



Flexible Cuning Search Optimization based Light Gradient Boost Machine Convolutional Neural Network for Harmonic Distortion Mitigation

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Abstract: Traction networks are attractive due to their advantages such as step-down of high voltage, precise speed control, energy efficiency, and lower maintenance. However, the railway traction loads inject a massive amount of harmonics into the traction power system, which leads to impacts such as thermal stress, mechanical fatigue, capacitor failure, electromagnetic interference, and high energy consumption, degrading the system performance. Hence, Total Harmonic Distortion (THD) mitigation is mandatory to improve operational stability and reliability performance of the traction network. Therefore, the research work considers the Flexible Cuning Search optimization-based Light Gradient Boost Machine Convolutional Neural Network (FCS-optimized GBCN) model to mitigate the harmonic distortion in the Traction Power Supply System (TPSS). The developed model adopts the time-varying and non-linear nature of harmonics to perform a more accurate and robust harmonic mitigation task. Especially, the FCS-optimized GBCN model predicts the harmonic distortion signal to remove the harmonics, which makes a clean sinusoidal waveform. Furthermore, the Flexible Cuning Search (FCS) optimization improves the solution quality, reduces the probability, and finds optimal solutions, which contributes to enhancing the model performance. Consequently, the FCS-optimized GBCN Model outperforms the switching output, train 1 current, train 2 current, train 1 voltage, train 2 voltage, power, and THD values are 4997, 2388.64 A, 846.49 A, 472.97 V, 538.70 V, 28022 W, and 0.68, respectively.

Keywords: Light Gradient Boosting Machine Classifier, Traction Power Supply System, Convolutional Neural Network, Total Harmonic Distortion and Harmonics

1. Introduction

In the traction transmission system, electrical energy is transformed into mechanical energy in high-speed trains, which considers torque transmission for train movement and provides a stable power source to the train network [1]. A high-speed traction drive system consists of an inverter, gear transmission system, and traction motor, which are involved in the complexity of an electromechanical coupling system [2]. In a traction drive system, the complexity of the operation and high-intensity working state avoid equipment damage [3]. AC electric locomotives operate at high density, due to the increase in railroad operation capacity, which helps to interact with the TPSS [4]. In the traction network, the distributed inductance and capacitance are present [5] with the multi-conductor transmission line, which makes a strong non-linear coupling relationship between the train and network [6]. High-frequency harmonic currents are generated [7], which produce resonant overvoltage

in the four-quadrant converter (4QC) of the locomotive [8]. Harmonic voltages and resonance have occurred while matching the peak impedance of the traction network to the train harmonics. Moreover, these harmonics introduced security problems in traction networks like tripping, lightning arrester burnout, and train outages, which also affect the power arm of the train network [9].

In an AC electrified railway system, the harmonic distribution system is introduced due to the substation distance, locations of the train feeder area, and rail-to-earth conductance [10]. Harmonic orders are produced by the diode rectifiers [11], and the GSC unit of 4QC operates in a carrier phase-shifted PWM (PS-PWM) mode [12], which eliminates the harmonic currents [13]. A passive filter is a harmonic control equipment, and the C-type filter has low power loss and a high-pass filtering effect. In non-sinusoidal conditions [14], the filters are utilized to improve the transformer

load capacity [15] and contribute to harmonic suppression by the single-tuned and C-type filters [16]. Moreover, thyristor-controlled filters [17] control the harmonics in the arc furnace [18], HVDC system, and speed system [19, 20], which excel in the reactive power compensation process. In urban areas, diode rectifiers are connected to the DC overhead transmission lines to provide the power supply [21]. When breaking the power flow from the traction system, the train acts as a generator in a bidirectional railway substation, which dissipates the heat energy while braking the rheostats [22].

In the high- and low-voltage systems, higher-order harmonics are injected, which decompose the time and frequency-domain combination, making overvoltage identification [23]. Moreover, wavelet transform method [24], principal component analysis [25], and singular entropy spectrum methods are considered for the overvoltage classification [26]. Characteristic information is required to obtain high accuracy in overvoltage extraction. Duration and peaks of overvoltage [27], and harmonic frequency affect the performance, whereas identification and generalization of the model were poor due to the peak overvoltages [28]. In a step-down laboratory test, a low voltage level of 220 V and a real system-rated voltage of 25 kV are carried out for the harmonic mitigation process [29, 10]. In addition, two modes of hysteresis switching are used in the Cascaded H-Bridge (CHB) multilevel inverter, which eliminates the time delay [30] due to digital computation. Moreover, the switching methods do not consider the grid connections and the sampling period on the grids. However, the high-frequency primary-side harmonics are affected due to the difficulty of multi-converter synchronization. Multiple carriers were used for the sampling, and hardware resources were required to ensure the sampling accuracy. Multiple converters are operated in parallel, which affects engineering applications due to the usage of more hardware resources [8].

To tackle these issues, the research work employs the FCS-optimized GBCN model to perform the harmonic mitigation task in the traction system. Deep, non-linear hierarchical representations such as raw voltage/ current distortions are extracted to perform the detection task effectively. Missing data and variable operating environments are handled to prevent overfitting on noisy traction data. The developed model determines the accurate harmonic distortions and disconnects the harmonic sources in the real network. Specific features are considered to make the forward transfer function, which contains fewer parameters. Data and time series feature extraction, and feature weight distribution characteristics are inspired by this GBCN classifier to perform the harmonic prediction task. Utilization of filters cancels out the predicted harmonics to improve power factor, eliminates signal interference and prevents transformer overheating.

Flexible Cuning Search Optimization-based GBCN classifier: Nonlinear harmonic patterns and spatial feature extraction contribute to accurate distortion source identification. Corrective control actions are predicted and triggered by the GBCN model, which improves overall operational efficiency by mitigating harmonic distortion. Specifically, the developed model offers significant benefits like memory usage reduction, maximum accuracy, and large data handling. The low computational cost and high accuracy of the neural network testing the samples to classify the overvoltage signals in the traction network. The developed FCS optimization is considered to optimize the parameters of the GBCN classifier, which provides optimal solutions to perform the harmonic mitigation task effectively.

The research organization is derived as follows, and Section 2 describes the existing methods and their drawbacks. In Section 3, the FCS-optimized GBCN model provides a detailed explanation for the mitigation of Harmonic Distortion. The model's performance is discussed detail in Section 4, and the detailed conclusion is provided in Section 5.

2. Motivation

In the train traction network system, the harmonic distortion factor affects the position of the train and the power consumption of the network. Harmonic distortions introduce dynamic behaviours, which can shut down the entire electrical train network system. Negative impacts are produced by the high-order harmonics in the railway system, and high-frequency resonant overvoltage is generated when the frequency of harmonic current matches to the resonant frequency. Evaluation of the resonance frequency is complex to suppress harmonic resonance in the traction system. Therefore, a contribution is needed.

2.1 Literature Review

In the literature review section, harmonic in traction network research papers are separated into filtering techniques, harmonic resonance techniques, data-driven techniques, and control techniques, which contributes to strengthening the research work quality.

2.1.1 Filtering Techniques

Wei Wang *et al.* [31] presented the active power filtering method to minimize the ripple power in traction systems. A decoupling model was established in the transmission process, and the Model Predictive Control (MPC) method suppressed the second-order ripple voltage. Capacitor current reference was compensated to minimize the residual ripple voltage on the DC link. However, duty cycle delay leads to poor tracking on target capacitor current and voltage. Chakrit Panpean *et al.* [32] introduced the APF control strategy to eliminate

harmonics and improve the power factor in the traction system. APF reference current was determined to attain the reference current value and achieve fast computation. Additionally, the digital delays compensated and contributed to ripple reduction. Although a harmonic elimination performance test was conducted to provide the final validation.

2.1.2 Harmonic Resonance Techniques

Shaofeng Xie and Fan Zhong [33] developed the harmonic resonance prevention measure in the train interaction system and also considered the Comprehensive Resonance Impact Factor (CRIF) to identify the resonance-affecting factors accurately. Series-parallel resonance prevention was achieved by optimizing the control and filter components of RPC. Nevertheless, a change of impedance/admittance was needed to alert the risk of wideband series-parallel resonance. Jian Gao *et al.* [8] introduced a harmonic suppression technique to optimize the multi-converter pulses and generate low harmonic content. Notably, the modulation strategy minimizes the amplitude of high-frequency harmonic current and estimates the sampling period. Nevertheless, the critical sampling period occurred while considering the number of parallel operating converters, switching frequency and synchronous carrier generation.

Shihui Liu *et al.* [9] presented the harmonic resonance suppression technique to suppress the resonance of unknown harmonic sources. Additionally, equivalent impedance can be reduced while considering the parallel additional virtual impedance by the impedance reshaping control. However, the resonance suppression method needs additional active power filter converters, which leads to high operational costs.

2.1.3 Data-Driven Techniques

Nishad *et al.* [34] developed the ANN-Lyapunov optimization-based control strategy to enhance power quality and maximize system stability. Notably, the APF-based custom power device acts as a harmonic isolator to improve the PQ performance. Fast and accurate reference generation was needed for the complex control system of UPQC. However, the incorporation of stochastic modelling of load variations was required to enhance the model performance. Hexiang Wu *et al.* [20] introduced the designed C-type filter, which considers harmonic dynamic characteristics for harmonic compensation. Furthermore, the improved firefly algorithm was employed to tune the filter hyperparameters. Nevertheless, the consideration of filter inductance and capacitance was needed for inverter control design, which makes the system as complex.

2.1.4 Control Techniques

Hamed Jafari Kaleybar *et al.* [35] presented the adaptive discrete wavelet transform-based control scheme to enhance the controller performance under fluctuating operating conditions. Maintaining low THD and reducing negative-sequence current were considered as the significant benefits, which improve PQ and system stability. Nevertheless, longer settling and stabilization time was occurred due to the cost of slower dynamic response.

2.1.5 Others

Marini *et al.* [22] developed real-time active damping for front-end inverters in energy recovery applications. The inverter current control strategy determines the DC-side resonant frequency and isolates the DC voltage oscillations. Although the AC-side current quality was affected due to increasing the attenuation coefficient, and voltage imbalance leads harmonics on the catenaries. Ka Zhang *et al.* [3] introduced the electromechanical coupling model that includes transmission system connection, traction motor circuit, and torque control. In the train model, constant speed, traction and braking conditions were considered while simulating the traction train model. However, a noticeable abrupt change occurred in the rotor current while changing the constant speed to tracking.

Nihan Tong *et al.* [13] presented the high-frequency resonance and harmonic elimination technique to eliminate high-order harmonic currents in the grid-side converter. In addition, an inductive filtering-based onboard traction transformer (IFTT) was considered to avoid the resonance phenomenon and absorb high-frequency. Nevertheless, the four-Quadrant Converters (4QCs) generate harmonic currents, and the filtering circuit should exhibit high power-frequency impedance. Miaoxin Jin *et al.* [28] developed the singular value decomposition algorithm to identify the harmonic impedance and reduce the error rate on the traction system. Additionally, the higher harmonic points were analysed based on the harmonic coupling mechanism. However, the transformer capacity was affected due to the high-order harmonics in the low-voltage three-phase system.

Qiujiang Liu *et al.* [10] introduced the accurate calculation of the resonance frequency on the distributed parameters of traction transformers. Primary and subordinate factors were determined by the marginal utility. Although the irregularly shaped conductors lead to difficulty while calculating their impedance.

2.1.6 Analysis of With and Without FACTS Devices

In this analysis section, the harmonic mitigation techniques such as power electronic converters, multilevel inverters, and passive filtering technologies are illustrated as follows and are represented in the following Table 1.

Table 1. Analysis of Harmonics Mitigation Techniques

Reference	Harmonic mitigation technique	Technology classification	Harmonics addressed	THD before/after mitigation (%)	Key limitations
[8]	Four quadrant converters	Power electronic converter	Voltage and current	THD drops from 0.91% to 0.84%	sampling grid period sync is difficult because frequency fluctuates in traction system
[9]	Auxiliary converter	Converter based mitigation	Voltage	THD drops from 14.49% to 2.61%	Exhibits resonance detection delay and heavily relies on auxiliary converter
[22]	Current controlled NPC inverter	Multilevel inverter	Current	-	Only handles the dc-side resonant frequency not the ac-side high-frequency resonance
[3]	Three-level voltage type inverters	Multilevel inverter	Current	-	The model did not classify resonance under variable conditions
[20]	C-type filter	Passive harmonic filter	Current	THD drops from 3.13% to 1.28%	Only considers passive filtering, which lead to system instability
[13]	Two-level PWM converter	PWM based converter	Current	THD drops from 3.48% to 0.83%	Increased transformer complexity and cost due to the addition of filtering winding
[28]	Not specified	Cannot classify	Voltage	-	Needed huge number of features to classify overvoltage data because fault data is very limited

Besides, the power electronic converters indicate the semiconductor-based switching devices, such as four-quadrant converters, that adjusts the input currents and regulate power flow between the grid and traction loads. Additionally, the multilevel inverters involve advanced converter topologies such as neutral point clamped (NPC) and cascaded H-bridge inverters that produced the output voltage waveforms with lower harmonic distortion and mitigated the voltage stress. Furthermore, the passive harmonic filters consist tuned RLC networks and C-type damping filters, which offer low-impedance shunt paths for specific characteristic harmonic frequencies without requiring active control loops. However, the conventional power electronic converters, multilevel inverters, and passive C-type filters are heavily relied on fixed switching function and static Inductor-Capacitor tuning. Therefore, the FCS-optimized GBCN framework utilizes the LC filter bank to manage the switching states of the passive elements, which neutralizes non-linear harmonic distortions and decreases resonance overvoltage in the traction network. Additionally, the real-time voltage and current measurements from the Point of Common Coupling (PCC) is used to predict incoming harmonic profiles, the substation controller automatically switch the LC filter

branches into the catenary line, which absorb high-frequency distortion waves.

2.2 Challenges

- Imbalanced voltage of transformer windings, eliminating inductances of cables and catenaries, and parallel circuit voltage inductances cause harmonics in the traction network [22].
- The design of the filter inductance and capacitance is more complicated than the parallel filter [21], and the position of harmonic injection was rapidly changed [23], which makes the difficulty of harmonic compensation in passive filters [20].
- Resonance points are generated by the LCL filters, which reduce system stability due to harmonic resonance [15], and the modulation strategy methods do not contain multiple controllers, which makes it difficult to apply in practical engineering [8].
- In the skin effect, the formulae of conductor impedance are not directly applied to the catenary and TPSS railway system [26, 24], and

the lumped parameters introduce errors when the actual supply is unlimited [10].

In the related works, traction power quality, converter impedance shaping, active filtering, resonance suppression and data-driven harmonic analysis introduced certain drawbacks such as duty cycle delay, critical sampling period, necessity of additional active power filter converters, stochastic modelling of load variations, longer settling and stabilization time. However, the FCS-optimized GBCN model avoids stabilization delays and speeds up transient response by forecasting the next-state distortion profile. During rapid frequency shifts, the developed model utilized asynchronous data windows and minimized the strict requirement for phase-locked loop (PLL) lock stability. Additionally, the multi-level modulation was optimized by the developed method, which eliminates the necessity of bulky new hardware filters.

3. System Model of the Train Network

Figure 1 indicates the traction train network model. A standard radial distribution system of the IEEE33-bus system is used to evaluate the performance of the power system, which considers the voltage stability and power losses of the traction network to mitigate the harmonics. In the transportation sector, the role of the electric multiple unit (EMU) high-speed train is important, and the power distribution system is used in the train drives. In the traction network, the presence of linear and non-linear loads causes harmonic currents, imbalanced currents, and reactive power. Power loss in distribution systems, short lifespan of electrical devices, arcing, and malfunction factors reduce the power quality. In the acceleration stage, the load current is increased, and the train moves at a constant speed. In the braking mode, the invariable load current introduces a change in the train speed, which reduces the load current accordingly. The power quality depends on the behaviour of the load current, which degrades the system efficiency and produces harmonics in the power signal under transient conditions. The traction train network consists of transmission lines, rails, and positive feeders, and the whole network is equivalent to an RLC network. Single-phase electricity is used for the traction side converter and auxiliary converter in the TPSS network. Train converters generate the harmonics, which are transmitted into the traction network and cause harmonic resonance leading to overvoltage. The resonant voltage amplitude is determined by the product of harmonic current and impedance amplitudes. The resonance frequency is determined by the impedance parameters, and the resonance suppression is mainly focused on eliminating the harmonic contents in the resonance frequency. Reduction of impedance amplitude is used to suppress the resonance in the traction network. The TPSS consists of a supply voltage range of 13.2kV, and the fundamental frequency range

is 50Hz, respectively. Auxiliary Power Unit (APU) contains a diesel engine which is coupled with a compressor and alternator to maintain battery charging, pressure, and HVAC system operation.

3.1 Flexible Cuning Search Optimization-based Light Gradient Boost Machine Convolutional Neural Network for Mitigation of Harmonic Distortion

In power distribution systems, harmonic distortion increases losses and equipment damage. Moreover, additional resistive and eddy current losses occur due to the non-linear loads and variable speed drives in power cables and transformers. The main goal of this research is to predict and mitigate these harmonics using the FCS-optimized GBCN model in the traction network system. At first, the current and voltage of TPSS are simulated, and their values are determined at significant time intervals. In this developed research, the simulated values are used to determine the total harmonic distortion (THD). Further, the THD prediction is carried out effectively using the FCS-optimized GBCN classifier. Initially, the simulated data is taken as an input to perform the prediction task. Afterwards, the preprocessing stage is considered to avoid irrelevant and redundant data. Moreover, amplitude, power factor, fundamental frequency and phase angles are evaluated in the feature extraction process. Furthermore, the optimized GBCN classifier pertains to the aforementioned features to predict the harmonic distortion effectively. The proposed FCS optimization algorithm is incorporated into the developed model for fine-tuning the parameters of the classifier. Afterwards, filters are utilized to cancel out the predicted harmonic signal, which helps to improve the traction network power transmission significantly. To achieve the reported THD reduction, the FCS-optimized GBCN framework utilizes a LC filter bank within the TPSS. The FCS-optimized GBCN model processes real-time voltage and current measurements from the PCC to predict the incoming harmonic distortion profiles. Additionally, the predicted harmonic signals are translated into accurate gating control signals for the substation circuit breakers, which allows the parallel LC filter bank to automatically switch its tuned branches into the traction catenary line. This switching actively neutralizes harmonic currents at the source before they circulate into the IEEE 33-bus distribution network. The block diagram of the integrated FCS-optimized GBCN model is given in Figure 2.

3.2 IEEE33 Bus System

The behaviour of the power distribution network is analyzed and simulated to mitigate the harmonics in the train traction network.

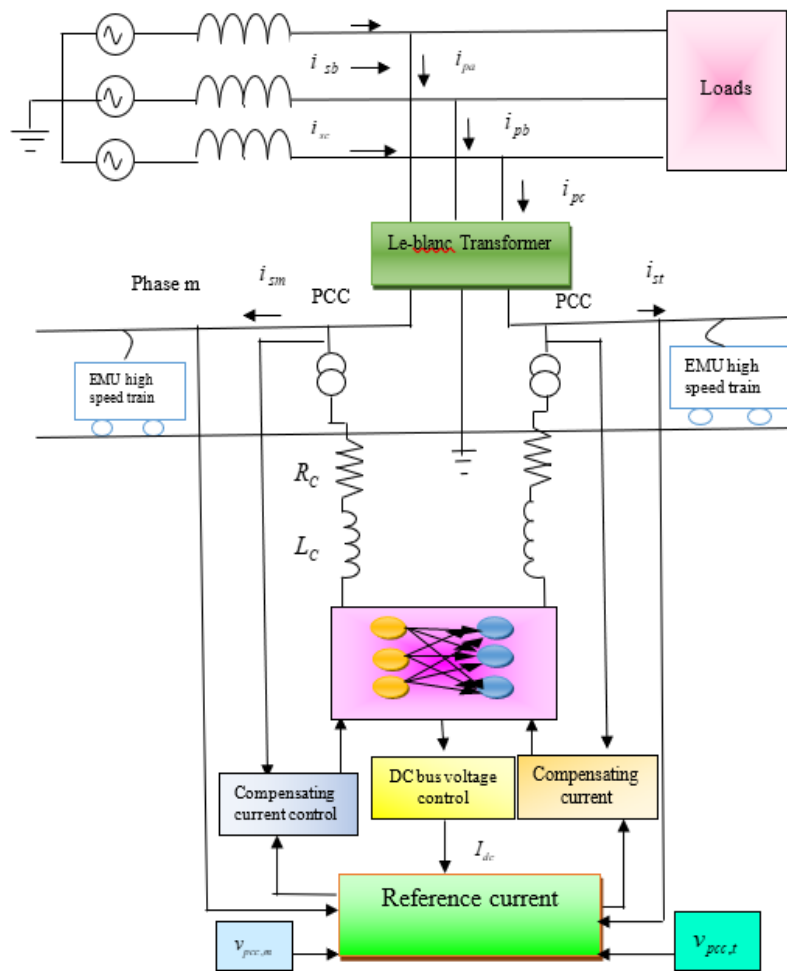


Figure 1. Traction train network model.

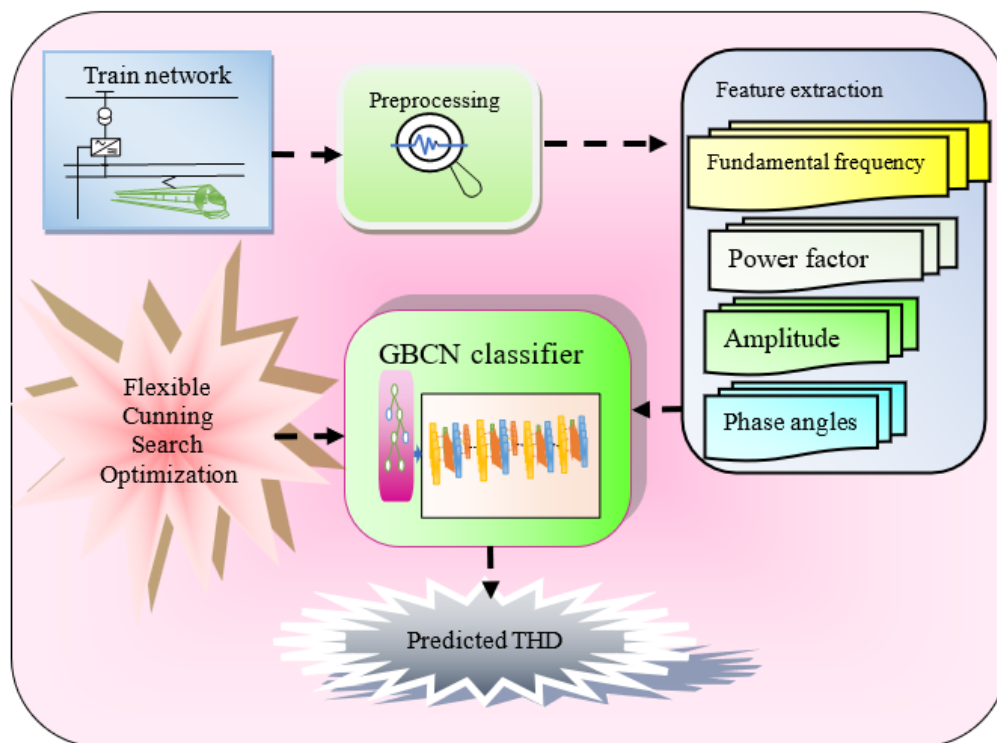


Figure 2. Block diagram of the FCS-optimized GBCN Model.

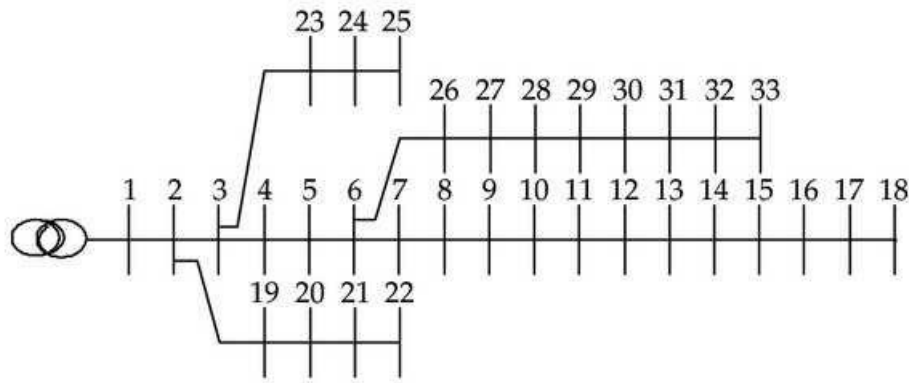


Figure 3. IEEE33 bus system.

In addition, the impact of traction load is analyzed under varying operating conditions to enhance the voltage stability performance. In this research work, the IEEE33 bus system is linked with the traction train network, which supplies the power to the railway traction system. Different fault signals are generated in the distribution system, and the line current signals are transferred to the faults in the traction network. Figure 3 indicates the IEEE 33 bus system, which consists of 33 buses, 32 loads, and a slack bus.

3.3 Train Network

The electrical supply substation (ESS) obtains power from the public grid, which is divided into four parts of up and down tracks, catenaries. A single-phase power grid is used in the traction network, and the three-phase voltage of the grid voltage is stepped down, which is divided into two single-phase voltages with the help of a traction transformer. Grid system impedance and leakage impedance are present in the transformer. The catenary is used to deliver the required energy to the train traction network, and the regenerative braking energy is transmitted by the feeder line. The common parameters of THD mitigation in the traction network include rectifiers, braking choppers, and controllers. Two substations, A and B, provide power to the DC traction system, which has three passenger stations between the substations. Train movement depends on the speed profile, and the resistance is used for the train position function, which is used to change the tracks based on the speed. Two cycles of speed profile are represented, and the train moves from passenger station PS_A to PS_B in the 1st cycle. Then the train moves from PS_B to PS_C in the 2nd cycle. Acceleration power and deceleration power can be calculated in the MATLAB Command Window. Substations A and B have a phase voltage of 13.2kV, and the frequency of Substations A and B is 50Hz. The activation and shutdown voltage of the braking chopper is 720 V, and the range of bus capacitance is 0.01875F. The Dynamic load is connected to the traction system, and the train moves based on the speed profile, which alters the resistance of the tracks to change the position of the train. The

traction train network T is expressed mathematically as follows,

$$T = \{V_n, I_n\} \quad (1)$$

where, V_n and I_n are the simulated voltage and current signals in the traction train network.

3.4 Preprocessing

The harmonic components are induced in the high-voltage side, which is based on Kirchhoff's current law, and then the preprocessed signal is transmitted into the feature extraction to obtain the pertinent features. The traction converter and locomotives are considered the harmonic sources in the railway system. RC filters are used to absorb all the harmonics, which do not cause an impact on power frequency energies, and are used to control the parameters and filter the harmonics in the traction system. Here, different harmonic sources are available in the traction network; hence, the filters are used only to filter a certain region of harmonics. Then the feature extraction takes place in this traction network. Then the mathematical expression of the preprocessing stage is derived as follows,

$$P_T = \{V_{pn}, I_{pn}\} \quad (2)$$

where, V_{pn} and I_{pn} are the preprocessed voltage and current signals, and the preprocessing stage is declared as a variable of P_T .

3.5 Feature Extraction

The amplitude, power factor, phase angle and amplitude features are extracted in the feature extraction region. On the traction network side, variable-frequency current is applied to measure the amplitude and phase currents on the filter side. Moreover, low-frequency and high-frequency bands provide the minimum and maximum amplitude response. In the filter circuit, current transmission is not affected by the spikes of amplitude and frequency response, while harmonic current absorption. The dimensions of the first and second train

voltage, current, and power are 25000×6 . The dimensions of electrical variables are stated as 25000×6 , which contains 25000 sets of features at equal time intervals, where obtained with their corresponding signal value without will be extracted. Then, the label of total harmonic distortion is $[1, 25000]$, and the feature extraction process is formulated as,

$$f_{p_r} = \{A, f_s, p, f, \phi\} \quad (3)$$

Where A, f_s, p, f, ϕ are the features of amplitude, frequency, power factor, and phase angle, respectively. Here, the feature extraction subset is denoted as a variable of f_{p_r} .

3.6 Light Gradient Boost Machine Convolutional Neural Network (GBCN) for Total Harmonic Distortion Mitigation

The GBCN model incorporates the CNN and LightGBM classifier to perform the harmonic prediction task in the traction system. The hybrid model includes a two-step process like pattern recognition and feature extraction. Raw time-series data, such as traction current and catenary voltage, are fed into the automatic feature extractors of CNN layers, which utilize convolutional and pooling layers to extract high-level, non-linear spatial characteristics and complex traction load profiles. The extracted high-level features from the CNN are fed into the LightGBM classifier to predict the harmonic levels. Convergence speed and generalization ability are improved by batch normalization.

In CNN, generated harmonic data are deduced by the decomposition method, and the harmonic measuring points are found out by the harmonic coupling. Electric Multiple Units (EMUs) consist of high-frequency resonance overvoltage, and the texture feature of harmonic data is transferred into the neural network model for training purposes. For training purposes, samples were selected, and the remaining were used for testing, and the overvoltage signals were entered into the neural network for the identification process. The GBCN model prediction accuracy is improved by determining the weights based on the error values, which is called the residual weight method. The mathematical expression for the weights of the ensemble model is derived as follows,

$$O(y) = \sum_i \sigma_i(t-1)g(y) \quad (4)$$

where, $\sigma_i(t-1)$ represents the weight of the i^{th} model, $g(y)$ denotes the prediction output and $O(y)$ is the prediction result of the ensemble model. A series of new weights are determined by the residual weight method to improve the stability of the system, and the expression of new weights is derived,

$$\sigma_i(t) = \frac{1}{u} \sum_{k=1}^u \sigma_i(t-k) \quad (u=4) \quad (5)$$

where, u represented as the time step of the weights.

Figure 4 indicates the architecture diagram of the GBCN model. The GBCN model is used for the time series prediction of harmonics in the traction network and overcomes the shortcomings of other models to achieve accurate prediction results. This model predicts the harmonics by decomposing the Intrinsic Mode Function (IMF) components, which is used to obtain accurate results. Node segmentation of the decision tree is improved by the histogram algorithm, which reduces the computational time and memory. The regularization effects prevent the model from overfitting issues in the traction network. Previous trees are constructed in the new decision tree to address the residual errors, and the mathematical expression is derived given below,

$$A_s(y) = A_{s-1}(y) + \beta \bullet l_s(y) \quad (6)$$

where, $A_s(y)$ denotes the S -th step of the prediction model and $l_s(y)$ denotes adding a new tree on that step, the learning rate is represented as β . The hyperparameters of the LightGBM are learning rate β , estimator count n_s , bagging fraction f_b , number of leaves n_l , maximum tree depth d_{max} , and lambda l . The optimum set of hyperparameters P_{opt} is identified to minimize the cost function, and the mathematical expression is represented as given,

$$P_{opt} = \{\beta^*, n_s^*, f_b^*, d_{max}^*, n_l^*, l^*\} \quad (7)$$

Finally, the prediction results are combined by the error inverse method, and the predicted value of a neural network is indicated $N(y)$ and the LightGBM predicted value is denoted as $A_s(y)$. The prediction result of the ensemble model is represented as $O(y)$.

$$O(y) = \sigma_1 N(y) + \sigma_2 A_s(y); y = 1, 2, \dots, n \quad (8)$$

$$\sigma_1 = \frac{\mu_l}{\mu_p + \mu_l} \quad (9)$$

$$\sigma_2 = \frac{\mu_p}{\mu_p + \mu_l} \quad (10)$$

where, μ_p and μ_l are the relative errors of the ensemble model of the hybrid LightGBM neural network. The Mean Squared Error (MSE) (mSe) is selected as the loss function, which is formulated as follows,

$$mSe = \sum_{d=1}^m (\phi - \Im)^2 \quad (11)$$

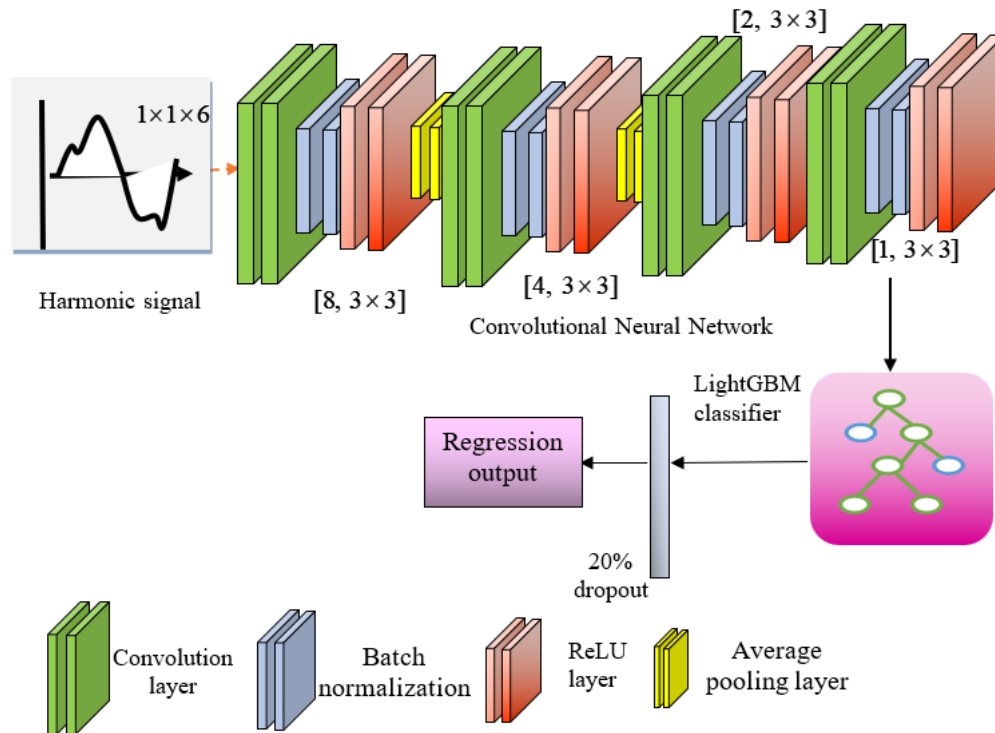


Figure 4. Architecture diagram of GBCN model.

Here, the target output value is demonstrated as $\hat{y}$, and the predicted output value is exhibited as $\tilde{y}$. The FCS optimization is implemented in the GBCN to improve the performance of the model, and the training data is used to calculate the optimal value of hyperparameters like “n_estimators”, “learning_rate” and “num_leaves”. After declaring the values, a set of experiments is performed by changing the number of layers and parameters to obtain good accuracy.

The final prediction output represents the instantaneous harmonic distortion profile of the traction network. The algorithmic prediction value is transformed into a physical counter-measure and the predicted waveform is processed by a substation controller to determine the optimal filter configurations. Further, this predictive tracking data is translated into accurate gating control commands for the circuit breakers. The controller loop utilizes these commands to manage the switching states of the parallel filter branches and connect into the network. Since the LC filter bank is placed at the PCC, the calculated waveform triggers the specific circuit breakers to connect the exact tuned LC branch needed to suppress the distortion. This targeted switching eliminates the distortion waves and ensures low THD across the traction network.

3.7 Flexible Cuning Search Optimization

In the FCS optimization method, the cuckoo search algorithm (CSA) [36], Parrot Optimizer (PO) [37], and Sparrow Search Algorithms (SSA) [38] are

hybridized due to their adaptive multi-swarm guidance, Levy flight exploration and fast local exploitation, which helps to track dynamic power fluctuations and escape local optima. Additionally, the methods such as CSA, PO, and SSA provide a strong search capability, but they frequently experience stagnation when applied to non-linear, high-frequency time-varying PQ problems due to fixed step sizes and update rules. Therefore, the FCS optimization algorithm is introduced to overcome these limitations, because the FCS dynamically divide its search agents based on the normal distribution factor, which allow the search agents to smoothly transition between levy flight exploration and local exploitation. Additionally, the FCS optimization technique reduced the chattering issues and deviation problems, which ensure quick convergence toward minimal THD without getting trapped in local optima caused by sudden regenerative braking spikes. Moreover, the developed technique has enhanced global exploration to avoid premature convergence on suboptimal controller parameters. Improved local exploitation and balanced convergence speed contribute to stabilize the error gradients of prediction models. Notably, the FCS technique adopts dynamic conditions such as sudden, high-amplitude load variations on the traction networks. In addition, the FCS optimization method ensures that the GBCN model predicts accurate switching variables, which enable the LC filter bank to activate its tuned branches and mitigate the network THD.

3.8 Population Initialization

The initialization formulation for the proposed method considers the total population as N , the maximum iteration as Max_i , with search space limits as l_b and u_b , respectively. Then this X_i can be denoted as,

$$X_i = l_b + (u_b - l_b) \cdot R(0,1) \quad (12)$$

Where, X_i is the position of the solution in the initial phase, and $R(0,1)$ term denotes the initial position arbitration of the solution $\in (0,1)$. Moreover, l_b and u_b are the lower and upper bounds, respectively.

3.9 Fitness Function

The optimal solution fitness function compared with the current optimal solution, and the lower fitness value is considered as the optimal solution. The population size is sorted to select the small fitness value, which is considered the best solution by the adaptive local search. Then, the fitness function is derived using the following equation,

$$fit(X_i) = \min(THD(X_i)) \quad (13)$$

3.10 Solution Updation

In the solution updation phase, the solutions are updated in the search space. When the condition of $t < t_{max}$ is satisfied, the solutions are updated in the various phases. Here, t denotes the location of the best search space and S_T denotes the nearby location of the solution.

Exploration Phase (Follower phase): If $R_i \geq S_T$

In the follower phase, the search space and host solutions are considered to find the proper location to update the solutions. When the condition of $R_i \geq S_T$ is satisfied, the solutions are updated in the following phase, otherwise, the discoverer phase occurs. Here, R_i denotes the location of the best search space, and S_T denotes the nearby location of the solution. This condition denotes that the probable location of the best search space is out of the nearby location of the solution. This may be due to the solution's inexperience in finding the position in the early stage. After some time, due to its combination of foraging and effective finding behaviours, the solution estimates the approximate location of the best position, which is done by the leading solution of the group, and has a wide range of searching capabilities. Local optimal levels are improved in the exploration phase, which leads to the memory level of the solution. The mathematical expression of the solution is denoted as,

$$X^{t+1} = 0.5(X^t + L \bullet T) + 0.5 \left[(X^t - X_{best}) \text{levy}(\lambda) + r_1 \left(1 - \frac{t}{t_{max}}\right)^{2/\mu} \bullet X_{mean} \right] \quad (14)$$

$$T = \frac{1}{\sigma \sqrt{2\pi}} e^{\frac{1}{2} \left(\frac{x-\mu}{\sigma} \right)^2} \quad (15)$$

where, L is the lack of experience factor, T is the normal distribution factor, σ is the standard deviation in solution's position, r_1 is the observation factor, μ is the mean position of all solutions in the group, $\text{levy}(\lambda)$ is represented as the Levy flight factor, X_{best} is the best position of the solution, X_{mean} is represented as the average position of solutions in all iterations.

3.11 Exploitation Phase (Discoverer Phase)

In this discoverer phase, a number of solutions and their fitness values are presented to search the better solutions. Entire solutions are guided by the leading solution to maintain the search process.

Case (ii): If $R_i < S_T$

This phase occurs when the solution finds the best search space that comes within the nearby location of the solution. In this situation, the solution selects the best position in the search space, which makes it even more effective to make the best parasitic solution. After the solution's movement depends on two conditions. The mathematical expression of generating a parasitic solution is written as,

$$X^{t+1} = X^t + \alpha \oplus \text{levy}(\lambda) \quad (16)$$

Where α is the step size factor, $\oplus$ is the entry-wise addition.

Subcase (i): Safety phase: If $|S_H| < |S_Y|$

Staying and boundary characters are adopted in the safety phase, which maintains a stable position at a certain period in the boundary to prefer the best solution. Here, S_H denotes the sensing factor of the host solution, and the average sensing factor of finding the intruder's presence is denoted as S_Y , respectively.

This condition denotes that the host solution has a sensing factor that should be less than that of the average sensing factor for finding an intruder's presence. This means the host solution prefers to stay with the parasitic solution so that the solution stays inside the boundary. This shows the staying behaviour inside the boundary, and so the parasitic solutions are considered as better solutions when compared to other host solutions. The mathematical expression for the safety parasitic solution's position is,

$$X^{t+1} = 0.5(X^t + X_{best} \bullet Levy(\lambda) + r_2)0.5\left(X^t + K\left(\frac{|X^t - X_{worst}|}{f(X^t) - f(X_{worst}) + \varepsilon}\right)\right) \quad (17)$$

where, r_2 terms show the resting factor and K are represented as consecutive movement factors in a clockwise or anticlockwise direction $(-1,1)$. X_{worst} is the position of the solution that needs improvement in the group. Fitness factors of X_t and X_{worst} solutions represented as $f(X_t)$ and $f(X_{worst})$. ε is a small value which is not equal to zero.

Subcase (ii)

Elimination phase: If $|S_H| \leq |S_Y|$

In this elimination phase, alarming and sensing factors are used to remove the parasitic solutions from the search space. This condition denotes that the host solution has a sensing factor that detects the parasitic solution, and it has an alarming factor, which increases the sense of removing the worst solution (parasitic solution) to improve the other solutions in the selected search space. This effective approach is achieved by the combination of communicative and distancing behaviour, which distances itself from unfamiliar parasitic solutions and seeks safety for its own generated solutions. Then the updated position of the solution is denoted as,

$$X^{t+1} = 0.5(X^t + r_3 \cos(0.5\pi \frac{t}{t_{max}})(X_{best} - X^t) - \cos(r_4 \pi \frac{t}{t_{max}}) \bullet (X^t - X_{best})) + 0.5(X_{best} + \beta |X^t - X_{best}|) \quad (18)$$

where, r_3 denotes the making distance from the unfamiliar solution and r_4 denotes the confirmation factor, which checks whether any other presence of intruders after removing the worst one from the host solution, and the value of r_4 is approximately one. $\cos$ is the cosine factor, and β is the step-size parameter, respectively. In this hybrid optimization, the evaluation metric of the accuracy level is increased while increasing the population size. Amplitude, frequency, power factor, and phase angle parameters are estimated, which are associated with the harmonic components. These parameters are optimized by the FCS optimization, and the robust performance is evaluated by estimating the parameters of power system harmonics. Overall, the FCS optimization method improves the model's performance for predicting the harmonic distortion by tuning the classifier parameters. Figure 5 indicates the flowchart of FCS optimization.

4. Results and Discussions

In this results section, the efficient outperformed waveforms are obtained to mitigate the harmonic distortion in the FCS-optimized GBCN model.

4.1 Experimental Setup

The experimental setup of the FCS-optimized GBCN model is implemented on MATLAB R2020a with a memory usage of 8 GB RAM. Moreover, the experimental setup details are tabulated in Table 2.

4.2 Parameter Specifications

The parameter specifications of the proposed FCS-optimized GBCN are derived from the Simulink diagram, which is represented in Table 3. Furthermore, all comparative models were evaluated under same hardware settings and same training procedure using a data split consisting of 90% training data and 10% testing data. The equivalent simulation conditions were maintained by running all models against the same dynamic locomotive acceleration profiles within the IEEE 33-bus network. Consistent THD measurement procedures were ensured by using the identical Fast Fourier Transform (FFT) analysis blocks within the Matlab environment at the PCC for all comparative tests. Notably, the parameter specification of the comparative method is illustrated in Table 4.

4.3 Simulation Results

THD results, RMS current results, and output voltage are exhibited to show the system's effectiveness. The simulation diagram consists of the IEEE33 bus system, substations A and B, a DC traction arrangement, single-phase supply, regenerative braking and 13.2kV source. Based on the train movement, the traction network is connected between different buses except the slack bus, with respect to time and load variations handled by the power grid that supplies electrical energy to moving electric trains. DC motor and a traction substation are considered in the train network, which contribute to determine the dynamic power consumption. The main AC distribution network of the IEEE33 bus system consists of 33 buses and 32 sectional lines, to provide voltage profile and baseline power flow. Step-down transformers and rectifiers are utilized to connect the AC grid to the DC traction loads. Locomotive dynamics, resistance forces, and tractive effort are considered in the electric train model. DC catenary line fulfils the power demand for train operation, and the traction substation performs active/reactive power injection at a specific node of the IEEE33 bus system. Voltage drop issues occurred while increasing train acceleration, which leads to power demand spikes at the IEEE33 bus system and the simulation tracks power quality impacts, line losses, and real-time voltage deviations across all nodes. Furthermore, steady-state or dynamic transient response is calculated by the iterative power flow solvers.

THD: Voltage THD or Current THD values are directly measured at the locomotive pantograph/onboard converter interface.

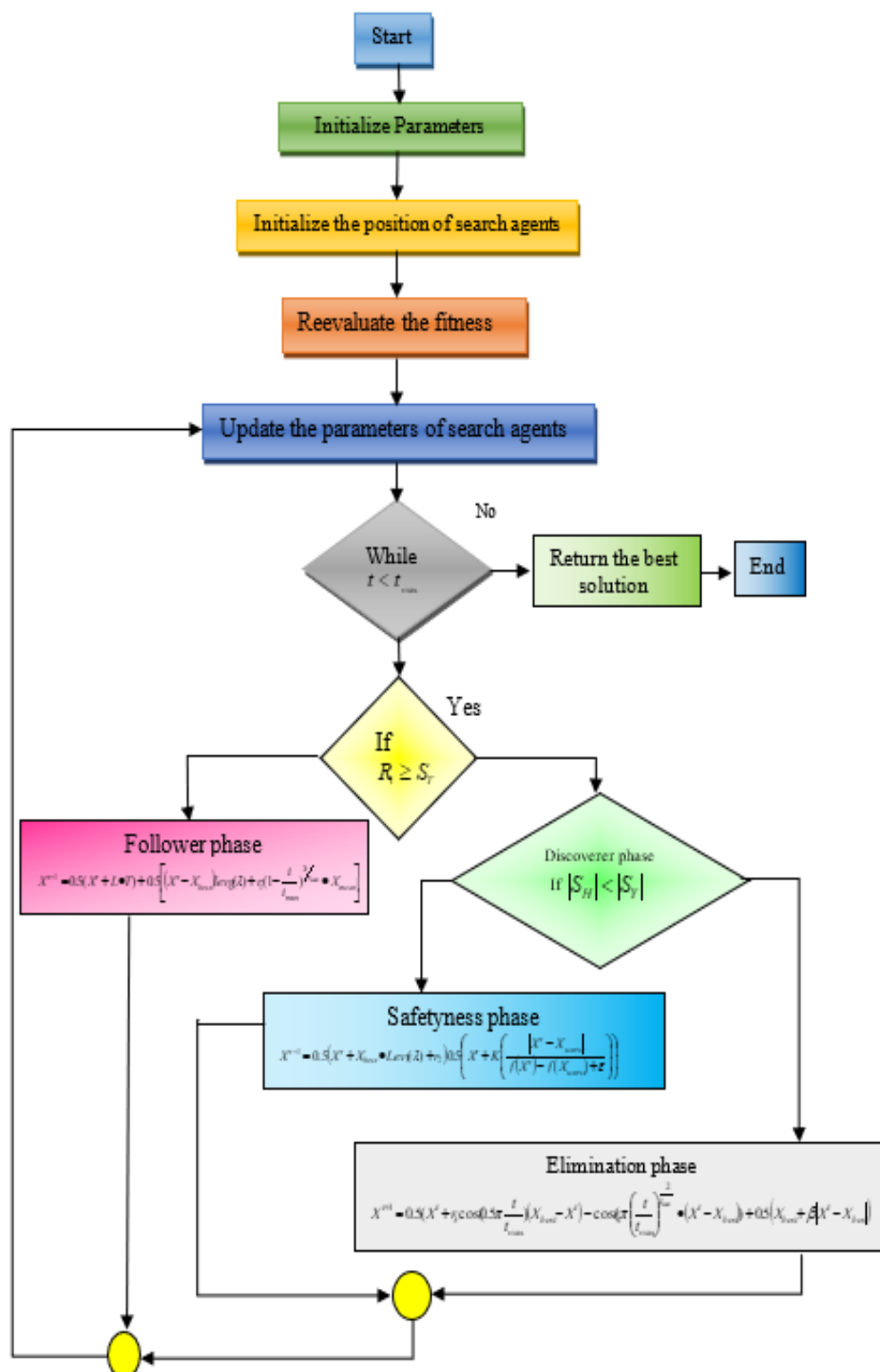


Figure 5. Flowchart diagram of proposed FCS optimization.

Table 2. Experimental setup details

Processor	Intel Core i7
ROM	100GB
CPU	3.2GHz
System type	64-bit OS
Operating system	Windows 11

Table 3. Parameter specifications of the proposed FCS-optimized GBCN

Parameters			Specifications
Substation A	Frequency		50Hz
	Phase voltage		13.2kV
Substation B	Frequency		50Hz
	Phase voltage		13.2kV
Braking chopper	Activation and shutdown voltage		720V
	Bus Capacitance		0.01875F
Initial Capacitor voltage			700V
DC link nominal voltage			800V
Braking resistor			1 Ω
Chopper ON voltage			0V
Chopper OFF voltage			2V
THD	FFT window wavelength		1024
	Sampling frequency		10KHz
	Number of cycles		4
CNN	Input dimension		25000×6
	Input format		1D feature sequence
	Number of convolutional layers		2
	Convolutional layer filters		64
	Kernel Size		3
	Stride		1
	Activation function		ReLU
	Batch normalization		Applied after convolutional layers
	Pooling operation		Max pooling
	Pooling size		1
	Dropout rate		0.2
	Output dimension		1
	Validation set		10% of testing data
	Random seed		42
	Sampling interval		10 ⁻³ ms
	Signal duration per operating cycle		0.3s
	Number of operating scenarios		1
FCS algorithm	Fitness function		THD
	Total iteration		100
	Total population		100
Filter	No.of series RLC branch		5
	Branch 1	Resistance	6.25 Ω
		Inductance	3.3157e-1H
		Capacitance	3.3953e-6 F
	Branch 2	Resistance	6.25 Ω
		Inductance	1.9894e-1H
		Capacitance	2.0372e-6 F
	Branch 3	Resistance	6.25 Ω
		Inductance	1.421e-1H
		Capacitance	1.46e-6 F
	Branch 4	Resistance	12.25 Ω
		Inductance	2.2105e-1H
		Capacitance	0.57e-6 F
	Branch 5	Resistance	12.25 Ω
Inductance		1.8086e-1H	
Capacitance		0.46e-6 F	

LightGBM	Number of trees	100
	Learning rate	0.1
	Maximum depth	5
	Minimum Samples leaf	10
	Minimum samples split	2
	L2 regularization	0.1
	L1 regularization	0.1
	Objective	Regression
	Metric	MSE
	Early stopping rounds	10
	Boosting type	Gradient Boost Decision Tree
	Subsample	0.8
	Subsample frequency	1
	Feature fraction	0.8

Table 4. Parameter specifications of the comparative methods

Parameters	Specifications
Hyperparameters of ANN	
Number of layers	3
Number of neurons per layer	128
Activation function	ReLU
Learning rate	0.001
Batch size	64
Number of epochs	100
Regularization	L2 with lambda = 0.001
Dropout rate	0.2
Early stopping	patience = 10, min_delta = 0.001
Optimizer	Adam
Loss function	MSE
Hyperparameters of Fractional Order PI controller	
Proportional gain	0.1
Integral gain	0.01
Derivative gain	0.001
Sampling time	0.01s
Controller order	2 nd order
Controller type	PI
Hyperparameters of Fuzzy based robust control	
Number of fuzzy sets	3
Membership functions	Gaussian
Rule base	Mamdani
Fuzzy controller order	2nd order
Fuzzy controller type	PI
Hyperparameters of LightGBM	
No of Trees	100
Learning rate	0.01
Maximum depth	5
Minimum child samples	10
Minimum gain to split	0.01
Lambda L1	0.01
Lambda L2	0.01
Subsample	0.8
Feature fraction	0.8

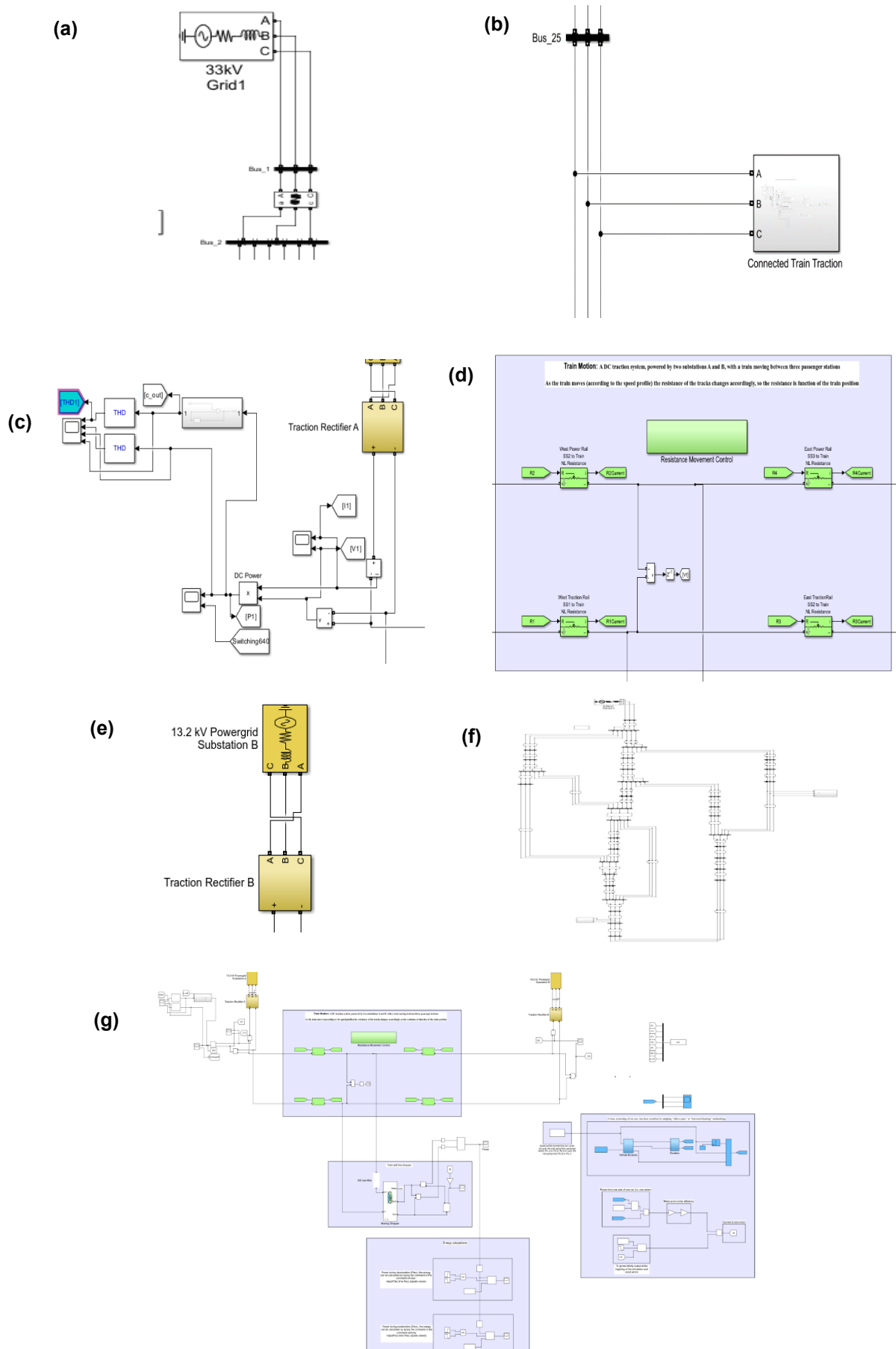


Figure 6. Simulation diagram of (a) Grid system connected to the traction substation, (b) 25th bus connected to train traction, (c) THD measurement location, (d) Train model and sensing point, (e) Harmonic source, (f) IEEE33 bus system, and (g) Overall simulation diagram.

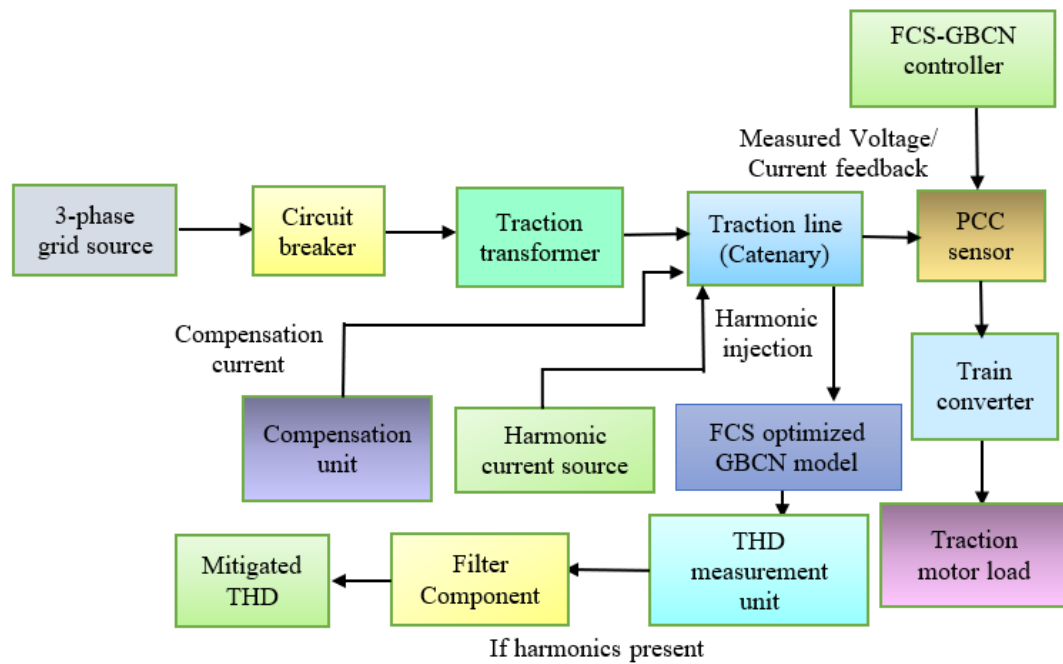
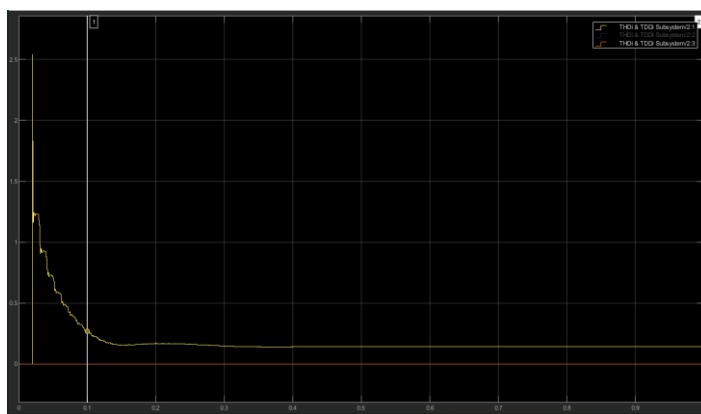
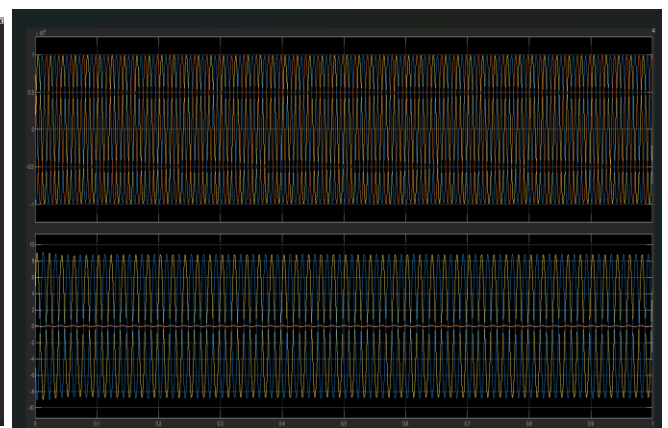


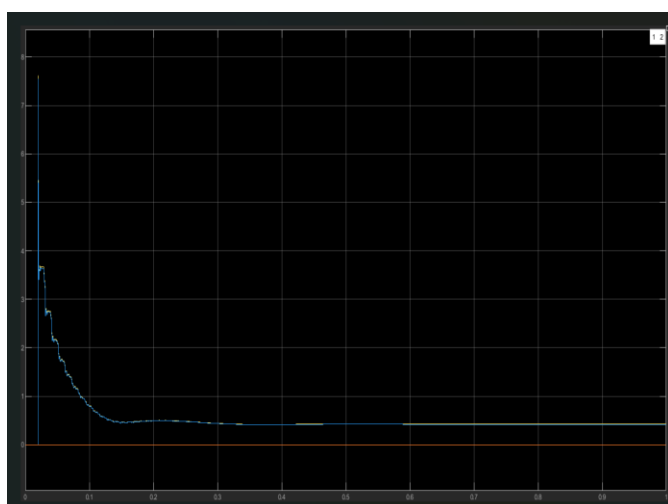
Figure 7. Complete electrical interconnection diagram of IEEE33 connected Traction network.



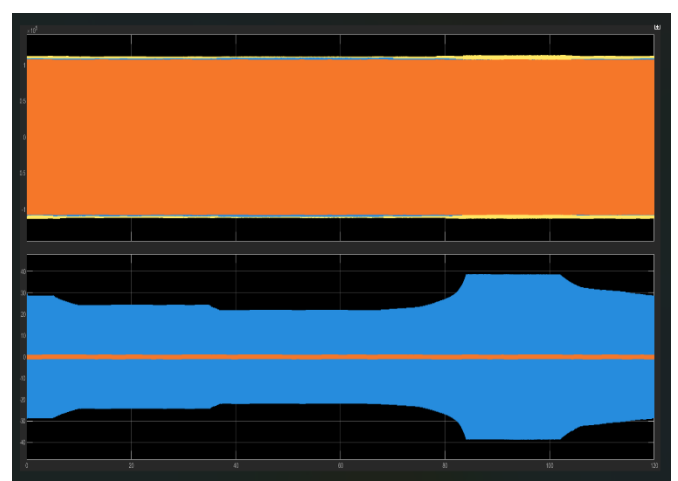
(a)



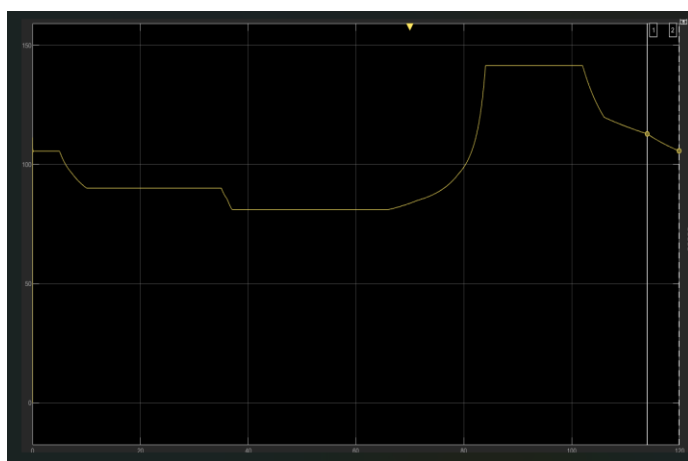
(b)



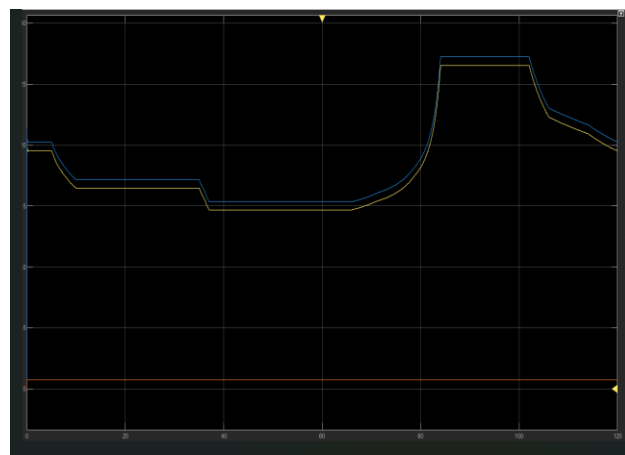
(c)



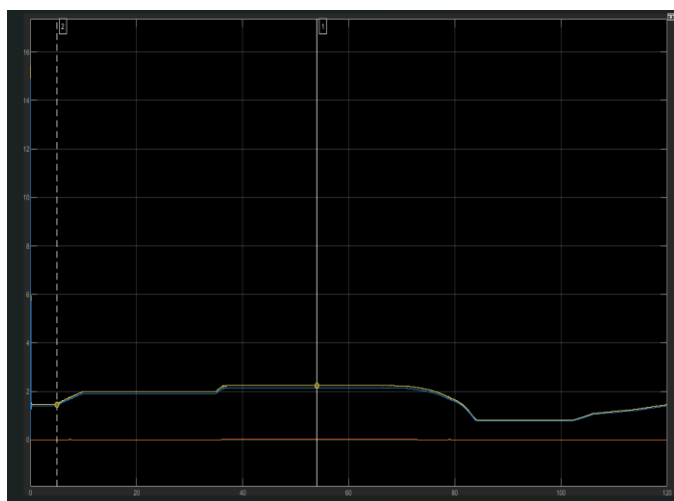
(d)



(e)



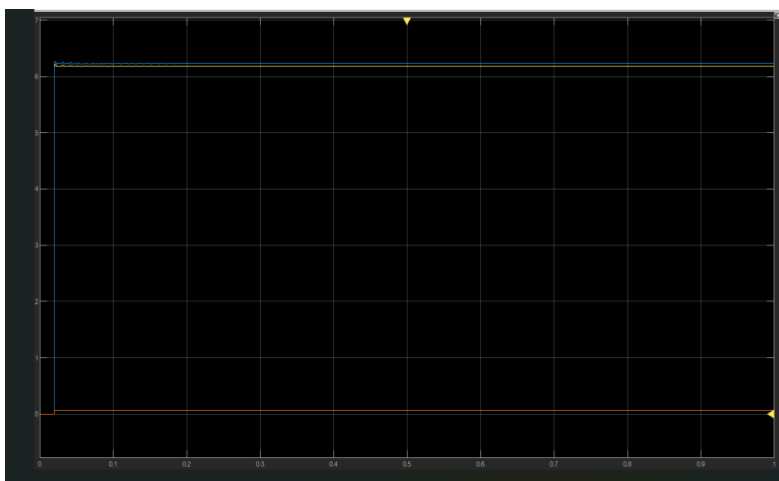
(f)



(g)



(h)



(i)

Figure 8. Simulation results for (a) THD 2 signal, (b) Output voltage for after THD mitigation, (c) THD 1 signal after mitigation, (d) Output voltage before THD mitigation, (e) RMS current 1 before THD mitigation, (f) RMS current 2 before THD mitigation, (g) THD signal for before mitigation, (h) RMS current 1 after THD mitigation and (i) RMS current 2 after THD mitigation.

Traction load fluctuations depend on several factors like train acceleration, cruising or regenerative braking. THD is defined as the ratio of the RMS value of all harmonic components to the fundamental frequency. Moreover, the THD expression is evaluated as below,

$$THD_v = \frac{\sqrt{V_2^2 + V_3^2 + V_4^2 + \dots}}{V_f} \quad (19)$$

where, THD_v is the voltage THD, V_2, V_3 and V_4 are the voltage harmonic components, and V_f is the fundamental

frequency, respectively. Furthermore, the expression for current THD is depicted as below,

$$THD_I = \frac{\sqrt{I_2^2 + I_3^2 + I_4^2 + \dots}}{I_f} \quad (20)$$

where, THD_I is the current THD, I_2, I_3 and I_4 are the current harmonic components, and I_f is the fundamental frequency, respectively. Figure 6a represents the simulation diagram of grid system connected to the traction substation; Figure 6b indicates the 25th bus connected to the train traction; Figure 6c presents the THD measurement location; Figure 6d indicates the train model and sensing point; Figure 6e represents the harmonic source; Figure 6f indicates the IEEE33 bus system, and Figure 6g indicates the overall simulation diagram.

The complete electrical interconnection diagram is provided in Figure 7. Moreover, figure 8a indicates the simulation result for THD 2 signal, figure 8b shows output voltage for after THD mitigation, Figure 8c indicates the THD 1 signal after mitigation, Figure 8d denotes the output voltage before THD mitigation, Figure 8e refers the RMS current 1 before THD mitigation, Figure 8f illustrates the RMS current 2 before THD mitigation, Figure 8g indicates the THD signal for before mitigation, Figure 8h represents the RMS current 1 after THD mitigation and figure 8i shows the RMS current 2 after THD mitigation.

4.4 Performance Analysis

Figure 9a presents the switching output of the FCS-optimized GBCN model. The FCS-optimized GBCN model achieves switching output values are 4253.05, 4589.47, and 4997 with respect to time. Figure 9b presents the train-1 current of FCS-optimized GBCN model. The current in train 1 achieves efficient values of 2183.27 A, 2187.83 A, and 2388.64A by the FCS-optimized GBCN model, which depends on time. Figure 9c presents the train-2 current of FCS-optimized GBCN model. The FCS-optimized GBCN model achieves train-2 currents of 782.01A, 788.28A, and 846.49A, respectively. Figure 9d presents the power of FCS-optimized GBCN model. The power values of 22754W, 23295W, and 28022W are achieved from the FCS-optimized GBCN model. Figure 9e presents the THD of FCS-optimized GBCN model. The THD values of the FCS-optimized GBCN model are 0.74, 0.73, and 0.68 with respect to time, which are considered as efficient values for THD mitigation. Figure 9f presents the train-1 voltage of FCS-optimized GBCN model. The FCS-optimized GBCN model achieves train-1 voltages of 450.22 V, 451.63V, and 472.97 V, which vary depending on the time. Figure 9g presents the train-2 voltage of FCS-optimized GBCN model. Train-2 voltage values of the FCS optimized GBCN model are 452.82V, 468.99V, and 538.70V, respectively.

4.5 Comparative Analysis

In the comparative analysis, ANN [34], Fractional order PI controller [39], Fuzzy-based robust control [40], LGBM-deep CNN with SSA [41], and LGBM-deep CNN with COA [42] techniques were compared with the FCS optimized GBCN model.

In Figure 10a, the C out value of the ANN technique is 4253 with respect to time. However, the FCS-optimized GBCN model achieves a higher C out value of 4997, which has a performance improvement of 14.89%, 8.16%, 7.57%, 5.89%, and 3.80% over the comparative techniques. Here, the higher switching output handles higher pulse frequencies to improve system efficiency and provides faster dynamic response. Moreover, high-frequency resonant overvoltages are suppressed and contribute to improving dynamic load response.

From Figure 10b, the FCS-optimized GBCN model achieves a train-1 current value of 2388.64A, respectively. However, the developed technique attains a maximum train-1 current higher than existing techniques, which represents a significant improvement of 8.60%, 8.41%, 7.27%, 7.07%, and 4.72% over the competent techniques. Notably, higher train-1 current offers faster clearance of heavy loads, stronger dynamic acceleration, and superior adaptability under high-gradient starting phases.

In Figure 10c, the fuzzy-based robust control method attains a train-2 current value of 790.58A, respectively. Nevertheless, the FCS-based GBCN model exhibits a train-2 current of 846.49A, which has a performance improvement of 7.62%, 6.88%, 6.61%, 5.48% and 3.90% over the competent techniques. Specifically, the developed model strategy improves dynamic load tracking and improves pantograph voltage stability significantly.

From Figure 10d, the power value of the fractional-order PI controller is 23972W, respectively. Although the FCS-based GBCN model outperforms the power value of 28022W, which had performance improvement of 18.80%, 14.45%, 12.99%, 12.46%, and 1.05% over the existing techniques. As a result, faster dynamic compensation and wider voltage support handle peak regenerative braking loads and suppress high-order harmonics to provide superior voltage stability while handling heavy peak loads in the traction network.

In Figure 10e, the comparative method of LGBM-deep CNN with COA technique exhibits a THD value is 0.74, respectively. Nevertheless, the FCS-based GBCN model attains a low THD level is 0.68 with respect to time. After filter usage, a lower THD level is achieved, which offers reduced thermal stress on equipment, minimal risk of low-frequency oscillations and lower copper losses.

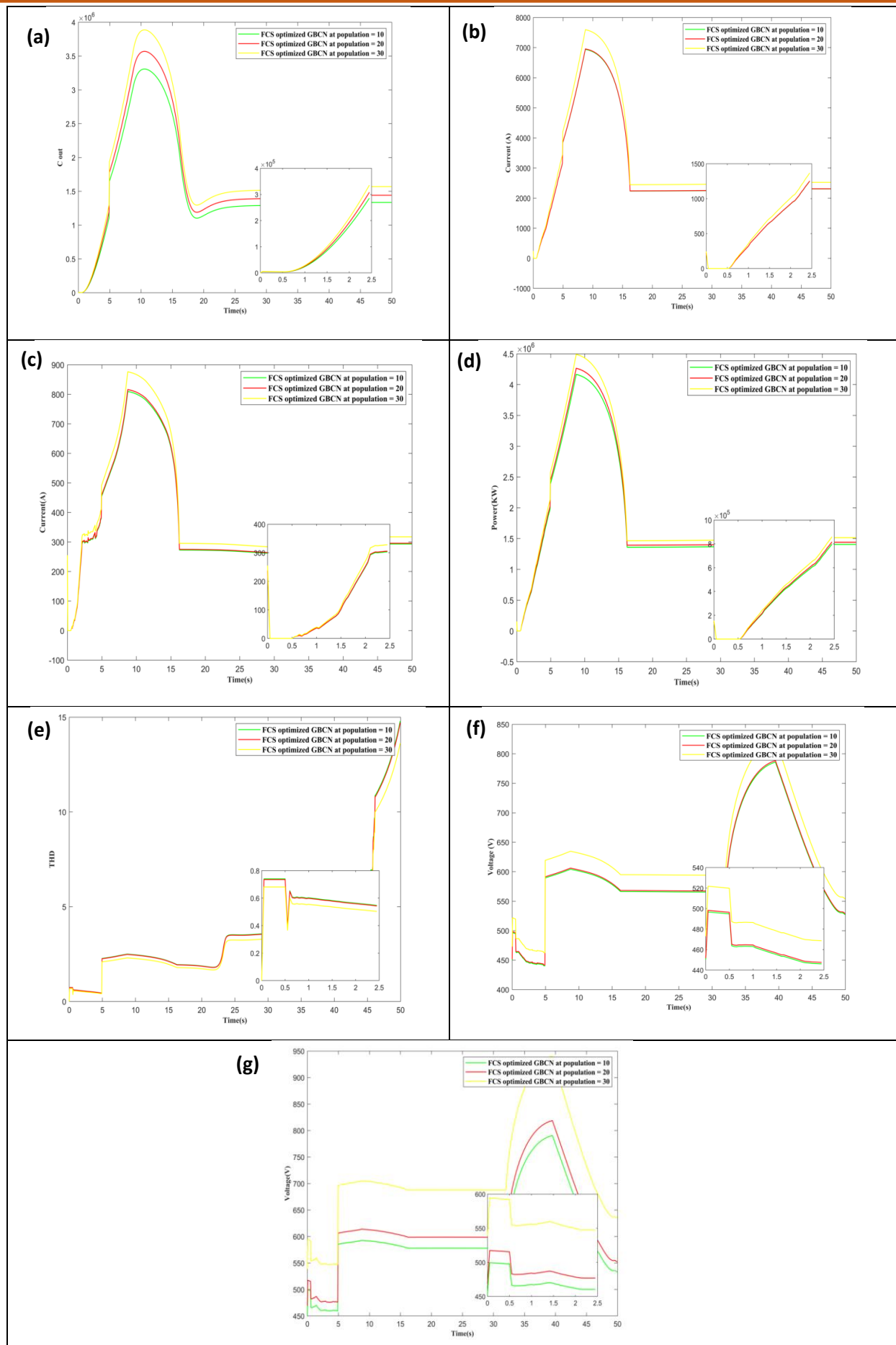


Figure 9. Performance analysis of (a) Cout (b) current in Train 1 (c) Current in Train 2 (d) Power (e) THD (f) Voltage in Train 1 (g) Voltage in Train 2.

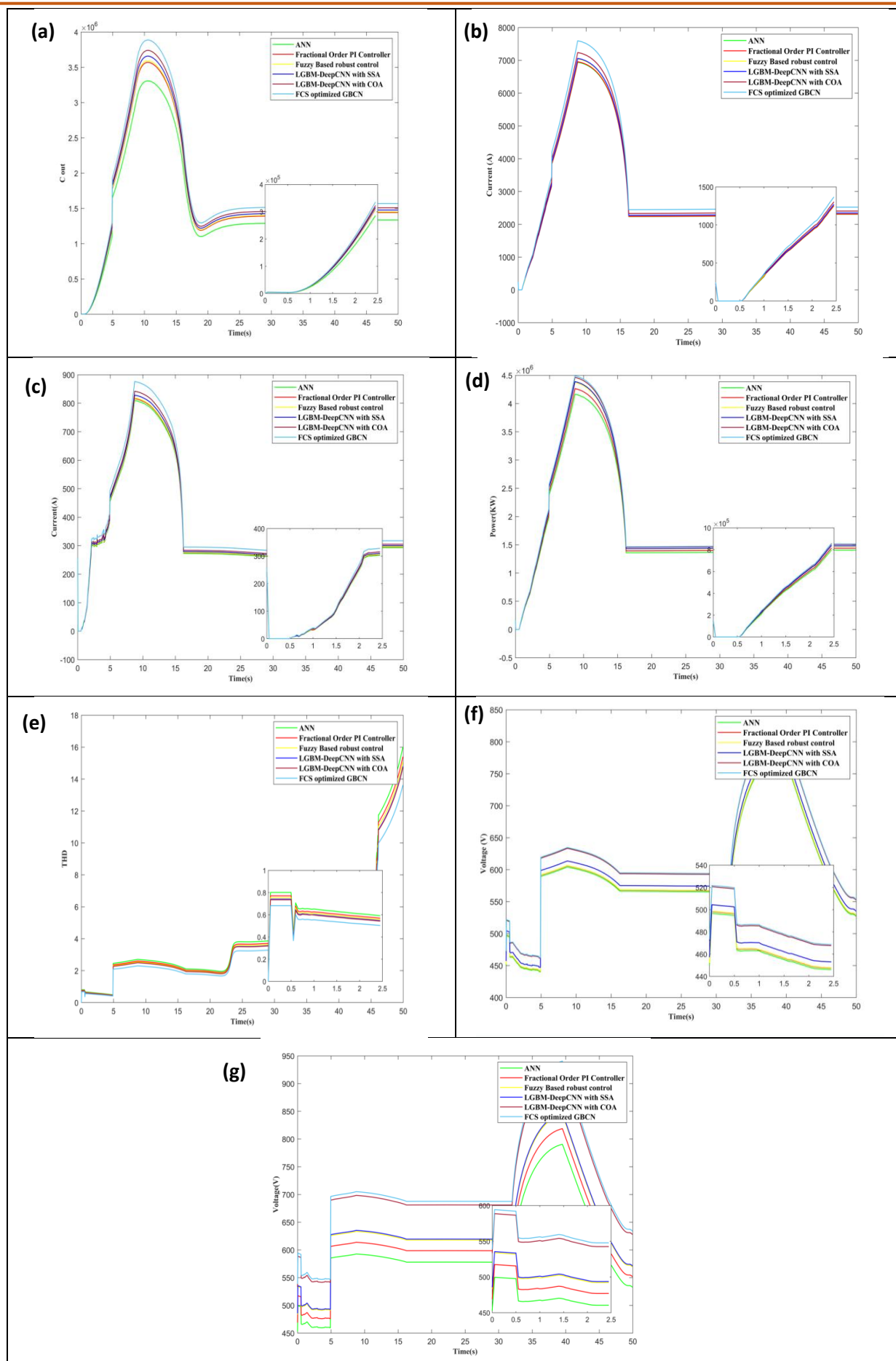


Figure 10. Comparative analysis of (a) Cout, (b) current in train 1, (c) Current in train 2, (d) Power, (e) THD, (f) Voltage in train 1, (g) Voltage in train 2.

The fuzzy-based robust control strategy outperforms the train-1 voltage of 451.93V, respectively. Nevertheless, the FCS-optimized GBCN model exhibits 472.97V of train-1 voltage and is indicated in Figure 10f. During peak loads, high train-1 voltage prevents under-voltage drops, lowers power losses and improves the voltage profile significantly. From Figure 10g, the comparative method of the ANN technique outperforms the train-2 voltage of 452.82V, respectively. However, the developed model of the FCS-optimized GBCN technique offers a train-2 voltage of 538.7V, respectively.

4.5.1 Comparative Discussion

Table 5 indicates the comparative discussion table for reimplementing baseline methods under the present study's simulation conditions. In the comparative discussion table, ANN, Fractional order PI controller, Fuzzy-based robust control, LGBM-deep CNN with SSA, and LGBM-deep CNN with COA methods are compared to the FCS optimized GBCN. In the ANN harmonic distortion network, complexity is produced when handling multiple harmonic sources and changing the impedance of the system. The fractional-order PI controller reduces the THD in the stator current, however, this method does not produce a fast transient response, which is considered as a major drawback of the system. The construction of fuzzy rule tables and assigning optimal values generates complexity in the fuzzy-based robust control method. However, our proposed FCS-optimized GBCN has the effective characteristics of a low-dimensional feature space,

learning of non-linear equations, avoiding the overfitting issue, and a low level of computational complexity. Hence, the efficient characteristics of the FCS-optimized GBCN mitigate the harmonic distortion in the power signal, and the efficient method achieves a THD rate of 0.68, which is lower than the other comparative methods.

In traction systems, harmonic behaviour depends on the train speed, control mode and their positions, which affects the load impedance, fundamental electrical frequency and resonance interaction between the grid and train. In the acceleration stage, the converters operate at high modulation indexes and switching ripples are increased by the control transitions among the network inductance. Moreover, converter switching states and fundamental current are stabilized by the stable power flow, which lowers the RMS current to reduce voltage drop fluctuations under constant speed operation. Furthermore, the phase angle shift between grid and converter voltage produces reverse power flow and high-frequency resonance risks occur during the line filters interaction. Under train position variation, resonance nodes cause impedance mismatching and shift the parallel and series resonance frequencies by the distributed RLC parameters. Nevertheless, the developed model predicts the low and mid-range integer harmonic orders and captures non-characteristic switching frequency sidebands, which linked to the PWM carrier ratios. In resonance locations, the developed model considers LC network interaction, spatial frequency tracking and shifting the impedance peaks.

Table 5. Comparative discussion table for reimplementing baseline methods under the present study's simulation conditions

Techniques	C out	Train 1 Current (A)	Train 2 Current (A)	Power (W)	THD	Train 1 Voltage (V)	Train 2 Voltage (V)
ANN [34]	4253	2183.27	782.02	22754	0.80	450.22	452.82
Fractional-order PI controller [39]	4589	2187.83	788.29	23972	0.77	451.63	468.99
Fuzzy-based robust control [40]	4619	2215.08	790.58	24383	0.75	451.93	483.96
LGBM-deep CNN with SSA [41]	4702	2219.77	800.14	24529	0.74	457.22	485.4
LGBM-deep CNN with COA [42]	4807	2276.01	813.45	27728	0.74	471.94	533.58
FCS optimized GBCN model	4997	2388.64	846.49	28022	0.68	472.97	538.7

Table 6. Comparative discussion table for RMS current after mitigation and before mitigation

THD 1 signal	0.5%
THD 2 signal	0.3%
Before THD mitigation	
RMS current 1	102A
RMS current 2	10A
After THD mitigation	
RMS current 1	33A
RMS current 2	6.2A

Table 7. Comparative discussion table from cited publications.

Research Paper	Primary domain	Operational mechanism	Key Limitation	Literature reported Key performance metrics	Independently obtained THD metric
ANN [34]	Resonance, impedance interaction	Grid impedance compensation, harmonic mitigation, real-time active filtering	Complicate control loops were introduced due to the double-frequency power ripples.	THD-4.52%	0.8
Fractional Order PI control [39]	Regenerative braking, Voltage stability	Dynamic energy capture, stabilizing DC link voltage during massive power injections	High computational complexity, increasing processing delay and hardware costs	66% reduction in DC link voltage overshoot	0.77
Fuzzy sliding mode control strategy [40]	Switching effects, Harmonic behaviour	Mitigating chattering, nonlinear tracking, filtering high-frequency inverter noise.	Highly intricate and computationally demanding.	35.84% total energy recovery and 41.7% increase in traction drive efficiency	0.75
LightGBM-deep CNN [41]	Regenerative braking, voltage stability	Predicting load-dependent rolling stock power consumption	Heavily relies on historical consistency of data	High predictive accuracy MAE-0.082692	0.74
FCS optimized GBCN model (Proposed)	Power quality and Harmonic behaviour	Addressed the identification, prediction, and optimal filtering of complex, time-varying harmonic distortions caused by nonlinear locomotive loads.	Real-time latency risks need to be considered.	-	Minimum THD-0.68

Notably, the FCS-optimized GBCN model excels at periodic load profiles and steady acceleration regimes. The performance metrics of switching output, train currents, and voltage and power are obtained from the FCS-optimized GBCN model.

Table 6 represents the comparative discussion table for RMS current after mitigation and before mitigation. In the research work, FCS optimized GBCN model predicts the THD in the traction network and utilizes the filters to mitigate the predicted THD.

Table 7 indicates the comparative discussion table from cited publications. Fractional-order PI controllers [39] stabilise the catenary voltage and prevent overvoltage tripping, and also alter the output impedance of the converter to prevent negative impedance instability while interacting with the train's onboard traction inverters.

However, high-frequency switching losses and DC ripples occurred in the bidirectional DC-DC converters. Thermal saturation or sudden voltage surges affect the fixed optimizer constraints during sudden, heavy regenerative braking events. Moreover, a fuzzy-based robust control strategy [40] tackles the parameter uncertainties and smooth out the control actions accurately. Nevertheless, high computational demand occurs during the design and tuning of fuzzy membership functions. Residual chattering can interact with electrical components or high-frequency structural resonances. Additionally, the LightGBM model predicts passenger load factors and anticipates localized power surges to handle expected power fluctuations [41]. However, LightGBM models heavily rely on the historical consistency of data, which struggles to predict anomalies and sudden macroeconomic shifts. The LightGBM model does not predict high-speed electrical parameters such as harmonic behaviour, switching frequency effects or instantaneous voltage stability due to the lack of dynamic/real-time transient awareness. Lyapunov optimization [34] ensures overall system convergence and cancels out harmonics due to the usage of shunt and series active power filters. However, unpredictable harmonic noise was distributed across adjacent signal bands, and negative impedance frequencies were experienced at higher frequencies.

Dynamic impedance shifts trigger unexpected harmonic resonances or control-loop instability in the single-phase track model. To overcome these drawbacks, the research work suggests the FCS-optimized GBCN model, which extracts deep features such as phase angles and waveforms from complex raw current and voltage tracking data. High-order parallel or series harmonic resonance over-voltages are prevented by adjusting their admittance. Stochastic switching transients are filtered out to ensure the control framework acts purely on actual underlying harmonic anomalies. Suppression of resonance over-voltages, mitigation of switching effects, dynamic voltage stability compensation, and managing regenerative braking influx are performed by the developed FCS-optimized GBCN model, which contributes to harmonic mitigation in traction railway systems effectively.

4.7 Convergence Analysis

Figure 11 indicates the convergence analysis for the proposed method. The GWO algorithm exhibits the loss values of 0.57, 0.34, 0.27, 0.22 and 0.20, respectively. Moreover, the bat algorithm (BA) attains the loss values of 0.48, 0.33, 0.21, 0.17 and 0.15, respectively. Furthermore, the PO algorithm attains loss values of 0.80, 0.51, 0.28, 0.17 and 0.08, respectively. The SSA attains the loss values of 0.84, 0.78, 0.33, and 0.29 with respect to the various epochs. Likewise, the COA optimization attains the loss values of 0.72, 0.17, 0.02, and 0.01 with respect to the various epochs. However, the proposed FCS optimization exhibits lower loss values than the comparative methods, which represents the good performance of the model and increases the convergence ability than existing methods.

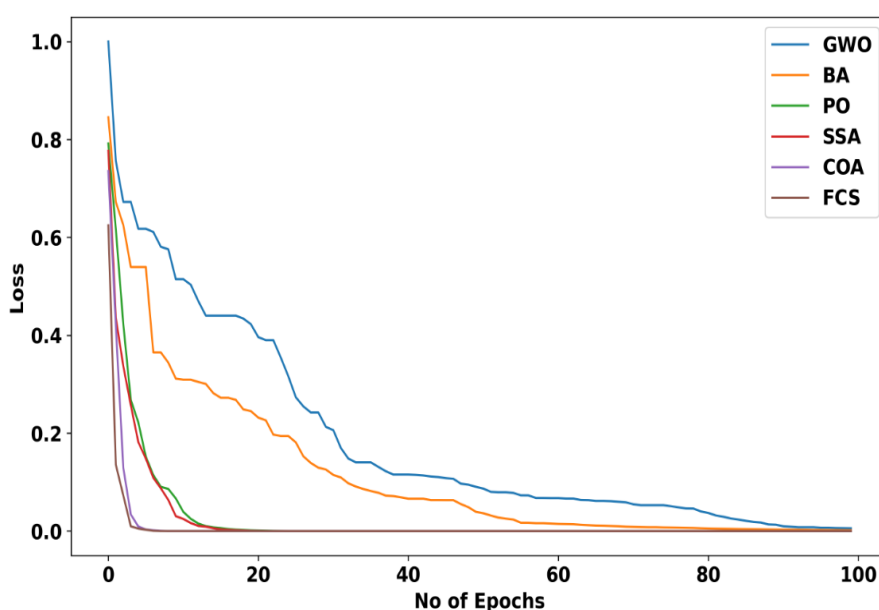


Figure 11. Convergence Analysis.

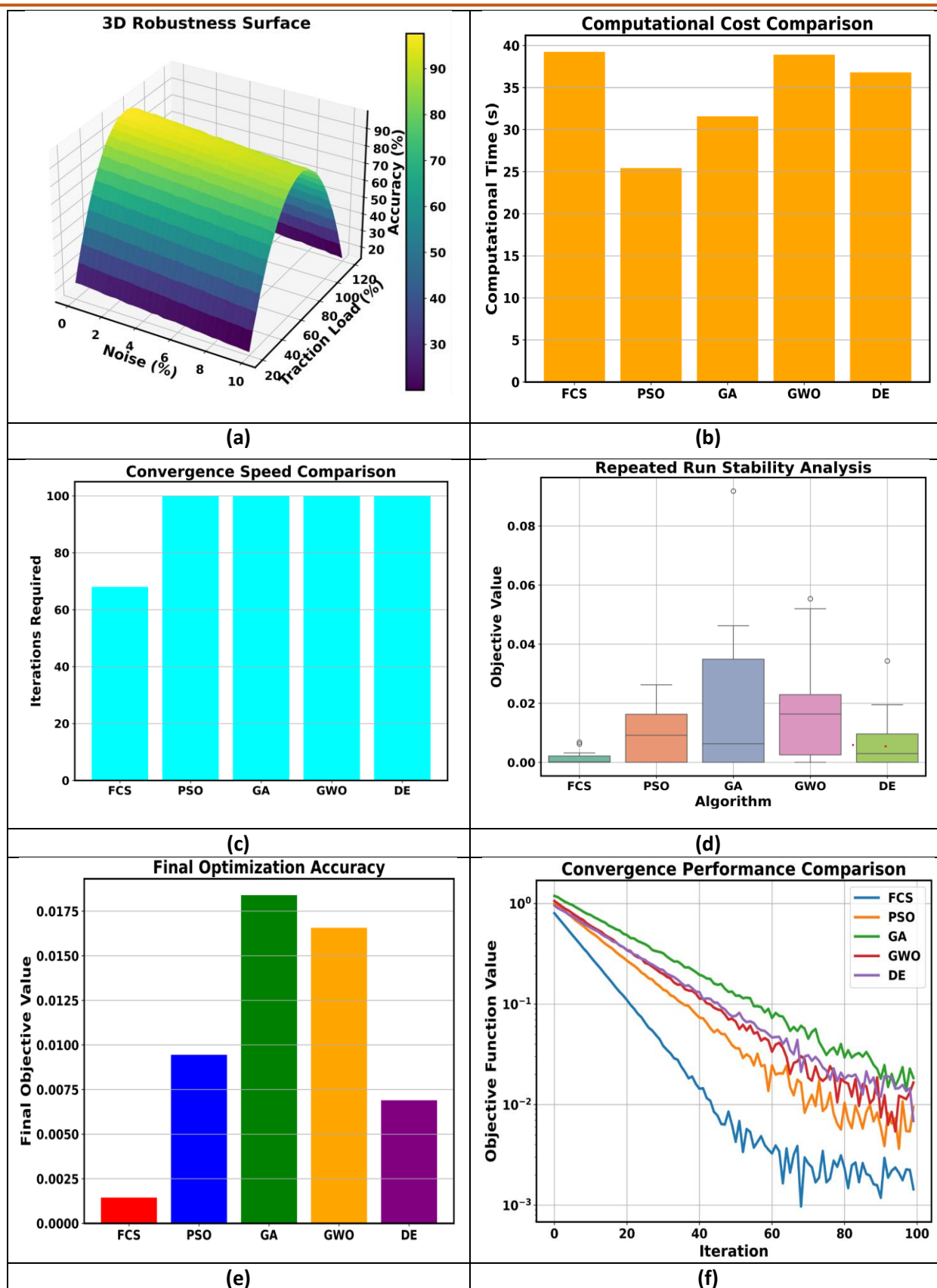


Figure 12. Convergence analysis based on different factors (a) 3D robustness surface, (b) computational cost comparison, (c) convergence speed comparison, (d) repeated run stability analysis, (e) final optimization accuracy and (f) convergence performance comparison.

Figure 12 indicates the convergence analysis based on different factors. Figure 12a represents the 3D robustness surface, Figure 12b indicates computational cost comparison, Figure 12c refers convergence speed comparison, Figure 12d indicates repeated run stability analysis, Figure 12e presents final optimization accuracy, and Figure 12f indicates convergence performance comparison. Here, the mean objective values of PSO, GA, GWO, and DE are 0.0094, 0.0184, 0.0166, and 0.0069, respectively. However, the developed FCS optimization algorithm had a mean objective value of 0.0014 with respect to time. Additionally, the compared optimization techniques offer the standard deviation values 0.002, 0.0081, 0.0243, 0.0163 and 0.0089, respectively. Nevertheless, the standard deviation of FCS is 0.002 with respect to time.

4.8 Ablation Study on Model

Figure 13 indicates the ablation study based on model with respect to THD metric. In the ablation study analysis, the CNN, LightGBM, CNN-LightGBM, tuned CNN-LightGBM attain THD values of 6.46%, 11.36%, 5.46% and 4.76%, respectively. However, the FCS-tuned CNN-LightGBM exhibits the lowest THD level of 2.35%, which satisfies PQ constraints and validates the system's ability to lessen severe locomotive-side harmonic distortions under dynamic loading conditions.

4.9 Sensitivity Analysis

Figure 14 indicates Sensitivity analysis based on train characteristics 14(a) overall robustness evaluation, 14(b) traction load sensitivity, 14(c) converter switching frequency sensitivity, 14(d) robustness against train location, 14(e) impact of source impedance variation, 14(f) effect of measurement noise and 14(g)

sensitivity to parameter uncertainty are analyzed to ensure a traction system perform as safe, stable and reliable operation. During heavy acceleration or braking conditions, traction load sensitivity ensures DC link voltage stability and prevents system crashes during load fluctuations on the traction system. Moreover, converter switching frequency sensitivity indicates power loss and equipment overheating while changing the converter switching speed, which helps to determine the filter size and maintain electromagnetic interference (EMI) in safer limits. Robustness against train location depends on changes in overhead catenary wire inductance and resistance, which prevents control loops or unexpected voltage drops. Notably, source impedance variation analysis evaluates system stability while connecting with weak utility grid that protects equipment from sudden load fluctuations. Furthermore, the effect of measurement noise ensures false signals and verifies that the software filters contribute to ensuring system stability performance.

4.10 Computational Complexity Analysis

Figure 15 indicates the computational complexity analysis. Here, ANN, fractional order PI controller, fuzzy-based robust control, LGBM-deep CNN with SSA, and LGBM-deep CNN with COA attain the computational time of 9.47ms, 9.47ms, 9.56ms, 9.58ms and 9.70ms, respectively. Nevertheless, the developed technique of FCS optimized GBCN exhibits a computational time of 8.82ms, which contributes to provide fast real-time response, quick adaptation of sudden load fluctuations and lower hardware costs. The low computational time of FCS optimized GBCN model offers less energy consumption, quick response, high stability, and fast fault detection to maintain system reliability.

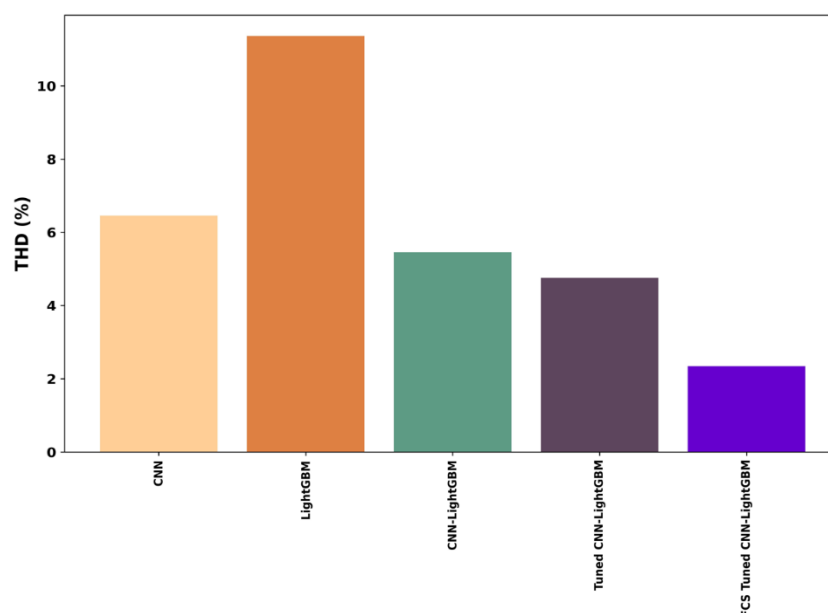


Figure 13. Ablation study based on THD metric.

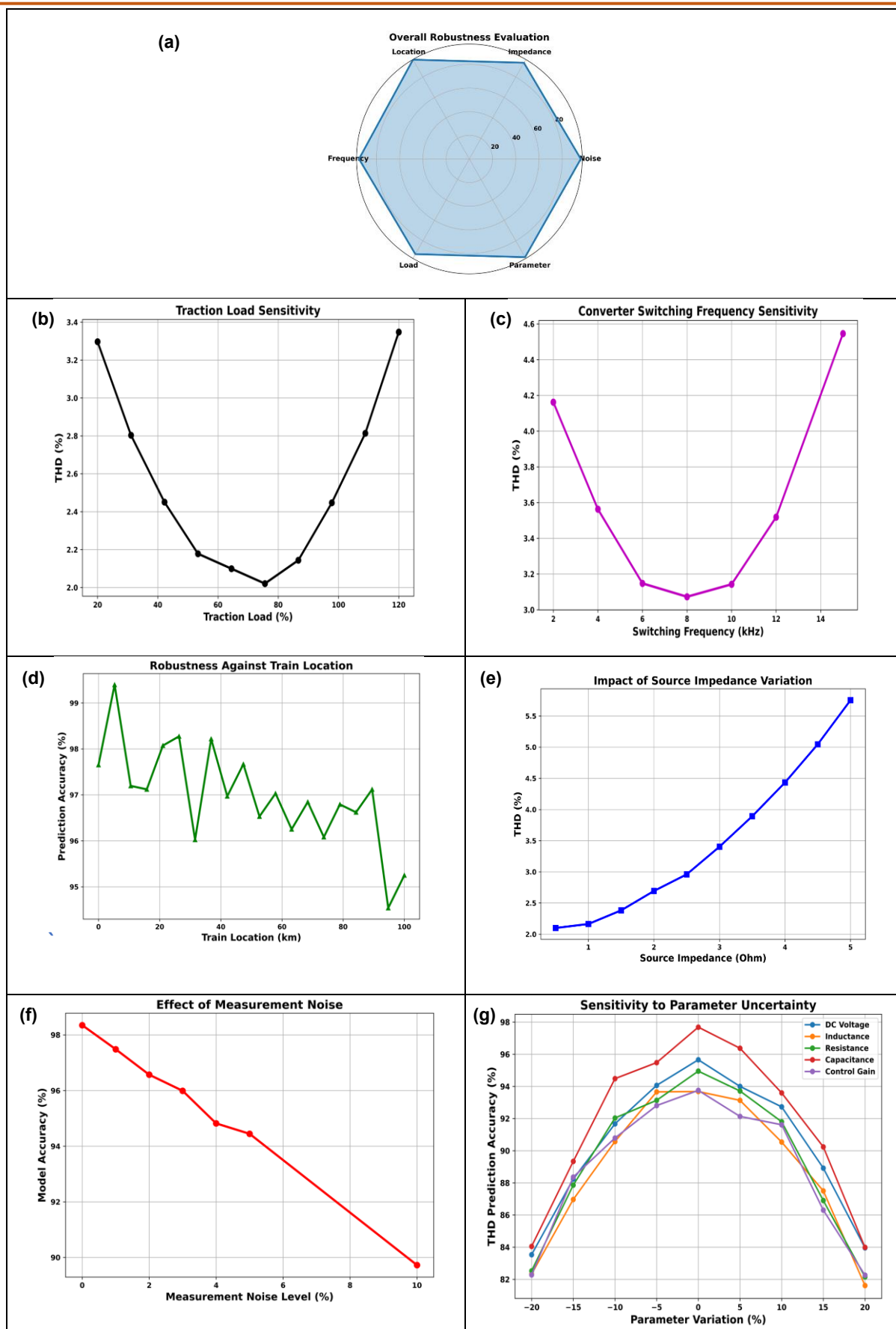


Figure 14. Sensitivity analysis based on train characteristics (a) overall robustness evaluation, (b) traction load sensitivity, (c) converter switching frequency sensitivity, (d) robustness against train location, (e) impact of source impedance variation, (f) effect of measurement noise and (g) sensitivity to parameter uncertainty.

4.11 Ablation Study based on Optimization

The ablation study based on optimization with respect to THD value is included in Figure 16. The method such as CSO-GBCN, PO-GBCN and SSA-GBCN exhibited the THD values of 6.46%, 4.46%, 5.76%. On the other hand, the proposed FCS-GBCN method exhibited the lowest THD of 2.35%, which indicates that the proposed FCS optimization method stabilizes the error gradients under severe locomotive acceleration profiles, reduces target tracking delays and allow the filter to produce highly accurate gating control sequences that helps to achieve harmonic distortion mitigation.

4.12 Ablation Analysis on Before- and After-Harmonic Mitigation

Figure 17 depicts the ablation analysis on before- and after-harmonic mitigation. Notably, the THD value of 8.98% are attained before using the FCS-GBCN method. Meanwhile, after using the FCS-GBCN model, the THD level is decreased to 2.35%, which indicates a significant reduction of 6.63% in THD and enhances overall PQ by mitigating unwanted reactive power losses, increasing transmission efficiency, and stabilizing the grid infrastructure under varying load conditions.

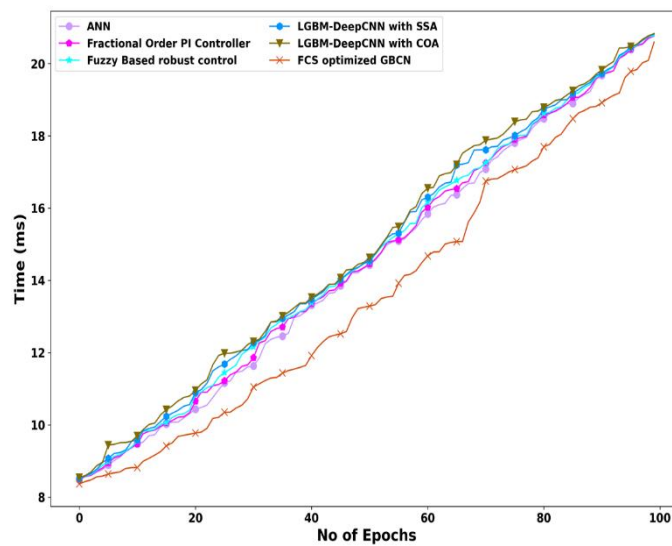


Figure 15. Computational Complexity Analysis.

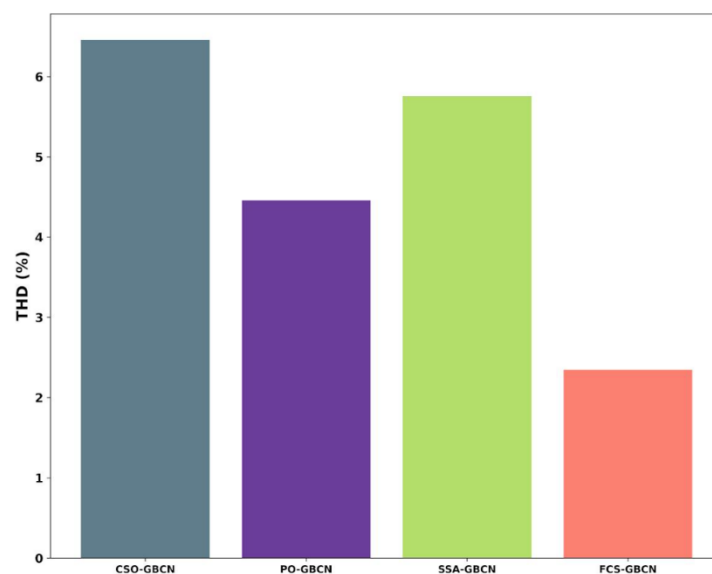


Figure 16. Ablation study based on Optimization.

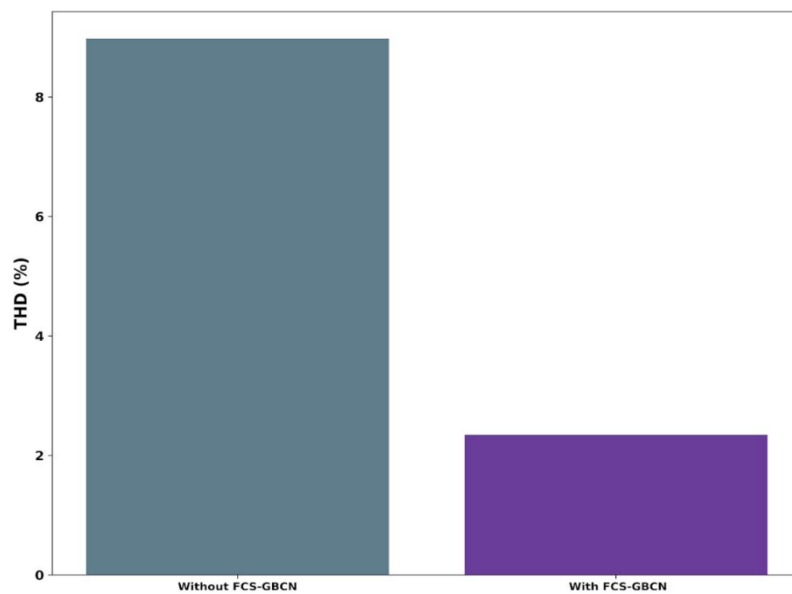


Figure 17. Ablation analysis on before- and after-harmonic mitigation.

Table 8. Statistical test analysis

Techniques		C out	Train-1 Current (A)	Train-2 Current (A)	Power (W)	THD	Train-1 Voltage (V)	Train-2 Voltage (V)
ANN	Best	3308275	6957.74	809.67	4166267	16.01	785.88	790.56
	Mean	1538429	2958.114	360.61	1793825	3.39	598.98	604.91
	Standard deviation	765433	1630.112	183.5	968413.9	3.15	84.05	82.22
Fractional order PI controller	Best	3569993	6957.74	816.16	4265421	15.4	788.35	818.79
	Mean	1660123	2964.542	363.52	1836699	3.27	600.86	626.52
	Standard deviation	825846	1633.404	184.96	991356	3.03	84.32	85.16
Fuzzy-based robust control	Best	3592980	7044.414	818.53	4372193	15.07	788.86	844.94
	Mean	1670779	3001.453	364.57	1882637	3.2	601.25	646.52
	Standard deviation	831183	1653.73	185.48	1016197	2.97	84.37	87.88
LGBM-deep CNN with SSA	Best	3658213	7059.301	828.43	4389255	14.79	798.09	847.44
	Mean	1700969	3007.684	368.97	1889861	3.14	608.29	648.43
	Standard deviation	846380	1657.167	187.73	1020200	2.9	85.36	88.14
LGBM-deep CNN with COA	Best	3739422	7238.166	842.21	4464492	14.73	823.8	931.56
	Mean	1738723	3083.86	375.12	1922283	3.13	627.88	712.8
	Standard deviation	865180	1699.21	190.84	1037642	2.9	88.11	96.89
FCS optimized GBCN model	Best	3887049	7596.344	876.42	4491357	13.63	825.59	940.51
	Mean	1807362	3236.382	390.35	1033854	2.89	629.25	719.65
	Standard deviation	899343	1783.429	198.59	1043880	2.68	88.29	97.82

4.13 Statistical Test

A statistical test is conducted and is illustrated in Table 8, which consists of best, mean and standard deviation values for comparative methods.

5. Conclusion

The research work develops the FCS optimized GBCN model to predict the THD in the traction network, which contributes to improve the traction network power transmission, prevent from equipment damage and reduced power losses, significantly. Signal

decomposition is performed by the GBCN model, which considers non-linear harmonic patterns and spatial feature extraction to perform harmonic prediction task. Vibration, noise, and current signals are collected to mitigate distortion, and the ensemble model of GBCN is used to decompose the signals and to predict the harmonics in the network. The FCS optimized GBCN model effectively mitigates harmonic distortion, and the various performance metrics are reported, which explicates the efficiency of the model. FCS optimization optimized the feature parameters to evaluate the robust performance of the model. Actual and forecast error values are compared with the various models; nevertheless, FCS optimized GBCN model fetches and summarizes the information effectively to improve performance due to its characteristics of regularization effect, overfitting prevention, and training data reduction. In the FCS optimization, adaptive search and sine-cosine search are incorporated, which improve the solution quality, reduce the probability, and assist in attaining the optimal solution that boosts the overall performance. FCS optimized GBCN model attains the switching output, train 1 current, train 2 current, train 1 voltage, train 2 voltage, power, and THD values of 4997, 2388.64A, 846.49A, 472.97V, 538.70V, 28022W, and 0.68. However, the developed model leads to high sensitivity to hyperparameter tuning, poor extrapolation and error accumulation across sequential stages. Different type of filters needs to be considered in future to mitigate the THD levels in shorter time periods, and the next validation stage is performed through the hardware-in-the loop testing, laboratory-scale experimentation, or real-traction system measurements.

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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Author Contributions

Sushma V. Sangle: Investigation, Methodology, Formal analysis, Writing - Original Draft. Prakash G. Burade: Supervision, Writing - Review & Editing. Both authors read and approved the final version of the manuscript.