μ	0.06	-
Drag coefficient	C_d	0.24	-
Front area	A_v	10	m2
Gearbox ratio/Final drive ratio	γ_g / γ_f	11.6/5.1	-
Drivetrain efficiency	η_{dri}	0.95	-
Electric motor maximum power	$P_{m\_\max}$	157	kW
Nominal battery capacity	U_{oc}	618	V
Battery pack initial resistance	R_0	1.9	mΩ
Battery pack initial capacity	Q_{init}	456	Ah

The calculation environment is MATLAB R2021b with an Intel Core i7-8750H at 2.2GHz and 16GB of RAM. It should be noted that the accuracy of the global optimal solution of dynamic programming depends on the grid number. In the simulation, the distance interval of two adjacent stages is set as 0.01m. The grid number of the state variable is 4000 and the grid number of the control variable is 1000.

In addition, typical speed trajectories are extracted and summarized from the real trajectories of skilled drivers and used for comparison as baselines. The typical trajectory is constructed by three phases: acceleration, constant velocity, and deceleration. In the acceleration phase, the wheel loader starts at constant torque, then accelerates at rated power. After reaching its maximum speed at low gear, the wheel loader will operate with constant velocity and finally decelerates with a constant negative acceleration.

4.2. Simulation Results under One Typical Distance and Average Speed

The typical and optimized speed trajectories as well as corresponding characteristics with respect to time are shown in **Figure 2**. At the first half of the trajectory, the optimal trajectory uses tapered torque to accelerate the wheel loader. Since the change of torque at low speed has little effect on the motor efficiency (**Figure 2** (d)), higher torque can improve vehicle speed with the same energy consumption. After the wheel loader reaches a high speed, the typical trajectory will keep at this speed and then slow down with energy recovery braking, while the optimal trajectory still operates at high motor efficiency region first, then coasts in the deceleration process and finally adopts the braking action. The braking process of the typical trajectory is much longer than that in the optimized trajectory, which makes the motor operate at a low-efficiency region thus aggravating the battery burden. In addition, coasting is adopted for the optimized trajectory in the deceleration process and this will temporarily reduce battery usage and significantly decrease the accumulated FEC.

As is depicted in **Figure 2** (c) and (f), after driving one complete distance, the optimized trajectory can reduce average power and accumulated FEC with 19.9% and 23.8%, respectively. In addition, the energy consumption of the optimized trajectory also shows a slight decrease, which is shown in **Figure 2** (e). This may benefit from the transfer of the electric motor operating points, where the inefficient energy recovery during long braking of the typical trajectory is replaced by coasting and efficient short-time braking.

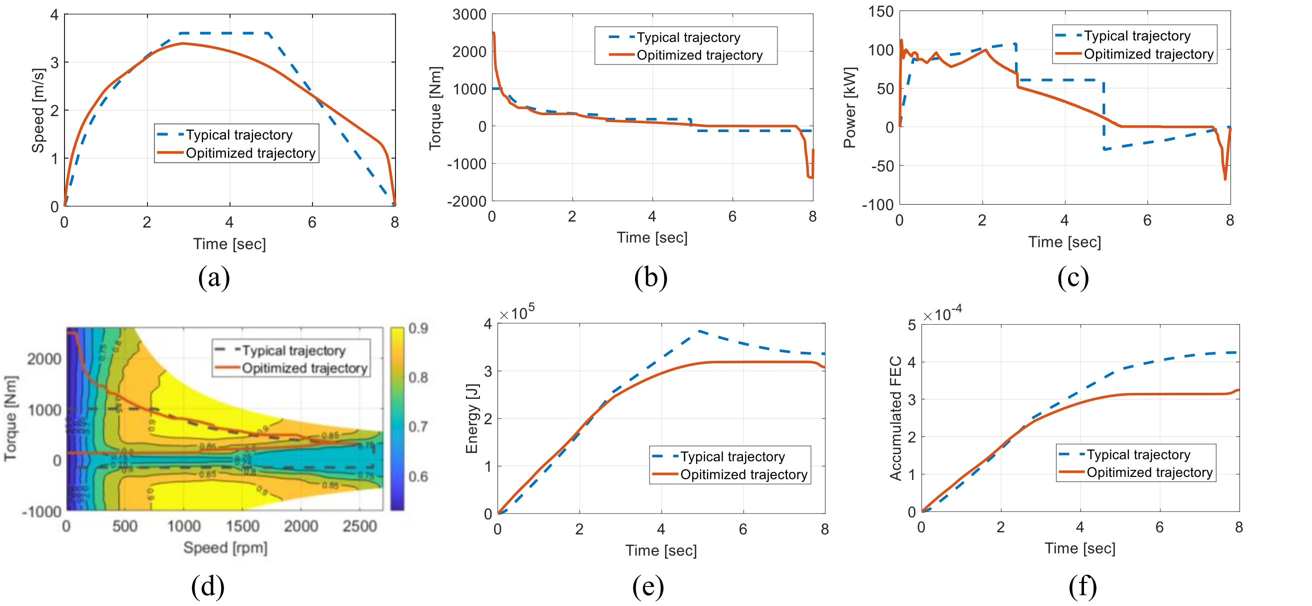


Figure 2: The typical and optimized speed trajectory with respect to time (a) Speed (b) Torque (c) Power (d) Electric motor operating points (e) Energy (f) Battery usage equivalent cycle

Based on the typical and optimized trajectories, a one-day working cycle is designed, which includes double 3-h repeated working cycles, double 3-h charging time (around 0.33C), and 12-h rest time. The accumulated FEC result is depicted in **Figure 3**. It can be found that over the 12-h charging/discharging process, the FEC is greatly down from 1.36 to 1.25 times, which reduces the usage time of the battery with a drop of 8.09%. The decline is smaller than that in one single movement shown in **Figure 2** (f). This is because the FEC is not only influenced by the discharge process but also charge process. And the optimization object in the discharge process does not include the working system. In a one-day cycle, as can be seen in **Figure 4**, the propulsion system takes 51.75% of discharge energy and only 25.85% of total energy. In other words, the accumulated FEC of the battery can be reduced by 8.1% in a full day's cycle just from speed trajectory optimization, without changing the wheel loader hardware configuration.

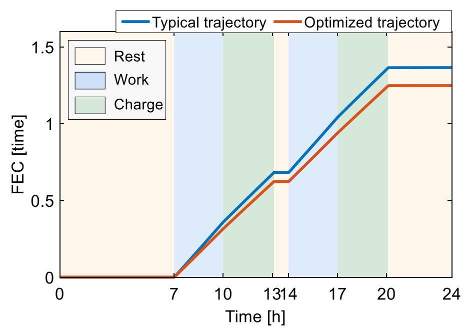


Figure 3: Accumulated FEC in one-day work under the typical and optimized trajectories

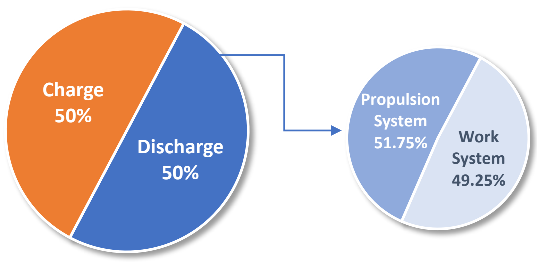


Figure 4: The FEC proportion of propulsion system in one-day cycle

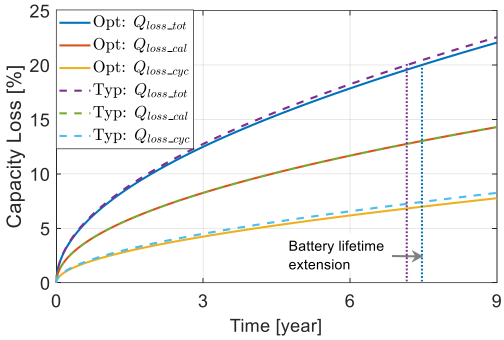


Figure 5: Cycle and calendar aging capacity losses under the typical and optimized trajectories

Based on the typical and optimized trajectories, a 9-year working period with 365 continuous working days in one year is applied in the virtual experiments and simulation results are depicted in **Figure 5**. The total battery capacity loss is decreased by 2.40% after 9 years of continuous operations with the optimized trajectory. The two calendar aging curves are very close since the given temperatures as well as the time periods are the same, and the battery SOCs are also very close for the two simulations. Taking the battery capacity decreases to 80% of the initial capacity as its end of life, the battery pack can be used for only 2529 days under the typical trajectory while 2635 days under the optimized trajectory, meaning that the battery lifetime can be extended by 4.19%.

4.3. Simulation Results under Different Distances and Average Speeds

The speed trajectories and the corresponding variations in battery power for various average speeds are shown in **Figure 6**. As the average speed decreases, the peak power gradually decreases and the power curves are getting smooth. The recovery power also decreases with the average speed decreases. In addition, all the speed trajectories contain 4 parts: speed up, cruising, coasting and deceleration, meaning that such a speed trajectory composition can minimize the battery usage frequency and average discharge current. Furthermore, the power curve shows fluctuation for the trajectories with low average speed. This is due to the coarse grid of state variables in dynamic programming and can be smoother by increasing the grid density.

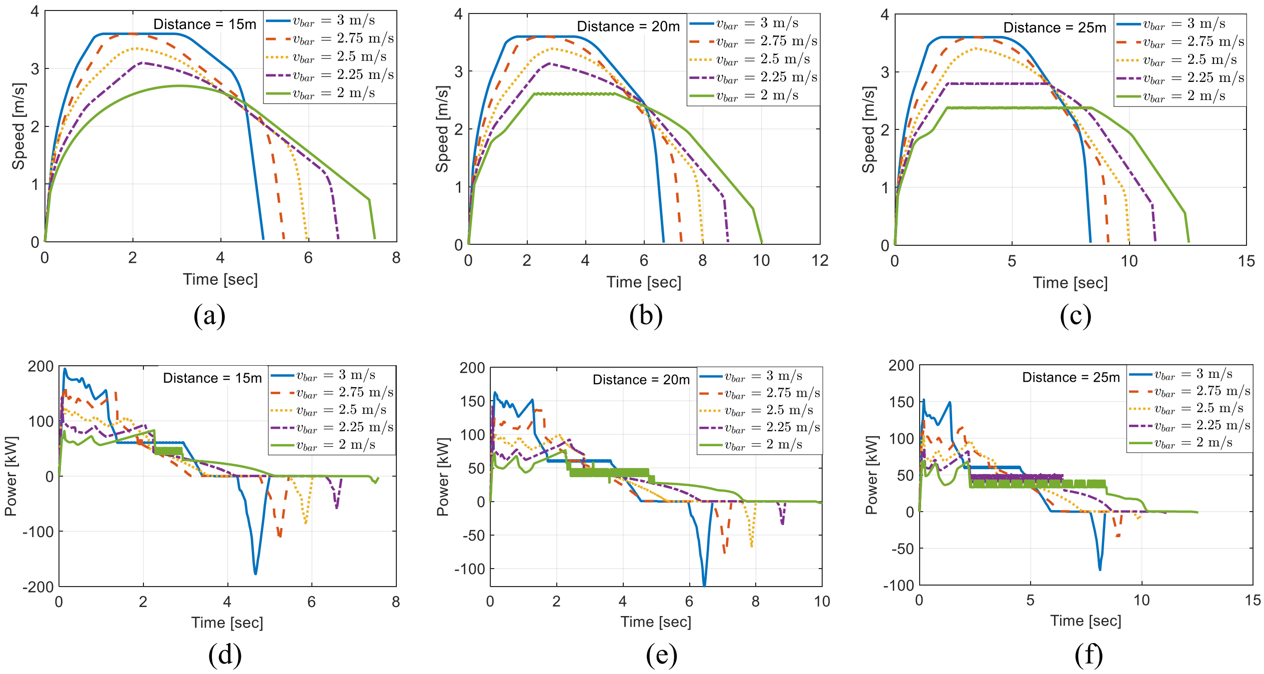
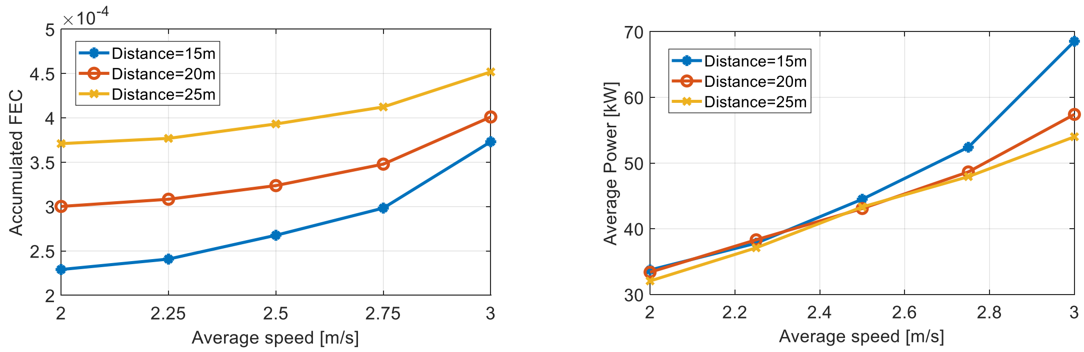


Figure 6: Cycle and calendar aging capacity losses under the typical and optimized trajectories

Numerous simulations utilizing different distances and average speeds are performed and results show that the optimized trajectories reduce accumulated FEC and average power in all tested cases, with average savings of 20.90% and 19.24%. Following prolonged continuous operation, the battery can be utilized for an average of 2632 days when using the optimized trajectory, resulting in a 4.48% extension of the battery's lifetime.

The accumulated FEC and average power of the optimal trajectory at different average speeds are shown in (a) (b)

Figure 7 (a) and (b), respectively. As average speed increases, the wheel loader must speed up and down in a short time, thus both the accumulated FEC and average power show an increasing trend, therefore burdening the battery degradation. On the other hand, under the same speed, the accumulated FEC shows positively correlated with the distance. This is because a long distance consumes more energy, thus increasing the accumulated FEC. The average speed shows small differences for wheel loaders with the same driving distance and average speed, due to the similar work intensity and tasks.



(a) (b)

Figure 7: Accumulated FEC and average power of the optimal trajectory at different average speeds

4.4. Comparison of Computational Time

When dealing with trajectory optimization tasks, the classical optimal control problem usually takes travel time and speed as two state variables and distance sequence as the index. The problem can be solved by conventional dynamic programming while needing an unacceptable amount of time. The DP-BM algorithm is designed to give a rapid numerical solution to the upgraded problem with achieving the time constraints.

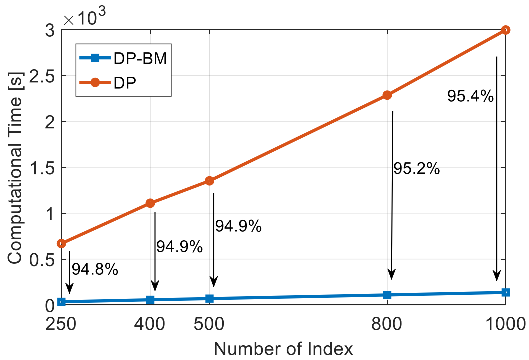


Figure 8: Comparison of computational time with direct dynamic programming

Figure 8 illustrates the computational time comparison between the conventional dynamic programming method and the proposed DP-BM approach for the identical trajectory optimization problem. The proposed approach demonstrates a significantly reduced computation time compared to conventional dynamic programming, with an average reduction of 95%. It should be noted that the calculation accuracy and calculation time of dynamic programming are contradictory. To further reduce computation time and simultaneously guarantee the accuracy of optimal trajectory, the speed trajectories under different driving distances and average speeds can be calculated offline and save the results in memory. The wheel loader planning system can directly look up the trajectory in the database based on the perceived distance and elapsed time.

5. CONCLUSIONS

This paper presents an optimization of the speed trajectory for an electric wheel loader, with the aim of extending battery lifetime. The optimization problem is formulated based on the modelling of wheel loader's powertrain and battery degradation. To reduce computational costs, a weighted penalty on travel time is included in the optimal control problem. An optimization algorithm, DP-BM, is developed to calculate the global optimal speed trajectory with a reduced computational burden.

A set of typical distances and average speeds is selected to provide a detailed characteristic description of the optimized trajectory. Numerous simulation experiments are conducted to provide an intuitive description of the optimized trajectories. Comparative results demonstrate that with the optimized trajectories, the average battery lifetime can be extended by 4.48% after 9 years of continuous operations. Moreover, the proposed approach significantly reduces computation time by an average of 95% compared to conventional dynamic programming.

In the future, the effectiveness of the DP-BM algorithm in extending battery lifetime will be verified through experiments, and to enhance the algorithm’s robustness. For the existing wheel loader equipped with visual perception, the algorithm will be integrated into the vehicle controller, and display the optimal speed trajectory of the vehicle through the dashboard or on-board screen to guide the driver in manoeuvring the vehicle properly. For future autonomous wheel loaders, it will be possible to directly track the speed trajectory output by this algorithm, achieving the maximum extension of battery lifetime.

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