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Parameters Assignment of Electric Train Controller by Using Gravitational Search Optimization Algorithm

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The speed profile of the train will be determined according to criteria such as safety, travel convenience, and the type of electric motor used for traction. Due to the passengers and cargo on the train, the electric train load is constantly changing. This will require reassigning the speed controller's parameters of the electric train. For this purpose, the Gravitational Search optimization Algorithm (GSA) will be used to minimize the error between the setpoint speed profile and the speed profile obtained from the speed controller by using the appropriate assignment of control parameters. This algorithm has a low computational cost and high accuracy, but tuning the adjustable parameters of this algorithm according to the decision space will increase its accuracy. Therefore, by using fuzzy logic Type-I and Type-II, and considering the diversity of population in decision space and generation of population, adjustable parameters of GSA such as K_{best} and α will be tuned. Finally, a dynamic model of the electric train between two traction power supply substations (TPS) and a proportional-integral-derivative (PID) controller will be simulated in MATLAB software to control the train speed. Then, the controller parameters will be assigned using the GSA algorithm.

1. Introduction

Railway transportation consumes less than 2% of the energy in the transportation sector while accounting for 8.5% of the traffic load. The International Union of Railways and the Community of European Railway and Infrastructure Companies have decided to increase the railway network's efficiency by 30%, which will lead to a 50% reduction in carbon dioxide emissions by 2030 [1].

Electric traction trains play a very important role in mass transportation systems, whether for the movement of goods or people. This system has undergone significant improvements by utilizing sciences such as mechanics and electricity through a long historical process that began in the early 19th century, but still requires other sciences for further development. "Traction" refers to all phenomena, equipment, and systems that cause the movement of a vehicle. The term "electric" encompasses the concept of providing mechanical power and direction of movement, which is supplied by one or more electric motors. Therefore, "electric traction" means the movement of a vehicle using electric power. Supplying the required electrical power is the responsibility of the electric traction substation [2]. In Direct Current (DC) electric railway transportation systems, the power required by the trains is supplied by an electricity distribution network and TPSs. Generally, TPSs have voltage transformers to reduce the voltage level and also have rectifiers to convert alternating current to direct current. Usually, in order to increase reliability, two series of equipment, consisting of a rectifier and a transformer, are installed in parallel to each other. To prevent a phase shift, one of the transformers is considered as Y - Δ and the other as Δ-Δ. Finally, a capacitor bank is installed at the output to stabilize the voltage. To increase safety, power circuit breakers can be used on both the Alternative Current (AC) and DC sides. Trains are supplied through an overhead catenary system (OCS) or a third rail. The

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voltage range is dependent on the demand and the length of the third rail. Usually, the voltage is between 600 and 750 volts, but systems with 1500-3000 volts are also in operation [3]–[7].

There have been numerous methods proposed for controlling the speed of electric trains. Camps et al. [8] proposed a distributed controller that has better performance than other conventional state-of-the-art controllers. Jing-Zi et al. [9] proposed a speed tracking control system by combining linear active disturbance rejection control and adaptive control. Frequency control is another controller of speed tracking that was used by Zihan et al. [10]. Further extensive research has been conducted in this field to improve the speed controller of trains, but each of them requires user adjustment. One of the most widely used adjustable controllers is PID. This controller was proposed by Minorsky [11], which has three adjustable parameters. There are several methods for tuning these parameters, but autotuning is more attractive. Population-based optimization algorithms can be a good choice for tuning PID controller parameters.

Humans have been seeking simplicity in problem-solving since ancient times. The simplest abstract solution method in the human mind is automatic problem solving. To achieve this goal, humans have needed machine learning. In 1950, Alan Turing proposed machine learning [12]. The first simulation of evolution was performed in 1954 by Nils Aall Barricelli at the Institute for Advanced Study in Princeton, New Jersey [13], [14]. Computer simulation gained strength in the 1960s [15], [16]. Population-based optimization algorithms can be considered in this category.

Population-based optimization algorithms belong to the category of derivative-free optimization methods. These algorithms are primarily designed based on iterative computations. Some of the population-based optimization algorithms include genetic algorithm (GA) [17], genetic programming [18], simulated annealing (SA) [19], ant colony optimization (ACO) [20], particle swarm optimization (PSO) [21], tabu search [22], and GSA [23].

GSA has several tunable parameters that can be adjusted to improve its performance for optimization problems. Fuzzy logic can be used for tuning the parameters of the GSA algorithm.

Fuzzy logic was developed by Lotfi A. Zadeh, a mathematician and computer scientist [24]–[26]. Zadeh introduced the concept of fuzzy sets in a 1965 paper titled "Fuzzy Sets," which was published in the journal Information and Control. Zadeh's idea was to extend classical set theory to allow for degrees of membership rather than the strict binary membership of classical sets. This allowed for a more flexible representation of uncertainty and imprecision in data and enabled the development of fuzzy logic, which uses fuzzy sets as a basis for reasoning and decision-making.

The combination of intelligent algorithms is very effective. In [27], GSA has been used for fuzzy clustering. In [28], GSA has been used for neural network (NN) training. In addition, in [29], fuzzy classification has been performed using GSA. In [30], the parameters of the algorithm are adjusted using a fuzzy system.

2. Speed Controller

In order to determine the load on the electric motor shaft, the train motion model must first be established. The parameters affecting the train's motion include position, velocity, and acceleration, which follow Newton's second law.

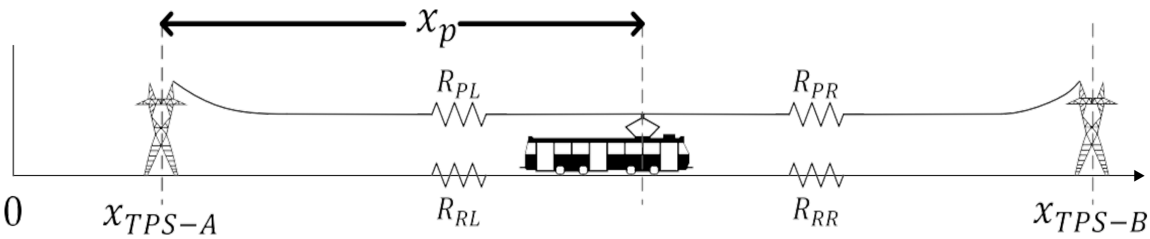

Figure 1. Schematic of train movement between two traction substations

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Equations (1) to (8) describe the motion model of the train.

$$F_{Trac} - \sum F_R = M\frac{dv}{dt} \tag{1}$$

$$F_R = F_{rr} + F_{ar} + F_{gr} \tag{2}$$

$$F_{rr} = f_r Mg\cos\alpha \tag{3}$$

$$F_{ar} = \frac{1}{2}C_w A\rho v^2 \tag{4}$$

$$F_{gr} = f_r Mg\sin\alpha \tag{5}$$

$$F_{Trac} = f_r Mg\cos\alpha + \frac{1}{2}C_w A\rho v^2 + f_r Mg\sin\alpha + M\frac{dv}{dt} \tag{6}$$

$$T = \frac{F_{Trac}r}{4n_c} \tag{7}$$

$$\omega_w = \frac{v}{r} \tag{8}$$

F_{Trac} is the traction force required by a train with weight $M(kg)$ moving at speed $v(km/h)$. F_R represents the total resistance of the train, which is the sum of running resistance F_{rr}, aerodynamic drag force F_{ar} , and gradient resistance F_{gr} (all forces are measured in kilonewtons - kN). The variable g represents the acceleration due to gravity (9.8 m/s^2), f_r is the coefficient of rolling resistance, α is the inclination angle, c_W is the drag coefficient, A is the frontal area of the train, ρ is the air density, T and ω_W are torque and speed for each axle, and n_c is the number of cars in the train.

Changing the train's position changes the track's resistance between the train and the two TPSs. As shown in Figure 1, depending on the direction of the train's movement (from left to right), the values of the resistances on the left side will increase, and the values on the right side will decrease. The resistance values in the simulation are calculated by multiplying the length of the track by the resistance value per kilometer.

2.1. Gravitational Search Algorithm

The GSA is inspired by the law of gravity in nature and is based on Newton's laws of gravity. In this algorithm, the individuals are a set of objects that can be considered planets in a system. The optimal region is similar to a black hole that attracts the agents towards itself. The execution sequence of this optimization algorithm is as follows:

1. Initialize the algorithm parameters and the population of search agents.

$$X_i = \left(x_i^1, \dots, x_i^d, \dots, x_i^n\right), i = 1,2,\dots,N \tag{9}$$

X_i is the ith individual of the population, and N is the population size.

2. Evaluate the fitness of each individual based on the objective function.

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t).M_{aj}(t)}{R_{ij}(t)+\varepsilon} \times \left(x_j^d(t) - x_i^d(t)\right) \tag{10}$$

$$R_{ij}(t) = \left\|X_i(t), X_j(t)\right\|_2 \tag{11}$$

$$F_i^d(t) = \sum_{j\epsilon Kbest, j\neq i} rand_j F_{ij}^d(t) \tag{12}$$

At a specific time t, F_{ij}^d is the dth dimension of applying force on mass i by mass j and R_{ij} is the distance between mas i and j. F_i^d presents all forces applied to mass i.

3. Update $best$, $worst$, and G for the minimization problem.

$$G(t) = G_0 e^{-\alpha\frac{t}{T}} \tag{13}$$

$$best(t) = \min_{j\epsilon\{1,\dots,N\}} fit_j(t) \tag{14}$$

$$worst(t) = \max_{j\epsilon\{1,\dots,N\}} fit_j(t) \tag{15}$$

Where T is the total number of generations and α is damping ratio.

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4. Calculate the mass of each agent.

$$q_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad (16)$$

$$M_i(t) = \frac{q_i(t)}{\sum_{j=1}^{N} q_j(t)} \quad (17)$$

5. Calculate the acceleration of each agent.

$$a_i^d(t) = \frac{F_i^d(t)}{M_i^d(t)} \quad (18)$$

6. Update speed and position.

$$v_i^d(t+1) = rand_i . v_i^d(t) + a_i^d(t) \quad (19)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (20)$$

7. If the stopping criterion is not satisfied, return to step 2.

2.2. Tuning GSA using fuzzy logic

Based on the equations presented in the previous section, GSA can be tuned using certain parameters such as α (damping ratio) and K_{best}. The reason for choosing these parameters is that they can be used to control the local and global searches of GSA. We therefore want the algorithm to operate as follow:

1. The algorithm should perform the global search in the early iterations.
2. The global search should gradually be reduced, and the local search should be performed in the final generations.

Two metrics are introduced to evaluate the conditions of the individuals in each generation.

The first is $Iteration$, which presents the generation of the algorithm.

$$Iteration = \frac{Current\ Iteration}{Maximum\ of\ Iteration} \quad (21)$$

$Maximum\ of\ Iteration$ is a predefined parameter representing the number of iterations of the algorithm.

The second metric is $Diversity$, which presents the diversity of population $S(t)$ in the search space.

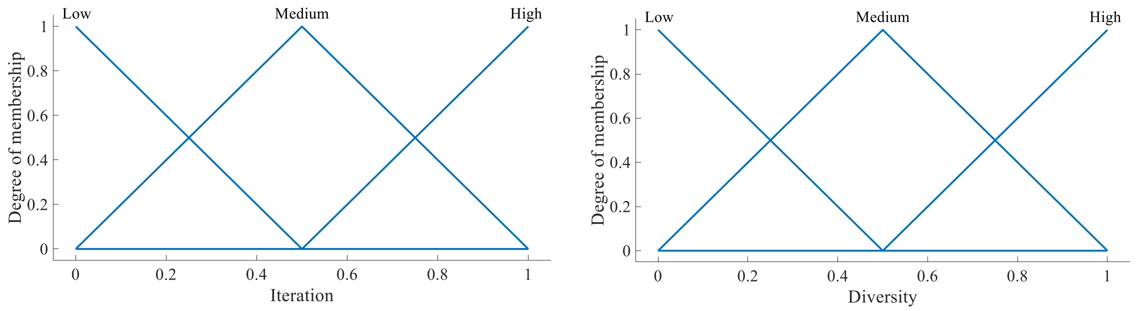

Figure 2. Inputs of Fuzzy type-I system

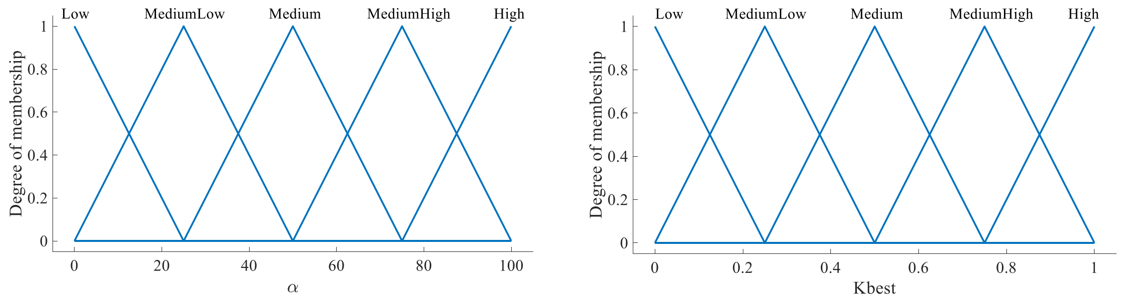

Figure 3. Outputs of Fuzzy type-I system

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Table 1.Rule base of fuzzy system

No	Input		Output	
	Iteration	Diversity	α	K_{best}
1	Low	Low	Low	High
2	Low	Medium	MediumLow	MediumHigh
3	Low	High	Medium	Medium
4	Medium	Low	MediumLow	MediumHigh
5	Medium	Medium	Medium	Medium
6	Medium	High	MediumHigh	MediumLow
7	High	Low	Medium	Medium
8	High	Medium	MediumHigh	MediumLow
9	High	High	High	Low

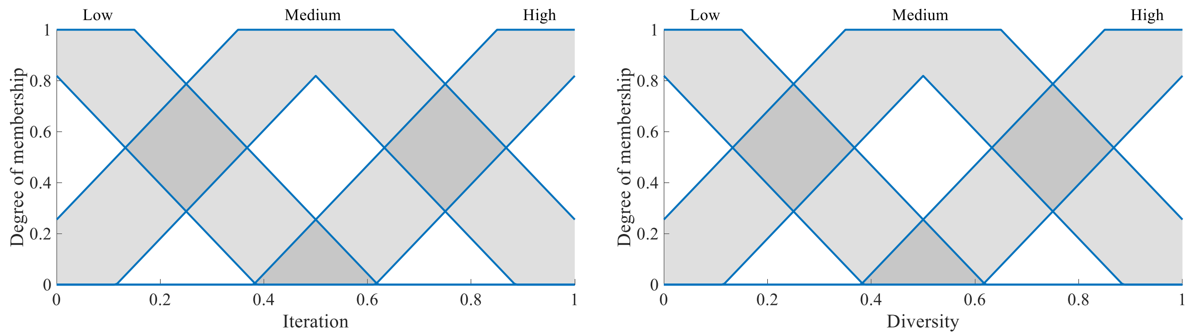

Figure 4. Inputs of Fuzzy type-II system

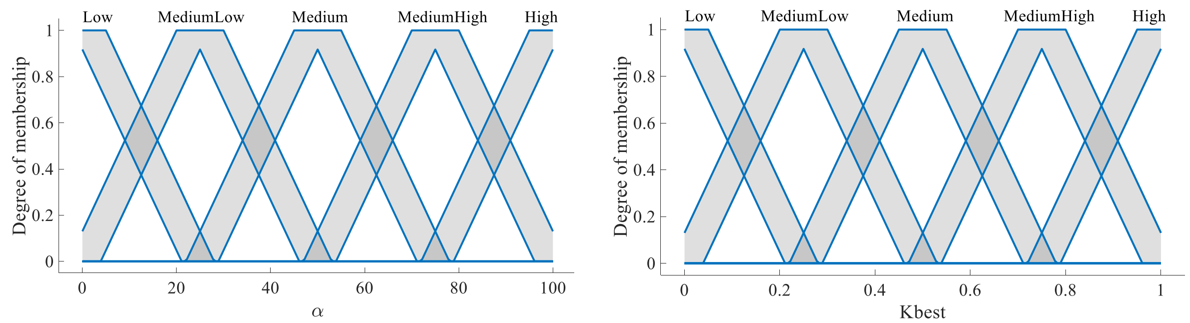

Figure 5. Outputs of Fuzzy type-II system

$$Diversity(S(t)) = \frac{1}{n_s}\sum_{i=1}^{n_s}\sqrt{\sum_{j=1}^{n_x}(X_{ij}(t)-\bar{X}_j(t))^2} \tag{22}$$

Figures 2 and 3 represent inputs and outputs of the fuzzy type-I system, and Figures 4 and 5 represent inputs and outputs of fuzzy type-II system. Table 1 represents nine rules of the fuzzy system.

3. PID Parameters Assignment

This section explains how to tune the parameters of a PID speed controller using GSA. First, Section 3.1 describes the cost function, and Section 3.2 describes the initialization of GSA.

3.1. Cost Function

The root mean square error (RMSE) between the output of the PID controller and the setpoint (train speed profile) is defined as the cost

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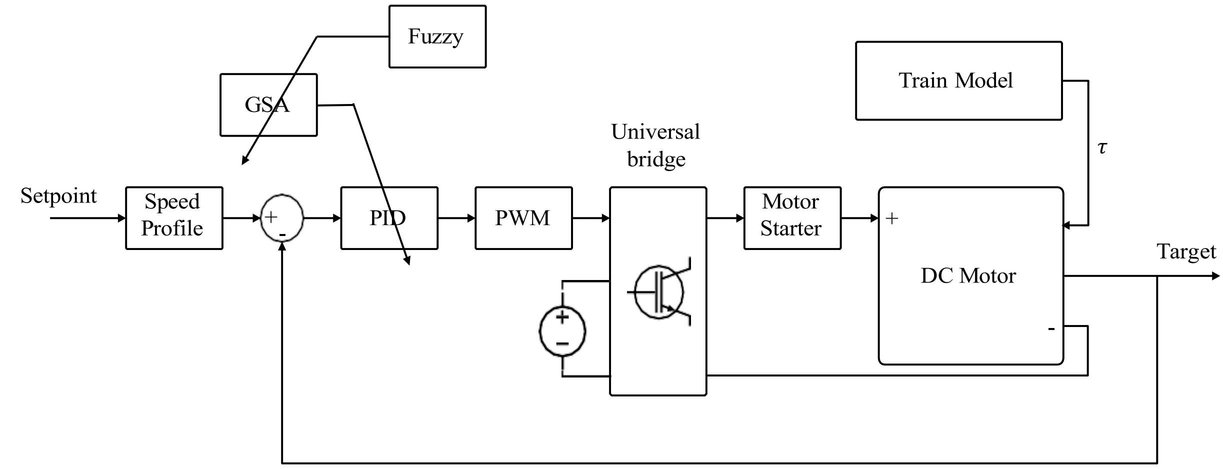

Figure 6. Shematic diagram of electric railway speed control system

function of the optimization algorithm.

$$RMSE = \sqrt{\frac{1}{N}(Target - Actual)^2} \qquad (23)$$

In equation 23, the term '$Target$' refers to the desired speed profile of a train, while '$Actual$' represents the measured speed of the train that is being controlled by a PID controller.

3.2. GSA Initialization

We consider three dimensions as three parameters of the PID controller for GSA. The population size is 20, and $v_0 = 0$ for all individuals. Damping ratio ($\alpha = 0$), $G_0 = 100$, and the termination condition is the maximum iteration with the value of 100.

4. Results and Discussion

As shown in Figure 6, GSA is tuned using fuzzy logic. The tuned GSA then starts to adjust the parameters of the PID controller. In each generation, each individual in the population, which are the PID controller parameters, controls the DC motor. The output of the PID

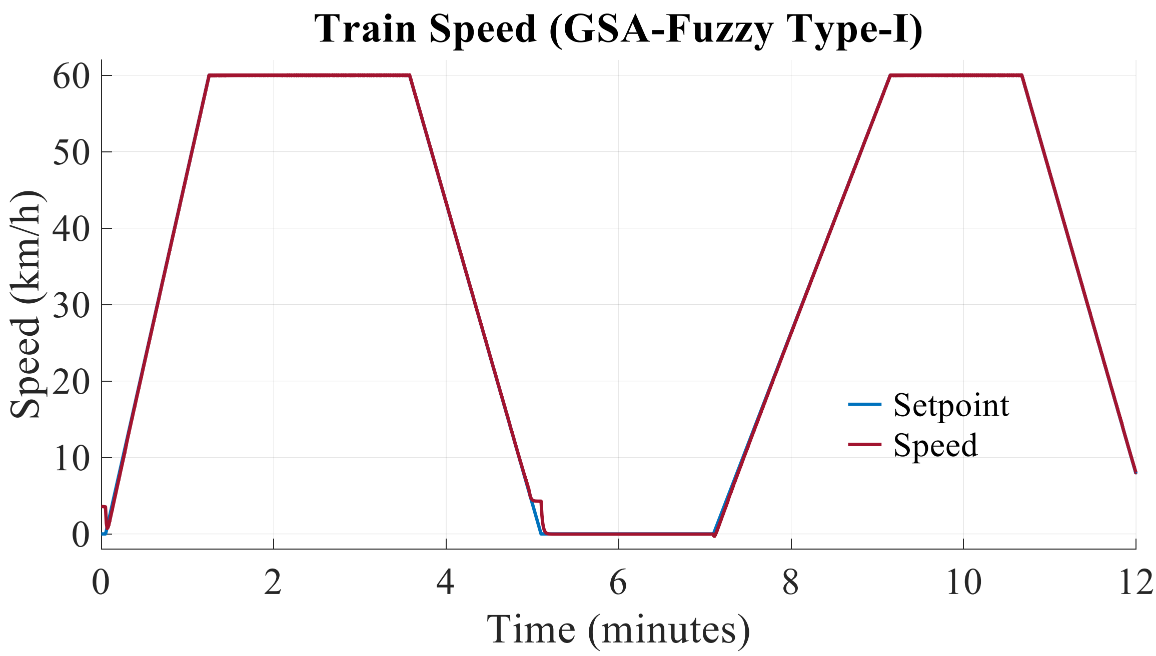

Figure 7. Speed control of electric train (GSA-Fuzzy Type-I)

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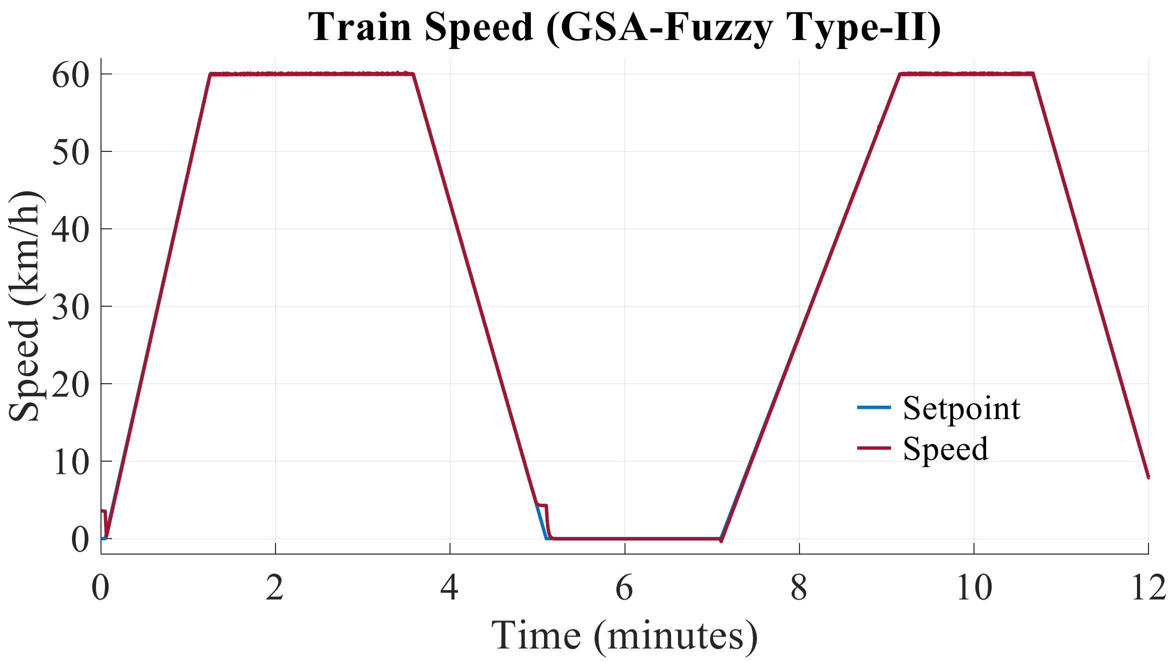

Figure 8. Speed control of electric train (GSA-Fuzzy Type-II)

controller is considered the input of a PWM, which is responsible for a four quadrant chopper. After connecting the four quadrant chopper to the DC motor, the speed is measured and compared with the setpoint. Finally, a control loop is formed. After 100 iterations of the fuzzy logic tuned GSA algorithm type-I, the values of the controller parameters are given in Table 2. Table 3 contains the parameters of the PID controller using the GSA algorithm tuned with the Type-II fuzzy logic system.

Table 2. PID parameters (Fuzzy type-I)

K_p	K_i	K_d	$RMSE$
0.0207	0.0915	0.2891	0.3796

Table 3. PID parameters (Fuzzy type-II)

K_p	K_i	K_d	$RMSE$
3.8144	0.6376	0.0157	0.3668

5. Conclusions

Despite its good speed and accuracy in finding the optimal solution, the Gravitational Search Algorithm, like other optimization algorithms, requires parameter tuning, which can be well addressed by fuzzy logic. This tuned algorithm is a good option to replace an expert in the process of adjusting the speed controller of a train, as the train speed controller is affected by the cargo and the number of wagons and requires readjustment. In this study, it has been shown that using the fuzzy logic type-I and type-II tuned GSA algorithm for the placement of PID controller parameters leads to very high accuracy of the controller when controlling the train speed.

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