

Article

Cascaded Dual-Observer-Based Decoupled Estimation of Mass and Track Gradient for Permanent-Magnet-Driven Electric Monorail Cranes

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Abstract

Precise data regarding the overall mass of the machinery and the gradient of the track are crucial for optimizing the control of monorail cranes and enhancing energy efficiency. Within the context of electric monorail cranes (EMCs), accurately estimating the total mass of the machinery and the track gradient poses a formidable challenge. This challenge arises from the strong coupling between the overall mass of the machine and the track gradient, the robustness of parameter estimation methods under varying operational conditions, and the generalizability of the algorithm to real-world operations and rail scenarios of EMCs. To address these challenges, this paper proposes a novel parameter estimation scheme that comprehensively considers the impact of parameter coupling relationships and multiple influencing factors in the transportation scenarios of EMCs under actual working conditions. First, to overcome measurement difficulties induced by strong coupling between the EMC mass and track gradient, a decoupling estimation method based on cascaded dual observers is proposed to jointly estimate the two states. Secondly, to mitigate track slope estimation errors under complex track types and diverse operating conditions, an enhanced immune optimization algorithm, integrating a Weibull function and Levy flight mechanism, in conjunction with an unscented Kalman filter (UKF), is developed. Furthermore, to achieve high-precision and stable parameter identification results, a Weibull dynamic forgetting factor is incorporated into the RLS algorithm, leading to the design of a WDFF-RLS estimator. Finally, real vehicle experiments were conducted on complex tracks at the test site to validate the accuracy and robustness of the proposed estimation method.

Keywords: electric monorail cranes; parameter identification; unscented Kalman filter; immune optimization; recursive least squares

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1. Introduction

As a crucial component of the mine production system, the auxiliary transportation system is responsible for transporting personnel, equipment, materials, and gangue. Its technological advancement and practical application directly influence the production efficiency and operational safety of coal mines [1–3]. Electric monorail crane technology has emerged as a focal point in the development of the mine auxiliary transportation industry,

owing to its advantages in energy conservation, emission reduction, low operational costs, high transmission efficiency, and high reliability.

High-precision estimation of fundamental parameters serves as the cornerstone for the research and application of high-performance operational control strategies for EMCs. Traditional methods for determining system operational parameters often rely on additional sensor signals or offline measurements. While these approaches can yield basic parameter values, they fall short in underground environments characterized by variable roadway cross-sections, complex routes, frequent slope variations, and dynamic load changes. In such scenarios, the real-time performance of the EMCs intelligent driving system is compromised, making it challenging to achieve precise operational control based solely on initially calibrated offline parameters. The advancement of sophisticated estimation algorithms offers an effective technical pathway for the online adaptive estimation of fundamental EMCs parameters, enabling the estimation of key parameters such as track slope and overall mass. Currently, the prevalent advanced estimation algorithms are primarily categorized into model-based estimation methods and data-driven estimation methods.

Model-based parameter estimation methods primarily comprise state estimation and parameter identification approaches. The state estimation method utilizes locomotive dynamics or kinematics models, in conjunction with diverse observers, to estimate system states in real time. This method can cater to the condition monitoring needs of locomotive systems across various transportation scenarios and accurately track the dynamic variations in key state variables, such as position and velocity. It offers the merits of high real-time performance and rapid dynamic response. References [4–7] have designed various improved Extended Kalman Filter (EKF) algorithm estimators to enhance the accuracy of parameter estimation. Due to the superposition of sensor data noise during vehicle operation, improper design of the noise covariance matrix can easily lead to a decline in estimation accuracy or even non-convergence, often necessitating the use of a high-performance filtering algorithm. Ying Peng et al. [8] constructed a wheel angular velocity filter observer and a tire lateral friction model, proposing a modular nonlinear estimator to simultaneously estimate vehicle speed and tire-road friction coefficient. The parameter identification method is grounded in system dynamics or kinematics models, combined with measured operational data, employing the least squares method and its derivatives, maximum likelihood estimation, and other techniques to deduce unknown parameters. Ye Ming et al. [9] introduced an improved double forgetting factor recursive least squares estimator for estimating time-varying mass and slope. Kanghyun Nam et al. [10] developed a recursive least squares method to identify vehicle lateral velocity and validated the feasibility of their proposed scheme through experiments.

However, each single estimation method has its own advantages and limitations. The estimation accuracy of the state estimation method is heavily contingent upon the precision of the underlying model. If the locomotive dynamics model fails to adequately account for intricate factors such as track irregularity, frictional nonlinearity, and vibration, it is prone to estimation bias. Conversely, the estimation accuracy of the parameter identification method hinges on the completeness and validity of the measured data. To combine the advantages of both approaches, an increasing number of studies in recent years have adopted hybrid estimation or cascaded estimation architectures. Yong Sun et al. [11] proposed a hybrid algorithm that combines the extended Kalman filter (EKF) and recursive least squares (RLS). In their approach, EKF was first employed to estimate the slope; subsequently, both EKF and RLS were used separately to estimate the mass, and the two estimates were then weighted to obtain a better mass value. The longitudinal dynamic parameters were iteratively decoupled in the process. Their results demonstrate that the hybrid method achieves higher accuracy and faster convergence than either algorithm

used alone. Li Gang et al. [12] proposed an estimation algorithm based on a dual cubature Kalman filter (DCKF) for the joint estimation of vehicle driving states and road adhesion coefficients. Their approach employs two parallel cubature Kalman filters: a state estimator responsible for estimating longitudinal velocity, lateral velocity, yaw rate, and other state variables, and a parameter estimator designed to identify the road adhesion coefficients of all four wheels. The two estimators are interconnected and form a closed-loop feedback loop during the estimation process, enabling real-time collaborative estimation of both states and parameters. Zhixin Chen et al. [13] proposed a joint estimation algorithm based on Federated Kalman filter and Ant Lion optimization for four-wheel independent steering electric vehicles. The distributed fusion architecture is adopted, and the sub-filter is based on the cubature Kalman filter (CKF) theory for state estimation; the main filter is responsible for information fusion and distribution, and the lower Ant Lion optimization module is used for online identification of noise statistics. The road adhesion coefficient estimator is designed to form a closed-loop collaborative estimation with the driving state estimator. The results show that this method has high accuracy in estimating the sideslip angle of mass center and road adhesion coefficient.

The data-driven estimation approach estimates state parameters by analyzing and processing the system information data that has been actually collected. This method does not rely on the mechanistic model of the system; instead, it directly utilizes the monitoring data gathered during system testing or operation for estimation purposes. References [14–16] apply neural networks to vehicle dynamics modeling and the estimation of centroid sideslip angles. Angelo Bonfitto et al. [17] proposed an ANN data-driven approach that integrates regression neural networks with classification neural networks to estimate vehicle running speeds. Using vehicle longitudinal acceleration, lateral acceleration, total steering angle, and other collected parameters as inputs, they first designed a NARX-based regression neural network tailored to dry, wet, and icy road conditions for speed estimation. Secondly, they constructed a two-layer feedforward pattern recognition classification neural network for precise road condition identification. Finally, the speed estimation result that matches the current road condition is selected from the outputs of the three regression neural networks. The effectiveness of this method has been validated through experiments under various driving conditions. Zygimantas Ziaukas et al. [18] incorporated data collected from the vehicle CAN bus into output feedback to construct a RANN for estimating sideslip angles under different road conditions.

Data learning-based estimation methods have garnered significant attention among researchers. Nevertheless, while data-driven approaches such as neural networks [19–21] and machine learning [22,23] obviate the need for specialized equipment, they still necessitate a substantial volume of training data. This data must encompass all operational conditions, and the effective correlation between input and output parameters remains indeterminate. Adjusting parameters proves challenging, resulting in limited adaptability to complex road conditions, poor generalization performance, and inadequate robustness.

Based on the above research, this paper proposes a hybrid estimation method that combines the Unscented Kalman Filter (UKF) and Recursive Least Squares (RLS) algorithms. A series structure is employed to jointly estimate the running track gradient and the overall mass of the monorail crane. The primary contributions of this paper are as follows:

1. A track gradient estimator based on an improved Unscented Kalman Filter is designed, incorporating an immune optimization strategy with Weibull–Lévy dynamic mutation to identify the statistical characteristics of system process noise. This enhances the accuracy of slope estimation and improves robustness against the model's nonlinear responses.

2. A parameter identifier centered on the Recursive Least Squares with a Weibull dynamic forgetting factor (WDFF-RLS) is constructed, which utilizes the track gradient information estimated in the previous step to estimate the overall mass of the system in real time. This identifier, together with the track gradient estimator, forms a cascaded dual-observer architecture, thereby enabling real-time acquisition of both the monorail crane mass and the traveling track gradient without requiring any additional information from positioning sensors.

The structure of this paper is organized as follows: Section 2 describes the model of EMCs. Section 3 outlines the algorithm flow for the cascaded dual observer estimation method. Section 4 presents the simulation and verification of the proposed estimator using Matlab R2018b/Adams 2020. Section 5 provides an experimental evaluation. Finally, the conclusions are drawn in Section 6.

2. Longitudinal Dynamic Model of Monorail Crane

In this study, the Distributed Drive Electric Monorail Crane (DDEMC) based on a permanent magnet synchronous variable frequency integrated machine is selected as the research object. The power system primarily comprises a permanent magnet synchronous variable frequency integrated machine, a power battery, and an overall machine controller, among other components. The permanent magnet synchronous variable speed integrated machine is connected to the driving wheel via a reducer and a coupling, and the driving is accomplished by the driving motor and its control system. Compared to the two-stage coupling, hydraulic pump, and hydraulic motor transmission mode employed in traditional diesel engine monorail cranes, the DDEMC exhibits higher transmission efficiency and mobility flexibility. The drive system and overall structure of the DDEMC are illustrated in Figure 1.

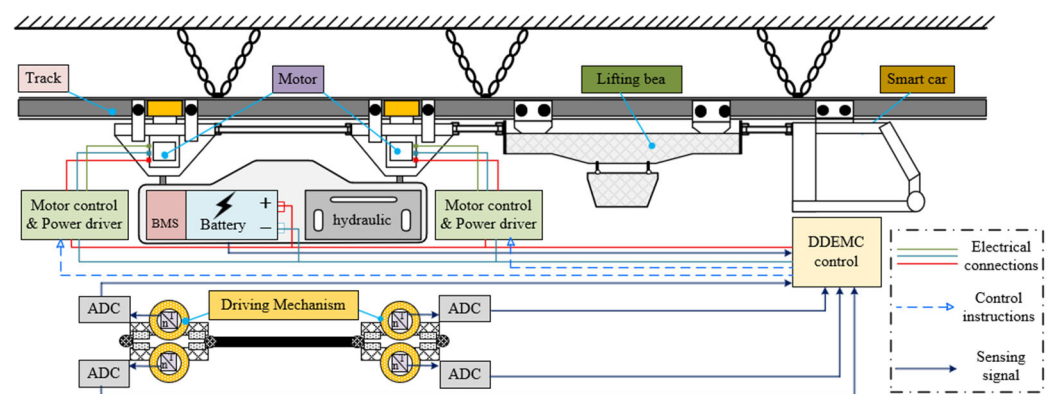


Figure 1. Schematic diagram of DDEMC.

The focal point of this study is EMCs. Based on Newton's second law, the nonlinear longitudinal dynamics of vehicles can be mathematically described using equations. The operation of DDEMC is illustrated in Figure 2, and the nonlinear longitudinal dynamics of locomotives can be expressed as follows:

$$F_{xi} = F_f + F_i + F_j \quad (1)$$

In the formula, F_{xi} represents the reaction force exerted by the driving wheel on the rail surface of the monorail crane under driving or braking conditions, F_f is the rolling resistance of the monorail crane, F_i is the grade resistance of the monorail crane, and F_j is the longitudinal acceleration resistance of the monorail crane.

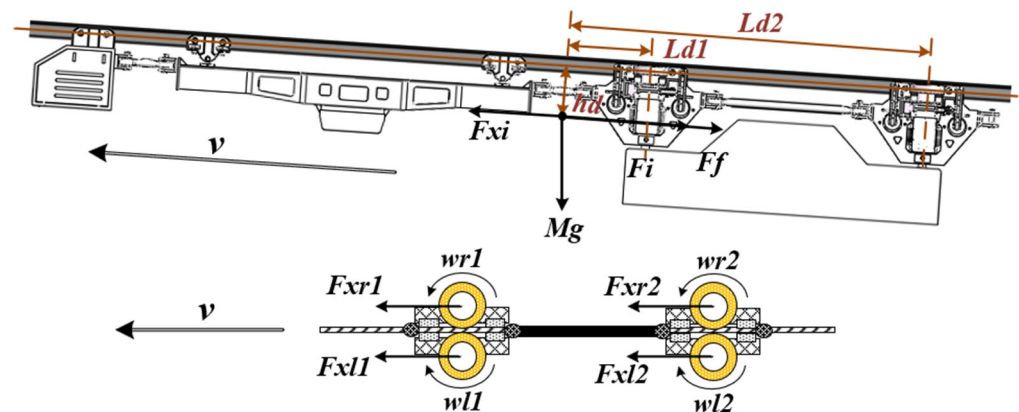


Figure 2. Schematic illustration of DDEMC in operation on a ramp.

Upon expanding Equation (1), the nonlinear longitudinal dynamics of the locomotive can be represented as:

$$\delta m \dot{v}_z = F_{xi} - mgf \cos \theta - mgsin \theta \quad (2)$$

In the equation, δ represents the conversion coefficient for the rotating mass of the monorail crane, m denotes the total mass of the vehicle, v_z signifies the longitudinal velocity of the monorail crane, r is the wheel radius, m is the mass of the whole monorail crane system, g stands for gravitational acceleration, f is the rolling resistance coefficient of the driving wheel, and θ indicates the track inclination. To accurately estimate this parameter and locomotive mass, the following assumptions are made within the operational DDEMC framework:

Assumption 1: The braking system of an electric monorail crane typically employs mechanical braking, and the braking force is challenging to measure. Consequently, this paper does not measure the braking force.

Assumption 2: During the operation of DDEMC, given its very slow speed with a maximum of only 2 m/s, the wind resistance is negligible compared to other forces. Therefore, the impact of wind resistance is not considered.

Based on the aforementioned assumptions, this paper proposes a cascaded dual observer DDEMC estimation algorithm.

3. Cascaded Dual-Observer Estimation Method

3.1. Hybrid Estimation of WLDL_IOA_UK and WDFF_RLS

To address the deep coupling between the mass parameters of the mining electric monorail crane and the track gradient, as well as the impact of strong interference during operational conditions, this paper proposes a Cascaded Dual-Observer-based Decoupling Estimator (CDODE), as shown in Figure 3. This estimator comprises an Unscented Kalman Filter (UKF) track gradient estimation unit based on the Weibull–Lévy Dynamic Mutation Immune Optimization Algorithm (WLDL-IOA) and a mass parameter identification unit based on the Weibull Dynamic Forgetting Factor Recursive Least Squares (WDFF-RLS). The state observer, centered on UKF, is employed to tackle the nonlinear and time-varying challenges associated with track gradient dynamics. Based on the kinematic model of the electric monorail crane, this unit utilizes the unscented transformation to precisely handle nonlinear terms within its dynamics model, thereby achieving optimal estimation of the track gradient. To mitigate the decline in estimator accuracy caused by unknown noise information, an immune optimization strategy featuring the Weibull–Lévy dynamic mutation is adopted to identify the statistical characteristics of system process noise during the UKF estimation process, thereby enhancing both the accuracy of

track gradient estimation and robustness against nonlinear model responses. Additionally, a parameter identifier centered on RLS is designed. This unit takes the real-time track gradient_estimates output by the Unscented Kalman Filter based on the Weibull–Lévy Dynamic Mutation Immune Optimization Algorithm (WLDMM-IOA-UKF) unit as input, transforms the coupled nonlinear dynamic equations into a linear regression model, and employs a recursive algorithm to achieve precise online identification of the monorail crane’s mass, ensuring both convergence and computational efficiency in parameter estimation.

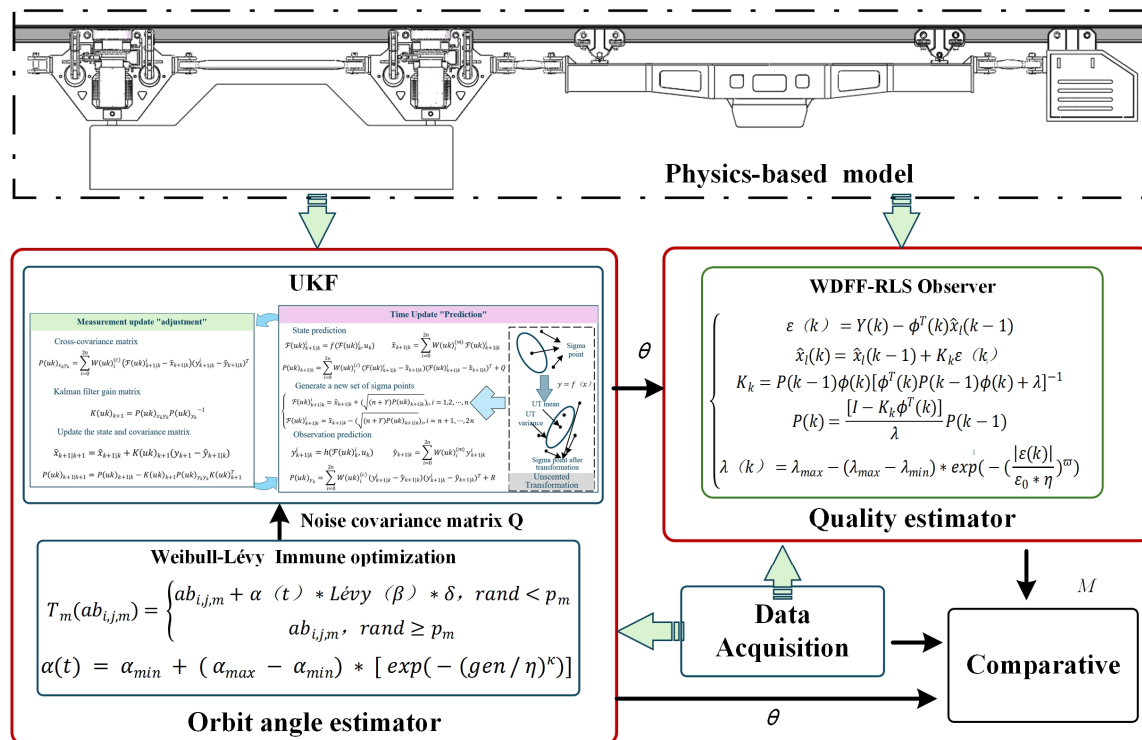


Figure 3. Estimation Method for Cascaded Dual Observers.

3.2. Track Gradient Estimator

3.2.1. Track Gradient Identification Model

When considering the operation of an electric monorail crane on a track with a track gradient, the signal value from the longitudinal acceleration sensor not only represents the instantaneous rate of change in the locomotive’s longitudinal velocity but also incorporates the acceleration signal resulting from the gravitational component force acting on the locomotive along the inclined track. Therefore, by fully leveraging the characteristics of the longitudinal acceleration sensor signal and analyzing the calculation formula for the acceleration sensor signal value [24], we can derive the locomotive’s kinematic model as follows:

$$A_{senx} = g \sin \theta + \frac{dV_x}{dt} = g \sin \theta + \dot{V}_x \quad (3)$$

Here, A_{senx} represents the signal value of the longitudinal acceleration sensor. The system state equation can be represented as:

$$x_k = \begin{bmatrix} V_x(k) \\ A_{senx}(k) \\ \theta_k \end{bmatrix} = \begin{bmatrix} V_x(k-1) + (A_{senx}(k-1) - g \sin \theta) \Delta t \\ A_{senx}(k-1) \\ \theta_{k-1} \end{bmatrix} + Q_{i(k-1)} \quad (4)$$

Here, $V_{x(k)}$ represents the longitudinal velocity of the monorail crane at a given instant, $A_{senx(k)}$ denotes the signal value of the longitudinal acceleration sensor at that moment, θ_k signifies the track gradient at the moment, and Δt indicates the sampling time.

Develop the system spatial model on the basis of Equation (4):

$$\begin{cases} x_{k+1} = Ax_k + w_k \\ y_k = Hx_k + v_k \end{cases} \quad (5)$$

In the equation, w_k represents the system noise, which arises from uncertainties in system modeling, parameter drift in electronic components, and noise in the test environment, with its covariance denoted as Q_k ; v_k denotes the observation noise, caused by errors in the system sensors, and its covariance is R_k .

The state variable in Equation (5) is represented as $x = [V_x \ A_{senx} \ \theta]$, and the observed variable is $y_k = [V_{x(k)} \ A_{senx(k)}]$. Given that this study solely acquires observation values via the CAN bus to estimate the longitudinal speed, acceleration of the locomotive, as well as the track gradient, without exerting any control operations on the system, no control input is applied. The state matrix A , observation matrix H , and system noise matrices Q_k and R_k are defined as follows:

$$A = \begin{bmatrix} 1 & \Delta t & -g \sin \theta \Delta t \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \quad (6)$$

$$Q_{k-1} = [Q_{1(k-1)} \ Q_{2(k-1)} \ Q_{3(k-1)}]^T \quad (7)$$

$$R_{k-1} = [R_{1(k-1)} \ R_{2(k-1)}]^T \quad (8)$$

As can be seen from the aforementioned derivation, Equations (5)–(8) delineate the state space system of the track gradient estimation algorithm.

3.2.2. Improved Unscented Kalman Filter

In contrast to the Extended Kalman filter algorithm [25], which incurs cumulative errors due to its first-order linearization approximation of nonlinear functions, this paper employs the Unscented Kalman filter algorithm [26–28]. The UKF process, grounded in the Unscented Transform (UT), encompasses initialization, time update, and measurement update phases. By integrating Equations (5)–(8) into the subsequent UKF recursive procedure, the track gradient estimation during system operation can be derived.

The discrete-time state-space equation for a nonlinear system can be formulated as follows, and it is assumed that $f_{uk}(\cdot)$ and $h_{uk}(\cdot)$ represent the state function and nonlinear observation function of the system respectively:

$$\begin{cases} x_{k+1} = f_{uk}(x_k, u_k) + w(uk)_k \\ y_k = h_{uk}(x_k, u_k) + v(uk)_k \end{cases} \quad (9)$$

where k represents an arbitrary time instant, x_k is the state vector of the system, y_k represent the measurement vector of the system; $w(uk)_k$ and $v(uk)_k$ denote the system process noise and measurement noise, respectively. It is assumed that $w(uk)_k$ and $v(uk)_k$ are uncorrelated Gaussian noises with zero mean, respectively, satisfying, $w(uk)_k \sim N(0, Q_k)$, $v(uk)_k \sim N(0, R_k)$, Q and R are covariance matrices.

For the aforementioned nonlinear system, the Unscented Kalman Filter (UKF) is employed to estimate the system state parameters. For the specific procedure, see References [26–28].

To develop a high-precision and high-stability system parameter identification method, it is essential to first establish the system noise covariance matrix Q . Improper design of this matrix can readily lead to a decline in the accuracy of identified parameter

estimation or even non-convergence. Given the nonlinear characteristics of the EMCs system, this paper proposes employing an immune optimization algorithm to determine the covariance matrix Q . Meanwhile, to enhance the adaptability and flexibility of the search process, balance exploration and exploitation, escape local optima, and improve search efficiency, a Lévy flight strategy is utilized to provide an efficient random step for the algorithm's mutation operation. The specific improvements are detailed as follows.

Firstly, Lévy flight random numbers are employed to replace the original uniform random disturbances, with the step size of Lévy flight [29] random walks adhering to a heavy-tailed distribution. When Lévy flight is applied to the mutation phase, it generates disturbances with either small or large step sizes. This approach maintains local fine-grained search capabilities while enabling occasional long-distance jumps with a low probability, thereby effectively avoiding local optima and enhancing global exploration capabilities. Secondly, the fixed step size scaling factor α is replaced with an adaptive variable step size $\alpha(t)$, which is dynamically controlled by the Weibull function. The original step size δ decreases linearly, a method that is overly simplistic and lacks the ability to adaptively adjust based on the search conditions. The Weibull function, a commonly utilized lifespan distribution function, allows for flexible control over the dynamic changes in step size scaling through parameter adjustments, enabling the step size scaling factor $\alpha(t)$ to gradually decrease from α_{max} to α_{min} . By controlling the step size of Lévy flight, adaptive adjustments are achieved. In summary, the mutation strategy of this algorithm can be described as follows:

$$T_m(ab_{i,j,m}) = \begin{cases} ab_{i,j,m} + \alpha(t) * \text{Lévy}(\beta) * \delta, & \text{rand} < p_m \\ ab_{i,j,m}, & \text{rand} \geq p_m \end{cases} \quad (10)$$

The formula for the Weibull adaptive time-varying step size factor is presented as follows:

$$\alpha(t) = \alpha_{min} + (\alpha_{max} - \alpha_{min}) * [\exp(-(gen / \eta)^\kappa)] \quad (11)$$

Here, gen represents the current iteration number; η is the scale parameter of the Weibull function, which controls the rate of change; κ denotes the shape parameter of the Weibull function, governing the form of the change curve; α_{max} and α_{min} indicate the maximum and minimum values of the step factor, respectively.

The mathematical representation of Lévy flight is given by Equation (12).

$$\text{Lévy}(\beta) = (\mu * \delta) / (|v|^{\frac{1}{\beta}}) \quad (12)$$

Among them, both μ and δ follow a standard normal distribution.

$$\delta = \left[\frac{\Gamma(1 + \beta) \sin(\frac{\pi\beta}{2})}{\beta \Gamma(\frac{1+\beta}{2}) 2^{(\frac{\beta-1}{2})}} \right]^{\frac{1}{\beta}} \quad (13)$$

$\Gamma(*)$ represents the standard gamma function, and β typically takes a value of 1.5.

The implementation steps of the WLDM-IOA algorithm are elaborated in detail below. The flowchart of the WLDM-IOA algorithm is depicted in Figure 4, with specific descriptions of each step provided as follows.

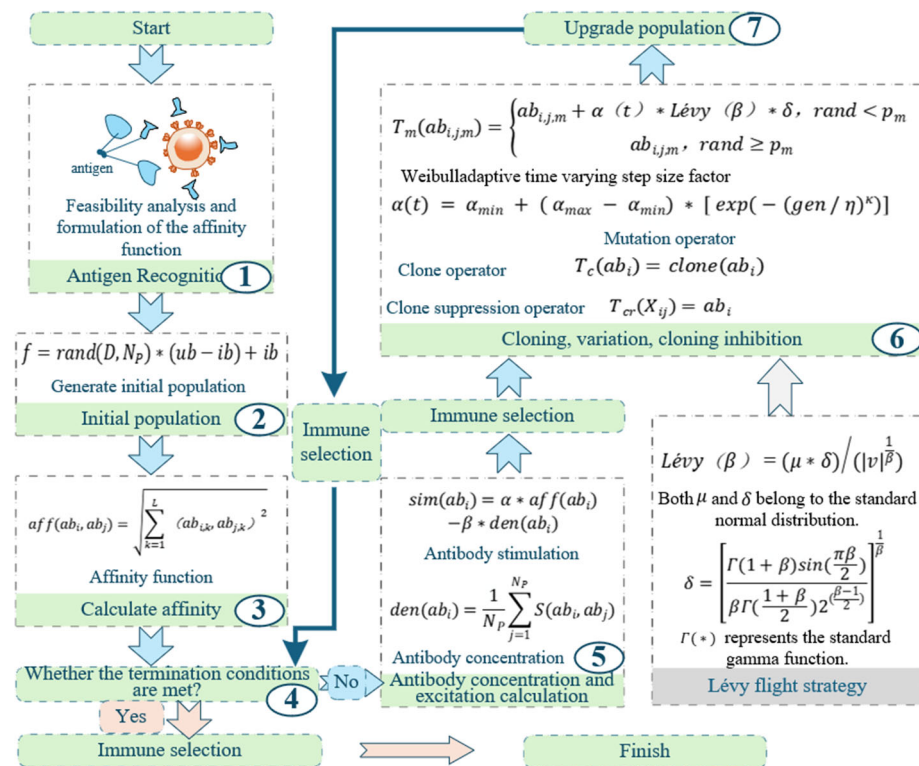


Figure 4. Flowchart of the WLDm-IOA Algorithm.

For the present system, the covariance matrix Q can be defined as:

$$Q = \text{diag}(Q_1, Q_2, Q_3) \quad (14)$$

Vector pending optimization:

$$y = [Q_1, Q_2, Q_3]^T \quad (15)$$

During the optimization process, each element in the vector y represents the position of an immune cell, and each immune cell possesses its own fitness function. To minimize the estimation error of state parameters and enhance estimation accuracy, the optimization objective function, namely the fitness function f_k , is defined as the root mean square error between the actual measured output and the estimated measured output:

$$\min f_k = \sqrt{\frac{1}{M} \sum_{k=1}^M (y_{k,i} - \hat{y}_{k,i})^2} \quad (16)$$

where i represents the dimension of the measurement vector; $y_{k,i}$ denotes the true measured value of the i -th measured variable at time k ; $\hat{y}_{k,i}$ signifies the identified value from the filtered output.

3.3. Complete Machine Mass Estimator

3.3.1. Adaptive Least Squares Method

Recursive least squares (RLS) is an algorithm applicable to online parameter estimation in linear systems. Its key characteristic lies in the ease of implementation of RLS identification. During the iterative process, parameter estimation can be refined using new data points to minimize the sum of squared prediction errors for old data points. However, classical RLS model parameter identification continuously accumulates historical data, leading to data saturation and a consequent decline in the algorithm's ability to track

the system [30]. Therefore, to enhance the corrective influence of new data and diminish the weight of old data, the forgetting factor λ is introduced to improve the accuracy of parameter identification. A smaller λ enables rapid tracking of abruptly changing parameters, albeit with a need to enhance parameter stability; during stable phases, a larger λ value is required to increase the weight of historical data, thereby enhancing the stability of parameter identification.

Therefore, a dynamic forgetting factor based on prediction error is introduced, enabling the λ value to adaptively adjust in accordance with the dynamic changes of the system. This approach enhances the algorithm's tracking capability and robustness with respect to system parameters. To strike a balance between the identification accuracy and stability of the algorithm, the Weibull distribution is extensively employed in reliability engineering and data fitting tasks. By adjusting its scale and shape parameters, the Weibull distribution can not only map to infinite-dimensional spaces but also prevent overfitting, ensuring continuous and smooth transitions. It mitigates estimation oscillations caused by abrupt parameter changes and flexibly accommodates the dynamic characteristics of diverse systems. The expression for WDFF-RLS is as follows:

$$\begin{cases} \varepsilon(k) = Y(k) - \phi^T(k)\hat{x}_l(k-1) \\ \hat{x}_l(k) = \hat{x}_l(k-1) + K_k \varepsilon(k) \\ K_k = P(k-1)\phi(k)[\phi^T(k)P(k-1)\phi(k) + \lambda]^{-1} \\ P(k) = \frac{[I - K_k\phi^T(k)]}{\lambda}P(k-1) \\ \lambda(k) = \lambda_{min} + (\lambda_{max} - \lambda_{min}) * \exp(-(\frac{|\varepsilon(k)|}{\varepsilon_0 * \eta})^\varpi) \end{cases} \quad (17)$$

In the equation, $Y(k)$ represents the system output, $\hat{x}_l(k)$ is the estimated parameter value at the current time, K_k is the system's estimated gain, $P(k)$ is the covariance at the current time, and $\phi(k)$ is the system's observed value. The WDFF-RLS dynamic forgetting factor $\lambda(k)$ varies with the system's dynamic changes, which helps to enhance the influence of historical data and improve parameter stability when the system error $\varepsilon(k)$ is small. Conversely, when the system error $\varepsilon(k)$ is large, reducing the λ value diminishes the impact of historical data, thereby improving algorithm accuracy and accelerating convergence speed. λ_{max} and λ_{min} denote the expected maximum and minimum λ values, respectively. $\varepsilon(k)$ represents the estimated residual at the current time, while ε_0 represents the preset reference error. When $|\varepsilon(k)| \gg \varepsilon_0 * \eta$, $\exp(\cdot) \rightarrow 0$, $\lambda(k) \approx \lambda_{min}$, and the system switches $\lambda(k)$ to the minimum value λ_{min} to enhance algorithm accuracy. Reducing η renders the system highly sensitive to errors, causing $\lambda(k)$ to rapidly decrease to λ_{min} once the error surpasses a small threshold. Similarly, increasing ϖ facilitates the rapid convergence of $\lambda(k)$ to λ_{min} . When $|\varepsilon(k)| \ll \varepsilon_0 * \eta$, $\exp(\cdot) \rightarrow 1$, $\lambda(k) \approx \lambda_{max}$, and the system switches λ to the maximum value λ_{max} to ensure parameter stability. Increasing η allows the system to maintain a value close to λ_{max} over a broader error range. Similarly, increasing ϖ enables $\lambda(k)$ to smoothly and rapidly reach λ_{max} .

3.3.2. Estimation Model for Overall Machine Mass

Unlike traditional electric monorail cranes, the permanent magnet drive speed-regulating integrated machine of distributed drive electric monorail cranes can accurately feed back the output driving torque. Consequently, by integrating the locomotive kinematics equation, the total torque T of the driving motor and the longitudinal acceleration A_{senx} of the locomotive are employed to ascertain the overall mass of the machine. Given that the cargo load remains constant during transit and factors such as fuel consumption, which could affect the vehicle mass, are not applicable to electric monorail cranes, the vehicle mass is considered nearly invariant in this study. Therefore, a track gradient estimation algorithm is devised using the recursive least squares method with an adaptive

dynamic forgetting factor. An estimation model for the fundamental mass parameters of the DDEMC is constructed, and Equation (2) is reformulated to align with the discrete least squares method as follows:

$$\delta m A_{senx} + mgf \cos \theta + mg(1 - \delta) \sin \theta = \frac{Ti_0 \eta}{r} \quad (18)$$

$$Y_k = \phi_k^T x_k + N_k \quad (19)$$

$$\begin{cases} Y_k = \frac{Ti_0 \eta}{r} \\ \phi_k = \delta A_{senx} + gf \cos \theta + g(1 - \delta) \sin \theta \\ x_k = m_k \end{cases} \quad (20)$$

Here, Y_k represents the system output at the current time instant (time k), ϕ_k denotes the observable value of the system, x_k is the parameter to be estimated, and N_k signifies the process noise of the system, which can be considered as Gaussian white noise. To address complex system models and mitigate the influence of outdated data, the real-time estimator for the overall mass of the machine is designed using the least squares method with an adaptive forgetting factor, thereby reducing the impact of noise on parameter estimation.

4. Analysis on Simulation Results

To validate the feasibility of the scheme proposed in this paper, simulation models and three-dimensional models for WLDM-IOA-UKF and WDFF-RLS are constructed using the MATLAB R2018b/Adams 2020 co-simulation platform. The three-dimensional model developed in Adams accurately simulates the motion state of the monorail crane locomotive. During the simulation tests, the wheel speeds of the four driving wheels are configured as depicted in Figure 5. The locomotive state values output by Adams are utilized as sensor measurements. Concurrently, these values are compared with the estimates obtained from traditional UKF and RLS estimators to verify the reliability and accuracy of the proposed method. To quantitatively describe the estimation methods for the overall mass and track gradient, the root mean square error (RMSE), maximum absolute error (MAE), mean absolute percentage error (MAPE), and root mean square percentage error (RMSPE) are employed as evaluation metrics. RMSE and MAE are utilized to measure the discrepancies between the estimated values and the actual road gradient values, while MAPE and RMSPE are applied to quantify the goodness of fit between the estimated and actual overall mass. The specific formulas are as follows:

$$RMSE = \sqrt{\frac{1}{M} \sum_{k=1}^M (y_{k,i} - \hat{y}_{k,i})^2} \quad (21)$$

$$MAE = \max_{1 \leq k \leq M} |y_{k,i} - \hat{y}_{k,i}| \quad (22)$$

$$MAPE = \frac{1}{M} \sum_{k=1}^M \left| \frac{y_{k,i} - \hat{y}_{k,i}}{y_{k,i}} \right| \quad (23)$$

$$RMSPE = \sqrt{\frac{1}{M} \sum_{k=1}^M \left(\frac{y_{k,i} - \hat{y}_{k,i}}{y_{k,i}} \right)^2} \quad (24)$$

where $y_{k,i}$ represents the reference value of the state quantity collected by the system at time instant k ; $\hat{y}_{k,l}$ denotes the estimated value of the state quantity obtained by the estimator at time instant k .

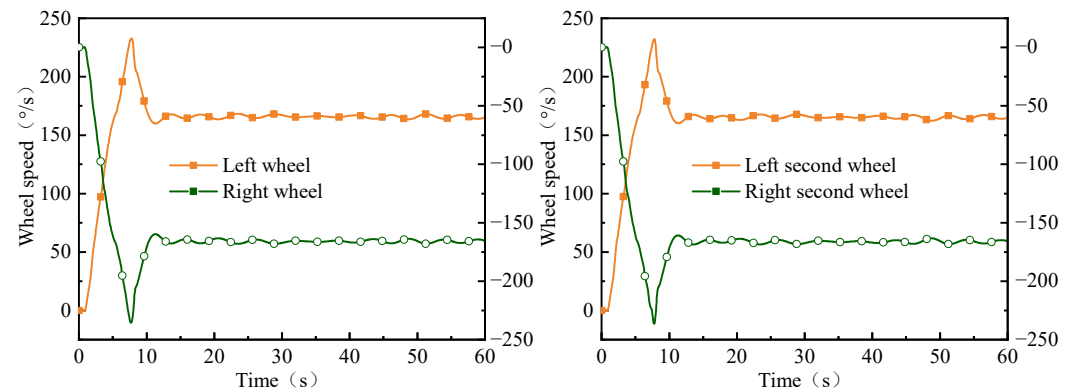


Figure 5. Driving Condition.

To validate the superiority of the proposed WLDM-IOA algorithm in terms of global search capability, optimization speed, and robustness, commonly used bio-inspired intelligent algorithms, namely the genetic algorithm, particle swarm optimization algorithm, and classical immune algorithm, are selected for comparative experiments. Three optimization test functions are introduced in this paper, which are sphere, Rosenbrock and Griewank functions. The performance test function is expressed as follows:

Sphere function:

$$f_n = \sum_{i=1}^n x_i^2 \quad x_i \in [-100, 100] \quad (25)$$

Rosenbrock function:

$$f_n = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2] \quad x_i \in [-2.048, 2.048] \quad (26)$$

Griewank function:

$$f_n = 1 + \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos\left(\frac{x_i}{\sqrt{i}}\right) \quad x_i \in [-600, 600] \quad (27)$$

To mitigate the impact of randomness, the statistical outcomes derived from 30 independent trials were subjected to analysis. To assess the efficiency and optimization precision of the algorithm, the following metrics were employed as the evaluation criteria: the minimum value of the objective function, the mean value of the objective function, variance, and standard deviation. The performance outcomes of various algorithms in optimizing test functions are presented in Tables 1–3. A comparative analysis of the convergence performance in test function optimization is depicted in Figures 6–8.

Table 1. Optimization test results of the Sphere function.

Algorithm	Average Value	Variance	Optimal Value	Standard Deviation
GA	4963.348913	813620.125163	3663.560162	902.008939
SCA	1.120867	4.166533	0.000187	2.041209
PSO	460.786050	14,494.114397	266.656708	120.391505
IOA	0.055214	0.000056	0.032956	0.007460
WLDM-IOA	0.000001	0.000000	0.000001	0.000000

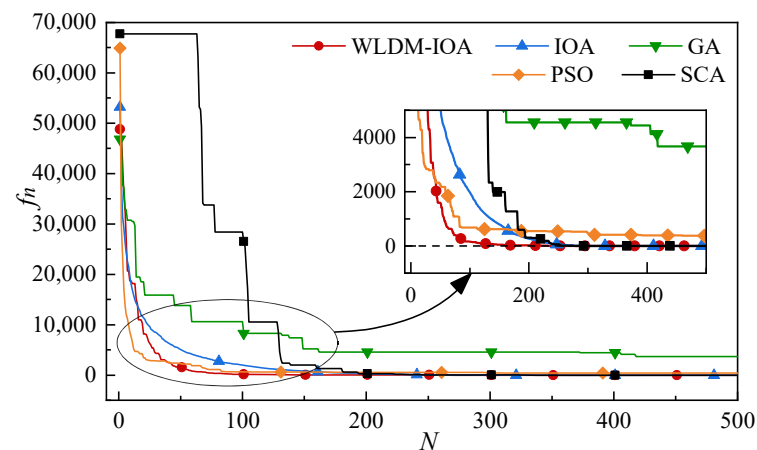


Figure 6. Convergence curves for the Sphere function.

Table 2. Optimization test results of the Rosenbrock function.

Algorithm	Average Value	Variance	Optimal Value	Standard Deviation
GA	333.655383	4360.086137	197.048487	66.030948
SCA	29.281399	3.318912	27.995492	1.821788
PSO	53.671396	183.144469	40.680247	13.533088
IOA	31.195839	50.567783	20.977706	7.111103
WLDM-IOA	18.641695	11.209218	11.530091	3.348017

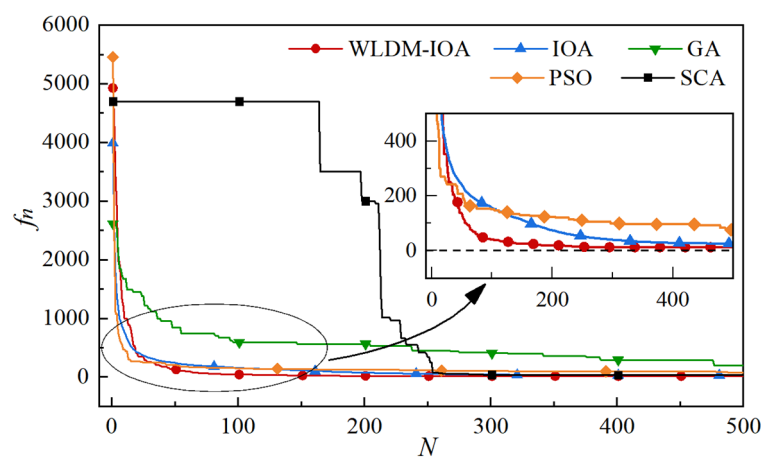


Figure 7. Convergence curves for the Rosenbrock function.

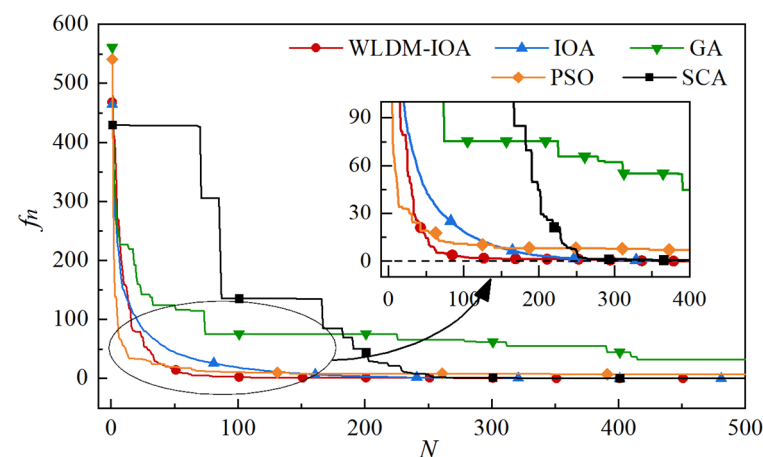


Figure 8. Convergence curves for the Griewank function.

Table 3. Optimization test results of the Griewank function.

Algorithm	Average Value	Variance	Optimal Value	Standard Deviation
GA	42.656238	53.136867	32.076938	7.289504
SCA	0.598242	0.086913	0.007697	0.294810
PSO	4.873748	1.238072	2.765986	1.112687
IOA	0.119241	0.000179	0.088181	0.013380
WLDM-IOA	0.000944	0.000008	0.000002	0.002782

The Sphere function can be used to evaluate the convergence performance and development ability of the algorithm. In the optimization experiment of the 30-dimensional test function, it can be seen that WLDM-IOA has the minimum mean, variance, optimal value, and standard deviation, and has been infinitely close to the target value, indicating that the WLDM-IOA algorithm has better optimization accuracy. In contrast, both PSO and GA become trapped in local optima far from the global optimum, exhibiting premature convergence. Compared with IOA and SCA, WLDM-IOA not only achieves faster convergence speed and higher accuracy, but also converges robustly toward the global optimum. The optimization of the Rosenbrock function is a typical complex optimization problem. The experimental results show that the WLDM-IOA algorithm has a smaller optimal value, variance and mean value than other algorithms, with good stability and high convergence accuracy. It can also be seen from the figure that the WLDM-IOA algorithm locates the potential region of the global optimum at the early stage of iteration and continues to refine the search in subsequent iterations. Its final convergence value is the lowest, indicating its strong ability to escape from local extrema and high local-search accuracy. The convergence curve of the WLDM-IOA algorithm is smooth and monotonically decreasing, which shows that its search process is stable, less affected by random initialization, and possesses strong robustness. The Griewank function is a classical multimodal, highly nonlinear optimization test function, which has high requirements for the global exploration ability and the ability of the optimization algorithm to escape from local extrema. The WLDM-IOA algorithm decreases rapidly and monotonically at the beginning of iteration and quickly approaches the optimal region with the objective value close to 0. The results show that the algorithm has strong global exploration ability, can effectively avoid the trap of a large number of local extrema, directly locate the potential area of global optimization, and shows excellent local refinement efficiency. Its final convergence accuracy is significantly better than that of other algorithms.

In general, the WLDM-IOA algorithm introduces Lévy flight to replace uniform random perturbations. It integrates the intelligent random behaviors of “short-range fine exploration” and “occasional long-distance jump” during the search process, which effectively alleviates the drawback that conventional algorithms are prone to falling into local optima. Meanwhile, the fixed-step-size strategy is replaced with an adaptive variable-step-size strategy based on the Weibull function, which realizes dynamic adjustment: large step sizes for global exploration in the early iteration stage and small step sizes for fine-tuned convergence in the later stage. The cooperation of these two mechanisms achieves an adaptive balance between exploration and exploitation. Consequently, the proposed algorithm delivers faster convergence speed, higher optimization accuracy and stronger robustness when tackling various complex optimization problems, including unimodal, narrow-valley and multimodal test functions.

4.1. Analysis of the Estimation Results for Track Gradient

To validate the accuracy of the proposed WLDM-IOA-UKF strategy for track gradient estimation, its estimation results are compared with those of the traditional UKF and KF. Figure 9 illustrates the test comparison results of three track gradient estimators when

the electric monorail crane operates under an unloaded condition with a track gradient of 5° . As depicted in the figure, there is a significant deviation between the estimation results of the traditional UKF and the actual values. The initial fluctuations are sharp, and during the convergence process, there remains a considerable overshoot. Additionally, substantial fluctuations persist in the steady-state phase, indicating an inability to effectively suppress process noise and resulting in poor steady-state accuracy. The estimated values from the KF in the initial stage are notably lower than the actual values. Although it can converge rapidly and stabilize, it fails to eliminate the deviation caused by the system's nonlinear factors, with a smaller fluctuation amplitude in the steady-state phase compared to the traditional UKF. In contrast, the WLDM-IOA-UKF proposed in this paper can maintain estimation errors within a narrow range. It swiftly reaches and approaches the actual values in the initial stage, demonstrating excellent initial convergence performance. In the steady state, it continues to exhibit minimal fluctuations, with a relatively smooth curve, indicating high stability. Compared to the KF and traditional UKF, the maximum absolute error of this method is reduced by 51.18% and 56.81%, respectively, while the root mean square error decreases by 44.64% and 66.3%, respectively. At a 5° track gradient, the WLDM-IOA-UKF proposed in this paper exhibits the smallest estimation error, the strongest stability, and almost no systematic deviation, effectively suppressing noise interference.

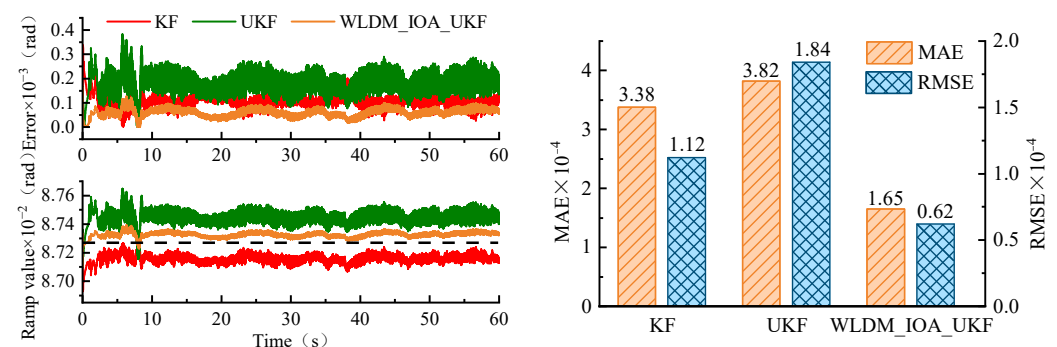


Figure 9. Estimation results of 5° track gradient, absolute error, and response evaluation.

To further validate the superiority of the proposed method in this paper under large inclination angles, estimation results for track gradient of 10° and 15° have been incorporated. As shown in Figures 10 and 11, the test results indicate that as the ramp inclination increases from 5° to 15° , the Kalman Filter (KF), being based on linear system calculations, is significantly affected by the strong coupling nonlinear characteristics between the gravitational component and operational acceleration under ramp conditions. Consequently, the estimation error increases markedly, and the estimated values deviate further below the measured values. Although the traditional Unscented Kalman Filter (UKF) achieves an approximate solution for the nonlinear system, with an increase in track gradient, the system's nonlinearity intensifies, leading to estimated values that exceed the measured values and an increase in error. In summary, WLDMIOAUK demonstrates superior performance compared to traditional UKF and KF, effectively reducing errors, exhibiting minimal sensitivity to track gradient, and displaying high robustness under nonlinear conditions, thereby confirming the effectiveness and feasibility of the WLDMIOAUK estimator.

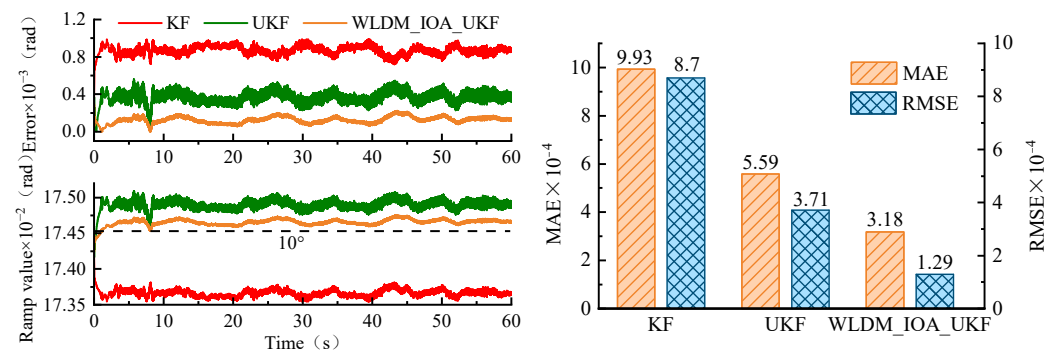


Figure 10. Estimation results of 10° track gradient, absolute error, and response evaluation.

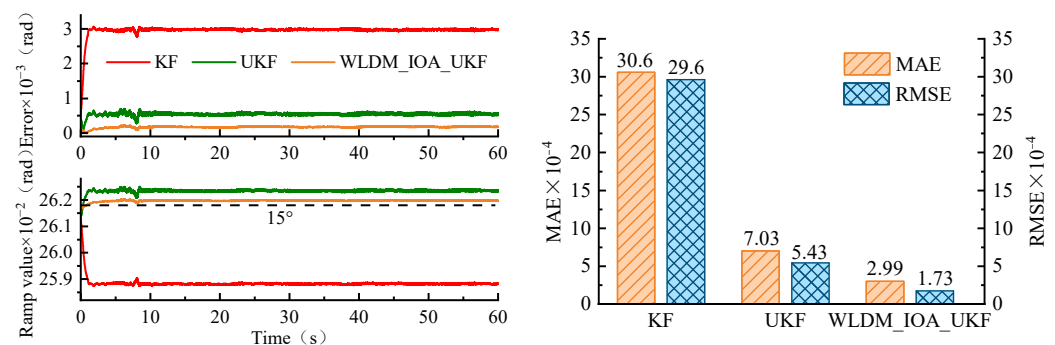


Figure 11. Estimation results of 15° track gradient, absolute error, and response evaluation.

4.2. Analysis on the Results of Mass Estimation

To evaluate the observation performance of the WDFF-RLS observer on the overall machine mass, tests were conducted on the CDOE under no-load and 2-ton load conditions. The monorail crane employed four methods—RLS, FFRLS_0.98, FFRLS_0.99, and WDFF-RLS—to observe the model parameters under various load conditions. The forgetting factors for FFRLS_0.98 and FFRLS_0.99, based on FFRLS, were set to 0.98 and 0.99, respectively. A comparison of these four different mass observers revealed parameter identification results as illustrated in Figures 12 and 13.

Figure 12 and Table 4 present the test results and errors of the monorail crane under no-load conditions. The findings indicate that the standard RLS estimator exhibits a slow convergence rate, making it challenging to swiftly correct initial errors. When employing a fixed forgetting factor, the algorithm achieves rapid convergence; however, the resultant curve demonstrates significant fluctuations, reflecting the time-varying nature of parameters that vary with traction force and speed, thereby posing difficulties in balancing transient response and steady-state performance. The WDFF-RLS algorithm proposed in this paper, through dynamic adjustment of the forgetting factor, not only converges rapidly during the initial phase and reaches a stable state first but also ensures a relatively smooth trajectory of mass estimation in the steady-state phase without burr phenomena. The steady-state MAPE is 1.1803%. Compared to the RLS, FFRLS_0.98, and FFRLS_0.99 estimators, this represents reductions of 60.12%, 5.76%, and 5.21%, respectively, while the steady-state RMSPE decreases by 71.81%, 5.56%, and 4.91%, correspondingly.

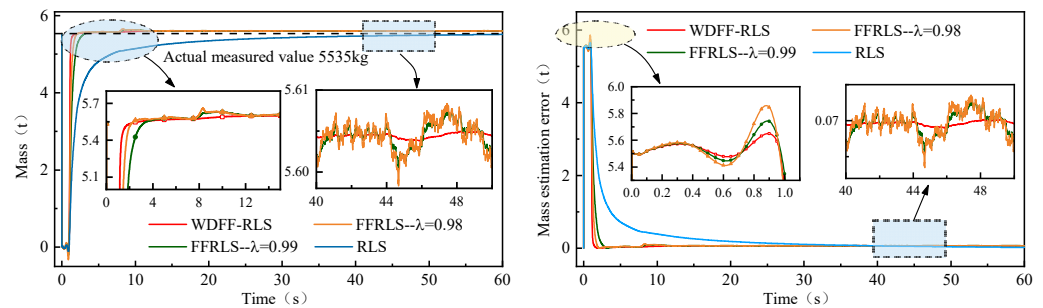


Figure 12. Estimation Results and Absolute Errors under No-load Condition.

Table 4. Error Comparison under No-load Condition.

Method	RLS	FFRLS_0.98	FFRLS_0.99	WDFP-RLS
Steady-state MAPE	2.9597%	1.2525%	1.2452%	1.1803%
Steady-state RMSPE	4.2340%	1.2638%	1.2551%	1.1935%

Figure 13 and Table 5 present the test results and error comparisons for the monorail crane when carrying a 2-ton cargo load. As depicted in the figure, the WDFP-RLS method proposed in this paper achieves the measured value at 1.73 s, demonstrating the fastest response time compared to other estimators. A closer examination of the local graph reveals that the result curve of this method is relatively smooth, exhibiting no significant chattering. The steady-state MAPE for WDFP-RLS is 1.2871%, whereas for RLS it is 2.9153%, for FFRLS_0.98 it is 1.3590%, and for FFRLS_0.99 it is 1.3514%. Similarly, the steady-state RMSPE of WDFP-RLS is reduced by 69.34% compared to RLS, indicating that the mass parameter identification using this method is also more accurate when the crane is loaded.

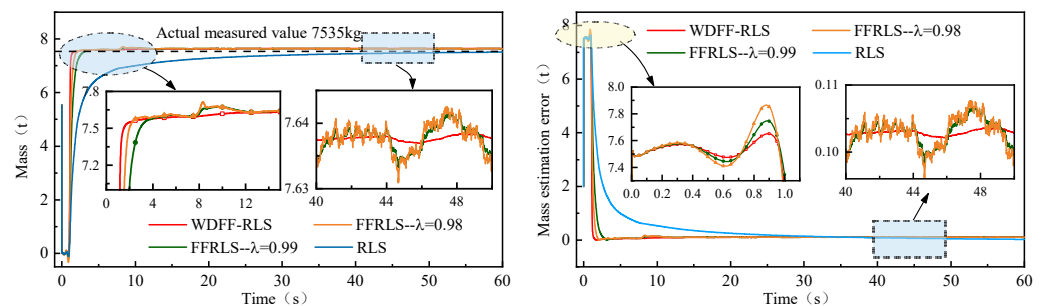


Figure 13. Estimation Results and Absolute Error for a 2-Ton Load.

Table 5. Error Comparison for a 2-Ton Load..

Method	RLS	FFRLS_0.98	FFRLS_0.99	WDFP-RLS
Steady-state MAPE	2.9153%	1.3590%	1.3514%	1.2871%
Steady-state RMSPE	4.2368%	1.3702%	1.3612%	1.2991%

4.3. Robustness Evaluation and Analysis

During actual operation, owing to the complex and variable underground working environment, the state estimation of the monorail crane system will inevitably be subject to interference from factors such as track gaps and uneven joints. The vibration and impact caused by track gaps are significant factors affecting the estimation of track gradient and mass. To further validate the robustness of the CDOE proposed in this paper against track gap disturbances, this section establishes typical gap conditions and compares and

analyzes the response characteristics of different estimation methods regarding the inclination and mass of the track ramp. Figure 14 illustrates the response curve for track gradient estimation of the monorail crane under track gap disturbances. As evident from the figure, the impact caused by track gaps results in pronounced peak disturbances and errors in the track gradient estimations of the KF and traditional UKF methods. In contrast, the estimation curve of the WLDMIOAUKF proposed in this paper is smoother, with disturbances effectively suppressed. Its maximum absolute error is reduced by 12.13% and 64.02% compared to the KF and traditional UKF methods, respectively, and it exhibits the smallest increase in root mean square error, indicating the highest estimation accuracy. Therefore, the proposed method demonstrates excellent anti-interference capabilities under track gap disturbances.

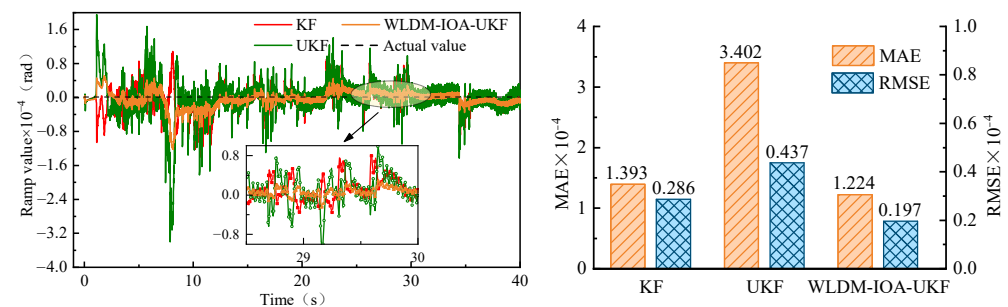


Figure 14. Estimation Results and Response Evaluation under Disturbed Operating Conditions.

The response curve for mass estimation of the monorail crane under track gap disturbances is depicted in Figure 15 and Table 6. The RLS exhibits an excessively long convergence time, whereas the FFRLS with a fixed forgetting factor can swiftly approximate the actual value. However, due to track interference, it experiences significant fluctuation amplitudes, with a steady-state error amplitude reaching up to 8.2%. In contrast, the mass estimation curve of the improved algorithm proposed in this paper demonstrates minimal overshoot, with a steady-state error amplitude of merely approximately 3%. It rapidly converges to the true value within 1.7 s. The steady-state MAPE, steady-state RMSPE, and STD are all minimized, indicating that the method presented in this paper effectively mitigates disturbances caused by track gaps, offers high estimation accuracy, and exhibits strong robustness, making it suitable for parameter estimation in complex underground environments.

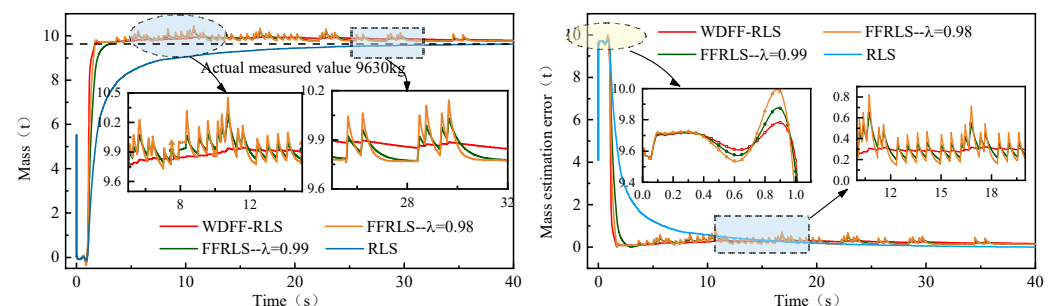


Figure 15. Mass estimation results and absolute errors under Disturbed Operating Conditions.

Table 6. Error Comparison under Disturbed Operating Conditions.

Method	RLS	FFRLS_0.98	FFRLS_0.99	WDFR-RLS
Steady-state MAPE	2.9696%	2.5716%	2.5597%	2.5128%
Steady-state RMSPE	4.5247%	2.8504%	2.7361%	2.5618%
STD	3.4141%	1.2296%	0.9665%	0.4985%

5. Experimental Validation

The experimental environment is selected as a segment of track at the auxiliary transportation rail test site of KESHI Group in Changzhou, while the test object is a distributed-drive electric monorail crane equipped with two drive units. The platform structure is illustrated in the figure. The complete system primarily comprises a driving power supply, an upper computer, a vehicle controller, four permanent magnet variable-frequency synchronous integrated machines along with their respective controllers. The driving motor torque is calculated through the conversion of data from the built-in current sensor in the driver, combined with the motor torque constant. The angular velocity of the driving wheel is measured using a motor encoder. During the experiment, a predetermined speed value is set for the locomotive. The operator regulates the vehicle speed via a remote control and maintains a constant speed thereafter. The locomotive is outfitted with corresponding sensors to gather experimental data on the current, voltage, and rotational speed of the driving motor. This sensor data is recorded and stored on a laptop computer through the CAN channel, utilizing the ZCANPRO tool (version 2.3.3). The collected real-vehicle test data is employed for state estimation verification. The vehicle status during the real-vehicle road test is depicted in Figure 16.

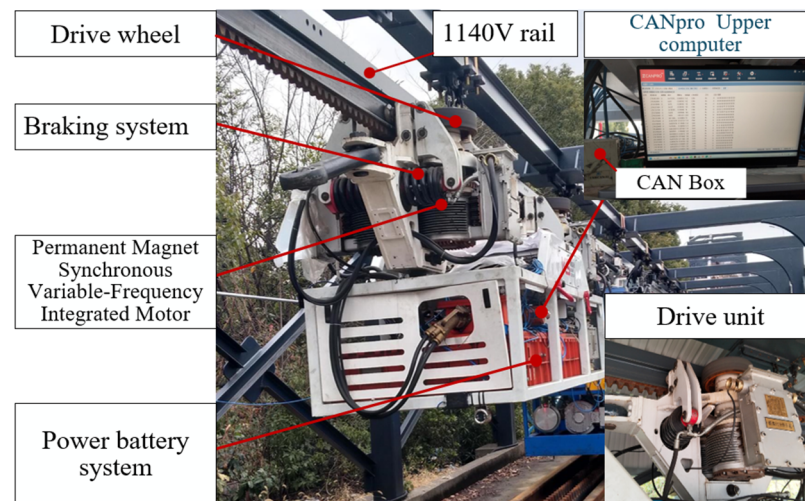


Figure 16. Experimental Test Platform.

As illustrated in Figure 17 and Table 7, the Kalman Filter (KF) based on the monorail crane kinematics model exhibits poor adaptability to system nonlinearity, resulting in significant estimation errors in the track gradient under strong interference conditions, thereby failing to effectively suppress disturbances. In contrast, the traditional Unscented Kalman Filter (UKF) employs unscented transformation to address nonlinear problems, achieving a 54.88% reduction in maximum error compared to KF. Nevertheless, it still cannot fully suppress disturbances under complex operating conditions, with error fluctuations persisting. By optimizing the noise covariance, the proposed method effectively filters out interference caused by unknown environmental factors such as track gaps, reduces errors, and exhibits no significant large chattering phenomena throughout the process. Whether evaluated by Mean Absolute Error (MAE) or Root Mean Square Error (RMSE), the estimation errors of the proposed algorithm are significantly smaller than those of both KF and traditional UKF algorithms. Consequently, the proposed algorithm demonstrates superior accuracy and robustness compared to the aforementioned two algorithms.

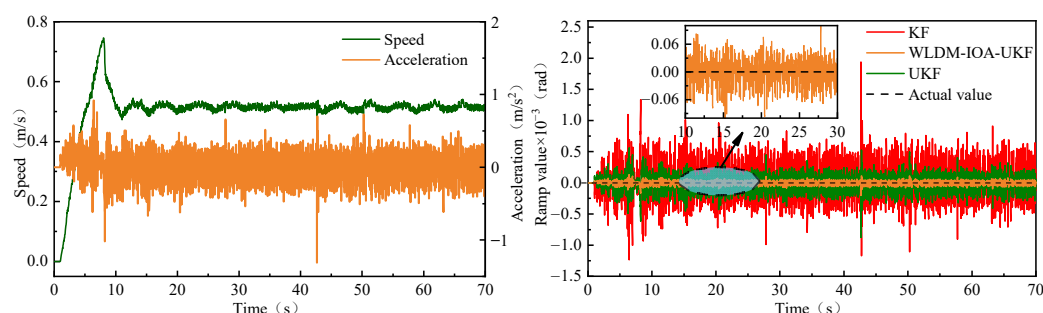


Figure 17. Experimental Results.

Table 7. Error Comparison Based on Experimental Results.

Method	KF	UKF	WLDM-IOA-UKF
MAE/rad	0.001935	0.000873	0.000203
RMSE/rad	0.29×10^{-3}	0.14×10^{-3}	3.11×10^{-5}

6. Conclusions

Given the challenges and high costs associated with the direct measurement of key operational parameters of DDEMC, this study proposes a cascaded dual observer method for estimating the mass of electric monorail cranes and track gradient in complex mine environments. The framework accounts for the coupling relationships among parameters in transportation scenarios, as well as multi-source factors such as system technology, locomotive characteristics, and track conditions, to achieve precise estimation of locomotive mass and track gradient. A UKF track gradient estimation algorithm based on adaptive immune optimization is devised, incorporating a Levy flight strategy to guide immune optimization and adaptively adjusting the noise covariance matrix of the key parameter system. This aims to enhance the algorithm's robustness and estimation accuracy under complex working conditions, enabling stable and real-time estimation of track gradient. To achieve high accuracy and stability in parameter identification results, a Weibull dynamic forgetting factor is introduced based on the RLS algorithm, leading to the design of a WDFR-RLS estimator. The results demonstrate that the proposed CDOE estimation method exhibits smaller errors, faster response speeds, and superior estimation accuracy, while also demonstrating stronger robustness under varying track gradient conditions, different loads, and significant interference from track gaps.

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