IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 10 February 2023, accepted 2 March 2023, date of publication 8 March 2023, date of current version 13 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3254501

RESEARCH ARTICLE

Automatic Generation Control Strategy Based on Deep Forest

BIN LI AND JINGYA CHEN
Guangxi Key Laboratory of Power System Optimization and Energy Technology, Guangxi University, Nanning 530004, China
Corresponding author: Jingya Chen (2012392005@st.gxu.edu.cn)

This work was supported in part by the Natural Science Foundation of Guangxi Province under Grant 2020GXNSFAA297117, and in part by the National Natural Science Foundation of China under Grant 51967001.

ABSTRACT As the scale of the power system continues to expand and the energy situation changes dramatically, the existing automatic generation control (AGC) strategy needs to be optimized and improved. The current grid AGC mainly adopts closed-loop PI control. By learning an excellent data set that incorporates the characteristics of PI control and DFT control, this paper proposes a real-time AGC strategy based on a deep forest network. The strategy selects the controller with better control performance in each assessment period as the controller for the assessment cycle for power deviation regulation studies. The simulation results show that the strategy can achieve real-time AGC regulation with a lower number of actions and outperform any of the learned strategies.

INDEX TERMS Automatic generation control, deep learning, deep forest, control strategies.

I. INTRODUCTION

Power systems operate safely and stably by maintaining a balance between power production and load demand. Due to fluctuations in load demand, it is difficult to maintain the relative balance between load and power generation, which affects system frequency and operational safety. In order to cope with the scarcity of fossil energy and the environmental pollution crisis, countries around the world are vigorously promoting the development of renewable energy represented by wind power and photovoltaic, modern power systems emphasize large-scale penetration of wind and photovoltaic, affecting the provision of system services by conventional power plants [1]. As intermittent new energy sources such as wind and photovoltaic are connected to the grid on a large scale, this leads to uncertainty in active power production, and the volatility of their output affects the frequency stability of the power system. Existing automatic power generation control strategies therefore need to be studied in depth and optimized and improved with a view of adapting to the needs of the grid. Automatic generation control (AGC) of power systems is used to regulate the system frequency to a set value, to keep the contact line power exchange value to a planned value and to keep the overshoot and stabilization time within acceptable limits [2]. The load frequency control (LFC) strategy is the core function of automatic generation control and serves to ensure the stability of the power system and frequency [3]. Research methods for AGC systems are divided into two major categories according to the control method: one is the study of direct control of AGC and the other is the optimization modelling method. In this regard, many scholars have conducted relevant research.

In the study of direct control strategies for AGC, the focus is on improving the classical proportional-integral (PI) control strategy or optimizing the PI control parameters. The literature [4] proposed a novel control design for an LFC of a hydro-hydro interlinked system based on joint actions of fuzzy logic with proportional-integral-derivative (PID) effectively optimized through particle swarm optimization (PSO) resulting in a Fuzzy-PSO-PID. The literature [5] proposed a simultaneous coordination scheme based on particle swarm optimization (PSO) along with real coded genetic algorithm (RCGA) is suggested to coordinate FLAGCs of the all areas. The literature [6] proposed a fuzzy-assisted PID controller parameter tuning method based on a combination of improved firefly optimization algorithm and

The associate editor coordinating the review of this manuscript and approving it for publication was Qichun Zhang.

pattern search technique (hIFA-PS) for frequency control of a five-area power system. The gravity search technique was designed in [7] to increase the reaction to a deviation in frequency between multi-area power systems. A hybrid PID-fuzzy controller for optimal automatic generation control of a two-area interconnected power system was proposed in the literature [8], and the controller parameters are developed using the simulated annealing (SA) technique. The literature [9] proposed the AGC with different renewable resources and an improved cascade controller. A new hybrid scheme based on the Improved Teaching Learning by Optimizing Differential Evolution (hITLBO-DE) algorithm applies to provide optimization of the controller parameters. The literature [10] proposed a fuzzy predictive-proportional integral derivative (FP-PID) controller approach for automatic generation controller. The parameters of the FP-PID controller were tuned using the grasshopper optimization algorithm (GOA) with the time multiplied squared error (ITSE) as the objective function.

In the modelling control strategy aspect, an AGC strategy model based on modern interior point theory for interconnected grids under control performance standard (CPS) was proposed in [11]. The model takes the optimal CPS1 index as the aim function, considers system constraints such as system power balance constraints and unit regulation capacity, and solves for an optimal set of AGC regulation commands, and shows the practicality of the proposed model with examples. In [12], the dynamic optimal scheduling model for AGC units was proposed, and the constraints describing the unit regulation characteristics in the model of [11] are improved by introducing the constraint relationship between the interconnection system frequency and the contact line power. In [13], an optimal mileage method (OMD) based AGC scheduling was proposed to optimize the allocation of real-time overall AGC scheduling commands between different AGC units, with the aim of minimizing the power deviation between the scheduling commands and the actual power regulation output. In [14], A novel random forest-assisted fast distributed auction-based algorithm (FDAA) was developed for coordinated control in large PV power plants in response to the AGC signals. In [15], the article proposed a novel framework based on proximal policy optimization (PPO) reinforcement learning algorithm to optimize power regulation among each AGC generator in advance. The control strategy of the optimization modelling method suffers from non-convergence of the model and poor timeliness because of setting strict control conditions, which does not easily enable real-time AGC and real-time response to area control error. However, the actual load of the power system changes at a fast rate and with large amplitude variations, which is a typical non-stationary strongly stochastic process, and the direct control strategy is a more suitable choice.

At the same time, domestic and international research teams are working on the research and application of machine learning in AGC. Machine learning can be divided into six categories: empirical inductive learning, associative learning, analogy learning, analytic learning, genetic learning, and reinforcement learning, and deep learning is associative learning. In [16], The literature proposed an integrated IoT architecture for dealing with cyber-attacks based on developing deep neural networks (DNNs) and rectifying linear units in order to provide reliable and secure online monitoring for automated guided vehicles (AGVs). The literature [17] proposed a weight initialization method for neural network with asymmetric activation function, which can improve the performance of the network. The literature [18] proposed an intelligent integration between a new IoT platform and deep learning neural network (DNN) algorithms for online monitoring of computer numerical control (CNC) machines. The literature [19] proposed a deep reinforcement learning-based control strategy for AGC, which mainly consists of multiple neural networks to fit the behavioral policies of the system for value assessment and improves the efficiency and quality of AGC exploration and the control performance of the system by introducing an improved behavior-criticism method with incentive heuristics. In other areas, the application of deep learning in power systems has become rich. With the development of deep learning, the transformation of active deep learning predictors to data-driven [20], [21] has been largely completed. The rapid development of data-driven approaches gives this paper a new way of thinking about data-driven AGC strategy research. In recent years, developing deep learning has showed superior results over shallow models in tasks such as agricultural biotechnology [22], facial recognition [23], and medical diagnosis [24], [25]. Deep neural networks (DNNs) are the foundation of deep learning, but they require large amounts of data, complex model structures, excessive hyper-parameters and strong computing equipment support. In this context, Zhou and Feng [26] proposed a new decision tree integration method, the deep forest algorithm. Deep forest (gcForest) is a derivative of random forest deep learning, with faster training speed and better parameter robustness.

For the above analysis of the two AGC control methods, the traditional PI control [27] and the discrete Fourier transform (DFT)-based AGC real-time control strategy [28] in the direct control strategy are selected as the two strategies for deep forest network learning in this paper. When the controlled data set is generated by offline control, PI control is selected in scenarios with sharp deviation fluctuations in area control error, and DFT control is selected in scenarios with moderate deviation fluctuations, and the controller with better performance is selected for each assessment period as the controller for that period for power deviation regulation. In summary, this paper proposes a deep forest algorithm-based automatic power generation control strategy to improve the AGC control strategy. The innovation of this paper is reflected in the following aspects:

(1) Fusing the characteristics of different AGC strategies to generate excellent control datasets: The deep learning approach needs the support of sufficient data to select the control strategy with better control performance to adjust

the area control error in different assessment cycles, to give full play to the performance of different control strategies under their respective advantageous working conditions, and to fuse the characteristics of both PI control and DFT control strategies well to obtain excellent control datasets.

(2) A new perspective on deep learning: a deep forest algorithm-based automatic generation control strategy is proposed, which does not study the intrinsic mechanism of automatic generation control, but is based on deep learning methods, using massive area control error (ACE) data training, directly build construct mapping relationships between known inputs and total regulation commands, which has better applicability in dealing with a variety of grid operating conditions and solves the problem of complex AGC modelling control methods and its non-convergence is solved.

(3) Deep forest strategy control process derived from conventional AGC strategy: Simplifying the conventional AGC process, the deep forest control strategy divides AGC into two steps: determining whether the unit is acting and calculating the exact total regional regulation power. A deep learning model for AGC strategy is constructed using a triple classification network and two regression networks, and a deep forest-based AGC real-time control strategy is proposed.

The paper is organized as follows. Section II introduces the basic principles of AGC and gives the evaluation criteria for AGC l performance. Section III presents the principles of the deep forest algorithm. Section IV explains the generation of the control dataset, the rationale for the selection of the network feature covariates and clarifies the AGC process based on deep forest. Finally, simulations are conducted in Section V, and Section VI concludes the paper.

II. BASIC AGC CONTROL PRINCIPLES

A. AGC PRINCIPLE

Automatic generation control is a control technique used to reduce losses and balance the total generated power with the total load demand [29]. During conventional AGC control, the regional grid dispatch center calculates the current power imbalance in real time, i.e. the area control error ACE, and reduces or eliminates the deviation by regulating the frequency regulation units, which is calculated at certain intervals with the following formula:

$$E_{ACE} = \beta\Delta f + \Delta P_T \tag{1}$$

where β is the regional frequency deviation factor; Δf is the frequency deviation; ΔP_T is the contact line exchange power deviation.

AGC control is a closed-loop feedback control process, the input variables are frequency deviation Δf and contact line exchange power deviation ΔP_T and other signals generated after ACE, according to a certain AGC control strategy to get the Frequency regulated generator sets new power ΔP_G, and then adjust the system frequency and contact line exchange power deviation, the control process is described in Fig. 1:

A variety of factors can influence the AGC's real-time control process, such as power supply structure and load.

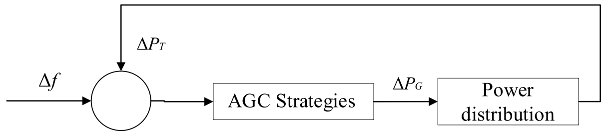

FIGURE 1. Description of AGC control process.

The volatility and intermittency of large-scale wind power and photovoltaic connections to the grid increase the pressure on system regulation, and loads with varying characteristics fluctuate from time to time. Therefore, the traditional AGC cannot meet the system requirements. Deep learning methods apply to the field of automatic power generation control strategies, using deep forest model learning to combine the advantages of different control strategies, so that it can make its own judgement to adopt the controller with better effect for unit regulation under different operating conditions.

B. ASSESSMENT CRITERIA

For the control performance index of the AGC strategy, since the 1960s, the North American Electric Reliability Council (NERC) has adopted the A1/A2 standard as the AGC performance evaluation index, and its control goal is to ensure that the ACE crosses zero. However, this standard has too many unnecessary adjustments and is not conducive to inter-regional frequency support. The control performance standard proposed by NERC overcomes the defects of the A standard and is more scientific. The CPS standard relaxes the requirement that "the ACE must cross zero within 10 minutes", which provides more space for the coordinated control of AGC. The CPS standard includes CPS1 and CPS2 standards. CPS1 is used to count the relationship between ACE variation and frequency deviation, and CPS2 is to count the ACE amplitude change, which is used to evaluate the ability of the control area to control the power flow deviation of the tie line. The CPS standard pays more attention to the long-term benefits of the AGC system, does not require the area control error to cross zero frequently, reduces the frequency of frequency regulation units, and the combination of the regional frequency deviation coefficient and the control limit is more scientific and reasonable.

CPS1 is a criterion for the relationship between the amount of statistical ACE variation and frequency deviation and should be less than a limit, focusing on assessing the contribution of AGC to frequency control. The expression is as follows:

$$K_{CPS1} = 2 - \sum \left[E_{AVE-min}\Delta F_{AVE-min}/(10B_i)\right]/n/\varepsilon_1^2 \tag{2}$$

where $E_{AVE-min}$is the average value of the one-minute ACE; $\Delta F_{AVE-min}$ is the average deviation of the one-minute frequency; $B_i$is the frequency response coefficient (MW/0.1Hz) for control zone i; n is the total number of minutes in the assessment period; ε_1 is the root mean square value of the one-minute average of the deviation of the actual frequency from the standard frequency of the interconnected grid during the one-year period.

CPS2 is used to assess the ability of the control area to control the tidal deviation of the contact line, i.e. the 10-minute average of the ACE, which must be controlled to a given limit value. Its indicator value is expressed as follows:

$$K_{CPS2} = |\frac{1}{N}\sum\nolimits_{t=1}^{N}\left(10B\Delta f^{t} + \Delta P_{T}^{t}\right)|L_{10} \tag{3}$$

$$L_{10} = 1.65\varepsilon_{10}\sqrt{(-10B_i)\,(-10B_s)} \tag{4}$$

where N is the assessment period, Δf^t is the frequency deviation, $\Delta P_T^t$is the tie-line power error, ε_{10} is the mean square value of the average frequency based on 10 minutes in a year and the standard frequency deviation, B is the frequency coefficient of the control area, B_s is the frequency deviation coefficient of the interconnected grid. According to the actual situation of Guangxi grid, the CPS assessment is qualified when 200% $\leq K_{\text{cps1}}$ or 100% $\leq K_{\text{cps1}}$ and $|K_{\text{cps2}}| \leq L_{10}$, where the average ACE limit L_{10} is taken as 100.

III. PRINCIPLE OF DEEP FOREST ALGORITHM

The rapid development of deep learning and deep neural networks has given rise to a supervised machine integration learning algorithm based on the random forest (RF) algorithm, the deep forest algorithm. Deep forest is an integrated method based on decision trees in depth and width. The complete algorithm comprises two processes: multi-grained scanning and cascade forest. The cascade forest is the core part of the deep forest algorithm.

A. DECISION TREE

Decision Tree [30] is a common algorithm that uses a tree structure to perform classification and regression tasks. A decision tree comprises a hierarchy of nodes containing sample attributes and branches containing test conditions for the attributes, and involves three processes: feature selection, decision tree generation and decision tree pruning. The aim of decision tree learning is to produce a decision tree with a high generalization capability. The decision tree algorithm is a simple and fast non-parametric classification algorithm with high recognition accuracy, but performance is difficult to improve with more complex data.

B. RANDOM FOREST ALGORITHM

Breiman proposed the RF algorithm for classification and regression [31]. Random forests include multiple decision trees based on the integrated learning technique of Bagging [32], after inputting the samples to be classified, the final classification is decided by voting on the output of each decision tree. The Random Forest algorithm does not require any prior knowledge and learns the training classification rules on a given sample to perform the classification.

C. CASCADE FOREST STRUCTURE

The model used in this paper is the latest Deep Forest (DF21: A Practical Deep Forest for Tabular Datasets). DF21 is an implementation of DeepForest 2021.2.1 with a cascade structure for its deep forest model. Each layer of the cascaded forest comprises several different forest algorithms as base learners, which are trained using the Stack strategy [33]. Each layer in the cascade forest receives feature information from the previous level and then generates new feature information to the next level after learning. All layers except the first level stitch the feature vectors output from the previous level with the original input feature vectors to form a set of vectors as the input of this level, so that the original features can be maintained and new feature vectors can be formed, which is a reinforcement of the original features and avoids the loss of feature information. The ultimate level is the evaluation level, where the generated category vectors are averaged and then the category corresponding to the maximum value is taken as the sample classification result. To avoid the risk of over-fitting the model, k-fold cross validation is used at each level of the training process, where the training data is trained *k-1* times, and *k-1* category vectors are generated and averaged, and the averaged values are used as augmented feature vectors for the next level. The Deep Forest algorithm automatically determines the number of levels of the cascade forest and uses a validation set to test performance whenever the number of training layers increase and stops increasing the number of cascade layers if the model accuracy performance no longer improves, unlike in deep neural networks where the model complexity must be set artificially.

Deep forest models use different forests per layer, a structure that increases the generalization and fault tolerance of the model. Deep forest has an arbitrary number, type, and number of forests, with the default parameters being a random forest model and a completely random forest as the two forests chosen for each layer. In a completely random forest, each tree picks a random feature as a split node in the split tree and grows until each leaf node is subdivided into only 1 category or only 10 samples. Each tree in an ordinary random forest selects $sqrt\,(k)$ (k denotes the input feature dimension, i.e. the number of features) candidate features by randomly selecting them, and then filters the split nodes by the Gini index.

IV. AGC STRATEGY BASED ON DEEP FOREST MODEL

A. CONTROLLED DATASET GENERATION

The literature [27] used PI feedback regulation control to design an AGC controller based on the area control error in 1953. Traditional PI controller design is simple and easy to adjust, but the dynamic performance is poor, the change time is long, easy to cause transient frequency oscillation, and the fixed coefficient PI control is difficult to meet the control requirements. Under the condition that the area control error fluctuates smoothly, because of the influence of fixed parameters may cause a large change value. The AGC real-time control strategy based on discrete Fourier transform (DFT) in literature [28] converts discrete power fluctuations from time domain to frequency domain, classifies ACE according to different response times, eliminates load fluctuations belonging to the range of primary frequency regulation and economic mobilization, only the AGC units are called upon to regulate load fluctuations in the medium frequency section, thus achieving refined control with a lower number of actions to get better control effect and qualification rate, to ensure the real-time control.

The original data came from a provincial grid after control using the current AGC strategy. The existing ACE data was first restored by using the PI control strategy principles and the restored data was used as the controlled data to generate the control data set. When generating the control dataset, the DFT strategy can achieve fine control, order fewer times, and regulate less, and have good economic benefits, as most of them are normal working conditions with small power deviation fluctuations, so the total regional regulation power is calculated and generated by the DFT strategy in most of the assessment cycles (10min). When the DFT strategy cannot guarantee the CPS standard pass in this assessment period, i.e., a small part of the harsh working conditions where the power deviation fluctuates drastically, the PI control strategy is used for fast regulation. When the DFT and PI control strategies are unable to meet the control requirements in a very small number of assessment cycles, a manual correction method is used to calculate the total regulation power to ensure the safe operation of the grid in the assessment cycle. Each assessment cycle represents a different operating environment. For each assessment cycle, a suitable controller is selected to generate a total regulation command to form a control data set, and a total regional regulation power calculation is performed every 20 sampling points in the generation of the data set.

B. SELECTION OF FEATURE PARAMETERS

In generating the data set required for network training, both PI control and DFT control utilise four variables, frequency deviation Δf, area control error *ACE*, *CPS1* and *CPS2*, in the step of calculating the total regulation power. The first two variables reflect the actual operating state of the grid at the time of sampling, while the second two variables reflect the ACE-based calculations at the time of sampling and over the preceding period. CPS does not require ACE to cross zero frequently, reducing the frequency of unit adjustment, and can be used as an indicator to determine whether the unit is operating. These four categories of variables are therefore chosen as the input feature quantities for the three deep forest networks, but the output variables were different because of the different network tasks. The output variables of the classification network are the AGC unit state quantities, with 1, -1 and 0 representing for increased power regulation, decreased power regulation, no action respectively; the output variables of the regression network are the positive and negative regional total regulation power values.

Tree models do not require data normalisation, such as decision trees, random forests, Boosting and Bagging integrated learning models. The tree model is constructed by finding the optimal splitting points to compose. The numerical scaling of sample points does not affect the split nodes and has no effect on the tree structure; the data does not change before or after scaling.

TABLE 1. Parameter setting of deep forest.

Hyper-Parameters	Classification network	Regression network
n-estimators	4	6
criterion	Gini	MSE
min-samples-leaf	1	1
n-trees	400	800
max-layers	10	20
n-tolerant-rounds	5	2
verbose	/	1

C. MODEL CONSTRUCTION

The generated supervised learning dataset is divided into a training set and a test set in the ratio of 7:3 to train the network.

The obvious advantage of the deep forest algorithm is that it does not require many hyper-parameters and the process of adjusting parameters is simple, with excellent results got for many tasks using default parameter values. The main parameters involved in this paper are: the number of forests in each cascade layer *n_estimator*, the number of trees in the forest *n_tree*, the criterion, the maximum number of cascade layers in the deep forest *max_layers*, the minimum number of samples required at the leaf nodes *min_samples_leaf*, etc. The above hyperparameters have been trained repeatedly to get more reasonable values. The hyper-parameters settings for the deep forest algorithm tested in this paper are shown in TABLE 1.

D. AGC FLOW BASED ON DEEP FOREST MODEL

PI control and DFT control strategies are different in terms of specific control methods, but there are commonalities in the control process. First, the regulation power demand value PR is calculated using the area control error *ACE*, and then the regulation dead-band value is calculated. When the regulation power demand value exceeds the upper limit of the dead-band value, the order is made only during this control cycle, otherwise no order is made. If an order is required during this control cycle, the total regulation power of the area $\Delta P_G$is calculated according to the calculation rules of each control strategy and then dispatched. The conventional AGC control flow is shown in Fig. 3.

The idea of the DF-based AGC control strategy in this paper is derived from the conventional AGC control process. AGC control must first determine whether the unit performs the commanded action in this control cycle and constructs a three-category network in the deep forest network to

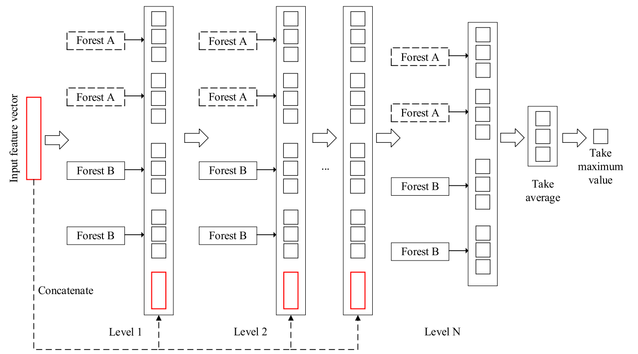

FIGURE 2. Procedure of cascade forest.

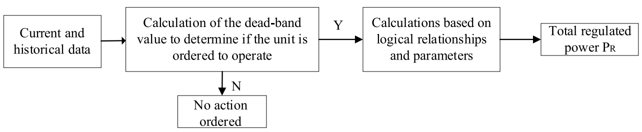

FIGURE 3. AGC control flow.

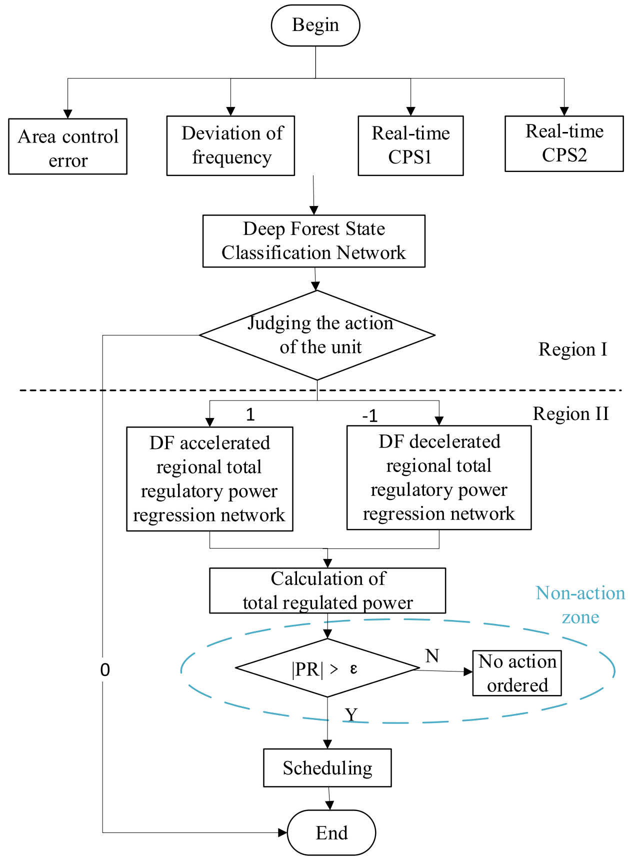

FIGURE 4. AGC control flow based on deep forest.

determine whether the unit is in action. In the control strategy, the non-action zone control threshold ε is set at 30 MW, because the unit does not need to respond to fast random load fluctuations, and if it responds to such load fluctuations, the AGC unit will action more often, with frequent back-and-forth adjustments will increase the mechanical loss of the unit. Therefore, no command is given during this control cycle when it is within the regulation dead-band. If it is greater than the regulation dead-band, the command will be given again.

If action is taken, in order to determine whether a positive or negative unit action is to be performed, two regression networks need to be constructed and used to calculate the total regulation power values of the ordered AGC units in the incremental and deceleration states. The AGC control process based on deep forest designed in this paper contains three trained DF models, namely the state classification model and the regression model of the total regulation power in the acceleration and deceleration regions, and the control process is shown in Fig. 4.

The specific steps are as follows:

The primary aim of region I is to determine whether the unit acts by the state classification model. The acceleration and deceleration time of the unit is limited to 40s, a control calculation is performed at every 20 sampling points. The four characteristic parameters Δf, area control error *ACE*, *CPS1* and *CPS2* at the moment of judgement are composed of raw data according to the requirements of the input data of the deep forest network and input to the state classification model to judge the state of the AGC unit. The output of the state classification network is the control state of the unit, i.e. 1 (increasing state), -1 (decreasing state) or 0 (constant state). If the output is 0, then the AGC unit does not act and the process ends; if the output is 1 or -1, then calculating the total regulated power value P_R in region II.

The major aim of region II is to calculate the total regulated power value. Taking the output result of the state classification network as 1 (incremental state), the original sample input to the state classification network is input again into the incremental regression model to get the regional total regulation power prediction data. When $|P_R| < \varepsilon$, no order is made in this control cycle. When $|P_R| > \varepsilon$, the unit is controlled at increasing speed according to the predicted data.

V. SIMULATION ANALYSIS

In this paper, Anaconda 4.7 + PyCharm2021 is used as the experimental platform. The deep forest model is trained under the TensorFlow deep learning framework, and the latest version of deep forest (DF21) released by Professor Zhou Zhihua is used, and the machine learning tool functions in the scikit-learn package are called to reduce the difficulty of the experimental implementation.

A. EXPERIMENTAL DATA AND DATA ANALYSIS

In this paper, the experiment selects data from a provincial power grid for five months from 6 to 8 and 10 to 11 of 2018, after restoration as the controlled data, with a sampling interval of 2s per day and 43,200 sampling points per day. The controlled data combine with the DFT control strategy and PI control strategy, and the control strategy with the better effect is selected as the controller to calculate the total regulation

TABLE 2. Qualified points of each control method in december.

Control strategies	Status of assessment points			Minimum qualified points	Average daily number of unit actions
	144	133~143	<135		
Without	3	15	12	113	/
With PI	10	16	4	127	1167
With DFT	10	16	4	126	772
With DF network	11	16	3	128	462

command in each control cycle to generate the final control dataset, and the deep forest model is trained. The trained model is validated with restored data from a provincial grid in December 2018, and the control results are analyzed in comparison with no regulation, PI control only, and DFT control only. The proportional and integral coefficients of PI control are set to 0.6 and 5 respectively according to the ''Guangxi Grid Automatic Generation Control (AGC) Primary Fixing Sheet''.

B. ANALYSIS OF EXPERIMENTAL RESULTS

Simulation experiment is conducted on the restored data of a provincial grid for the first 30 days of December 2018, and the results of unregulated control, PI control, DFT control, and deep forest network control are shown in the table below. The effect of AGC control is judged by the CPS criteria, and the CPS1 and CPS2 criteria assess every ten minutes, with 144 assessment points set throughout the day. The number of points passed for each control method in December is shown below TABLE 2 and Fig. 5.

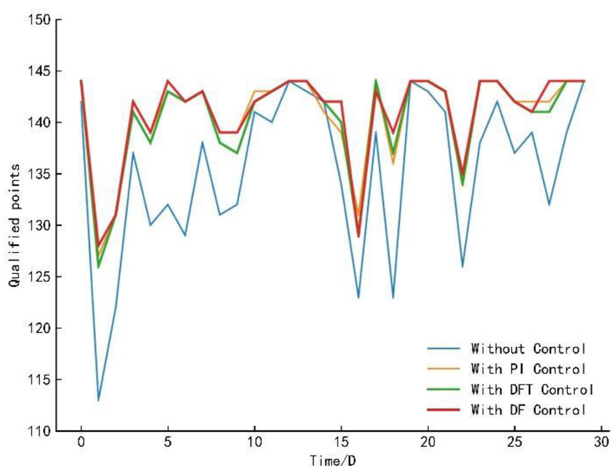

FIGURE 5. Each control method qualified points in December.

According to TABLE 2 and Fig. 5, the number of orders for DFT control is much smaller than that for PI control, and the deep forest network improves the average number of pass points per day by learning to fuse the advantages of these two

TABLE 3. Simulation of each control method on december 16.

Control strategies	Qualified points	Qualified rate /%	Number of unit actions	Positive regulation (MWh)	Negative regulation (MWh)
With PI	139	96.53	1254	81.51	-81.51
With DFT	140	97.22	817	18.04	-18.09
With DF network	142	98.65	542	20.39	-20.39

control strategies. The deep forest network control reduces the average daily number of orders by 60.41% and 40.16% respectively compared to PI control and DFT control, and the regulation effect is better overall than the two strategies alone.

In order to verify the effectiveness of the strategy proposed in this paper in more detail, select the real-time operation data of 16 December 2018 for simulation analysis, which has a sampling period of 2s and 43200 sampling points throughout the day. The control effects of the three control strategies throughout the day on 16 December are shown in TABLE 3, Fig. 6, Fig. 7, and Fig. 8.

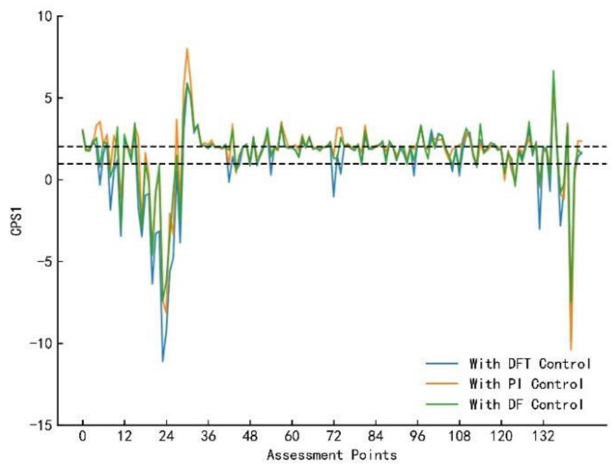

FIGURE 6. CPS1 comparison chart.

From TABLE 3, Fig. 6 and Fig. 7, it can be seen that the number of qualified points of the deep forest network control strategy on the day is 142, the qualified rate is 98.65%, the number of actions ordered by units is 542, 20.39 MWh and -20.39 MW of positive and negative unit miles throughout the day, with the Deep Forest Network control method having the highest number of qualified points among these three control method effects. Fig. 8 shows that the deep forest control strategy orders less often than the other two control strategies during the 144 assessment periods of the day. The number of orders and the large regulation volume of the PI control method confirm the large overshoot of this strategy, which can lead to over- or under-regulation. The number of orders and the regulation volume of the DFT strategy are much lower than those of the PI control strategy because of the refinement

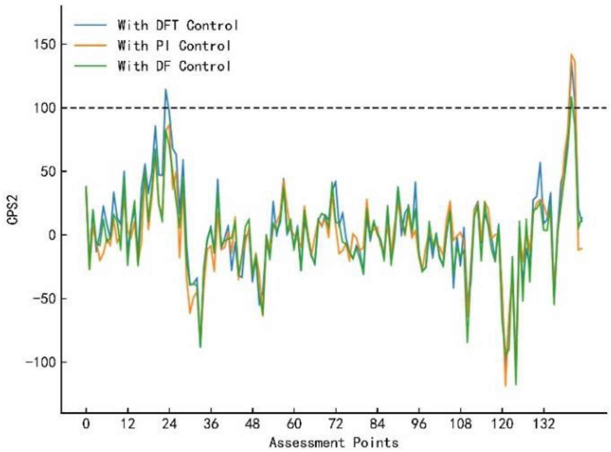

FIGURE 7. CPS2 comparison chart.

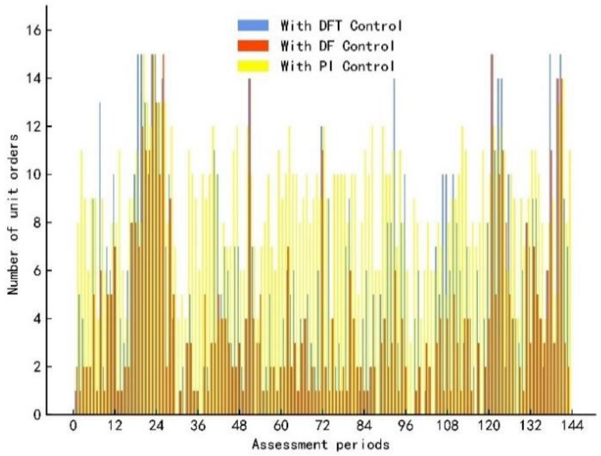

FIGURE 8. Number of orders for 144 assessment periods.

TABLE 4. Control situation of 22:10-22:20.

Control strategies	CPS1	CPS2	Number of actions
With PI	1.69	14.81	12
With DFT	1.76	11.79	9
With DF network	1.93	3.37	7

of the total regulation power. The deep forest network control method proposed in this paper combines the advantages of both, which can increase the number of qualified points with fewer orders and regulation amount and ensure the stable operation of the system.

A typical ten-minute detail analysis is selected from 22:10-22:20 on 16 December. The 10min is the 134th assessment point of the day, with 16 ordered points, and the results of the ordered situations and control effects of the three control strategies are shown in Fig. 9, Fig. 10, Fig. 11, Fig. 12, and TABLE 4.

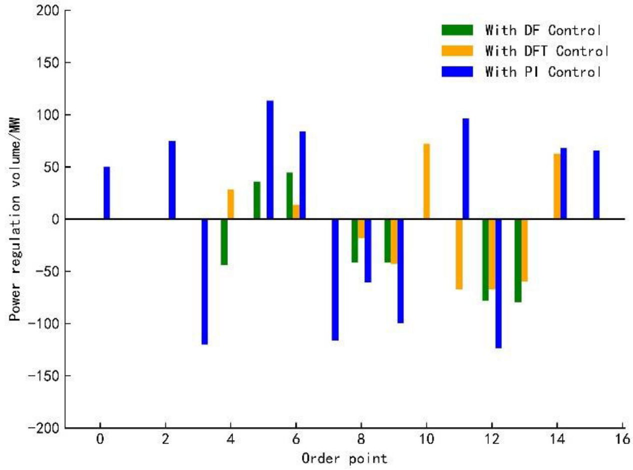

FIGURE 9. Ordered from 22:10-22:20.

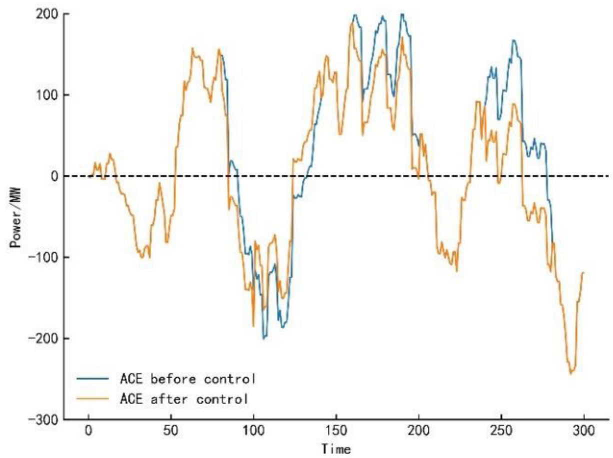

FIGURE 10. 22:10-22:20 Change in ACE before and after control.

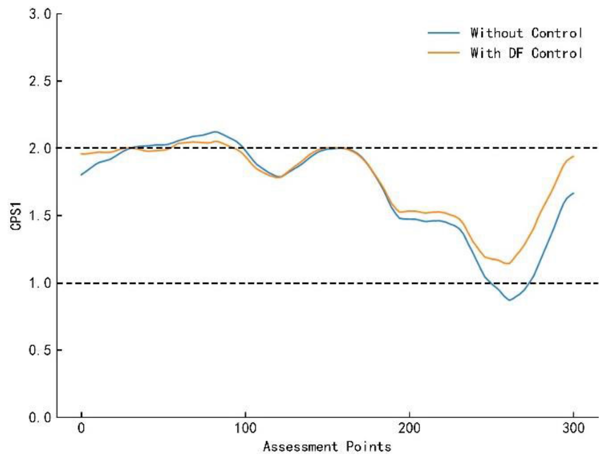

FIGURE 11. 22:10-22:20 CPS1 change before and after control.

From Fig. 9 and TABLE 4, the number of orders of the deep forest network control method is smaller than that of the PI control strategy and the DFT control strategy, and its regulation power value is similar to that of the DFT control strategy and much lower than that of the PI control

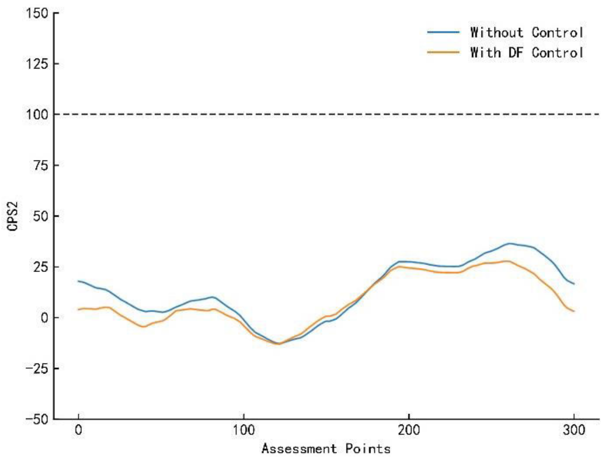

FIGURE 12. 22:10-22:20 CPS2 change before and after control.

strategy, indicating that its control effect is better. Fig. 10 shows that the working conditions of this assessment cycle are smoother and milder, and the regional control deviation does not fluctuate much during the period. Fig. 11 shows that the value of CPS1 is lower than 1 in the latter part of the period when the area is not controlled, which is a failed assessment period. The deep forest network control continuously orders to adjust the deviation and controls the CPS indicator within the range of the assessment pass.

VI. CONCLUSION

With the massive connection of wind power, photovoltaic and other renewable energy sources to the grid and the increase in the number of impact loads, the power system needs to optimize and improve the existing automatic generation control strategy. In this paper, based on the traditional PI control strategy and DFT control strategy, a network control strategy based on the Deep Forest algorithm is proposed, and the following conclusions are obtained through simulation.

(1) The strategy can complement the dominant operating conditions by learning from the excellent control data set that has been modulated by both control strategies.

(2) This network control strategy can effectively control the ACE deviation within the assessment range with a lower number of orders, improving the regulation accuracy and avoiding frequent actions.

(3) Compared to PI control strategies and DFT control strategies, deep forest networks for AGC can effectively reduce the frequency regulation capacity of the unit and improve economic efficiency.

(4) The strategy in this paper is based on a deep forest network algorithm for AGC scheduling. The size of the dataset for training the deep forest model and the grid operating states included is limited. In the future, more control strategies can be used to correct for the unqualified cycles of the dataset, the expansion of the dataset makes the training of the network more mature, and further research is conducted on the control strategy of an autonomic generation control system containing new energy sources.

REFERENCES

[1] K. Ullah, A. Basit, Z. Ullah, F. R. Albogamy, and G. Hafeez, "Automatic generation control in modern power systems with wind power and electric vehicles," *Energies*, vol. 15, no. 5, p. 1771, Feb. 2022.

[2] K. Ullah, A. Basit, Z. Ullah, S. Aslam, and H. Herodotou, "Automatic generation control strategies in conventional and modern power systems: A comprehensive overview," *Energies*, vol. 14, no. 9, p. 2376, Apr. 2021.

[3] A. Koehl, F. Michaud, S. Gubert, and J. Nicolas, "A generic method for the capability evaluation of hydraulic power-plant to participate to the load-frequency-control (LFC)," *La Houille Blanche*, no. 5, pp. 46–54, Nov. 2015.

[4] M. Joshi, G. Sharma, P. N. Bokoro, and N. Krishnan, "A fuzzy-PSO-PID with UPFC-RFB solution for an LFC of an interlinked hydro power system," *Energies*, vol. 15, no. 13, p. 4847, Jul. 2022.

[5] A. D. Falehi, "Optimal design of fuzzy-AGC based on PSO & RCGA to improve dynamic stability of interconnected multi area power systems," *Int. J. Automat. Comput.*, vol. 17, no. 4, pp. 599–609, Aug. 2020.

[6] K. S. Rajesh, S. S. Dash, and R. Rajagopal, "Hybrid improved firefly-pattern search optimized fuzzy aided PID controller for automatic generation control of power systems with multi-type generations," *Swarm Evol. Comput.*, vol. 44, pp. 200–211, Feb. 2019.

[7] R. K. Sahu, S. Panda, and G. T. Chandra Sekhar, "A novel hybrid PSO-PS optimized fuzzy PI controller for AGC in multi area interconnected power systems," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 880–893, Jan. 2015.

[8] M. Muntasir and A. Thamer, "Optimal design of automatic generation control based on simulated annealing in interconnected two-area power system using hybrid PID—Fuzzy control," *Energies*, vol. 15, no. 4, p. 1540, Feb. 2022.

[9] A. Behera, T. K. Panigrahi, P. K. Ray, and A. K. Sahoo, "A novel cascaded PID controller for automatic generation control analysis with renewable sources," *IEEE/CAA J. Automatica Sinica*, vol. 6, no. 6, pp. 1438–1451, Nov. 2019.

[10] R. Kumar and V. K. Sharma, "Automatic generation controller for multi area multisource regulated power system using grasshopper optimization algorithm with fuzzy predictive PID controller," *Int. J. Numer. Model., Electron. Netw., Devices Fields*, vol. 34, no. 1, p. e2802, Jan. 2021.

[11] B. Li, W. Hua, and N. Weitao, "AGC control strategy under control performance standard for interconnected power grid based on optimization theory," *Proc. CSEE*, vol. 28, no. 25, pp. 56–61, Sep. 2008.

[12] W. Yan, R. Zhao, X. Zhao, Y. Li, J. Yu, and Z. Li, "Dynamic optimization model of AGC strategy under CPS for interconnected power system," *Int. Rev. Elect. Eng.*, vol. 7, no. 5, pp. 5733–5743, Oct. 2012.

[13] X. Zhang, T. Tan, B. Zhou, T. Yu, B. Yang, and X. Huang, "Adaptive distributed auction-based algorithm for optimal mileage based AGC dispatch with high participation of renewable energy," *Int. J. Electr. Power Energy Syst.*, vol. 124, Jan. 2021, Art. no. 106371.

[14] X. Zhang, T. Yu, B. Yang, and L. Jiang, "A random forest-assisted fast distributed auction-based algorithm for hierarchical coordinated power control in a large-scale PV power plant," *IEEE Trans. Sustain. Energy*, vol. 12, no. 4, pp. 2471–2481, Oct. 2021.

[15] Z. Liu, J. Li, P. Zhang, Z. Ding, and Y. Zhao, "An AGC dynamic optimization method based on proximal policy optimization," *Frontiers Energy Res.*, vol. 10, p. 969, Jul. 2022.

[16] M. Elsisi and M.-Q. Tran, "Development of an IoT architecture based on a deep neural network against cyber attacks for automated guided vehicles," *Sensors*, vol. 21, no. 24, p. 8467, Dec. 2021.

[17] J. Liu, Y. Liu, and Q. Zhang, "A weight initialization method based on neural network with asymmetric activation function," *Neurocomputing*, vol. 483, pp. 171–182, Apr. 2022.

[18] M.-Q. Tran, M. Elsisi, M.-K. Liu, V. Q. Vu, K. Mahmoud, M. M. F. Darwish, A. Y. Abdelaziz, and M. Lehtonen, "Reliable deep learning and IoT-based monitoring system for secure computer numerical control machines against cyber-attacks with experimental verification," *IEEE Access*, vol. 10, pp. 23186–23197, 2022, doi: 10.1109/ACCESS.2022.3153471.

[19] L. Xi, J. Wu, Y. Xu, and H. Sun, "Automatic generation control based on multiple neural networks with actor-critic strategy," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 6, pp. 2483–2493, Jun. 2021.

[20] Q. C. Zhang, J. H. Zhang, and H. Wang, "Data-driven minimum entropy control for stochastic nonlinear systems using the cumulant-generating function," *IEEE Trans. Autom. Control*, Sep. 20, 2022, doi: 10.1109/TAC.2022.3208170.

[21] Q. C. Zhang and W. Hong, "A novel data-based stochastic distribution control for non-Gaussian stochastic systems," *IEEE Trans. Autom. Control*, vol. 67, no. 3, pp. 1506–1513, Mar. 2022.
[22] S. Dandrifosse, E. Ennadifi, A. Carlier, B. Gosselin, B. Dumont, and B. Mercatoris, "Deep learning for wheat ear segmentation and ear density measurement: From heading to maturity," *Comput. Electron. Agricult.*, vol. 199, Aug. 2022, Art. no. 107161.
[23] H. Sadeghi and A.-A. Raie, "HistNet: Histogram-based convolutional neural network with Chi-squared deep metric learning for facial expression recognition," *Inf. Sci.*, vol. 608, pp. 472–488, Aug. 2022.
[24] J. Jiménez-García, M. García, G. C. Gutiérrez-Tobal, L. Kheirandish-Gozal, F. Vaquerizo-Villar, D. Álvarez, F. del Campo, D. Gozal, and R. Hornero, "A 2D convolutional neural network to detect sleep apnea in children using airflow and oximetry," *Comput. Biol. Med.*, vol. 147, Aug. 2022, Art. no. 105784.
[25] I. K. Gupta, A. Choubey, and S. Choubey, "Mayfly optimization with deep learning enabled retinal fundus image classification model," *Comput. Electr. Eng.*, vol. 102, Sep. 2022, Art. no. 108176.
[26] Z. H. Zhou and J. Feng, "Deep forest," *Nat. Sci. Rev.*, vol. 6, no. 1, pp. 74–86, Jan. 2019.
[27] C. Concordia and L. K. Kirchmayer, "Tie-line power and frequency control of electric power systems [includes discussion]," *Trans. Amer. Inst. Elect. Eng. III: Power App. Syst.*, vol. 72, no. 3, pp. 562–572, Jun. 1953.
[28] B. Li, Z. Li, and X. Bai, "AGC real-time control strategy based on DFT method," in *Proc. IEEE 3rd Conf. Energy Internet Energy Syst. Integr. (EI2)*, Nov. 2019, pp. 1928–1932.
[29] B. V. S. Acharyulu, P. K. Hota, and B. Mohanty, "CLSA-MRPID controller for automatic generation control of a three-area hybrid system," *Energy Syst.*, vol. 11, no. 1, pp. 163–194, Feb. 2020.
[30] C. Zhang, Y. He, S. Jiang, T. Wang, L. Yuan, and B. Li, "Transformer fault diagnosis method based on self-powered RFID sensor tag, DBN, and MKSVM," *IEEE Sensors J.*, vol. 19, no. 18, pp. 8202–8214, Sep. 2019.
[31] C. Li, Y. Tao, W. Ao, S. Yang, and Y. Bai, "Improving forecasting accuracy of daily enterprise electricity consumption using a random forest based on ensemble empirical mode decomposition," *Energy*, vol. 165, pp. 1220–1227, Dec. 2018.
[32] C. Wang, J. Du, and X. Fan, "High-dimensional correlation matrix estimation for general continuous data with bagging technique," *Mach. Learn.*, vol. 111, no. 8, pp. 2905–2927, Mar. 2022.
[33] D. H. Wolpert, "Stacked generalization," *Neural Netw.*, vol. 5, no. 2, pp. 241–259, 1992.

BIN LI was born in Nanning, Guangxi, China, in 1975. She received the B.S. degree in power engineering from Zhejiang University, Hangzhou, China, in 1997, and the M.S. and Ph.D. degrees in power engineering from Guangxi University (GU), Nanning, in 2001 and 2011, respectively. She is currently an Associate Professor with GU. Her current research interests include power system optimization, intelligent distribution network planning and design, and the optimal operation of renewable energy sources.

JINGYA CHEN was born in Shaanxi, China, in 1998. She received the B.S. degree in power engineering from North China Electric Power University, Baoding, China, in 2020. She is currently pursuing the master's degree with the School of Electrical Engineering, Guangxi University. Her current research interests include the application of artificial intelligence in power systems and power system optimization.