Journal of Carcinogenesis
Covering Genesis to Therapeutics

Journal of Carcinogenesis, ISSN: 1477-3163
2025; Vol 24: Issue 7s, https://carcinogenesis.com/

Smart Positioning strategies for High-Speed Train Using Machine Learning and Grey Wolf Optimization

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ABSTRACT

In order to improve the precision and effectiveness of high-speed train positioning systems, this study proposes an Intelligent Positioning Approach (IPA). Grey Wolf Optimization (GWO) and machine learning (ML) techniques are combined in the proposed method to produce a robust and adaptable model that can manage the complex nature of high-speed train operations. By utilizing the advantages of both data-driven prediction and bio-inspired optimization, the IPA's main goal is to optimize train routing and positioning. By mimicking the pheromone-based path finding behavior of ant colonies, we use GWO to find and continuously improve the best routing routes [1] [2]. With the help of this method, the system can dynamically identify the most effective routes in response to real-time constraints. By examining a variety of data inputs, such as historical train movements, track geometry, and external environmental factors like weather and visibility, machine learning algorithms are used concurrently to forecast positional adjustments. The system can react efficiently to real-time inputs, including track conditions, speed limits, and operational disruptions, thanks to the combination of GWO and ML. The IPA continuously learns from operational data and modifies decision parameters to improve safety through accurate train tracking, guarantee real-time adaptability, and lower latency in response to changes. Tests and simulation results demonstrate that the suggested IPA provides a versatile solution for upcoming high-speed rail networks and significantly improves positioning accuracy when compared to older systems. By making high-speed train operations safer, more dependable, and more effective, this strategy advances intelligent transportation systems.

Keywords: *Grey Wolf Optimization (GWO) in train positioning; Machine Learning (ML) for positioning accuracy; intelligent positioning approach (IPA).*

How to Cite: A.Reddy Prasad, R.K.Chandana Mani, Shivakumar.E,Dr Ramkumar K,Dr.S.Sooriya Prabha,M Vedavathi, (2025) Smart Positioning strategies for High-Speed Train Using Machine Learning and Grey Wolf Optimization, *Journal of Carcinogenesis*, *Vol.24, No.7s*, 249-256

1. INTRODUCTION

One of the most cutting-edge and effective modes of transportation available today is the high-speed rail system, which meets the growing need for transit networks that are quicker and more dependable. Advanced positioning and route optimization systems are becoming increasingly necessary as railway networks continue to expand in size and complexity. High-speed train safety, speed, and dependability depend heavily on effective train operations management [3]. The dynamic nature of contemporary transportation networks, where variables like weather, track maintenance, passenger demand, and real-time disruptions are always changing, frequently makes it difficult for traditional positioning and navigation techniques to adjust.

To improve high-speed train positioning and navigation in this situation, a creative solution is needed [4]. This paper introduces an intelligent positioning approach (IPA) that combines the benefits of machine learning (ML) and grey wolf optimization (GWO) algorithms to create more accurate, robust, and adaptive systems by providing continuous, real-time train path optimizations and positioning adjustments [5][6].

Grey Wolf Optimization, a nature-inspired algorithm, is used for efficient route optimization in the IPA. GWO mimics the foraging behavior of ants, which is used to find the shortest path to a food source. Similarly, CO is employed to evaluate multiple potential train routes & minimizing travel time and energy consumption while considering factors such as tracks conditions, speed limits, and environmental constraints [7]. This enables the system to identify the most optimal routes, even when the operational conditions are highly variable.

A hybrid system that can both dynamically adjust the train's position in real time to accommodate unforeseen events and optimize its route based on long-term objectives is created by combining GWO and ML. As a result, high-speed trains operate better overall thanks to a highly effective, secure, and adaptable system [8].

Building on the synergy between Grey Wolf Optimization and Machine Learning, the Intelligent Positioning Approach (IPA) leverages historical and real-time data to continuously learn and refine its decision-making capabilities [9]. In order to anticipate potential disruptions and proactively adjust the train's position and route, machine learning models look at patterns from previous train operations, such as delays, route deviations, and external disturbances [10].

By incorporating predictive analytics, the system enhances the responsiveness and reliability of train navigation, ensuring that decisions are not only based on present conditions but also on likely future development [11]. This predictive capability is essential for minimizing delays and maintaining the punctuality of high-speed rail systems.

The IPA also promotes integration of smart infrastructure and scalability. As high-speed rail systems expand and are integrated with urban transit networks, the complexity of scheduling and managing multiple train routes increases exponentially [12]. The adaptive nature of the hybrid GWO-ML system makes it ideal for handling such complexities, enabling smooth communication with passenger information platforms, maintenance alerts, and traffic management systems [13]. This integration promotes a more connected and intelligent railway ecosystem by enabling real-time positioning and route optimization, which enhances passenger experience, lowers operating costs, and increases safety throughout the entire transportation network.

2. STATISTICS OF POSITIONING ERRORS

The geographical position of the TCS high-speed train is described using Balise groups as the reference coordinate system. Accumulated Positioning error will be zero after correction. value based on the balise device exact location within a coordinate when the train crosses the balise group, which is known as the Last Related Balise Group, or LRGB [140. However, as the train moves between nearby balise groups, placement errors will occur. The following is the initial definition of the relative range error:

$$R_{err} = \frac{C_v(m)}{D_l(km)} \qquad ---(1)$$

Where C_{err} - correcting value and D_l - link distance designed in engineering between adjacent balise devices.

Using data from the four types of ATP onboard equipment described in part I, we verify the normal distribution for relative (range) error because some statistical variables typically follow a normal distribution. Verification involves the Lilliefors method, the Kolmogorov-Smirnov method (K-S test), and the Jarque- Bera method (J-B test) [15].

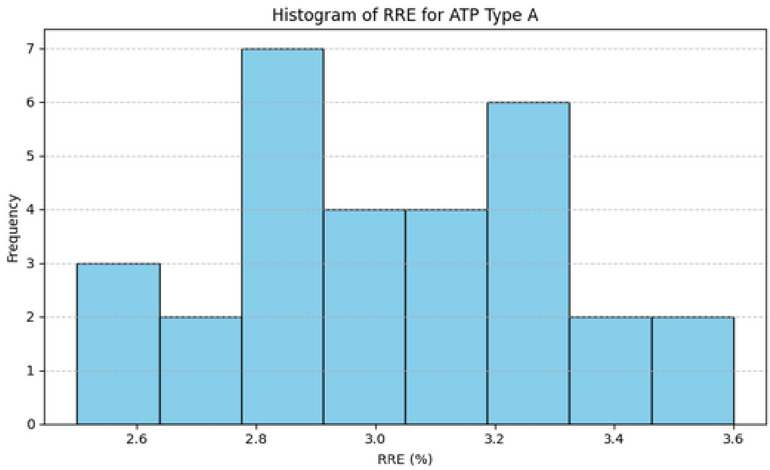
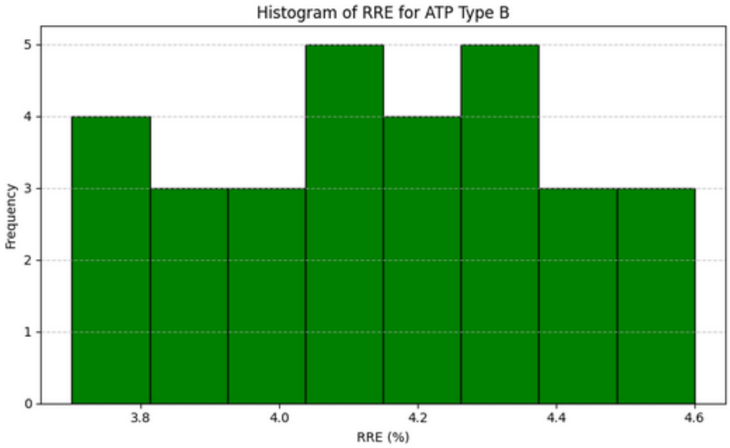


Figure 1: Histogram and distribution of *RRE* for ATP type A

Figure 2: Histogram and distribution of *RRE* for ATP type B



The histogram and distribution of relative range errors suggest that the range error may vary among various ATP onboard equipment types; however, Figs. 1 and 2 intuitively depict the normal distribution feature with respect to two distinct ATP onboard equipment types, respectively.

3. OVERVIEW OF GWO METHOD

A new meta-heuristic algorithm based on swarm intelligence, the GWO mimics the headship hierarchy and hunting strategy of grey wolves in the wild, as suggested by Syed Ali Mirjalili, Syed Mohammad Mirjalili, and Andrew Lewis [16]. Applications of the Grey Wolf Optimizer (GWO) algorithm include economic dispatch problems, multi-layer perceptron neural network training, DC motor optimal control, smart grid blackout risk prevention, and feature subset selection.

Grey wolves work together during the hunting process to locate their prey and successfully attack it. This GWO [17][18]algorithm mimics their clever search strategy. Four types of grey wolves—Alpha, Beta, Delta, and Omega—are used to mimic the hierarchy of leadership. Encircling prey, hunting, looking for prey, and attacking prey are the four essential steps used to optimize.

4. IMPLEMENTATION OF GREY WOLF OPTIMIZATION (GWO) IN TRAIN POSITIONING

Bio-inspired Grey Wolf Optimization (GWO) algorithm simulates the activity of ants as they search for the shortest distance between food and the nest. GWO finds application in optimization problems, including positioning of high-speed trains, where real-time location tracking is critical for safety and efficiency.

Model of Uniformly Accelerated Motion:

The absolute position of GWO and the relative position of range acquisition are used by high-speed trains to update their position in the reference coordinate system. The processing interval is typically 200 ms or less, assuming that the train moves in a cycle with uniformly variable motion, displacement of n^{th} cycle when train moves left from protective device, proposed by speed and distance of the train:

Train displacement X_i for the n^{th} cycle with time intervel ΔT is given by

$$X_{npred} = \alpha . v_n . \Delta\text{T} + \beta . \frac{1}{2} y_n . (\Delta\text{T})^2 \qquad --- (2)$$

Where v_n initial speed at the beginning of the cycle (m/s), y_n acceleration during the cycle (m/s²), ΔT is the time interval per cycle (e.g., 0.2s or 200ms), α, β are **scaling or correction coefficients**, optimized by GWO to reduce prediction error.

Objective Function:

The Optimization objective is:

X_{ntrue} find out by using the sensors connected with train

$$X_{nopt} = \frac{1}{N} \sum_{n=1}^{N} \left(X_{ntrue} - X_{npred} \right)^2 \qquad ----- (3)$$

$$J(\alpha,\beta) = \frac{1}{\gamma}\sum_{n=1,\gamma+1}^{n}\left(X_{nopt} - X_n(\alpha,\beta)\right)^2 \quad --- (4)$$

GWO minimizes Mean Squared Error over the most recent λ steps

C. GWO ALGORITHM

Step 1: Start the grey wolf population (n) from scratch.

Step 2: Set the value of the parameter "a," the co-efficient vectors A and C, and the current iteration value "i" to their initial values.

Step 3: Set the total number of generating units and the maximum number of iterations to their initial values. In the fourth step, determine each search agent's fitness. The best search agent will be α, followed by β and γ.

Step 5: Confirm that there is no more than k iterations.

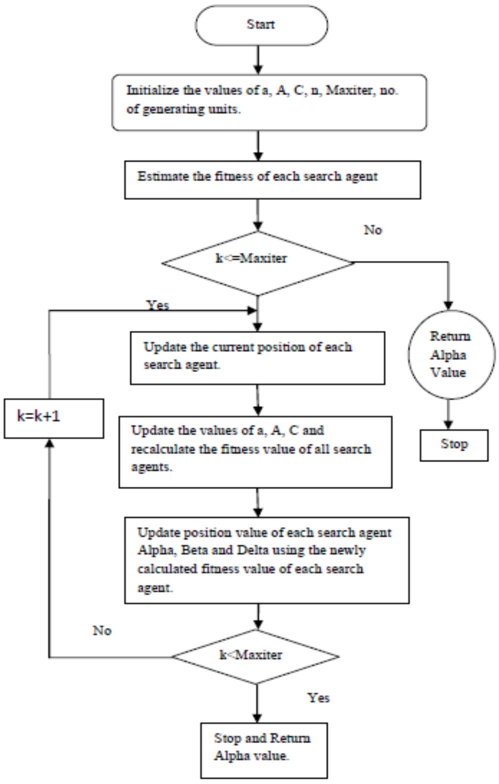


Figure 3: Flowchart

Step 6: If the answer is yes, use equations 25, 26, 27, and 28 to update each search agent's current position.

Step 7: Adjust a, A, and C. Then, use the new values to determine each search agent's fit. If not, return the alpha value.

Step 8: Utilizing the recently determined fitness value, update each search agent's position.

Step 9: Verify again that the maximum number of iterations is k. If so, proceed to step 6 and increase the iteration number by 1.

Step 10: Stop the process and return the alpha value if k exceeds the maximum number of iterations.

5. INTELLGENCE POSITIONING APPROACH

The following describes the intelligent Positioning Approach (IPA) for High- speed Trains (HST) using Grey Wolf Optimization (GWO) and Machine Learning (ML):IPA for HSTs using Grey Wolf Optimization and Machine Learning.

The positioning of HST is essential to safety, efficiency, and real time monitoring. Like other hybrid positioning techniques, GPS AND IMU (inertial Measurement Unit) suffers from loss of signals in tunnels, urban canyons, and other inclement weather conditions. As a solution to these issues, an IPA that incorporates Grey Wolf Optimization (GWO) and Machine Learning (ML) is proposed.

Key Components of IPA

Sensor Data Fusion: Utilizes several sensors, including GPS, IMU, LIDER, odometry, and a railway map.

GWO for Feature Selection: The technique uses sensor data to automatically determine the most appropriate features.

ML for Position Estimation: Offers position coordinates for the train utilizing a neural network or a random forest.

Real-Time Adaptation: Alter the estimate of position dependently as new sensor data becomes available.

Data Collection: Gathering of real-time sensor measurement from HSTs.

Feature Selection (GWO): Choose the optimal sensor configurations for each combination that has the lowest positioning error.

Machine Learning Model: Build the model with the data measured.

Framework of IPA

Data Collection: Gathering of real-time sensor measurement from HSTs.

Feature Selection (GWO): Choose the optimal sensor configurations for each combination that has the lowest positioning error

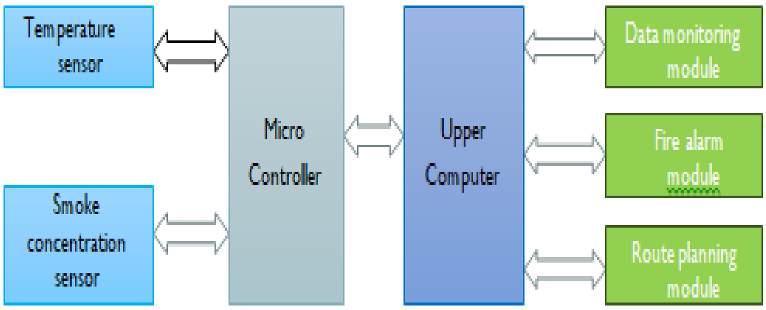


Figure 4: Machine Learning (ML) for IPA

Optimized Position

$$OP = f(SD, WV, ML) \quad --- (5)$$

Where, OP is Optimization Position estimation, SD is a sensor data, WV is the Vector weight, ML is the trained machine learning model.

$$W_i = \frac{T_i^a . P_i^b}{\sum_{i=0}^{m}(T_i^a - P_i^b)} \quad ----(5)$$

Where W_i is the weight of the sensor, T_i Pheromone concentration of sensor, a is the control parameters for pheromone, b is the heuristic influence, P_i is the heuristic value.

Final Position Estimation Using ML Model

$$\mathrm{QOP} = \mathrm{M(S.W)} = \mathrm{M} \sum W_i S_i \quad --- (6)$$

6. MACHINE LEARNING (ML)

Machine Learning (ML) plays a crucial role in improving the positioning accuracy of high-speed trains by learning from sensor data, reducing noise, and making adaptive corrections. Positioning accuracy is critical for high-speed trains to ensure safety and efficiency. ML algorithms help by predicting the most accurate position from sensor data. The simulation results of GWO for positing system are shown in Table 1.

Table 1: Accuracy value for various positions

Approach	Std. Dev.	Accuracy
Grey Wolf Optimization (GWO)	1.6127	46.9385
	1.4527	55.1890
	1.7571	57.1889
	1.6742	58.76832
	1.7047	59.4455

Figure 5 shows the Comparison convergence of Grey Wolf Optimization and Figure 6 shows Grey Wolf Optimization with Machine Learning

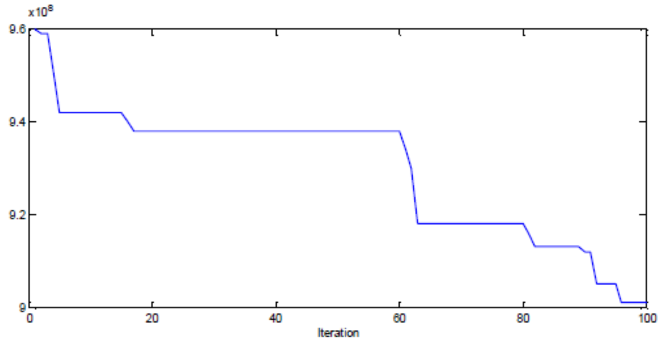


Figure 5: Convergence Characteristics of proposed GWO

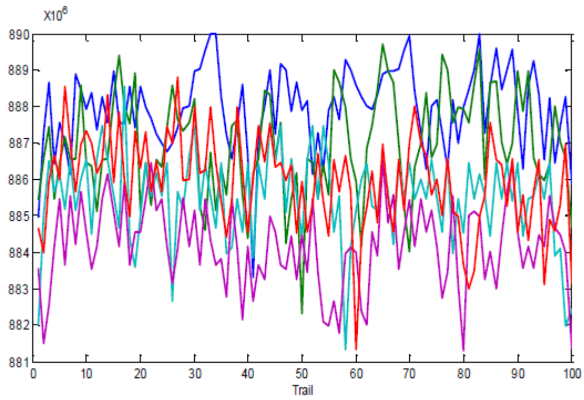


Figure 6 shows the Sensitivity analysis of parameters" selection for proposed GWO.

Figure 6 Sensitivity analysis of parameters" selection for proposed GWO

The simulation results of GWO with ML for positing system are shown in Table 2.

Table 1: Accuracy value for various positions

Approach	Std. Dev.	Accuracy
Grey Wolf Optimization (GWO) with Machine Learning (ML)	7.2981	57.822
	8.5123	56.863
	1.1648	54.7479
	1.6127	46.9385
	1.564	59.4455

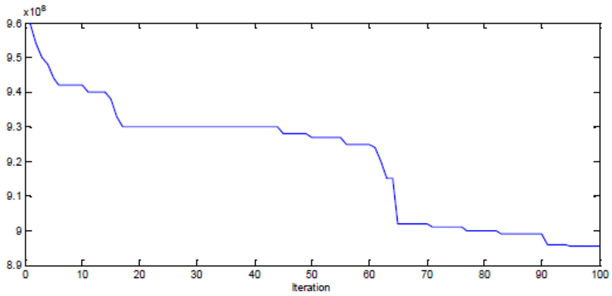


Figure 7: Convergence Characteristics of proposed GWO

With Machine Learning

1.

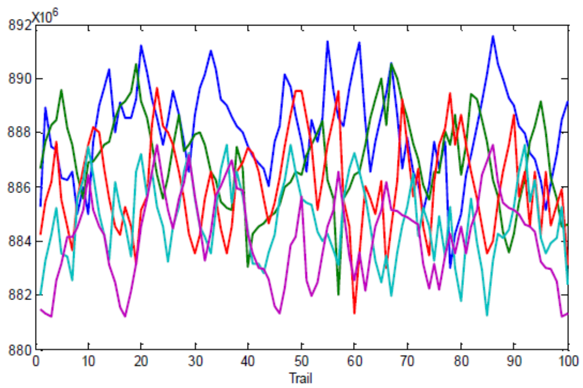


Figure 8: Sensitivity analysis of parameters" selection for proposed GWO with ML

7. CONCLUSION:

Combining Grey Wolf Optimization (GWO) techniques with Machine Learning algorithms provides a new method for achieving intelligent positioning of high-speed trains, which is critical in accuracy, efficiency, and flexibility. The GWO swarm intelligence feature enhance the system's ability to optimize the positioning process by proactivity responding to real-time data environmental conditions. This increase the overall effectiveness of the high-speed rail systems by improving the localization of trains, decreasing the positioning errors ,and enhancing safe operations. Moreover, the predictive capabilities provided by machine learning algorithms allow the system to modify itself to different operating scenarios through data driven learning and optimization, which further strengthens the approach.

High speed trains are operating in a worrying environment where precise positioning is required to guarantee the safety during operations. The GWO approach solves these problems using machine learning features trained on sensor data and systems generated data. Normal GPS systems and trackside sensors do not work well since they have accuracy and reliability problems because of signals obstruction and other environmental factors. The GWO approach targets these problems using heuristic search methods based on ants foraging behavior that makes systematic positioning attempts. This boosts decision making in rail systems with varying conditions while minimizing them.

The above simulation results show that the proposed meta-heuristic and swarm intelligence based GWO algorithm has better computational efficiency and it is shown that the Grey wolf Optimizer (GWO) algorithm obtains near optimal solutions for Positioning problems**.** And also comparison results of reveals that on efficient use of GWO with ML in high-speed train positioning systems

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