

Optimizing high-speed train tracking intervals with an improved multi-objective grey wolf

Lin Yue, Meng Wang, Peng Wang and Jinchao Mu

Signal and Communication Research Institute, China Academy of Railway Sciences Corporation Limited, Beijing, China

Abstract

Purpose – With the rapid advancement of China’s high-speed rail network, the density of train operations is on the rise. To address the challenge of shortening train tracking intervals while enhancing transportation efficiency, the multi-objective dynamic optimization of the train operation process has emerged as a critical issue.

Design/methodology/approach – Train dynamic model is established by analyzing the force of the train in the process of tracing operation. The train tracing operation model is established according to the dynamic mechanical model of the train tracking process, and the dynamic optimization analysis is carried out with comfort, energy saving and punctuality as optimization objectives. To achieve multi-objective dynamic optimization, a novel train tracking operation calculation method is proposed, utilizing the improved grey wolf optimization algorithm (MOGWO). The proposed method is simulated and verified based on the train characteristics and line data of CR400AF electric multiple units.

Findings – The simulation results prove that the optimized MOGWO algorithm can be computed quickly during train tracks, the optimum results can be given within 5s and the algorithm can converge effectively in different optimization target directions. The optimized speed profile of the MOGWO algorithm is smoother and more stable and meets the target requirements of energy saving, punctuality and comfort while maximally respecting the speed limit profile.

Originality/value – The MOGWO train tracking interval optimization method enhances the tracking process while ensuring a safe tracking interval. This approach enables the trailing train to operate more comfortably, energy-efficiently and punctually, aligning with passenger needs and industry trends. The method offers valuable insights for optimizing the high-speed train tracking process.

Keywords Tracking running, Train dynamics model, Multi-objective optimization, MOGWO, CR400AF electric multiple units

Paper type Research paper

1. Introduction

In recent years, the exponential growth of China’s high-speed railway network has been marked by a substantial increase in operational mileage and elevated train speeds. This rapid expansion has led to the saturation of operational schedules on several key routes, posing significant challenges to the existing transportation infrastructure. After nearly 20 years of development, China’s train control system has continuously improved the safety, reliability and maintainability of the system, and implemented safety reinforcement measures such as section occupancy logic inspection, track circuit tuning area inspection, track protection section setting and adding independent safety inspection software to the radio block center and train control center (He, 2024). Innovations of train operation control technology will continue



to emerge to enhance the functions of train operation control systems and raise the level of intelligence to meet the needs of high speed and high density (Mo, 2022). But the traditional train control systems, which are predominantly based on fixed block or moving block principles, are increasingly unable to satisfy the escalating demand for high-speed railway operation. As a result, there is an urgent necessity to increase train speeds, reduce tracking intervals for high-speed trains, augment line capacity. At the same time, shorten the travel time and improve the overall passenger experience. These advancements must be achieved while promoting the development of green and energy efficient high-speed railway systems across China.

However, China railway network is dense and application scenarios complex, the operational environment for high-speed train tracking is complex and dynamic, with real-time changes in block interval lengths. So it is difficult to adjust train operation plans in real time (Li & Li, 2021). This variability introduced additional layers of complexity to the already demanding task of ensuring precise and safe train operations. Furthermore, the increase in train speeds directly correlates with longer braking distances, which in turn imposes more stringent requirements on the high-speed train tracking control systems and driving safety protection. The need for enhanced precision and reliability of these systems is paramount to mitigate potential risks and ensure the seamless operation of high-speed rail networks.

The dynamic model of high-speed trains serves as the foundation for train tracking optimization. An accurate and reliable dynamic model is crucial for ensuring the safety and effectiveness of train control systems (Liu, 2020), making it a focal point in train tracking research. Researchers like Wang *et al.* (2018) constructed a microscopic simulation longitudinal train dynamics model to fully capture the instantaneous dynamic characteristics of the train. The validity of the longitudinal train dynamics model is assessed by comparing instantaneous model predictions against field observations, and evaluated in the domains of acceleration or deceleration versus speed and acceleration or deceleration versus distance. Liu, Chen, Guo, Yuan, and Yin (2023) consider the high efficiency of single-point model identification, and put forward a third-order single-point train dynamics model based on recursive least square method to describe the traction and braking forces of trains in different operating environments. Cao, Wang, Zhu, Wang, and Wang (2023) conducted a comprehensive analysis of the running state, control instructions, line conditions, and transportation loads of heavy haul trains. Leveraging these insights, they proposed a novel train dynamics modeling method grounded in a data-driven approach using a meta-learning model framework. In their study, a sophisticated data-driven train dynamics modeling method was developed by integrating the Attention Mechanism (AM) with the Gated Recurrent Unit (GRU) neural network. The proposed learning network is architecturally composed of encoding, decoding, attention, and context layers, which collectively capture the intricate relationships between train states, control commands, line conditions, and other influencing factors. This innovative approach enhances the accuracy and robustness of train dynamics modeling, offering a more reliable framework for predicting and optimizing train operations.

Current research on the train tracking process spans a broad spectrum of theoretical, computational, and practical domains, reflecting its critical role in modern rail systems. An (2022) explores the optimization of high-speed train tracking intervals under varying line conditions, such as different station throat lengths and long downhill gradients. Liu, Zhang, and Song (2024) established a tracking interval model for heavy haul trains based on the moving block system, integrating car-following theory from road vehicles and specific working condition selections. Xu *et al.* (2024) investigated the train tracking interval under a moving block system using vehicle-to-vehicle communication, proposing an optimization method based on the T value. Li and Peng (2021) examined the impact of additional line resistance of tracking interval times, comparing train tracking processes under different speed limit conditions to determine the influence of line conditions on tracking interval times. Zhao, Tian, and Zhang (2020) adhering to the UIC406 standard and considering the characteristics of quasi-moving block and station sectional unlocking, constructed a theoretical method for

interval time based on the block time diagram. [Yang et al. \(2015\)](#) proposed an adaptive least squares support vector machine (LSSVM) modeling and speed control method for the EMU running process, optimizing the real-time running speed of the CRH380AL EMU. [Cai, Sun, and Shangguan \(2019\)](#) designed a train tracking operation control strategy model based on the elastic interval model, proposing the train elastic tracking interval model to optimize train tracking intervals in real time. [Luo et al. \(2023\)](#) proposed a virtual marshalling tracking control method based on distributed robust model predictive control, employing a linear matrix inequality optimization algorithm to shorten the tracking intervals of different unit trains.

Despite the abundance of research on the train tracking process, most scholars redefine the process with different models and optimize it using various algorithms. However, there is a noticeable gap in multi-objective comprehensive optimization research, particularly concerning the energy efficiency and comfort of Electric Multiple Units (EMUs). Continuously pursuing shorter train tracking intervals without considering passenger comfort and train energy consumption is unlikely to be effective in practical applications.

Motivated by the above discussion, we can determine that this study aims to design a novel train tracking operation calculation method that can enable the trailing train to operate more comfortably, energy-efficiently, and punctually, aligning with passenger needs and industry trends. Firstly, to improve the accuracy of dynamics high speed train model, a multivariate dynamic model incorporating line conditions, track parameters and train parameters, is designed and implemented in the multivariate input problem of trains tracking. Moreover, to address the issue of insufficient data during the actual model building process, a model-independent a novel train tracking operation calculation method is constructed to allow it to learn the initialization parameters of the train tracing operation model between source tasks to adapt to the destination task quickly. Finally, to describe the operation process of high-speed trains more accurately, fulfill the development requirements of green high-speed railways, and enhance passenger comfort during travel, a multi-objective simultaneous optimization computational model- Improved Grey Wolf Optimization Algorithm (MOGWO) is proposed. To ensure the efficient computation and optimization of the train operation model, the proposed MOGWO model undergoes further refinement and enhancement.

Specifically, the main contributions of this work are presented as follows:

- (1) The proposed high-speed railway train dynamics model integrates comprehensive analyses of the vehicle state, track state, and train operating conditions. It also incorporates real-time considerations of the effects of multiple condition changes on the train tracking model. This holistic approach ensures that the established train motion model is more representative of actual scenarios, thereby enhancing its accuracy and reliability in simulating train dynamics.
- (2) The proposed multi-objective optimization framework, which prioritizes energy efficiency, punctuality, and passenger comfort, is more aligned with the development trends and strategic objectives of China's high-speed railway industry. This framework not only addresses the critical aspects of modern railway transportation but also supports the sustainable and efficient growth of high-speed railway systems.
- (3) The improved MOGWO algorithm is designed to simultaneously optimize multiple objectives, thereby providing a robust framework for achieving optimal train operation performance while adhering to the principles of sustainability and passenger satisfaction.

The focus of the study is primarily on accurately calculating the acceleration of the train at the next moment, based on its current operating state and the optimization objective. In this research, the following three assumptions are made:

First, abstraction of the train as a mass point. This abstraction is necessitated by the characteristics of the dataset, which primarily emphasizes the longitudinal motion of the train.

By focusing on the train's longitudinal dynamics, the model can more effectively capture the essential aspects of its movement. Second, in this paper, the interaction forces between the track system and the train are not taken into consideration. This decision is based on the dataset, which is sourced from the onboard computer and does not include data related to the forces exerted between the track and the train. Consequently, the model focuses solely on the train's internal dynamics and operational parameters. Third, cross-line interactions are not considered as a holistic network in this research. The study excludes the consideration of operating trains on other lines as part of the optimization problem. This assumption neglects the complexities associated with the cross-line operations of high-speed railway trains, thereby simplifying the analysis. By doing so, the research can focus more intently on the behavior of trains within the line and the impact of preceding trains on those that follow. This approach allows for a more concentrated examination of the intra-line dynamics and the sequential influence of train movements on the overall tracking process.

The rest of this paper is organized as follows. In Section 2, first examines the dynamics of high-speed trains, analyzing the dynamic models under different line conditions and constructing comprehensive dynamic models by balancing various operational factors. Secondly, based on the premise of safe train operation and aligned with actual operational requirements, a multi-objective optimization function is established with comfort, energy efficiency, and punctuality as the primary objectives in Section 3. Finally, in Section 4, the proposed improved algorithm is rigorously validated to confirm its ability to achieve rapid convergence across a range of parameter settings. This validation process ensures that the algorithm maintains robust and efficient computational performance, regardless of the specific parameters employed. The MOGWO algorithm is employed to optimize the tracking intervals of high-speed trains in real time, with simulation verification conducted across different line conditions.

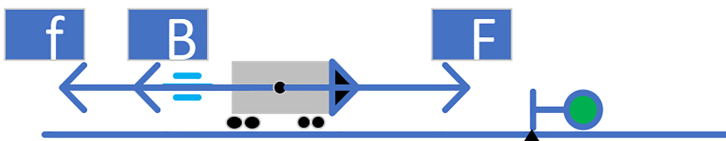
2. Description of optimization model of high-speed train tracking interval

2.1 Dynamic model of high-speed train

The precise mathematical modeling of the train tracking process constitutes the essential foundation for investigating the optimization of train tracking intervals. The dynamics of train operation are subject to a multitude of factors, notably including traction force, braking force, and frictional resistance. While the traction and braking forces can be explicitly defined at specific temporal points through the operational parameters of the traction and braking systems, the resistance forces experienced by the train are subject to significant variability due to differing line conditions and environmental circumstances.

In light of this, the present study undertakes a comprehensive and balanced analysis of the diverse factors influencing the operational dynamics of high-speed trains. This analysis culminates in the development of a high-speed railway train dynamics model, as depicted in Figure 1 below.

Assumed train weight m , at a certain point in time, the train is pulled by F , braking force B , total resistance f . At the moment its acceleration is a and speed is v .



Source(s): Authors' own work

Figure 1. Dynamic model of high-speed train

$$a = \frac{F - B - f}{m(1 + r)} \quad (1)$$

$$v = a \cdot \Delta T \quad (2)$$

Where, r is the rotational mass coefficient, which is used to convert the inertial resistance moment of rotational mass into the inertial resistance moment of translational mass, so as to accurately calculate and evaluate the kinematic performance of trains.

Total resistance of train f :

$$f = f_0 + f_i + f_r + f_s \quad (3)$$

The basic resistance of the train at this moment is f_0 :

$$f_0 = (a + bv + cv^2) \times G \quad (4)$$

Where G is the gravity of the train, $G = m \cdot g$, parameters a, b, c are the resistance parameter of different vehicle types.

Additional resistance f_i the ramp of the train at this moment:

$$f_i = \sin \theta \cdot kN = 1000 \sin \theta \quad (5)$$

Where, θ is the included angle of line slope, the mechanical unit is thousands of cattle. Because the railway line must have certain conditions, the ramp angle is generally very small, otherwise it will cause safety risks. When the value of θ is very small, $\sin \theta \approx \tan \theta$. In order to further facilitate the calculation, additional resistance f_i approximate calculation formula is

$$f_i = \sin \theta \cdot kN = 1000 \sin \theta \cdot N \approx 1000 \tan \theta \cdot N \approx \theta \cdot N \quad (6)$$

The additional resistance for the train passing curve is f_r :

$$f_r = \frac{600}{R} \cdot mg \quad (7)$$

Where, R is the radius of the curve.

For the additional air resistance f_s of the train, in order to handle it conveniently in engineering, the additional air resistance of the train passing through the tunnel is calculated concretely as follows:

$$f_s = 0.00013 L_{tun} \cdot mg \quad (8)$$

Where, L_{tun} is the tunnel length.

2.2 High-speed train tracking operation model

The train tracking scene is analyzed, and the dynamic tracking interval between the front Train 1 and the rear Train 2 is L_{tra} set as:

$$L_{tra} = L_2 + l_a - L_1 + \psi_2 + \psi_1 + \hat{l} \quad (9)$$

Where, L_2 is the braking distance of the rear car, $L_2 = \frac{v_2^2}{2a_2}$, L_1 is the braking distance of the front vehicle, $L_1 = \frac{v_1^2}{2a_1}$. For the captain of the front car l_a , ψ_2 and ψ_1 are the confidence distance of the

front car parking space at the front of the rear car. The \hat{l} is the reaction distance from the time when the rear car brakes to the time when the front car starts to decelerate, $\hat{l} = v_2 \cdot t_{react}$, v_2 is the running speed of the rear car.

Requirements $L_{tra} \geq L_{min}$, L_{min} is the minimum tracking segment length. To enhance the model's safety, it is imperative to consider the most unfavorable factors when determining the minimum tracking segment length and the associated acceleration parameters. Specifically, the analysis should incorporate the standard braking deceleration and the acceleration characteristics of the trailing vehicle. Furthermore, the most conservative approach necessitates the inclusion of the emergency braking deceleration of the leading vehicle. This comprehensive consideration ensures that the model accounts for the most stringent safety conditions, thereby providing a robust framework for assessing and optimizing train tracking intervals.

$$L_{min} = \frac{v_2^2}{2a_{ser}} + l_a - \frac{v_1^2}{2a_{em}} + \psi_2 + \psi_1 + \hat{l} \tag{10}$$

Where, for the common braking acceleration of the rear car a_{ser} , a_{em} is the emergency braking acceleration of the front vehicle.

2.3 Multi-objective optimization model

According to the train dynamics model and tracking model, combined with the actual operation situation, the multi-objective optimization function is established. The optimization goal of high-speed train tracking operation is

$$\Phi = \min(\Phi_C, \Phi_E, \Phi_T) \tag{11}$$

Among them, the evaluation function Φ_C of train running comfort is:

$$\Phi_C = \int \left| \frac{da}{dt} \right| dt \tag{12}$$

Where, a is the acceleration of the train, which is obtained from the train dynamics model. For t is the time, d is a differential symbol.

Evaluation function of train energy consumption Φ_E for

$$\Phi_E = \frac{1}{\eta} \int_0^{T_1} F dt - \alpha \int_{T_1}^{T_2} F dt \tag{13}$$

Where, α is the regenerative braking energy feedback coefficient, η is traction efficiency, and $0 - T_1$ the train is in Traction at all times, $T_1 - T_2$ the train is in braking force.

Evaluation function of train punctuality Φ_T :

$$\Phi_T = \sum_{i=1}^k (\Phi_{i_t} - \Phi_{T_i}) \tag{14}$$

Where, k is optimized the number of trains, Φ_{i_t} is the actual arrival time of the i train, Φ_{T_i} is the planned arrival time of the i train.

The optimization of the multi-objective optimization function, is achieved by determining the optimal acceleration profile for the trailing vehicle (denoted as a_2 , representing the acceleration of the rear vehicle in the train tracking model). The aim is to achieve the highest possible speed during the tracking process, thereby optimizing the high-density tracking

intervals of trains. The detailed optimization solution for this multi-objective function will be elaborated in subsequent sections.

3. Multi-objective optimization algorithm of train tracking interval

The dynamic optimization of train tracking is inherently a multi-objective problem that necessitates the simultaneous satisfaction of safety, comfort, energy efficiency, and punctuality. These objectives are often interdependent and may conflict with one another. The MOGWO (Multi-Objective Grey Wolf Optimizer) algorithm is adept at identifying the Pareto optimal solutions in multi-objective optimization problems by emulating the social hierarchy and predatory behavior of grey wolves. MOGWO enhances the original Grey Wolf Optimizer (GWO) by incorporating a multi-objective strategy to address multiple, potentially conflicting, objective functions.

In recent years, there are many research results on the improvement of MOGWO algorithm. [Li et al. \(2024\)](#) introduced Chaos-Faure initialization, Log convergence factor adjustment, and optimal solution adaptive update operators to enhance its adaptability and balance the global and local search of the algorithm. The IMOGWO incorporates improved initialization, local search strategies, and binary mutation operators to refine exploration-exploitation balance. [Wang et al. \(2025\)](#) incorporated Q-learning into an enhanced multi-objective grey wolf optimization framework, developing a state-action mechanism that systematically balances exploration and exploitation. By introducing dynamic parameter tuning that dynamically regulates solution updates, the approach optimizes adapts throughout the optimization process via stage-aware self-adaptation. The improved gray wolf optimizer fitness function is calculated using a machine-learning-based surrogate model, which is constructed based on the adaptive boosting (AdaBoost) ensemble algorithm to predict the output performance under different parameters ([Li et al., 2023](#)). The existing algorithms exhibit high efficacy in achieving fine-grained optimization. However, their application to high-speed railway operation optimization is not appropriate. This is primarily due to the high speed nature of railway systems, where an excessive emphasis on optimization precision can lead to a significant increase in computational time. Consequently, this diminishes the practical utility of the optimization algorithm in real-time decision-making processes critical for high-speed railway operations. In light of this, the present study proposes a Multi-Objective Grey Wolf Optimizer (MOGWO) algorithm for high-speed railway speed optimization, which is based on a comprehensive evaluation of the trade-off between computational time and optimization efficacy.

The search mechanism of the MOGWO algorithm, which primarily relies on the information of the alpha, beta, and delta wolves (α, β, δ), may lead to convergence to local optima and neglect potentially superior global solutions. Additionally, the algorithm's lack of variation and adaptive mechanisms in position selection can result in reduced diversity and slower convergence, particularly when dealing with high-dimensional problems. To address these issues, this paper proposes several enhancements to the MOGWO algorithm, aiming to achieve a balance between comfort, energy efficiency, and punctuality in the context of close train tracking:

- (1) Chaotic Sequence Initialization. To enhance the variability of the initial population and maintain global diversity, chaotic sequences are generated using Logistic Chaos Mapping as a means of initializing the population within the search space.

$$\begin{cases} X_{n+1} = \xi \cdot X_n \cdot (1 - X_n) & n = 1, 2, \dots, k - 1 \\ 0 < X_0 < 1 \end{cases} \quad (15)$$

- (2) Gaussian Mutation. To increase the diversity of individuals during the updating process and improve the algorithm's search capabilities and convergence accuracy,

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$X_{best}(t+1) = X(t)(1 + f_{Gaussian}(t))$$

$$\begin{cases} X_{best}(t+1), & \text{other} \\ X(t), & \Phi(X(t)) < \Phi(X_{best}(t+1)) \end{cases} \quad (16)$$

- (3) **Dynamic Adjustment of Linear Decreasing Strategy.** To balance the algorithm’s global search and local optimization capabilities, a linear decreasing strategy is employed to dynamically adjust the strength of the Gaussian perturbation. This adjustment is designed to improve the search efficiency and the quality of the optimal solution.

$$\sigma(t) = \sigma_{initial} - \left(\frac{\sigma_{initial} - \sigma_{final}}{T} \right) \cdot t \quad (17)$$

$\sigma(t)$ is the standard deviation at the first iteration, $\sigma_{initial}$ is the initial standard deviation, and σ_{final} is the termination standard deviation. T is the maximum number of iterations, t is the current number of iterations.

- (4) **Convergence Assessment.** To ensure the algorithm converges within the desired range, a convergence calculation is introduced to assess the algorithm’s convergence during the optimization process.

$$R = \frac{1}{T} \sum_{t=1}^T \sqrt{\frac{(\Phi_t - \Phi_{gt})^2}{(\Phi_{t-1} - \Phi_{gt})^2}} \quad (18)$$

Where Φ_{gt} is a constant value that we assume the MOGWO algorithm maintains during the optimization process for the period of time during which the next global optimum is searched.

The dynamic optimization algorithm flow for high-density train tracking operations is as follows:

Step 1: Initialization.

Input the basic parameters of train tracking optimization (including basic train characteristics parameters and interval line parameters, etc.), set the algorithm initialization parameters $\xi = 4$, $\sigma_{initial} = 0.5$, $\sigma_{final} = 0.01$, the number of optimized cars $k = 30$, the maximum number of iterations of the optimization algorithm $T = 100$, the size of the archive *archive_size* = 100 and other parameters. Randomly initialize the population positions, generating the initial grey wolf population $X = \{X_1, X_2, \dots, X_k\}$, where each individual X_i represents a decision vector for the train tracking optimization scheme.

Step 2: Evaluation and archiving.

Calculate the objective function value $[\Phi_C(X_i), \Phi_E(X_i), \Phi_T(X_i)]$ for each individual, determine the dominance relationship, and archive the non-dominated solution.

Step 3: The first wolf chooses.

According to the crowding degree in the archive, choose the head wolf (α, β, δ) .

Step 4: Gaussian Mutation and Linear Decreasing Strategy.

Introduce Gaussian mutation and apply the linear decreasing strategy to adjust the perturbation strength.

Step 5: Position update.

Update the positions of the grey wolves.

Step 6: Archive update.

Compare the dominance relationships between the new population individuals and those in the archive, add the non-dominated solutions to the archive, and update the archive accordingly.

Step 7: Convergence calculation.

Calculate the convergence of the algorithm.

Step 8: Iteration and termination.

Repeat steps 3 through 7 until the maximum number of iterations is reached, then output the non-dominated solutions in the archive.

This enhanced MOGWO algorithm aims to provide a more robust and efficient solution for optimizing high-speed train tracking intervals, ensuring a balance between the conflicting objectives of comfort, energy efficiency, and punctuality.

4. Simulation and result analysis

4.1 Parameter settings

In this paper, CR400AF EMU operating on Beijing-Shanghai Railway is taken as the experimental object. In order to verify the effectiveness of the optimization model, the experimental line with slope, curvature and tunnel scenarios is designed. Set the tracking interval to 250–350s, and the emergency and common braking empty time to 1.7s and 2.3s (Zhang, Hao, & Liu, 2024; Yang & Liu, 2015), respectively. See Table 1 for the train parameters and line data of simulation experiment.

Mass, aerodynamic coefficients, and rolling resistance: Sourced from the CR400AF EMU technical specifications provided by the China Railway Rolling Stock Corporation (CRRC). Efficiency coefficients for energy consumption: Calibrated using onboard measurement data from operational high-speed lines (Beijing-Shanghai line, 2022).

The simulation hardware parameters are Intel (R) Core (TM) i7-8550U, CPU @ 1.80 GHz, RAM 8G. The simulation software is Matlab R2016a.

Table 1. Train parameters and line data

| | Parameter name | Value |
|---|--------------------------------|------------------------------|
| 1 | Vehicle type | CR400AF |
| 2 | Maximum operating speed (km/h) | 350 |
| 3 | Train mass/t | 489 |
| 4 | Basic resistance f_0/N | $2 + 0.0062 v + 0.00053 v^2$ |
| 5 | Rotating mass coefficient | 0.06 |
| 6 | Full length of tunnel/m | 1,010 |
| 7 | Curve radius/m | 12,000 |
| 8 | Slope/% | 1.58 |
| 9 | Slope length/m | 1,949 |

Source(s): Courtesy of Zhu (2021), Zhang *et al.* (2020)

4.2 Analysis of results

Based on the preceding analysis, this section first verifies the convergence and computational speed of the proposed train tracking optimization algorithm across different parameters. To ensure the validation results are both intuitive and precise, various population parameters are selected for repeated calculations across different optimization directions. The specific steps are as follows:

Step 1: Parameter selection

Select different population parameters respectively:

$$POPULATION\ SIZE = (100, 200, 300)$$

$$ITERATION\ NUMBER \in [130, 200]$$

Step 2: MOGWO calculations

Perform MOGWO calculations for all selected POPULATION SIZE and record the computation time and convergence performance for each calculation.

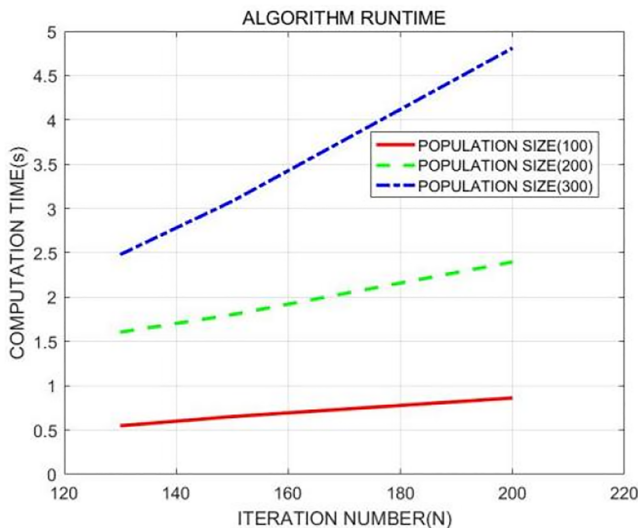
Step 3: Result averaging

Repeat Step 2 and average the results to obtain the final outcomes.

Step 4: Performance visualization

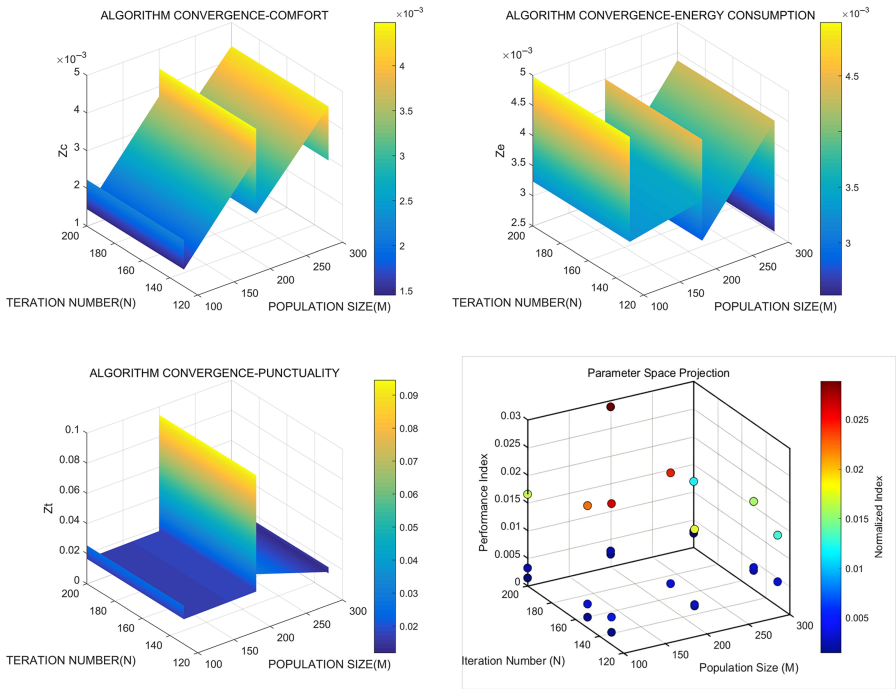
The computation time and convergence performance corresponding to each set of parameters are illustrated in [Figures 2 and 3](#), respectively.

The simulation results pertaining to the computation time of the Multi-Objective Grey Wolf Optimizer (MOGWO) algorithm unequivocally demonstrate that the algorithm's calculation time exhibits a direct correlation with increases in both population sizes and iteration counts.



Source(s): Authors' own work

Figure 2. Calculation time of MOGWO algorithm



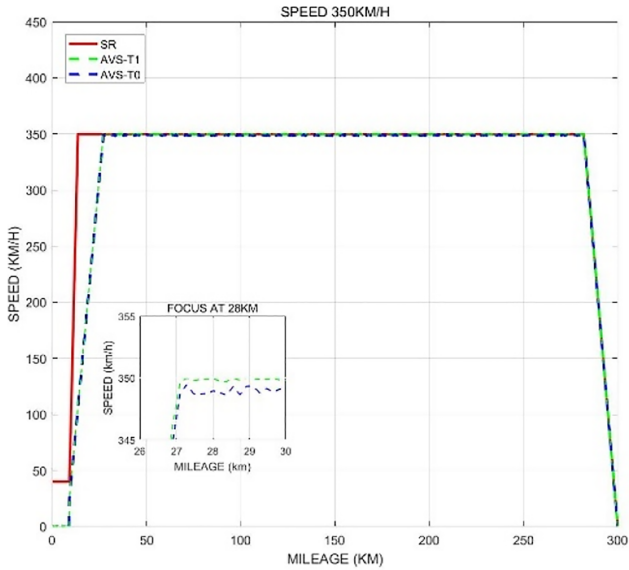
Source(s): Authors' own work

Figure 3. Performance of the algorithm convergence set with different parameter combinations (M, N)

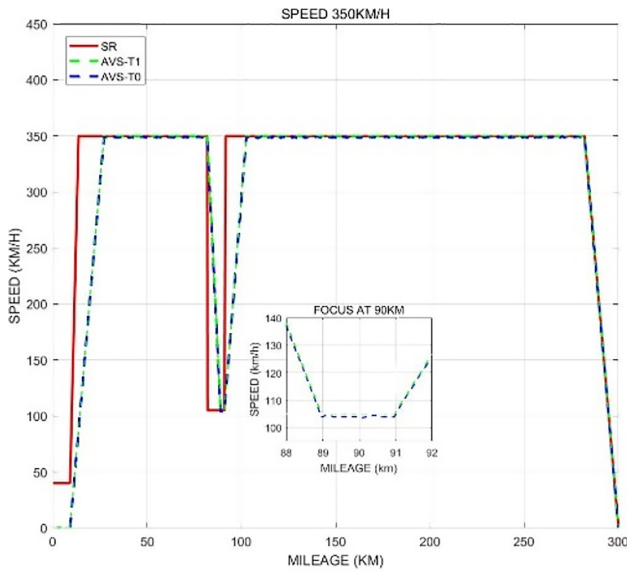
Specifically, as the population size and the number of iterations are augmented, the computational workload intensifies due to the inherent necessity for a greater number of calculations to be performed. This observed relationship is consonant with theoretical expectations and practical computational demands.

Despite the aforementioned increase in computation time, the MOGWO algorithm consistently yields results within a time frame of 5 seconds. This expeditious performance is pivotal as it unequivocally satisfies the stringent real-time requirements intrinsic to the optimization of train tracking systems. The ability to deliver timely and accurate results is crucial for maintaining the operational efficiency and safety of high-speed railway networks, where real-time decision-making is of paramount importance. While the MOGWO algorithm's computation time does increase with larger problem sizes, its capacity to provide solutions within the requisite temporal constraints underscores its efficacy and reliability in the context of real-time train tracking optimization. This characteristic renders the algorithm a robust and viable solution for enhancing the performance of modern railway systems.

In the simulation results graph, the coordinate axis X denotes the population size, the coordinate axis Y represents the number of algorithm iterations, and the coordinate axis Z illustrates the convergence performance of the algorithm with respect to the target objective. The convergence simulation results indicate that, after dynamically adjusting the Gaussian perturbation strength using a linear decreasing strategy, the algorithm exhibits robust global search capabilities in the early stages of the search process and shifts focus to detailed local search in the later stages. This strategic adjustment ensures that the algorithm maintains a balanced approach to exploration and exploitation, which is crucial for achieving optimal



Optimized speed-mileage diagram of 350km/h train tracking in normal
(a)



Optimized speed-mileage diagram of 350km/h train tracking with a speed limit
(b)

Source(s): Authors' own work

Figure 4. Optimized speed-mileage diagram of 350 km/h train tracking

solutions. Furthermore, the convergence behavior of the algorithm remains largely independent of the number of iterations and the population size. This characteristic underscores the algorithm's robustness and adaptability across varying problem scales and computational resources. Notably, the algorithm's convergence is inversely proportional to the population size when calculating the train punctuality rate. This phenomenon can be attributed to the fact that optimizing for a larger number of trains allows for better coordination of their tracking and travel processes on the line, thereby improving punctuality. By accommodating a greater number of trains, the algorithm can more effectively manage and synchronize their movements, thereby enhancing the overall punctuality of the railway system. The algorithm's ability to dynamically adjust its search strategy, coupled with its consistent convergence behavior across different parameters, highlights its efficacy in optimizing complex systems such as train tracking. The inverse relationship between population size and convergence in the context of train punctuality further emphasizes the importance of considering system-wide interactions when striving for optimal performance in railway operations.

The Optimized speed-mileage diagram of 350 km/h train tracking in normal and speed-mileage diagram of 350 km/h train tracking with a speed limit are presented in [Figure 4\(a\)](#) and [\(b\)](#).

In this figure, AVS-T0 represents the train's operating speed-mileage curve before optimization, while AVS-T1 depicts the curve after optimization. The comparison shows that the train operates within the 350 km/h speed limit after reaching the acceleration condition, with the overall speed closely approaching the maximum limit, thus maximizing the compression of the tracking interval. Additionally, the optimized AVS-T1 demonstrates smoother speed transitions, reduced acceleration and deceleration, enhanced overall comfort, and lower energy loss due to the absence of frequent traction and braking transitions. The algorithm also swiftly responds to temporary speed reductions caused by zone-specific speed limits, allowing AVS-T1 to quickly return to the target speed and maintain smooth operation under this constraint. This further optimizes the train speed curve without compromising safety, thereby providing passengers with a comfortable travel experience.

5. Conclusion

This paper proposes a Multi-Objective Grey Wolf Optimizer (MOGWO) based method for optimizing high density train tracking intervals, addressing the real-time control challenges posed by the dynamic variations and multi-objective computations inherent in the high-speed train tracking process. The complexity of these conditions necessitates a sophisticated approach to ensure optimal performance and safety in high-density railway operations. By analyzing the dynamic model of train operations, a kinematic model for train tracking is established to accurately describe the tracking process. Subsequently, a multi-objective optimization framework is proposed, targeting the objectives of passenger comfort, energy efficiency, and punctuality, and the MOGWO algorithm is employed to achieve this optimization.

The simulation results demonstrate that the proposed method effectively optimizes the high-speed train tracking process, enabling trains to meet the objectives of comfort, energy efficiency, and punctuality during the tracking process. This approach holds significant promise for practical applications. However, the method presented in this paper requires further refinement. The ultimate aim is to achieve a unified optimization of train tracking across the entire network. Future research will focus on the entire high-speed rail network, considering scenarios where trains operate across different lines. The aim is to achieve a unified optimization of train tracking across the entire network, thereby minimizing tracking intervals and enhancing the network's overall capacity.

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Corresponding author

Meng Wang can be contacted at: wangmeng0529@126.com



Meng Wang received her Master's degree from the China Academy of Railway Sciences. She is now an assistant researcher at the Signal & Communication Research Institute of China Academy of Railway Sciences Corporation Limited. Her research interests focus on automatic train operation control system and intelligent operation and maintenance of rail transit signal system.