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Harmonic Characteristics Data-Driven THD Prediction Method for LEDs Using MEA-GRNN and Improved-AdaBoost Algorithm

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ABSTRACT Light-emitting Diode (LED) lamps have been widely used due to versatility and energy efficiency. However, LEDs are nonlinear loads, the massive usage will inject harmonics into the lighting system, which has influenced the power quality. Total Harmonic Distortion (THD) is an important parameter to evaluate the power quality, but the prediction of THD for LEDs is a challenging task. This paper addresses this issue by designing harmonic characteristics detection experiment and using artificial intelligence algorithm. Firstly, LED lamps with different driving circuits were tested, the relevant data of each harmonic were sampled and analyzed. Then, a THD prediction method based on an improved AdaBoost algorithm is proposed. In this method, a Generalized Regression Neural Network (GRNN) model is established, and its parameters are optimized by Mind Evolution Algorithm (MEA) to improve the search ability of GRNN. On this basis, the AdaBoost algorithm is utilized to integrate multiple MEA-GRNN individuals to form a strong predictor, which improves the generalization ability of the model. To avoid the integration failure caused by improper selection of threshold value, a sigmoid adaptive factor is added to improve the accuracy of AdaBoost algorithm. Finally, the Ada-MEA-GRNN model is trained and simulated with the LED harmonic data collected by the experiment. The simulation results show that the prediction accuracy of the proposed method is better than BP and GRNN, which can reach 95.48%. Meanwhile, even if the input dimension is reduced, the error is still small.

INDEX TERMS LED lamps, THD prediction, ensemble learning, mind evolution algorithm (MEA), generalized regression neural network (GRNN).

I. INTRODUCTION

With the widespread application of new power electronic devices in the distribution network, the power quality problems caused by the harmonics injected into the network are becoming increasingly prominent. The research on harmonic control mainly focuses on the fields of new energy and large-scale industrial equipment, such as distributed photovoltaic generation connected to the grid, electrified railway, etc. The power quality problems due to lighting equipment have attracted little attention. Although the capacity of a single lighting device is small, the lighting power consumption accounts for approximately 20% of global total power consumption [1]. Therefore, the power quality problems caused by the large use of LEDs and other new lighting equipment cannot be ignored. Due to the advantages of energy saving, high efficiency and environmental protection, many governments have issued instructions to use LEDs or Compact Fluorescent Lamps (CFLs) to replace low energy efficiency incandescent lamps [2]. According to the prediction in [3], by 2030, most lighting technologies will be replaced by solid-state lamps based on semiconductor components such as LEDs.

LEDs work under a completely different principle from that of incandescent lamps. In LED lighting technology, when electrons and holes are combined, the energy is released

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in the form of light, which directly realizes the conversion of electric energy to light energy, so the energy efficiency is higher [4]. To achieve this, DC power supply is needed, so the rectifier is added to the lighting equipment which provide DC current to the LED chip. Rectifier is a typical harmonic source, it will produce high distortion harmonic current injected into the power grid, causing power quality problems.

As the fourth-generation light source, numerous studies were conducted on LEDs, but most researchers are more didactic in improving the rectifier circuit to advance the performance of LEDs [5], [6] or measuring its optical parameters for lighting effect analysis [7], [8]. Some scholars have conducted research on LED life and reliability prediction [9]–[11]. Lu *et al*. [9] combined BP neural network with AdaBoost algorithm to predict the life of white LED lamps. The model is 54% lower than the traditional neural network in terms of average relative error. Sun *et al*. [10] they summarized various models for predicting LED life and reliability, and analyzed the advantages and disadvantages of various methods including physical methods, statistical regression, Bayesian networks, Kalman filtering and neural networks. Sutharssan *et al*. [11] applied a data-driven approach to predict and monitor the health of high-power light-emitting diodes based on the failure mode of light output power degradation. This method has high application value. Only a few studies focus on the current distortion of LED lamps [12]–[15]. Shabbir *et al*. [12] evaluated the harmonic pollution of LED lamps in power system, investigated the influence of lighting load variation and illumination difference on harmonic, he found that the control load had significant influence on the harmonic distortion rate of LEDs current. McLorn *et al*. [13] analyzed the harmonic distortion characteristics of LED lamps when the applied voltage is changed, and established a polynomial load model including voltage, power and harmonic current characteristics. Islam *et al*. [14] and Lin *et al*. [15] they compared the CFL and LED lighting sources, measured the power quality related parameters, and putted forward the gradual replacement scheme of incandescent lamps. All of the above researches are involved in the power quality of LED lamps, and the Total Harmonic Distortion (THD) is an important index to evaluate the power quality of LED lamps. THD is the sum of the root mean square of each harmonic, it contains information about each harmonic, which can reflect the harmonic characteristics of the luminaire and the overall harmonic situation of the circuit more comprehensively than other parameters [16]. Therefore, it is of great significance to calculate the THD for evaluating the power quality of lighting circuits.

The prediction methods mainly include multiple linear regression (MLR) [17] and logistic regression [18] based on statistical principle. In recent years, artificial neural network (ANN) has also made some progress in the field of harmonic prediction: Zhai *et al*. [19] proposed a harmonic current extraction method combining RBF neural network and *ip-iq* method, which added low-frequency harmonic extraction links, and compensating for the deviation of *ip-iq* harmonic extraction. Mohamed *et al*. [20] they put a two-level converter control scheme based on predictive model control and feedforward neural network, which can reduce the THD and improve system stability. Singh *et al*. [21] took rolling bearings as the research object and summarized the machine learning algorithms for failure prediction and health management. Guo *et al*. [22] discussed recent research progress and applications of data-driven, physical-based and hybrid prediction methods in predictive model approaches for engineering systems. All of these works suggest that data-driven machine learning and deep learning algorithms will be mainstream direction for LED parameter prediction in the future. But at present, we have not found any research on prediction for LEDs Total Harmonic Current Distortion (THDi).

For the current harmonic distortion rate, ordinary watt-hour meters cannot perform data collection, and the traditional method is to use expensive power quality analyzer to measurement. These instruments are generally designed for high-power electrical equipment, so it is impossible to use for LED lamps in civil buildings on a large scale. Therefore, if the electrical parameters of the LED lamps in operation can be utilized to predict the current harmonic distortion rate with high accuracy, we can transform the existing watt-hour meter to determine the harmonic source of the lighting circuit in real time and minimize the pollution of the power system.

In this paper, for building the THDi prediction model, the electric characteristic data and harmonic data of LED lamps with different driving circuits are collected through design experiment. By analyzing these data, a prediction model of LED current harmonic distortion rate based on artificial neural network is proposed. In order to enhance the performance and robustness of the model, Using Mind Evolutionary Algorithm (MEA) to optimize the parameters of neural network and the AdaBoost algorithm is improved to enhance the generalization ability of the model. The rest of this paper is structured as follows: The Section II introduces the principle of Generalized Regression Neural Network (GRNN) and MEA as well as showing how to improve the AdaBoost algorithm. In Section III, the experimental procedures are described in detail and the collected data is visualized. In Section IV, the prediction model of LED current distortion rate is established and the simulation analysis is conducted. The conclusions are presented in Section V.

II. MEA OPTIMIZATION GRNN AND IMPROVED ADABOOST ALGORITHM

A. THE GRNN CURRENT THD PREDICITION METHOD

GRNN is a radial basis function network based on mathematical statistic, thus, it belongs to a kind of Radial Basis Function (RBF) network, and its theoretical basis is nonlinear regression analysis. GRNN has strong nonlinear mapping ability and flexible network structure, which makes it faster to learn, greater to fault tolerance and robustness, so it is

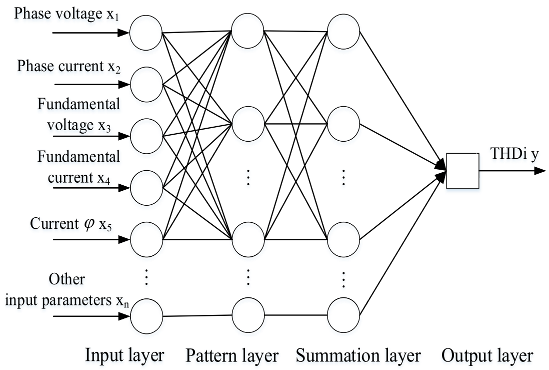


FIGURE 1. The topological structure of GRNN.

suitable for solving nonlinear problems [23]. Based on the characteristics of regression analysis, the GRNN can perform as well as Support Vector Machines (SVM) predictions when the amount of data is small.

GRNN consists of four layers: input layer, pattern layer, Summation layer and Output layer. The corresponding network input is $X = [x_1, x_2, \cdots x_n]^T$ and its output is $Y = [y_1, y_2, \cdots y_n]^T$. The topological structure of the LED's current harmonic distortion rate prediction model based on GRNN is shown in Fig. 1.

The phase voltage (x_1), phase current (x_2), fundamental voltage (x_3), fundamental current (x_4), current phase angle (x_5), K-factor (x_6) and other parameters (x_n) are used as inputs, the harmonic distortion rate of the LED lamps current is used as an output. The number of neurons in the pattern layer is equal to the dimension of the input quantity, and the transfer function of neurons contained in the pattern layer is shown in formula (1).

$$f_i = \exp\left[-\frac{(X - X_i)^T(X - X_i)}{2\sigma^2}\right] \tag{1}$$

$$\sigma = \frac{c_{max}}{\sqrt{2h}} \tag{2}$$

where, X is the input, X_i is the learning sample corresponding to the i-th neuron, σ is the variance of the Gaussian function, and C_{max} is the maximum distance from the center of the selected radial basis function. Formula (2) is the solution formula of σ, and h is the node number of pattern layer.

After the output of pattern layer, it enters the summation layer, which uses two types of neurons for summation. One type performs an arithmetic summation directly on the output of all pattern layer neurons. Another type is weighted sum of neurons in all model layers, whose connection weight is the j-th element in the i-th output sample. The two transfer function are as follows:

$$S_D = \sum_{i=1}^{n} F_i \tag{3}$$

$$S_{Dj} = \sum_{i=1}^{n} y_{ij} F_i \tag{4}$$

The output of this prediction model only includes the current harmonic distortion rate, so the number of neurons in the output layer is 1. Divide the output of the two types above that we can get the model output

$$y_i = \frac{S_{Dj}}{S_D} \tag{5}$$

Formulas (1)-(5) describe the transfer functions and outputs in each part of GRNN. From these formulas, the parameters affect the prediction performance of GRNN include radial basis function center C and Gaussian function variance σ. Generally, K-means clustering method can be applied to solve the center C of the basis function, so as to determine σ. the relevant theoretical was proofed in [24]. In addition, since GRNN also uses RBF as node activation functions, it is also affected by the radial basis expansion coefficient: SPREAD, which influence the number of responses generated in RBF neurons. So, rational selection of SPREAD is an important method to improve GRNN performance. The value of SPREAD is critical because if the value is too large, it will increase the complex of calculation and lead the output too smooth, however, if the value is too small, there will be insufficient neurons involved in the computation. Therefore, in order to solve the problem of SPREAD selection, the Mind Evolution Algorithm is chosen to optimize the parameter value in this paper.

B. THE FUNDAMENTALS OF MIND EVOLUTIONARY ALGORITHM AND MEA_GRNN

According to different input data, the number of RBF neurons in GRNN local response is different, and there is no prior knowledge to select the optimal value of SPREAD. For that the MEA of evolutionary algorithm is introduced to conduct cyclic optimization of SPREAD.

MEA is a kind of computational method which simulates the evolution process of human thinking, proposed by Sun [19]. It inherits the concepts of population and evolution from Darwin's theory of evolution and holds that the evolution of human minding has two processes: similartaxis and dissimilation. The process of similartaxis means that individuals learn from the winners, while the process of dissimilation is reflected in the transformation and development of individuals focus on their differences. Compared to traditional optimization algorithms such as genetic algorithms the proposed method has many advantages:

- It overcomes the shortcomings of traditional evolutionary algorithm, such as premature or slow convergence speed, and improves the search efficiency greatly.
- The role of similartaxis is to make each Sub-population mature in an optimal state: P, and dissimilation is to make the Sub-population move from state P to another optimal state which has a higher degree of adaptation, and gradually move to the global optimal state. The similartaxis and dissimilation of MEA can coordinate with each other and maintain a certain degree

of independence, which can improve the overall search efficiency of the algorithm.

- MEA could memorize more than one generation of evolutionary information, which can guide convergence and alienation in a favorable direction.
- Both crossover and variation operators in genetic algorithms are dual in nature, which means they may produce good genes or destroy the original genes, while similartaxis and dissimilation in MEA can avoid this problem.

The algorithm flow of MEA [25], [26]:

1) At the beginning of optimization, set N ($N = W + T$) Sub-populations, W is the number of superior Sub-populations, T is the number of temporary Sub-populations. The information of the winner in the competition process is recorded by the superior sub population and the temporary sub population records the global competitive process. Information includes the serial number, action and score of an individual or population, which is disseminated between individuals and populations through bulletin boards. Individuals within the sub population post their own information on local bulletin boards, and global bulletin boards are used to post the information of each sub population.

2) Similartaxis begins when Sub-populations are set up. Similartaxis refers to the process in which individuals compete to become winners, and a sub population is considered mature when its score no longer changes. If the score of the sub population is less than a certain temporary sub population, this winning sub population is replaced, and the individuals in the population are released to form a new temporary sub population, which continues to participate in the competition. This process is dissimilation.

3) The information of similartaxis and dissimilation is constantly updated to the global bulletin board and local bulletin board, calculation is performed in a loop, until a winning sub population defeats all other populations, then the individual with the highest score in that population is the global optimal solution.

The flow of our proposed MEA-GRNN algorithm:

The traditional method of SPREAD optimization is mesh division under Cross-Validation (CV). However, when the search range is large, the optimization process will become slow and easy to fall into local optimum [27]. Therefore, this paper takes the value of SPREAD as the optimization parameter of MEA algorithm and proposes MEA-GRNN algorithm to predict the THDi of LED lamps.

1) Determining fitness function. As shown in formula (6), the sum of absolute values of predicted current distortion rate errors in the training set under CV cross validation is taken as the fitness function value of MEA.

$$F = k\left(\sum_{i=1}^{n} abs(y_{\mathrm{i}} - o_{\mathrm{i}})\right) \tag{6}$$

2) Create the initial population. In the space S, there are N individuals, and the W excellent individuals with the highest scores are selected as the initial winning Sub-population P_{win} according to fitness; the remaining N-W individuals become temporary sub population P_{temp}.

$$S(0) = [S_1(0), S_2(0), \cdots S_{\mathrm{n}}(0)] \tag{7}$$

$$P(0) = P_{\mathrm{win}}(0) \cup P_{\mathrm{temp}}(0) \tag{8}$$

3) Similartaxis process, which can be expressed in formula (9). Similartaxis means that individuals continue to be selected around P_{win} to form a new Sub-population. Our model is to compare the prediction error of distortion rate among individuals and the score is judged. If the score of the newly selected individual is higher than the original one of P_{win}, this individual is the new winner of the population.

$$\begin{cases} P_{\mathrm{new}}(t) = [P_{\mathrm{win}}(t), S_1(t), \cdots S_{\mathrm{n}}(t)] \\ P_{\mathrm{win}}(t+1) = \max[P_{\mathrm{new}}(t)] \end{cases} \tag{9}$$

4) Dissimilation process. A superior Sub-population matures after similartaxis, and if the Sub-population's score is less than that of the adjacent temporary Sub-population, this superior group will be disbanded. That is, if the formula (10) is satisfied, the dissimilation operation is performed. In our model, the errors caused by different SPREAD values selected are also different. If the error is large, the population will be disbanded.

$$P_{\mathrm{temp}}(t) > \min[P_{\mathrm{new}}(t)] \tag{10}$$

5) Decode optimal individual. After the dissimilation operation is completed, MEA iteration optimization is completed. The best individual found is decoded according to the encoding rules, so that the optimal SPREAD value for GRNN is obtained.

C. IMPROVED GRNN-ADABOOST ALGOTITHM

According to the above description, GRNN with good prediction accuracy and robustness is first adopted as the basic prediction algorithm. Then MEA is used to improve the model performance, however, considering that LED lamps are equipped with the different types of ballasts, the collected training data will have some differences, and the prediction accuracy of a kind of algorithm may fluctuate when applied to different samples. To address this potential problem, the AdaBoost algorithm based on ensemble learning is introduced and improved in this paper.

In recent years, ensemble learning has become a research hotspot in the field of machine learning rely on the improvement of generalization ability of algorithms [28], [29]. AdaBoost is a widely used ensemble learning algorithm whose basic idea is to combine the outputs of multiple "weak" predictors to produce more effective predictions.

1. The algorithm flow of AdaBoost is as below [30]:

1) Set weak prediction algorithm and m group training data $[(x_1, y_1), (x_2, y_2) \cdots (x_{\mathrm{m}}, y_{\mathrm{m}})]$; set the number of weak predictors T and error threshold φ; initialize the sample weight according to formula (11).

$$\alpha_1 = \alpha_2 = \cdots = \alpha_{\mathrm{m}} = D_1 = \frac{1}{m} \tag{11}$$

2) When training the t-th weak predictor, the prediction sequence $g(t)$ can be obtained. To calculate the error ε_t between each predicted output value and the actual value and then sum up the ε_t to get E_t.

3) The weight of each weak predictor is calculated by formula (12).

$$\omega_t = \left|\frac{1}{2}\ln\left(\frac{1-E_t}{E_t}\right)\right| \tag{12}$$

4) To adjust the weight of training data, the formula is as follows:

$$D_{t+1}(i) = \frac{D_t(i)}{B_t} * \begin{cases} \exp[-\omega_t y_i g_t(x)] & \varepsilon_t > \phi \\ 1 & \varepsilon_t \leq \phi \end{cases} \tag{13}$$

where, B_t is the normalization factor, the purpose of which is to make the sum of distribution weights equal to 1 under the condition that the weight ratio remains unchanged.

5) After T-rounds training, the mathematical model $f_i(x)$ of T weak predictors is combined into a strong predictor $G(x)$ by using equation (14).

$$G_i(x) = \sum_{t=1}^{T} \omega_t f_t(x) \tag{14}$$

Formula (12) shows that weak predictors with smaller prediction errors could get larger weights, which reflects the improvement of prediction performance by the AdaBoost.

2. Improvements of AdaBoost algorithm.

However, we can also find that the AdaBoost algorithm is sensitive to the threshold φ in formula (13). Too large φ will lead to a decrease in prediction accuracy, while too small will result a great increase in the amount of calculation. Therefore, this paper improves the threshold selection of the traditional AdaBoost algorithm by replacing it with an adaptive factor based on Sigmoid function to avoid the performance degradation caused by improper threshold selection.

First, the Root Mean Square Error (RMSE) of each weak predictor prediction result is calculated as a reference for adaptive adjustment.

$$\varepsilon_{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\varepsilon_t^2} \tag{15}$$

Then replace φ with an adaptive variable according to formula (16).

$$\varphi_{t+1} = \begin{cases} \varphi_t(1+\gamma) & \varepsilon_{RMSE}^{t} \geq \varepsilon_{RMSE}^{t-1} \\ \varphi_t(1-\gamma) & \varepsilon_{RMSE}^{t} < \varepsilon_{RMSE}^{t-1} \end{cases} \tag{16}$$

The expression of γ in the formula is as follows. To make the formula more concise, use $\varepsilon\,(t)$ instead of ε_{RMSE}^{t}.

$$\begin{aligned} \gamma &= \frac{1}{1+e^{-|\varepsilon(t)-\varepsilon(t-1)|}} - \frac{1}{2} \\ &= \frac{1-e^{-|\varepsilon(t)-\varepsilon(t-1)|}}{2\left(1+e^{-|\varepsilon(t)-\varepsilon(t-1)|}\right)} \end{aligned} \tag{17}$$

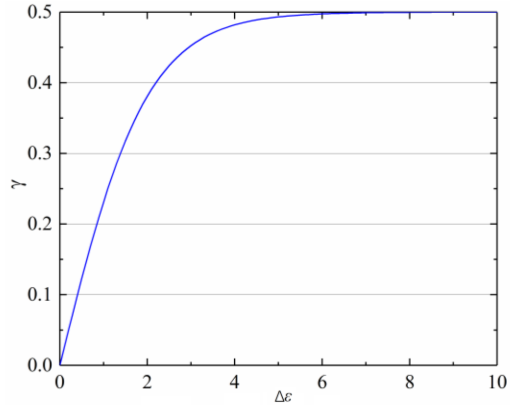


FIGURE 2. Adaptive factor function diagram.

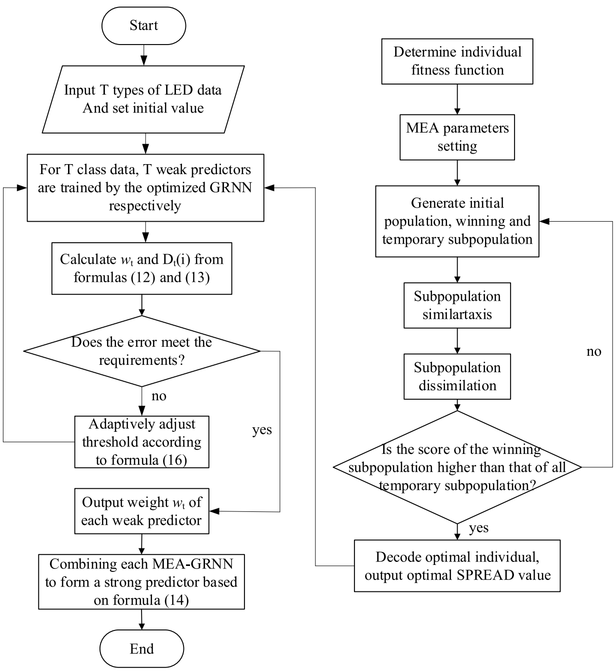


FIGURE 3. Flowchart for predicting current harmonic distortion rate of LED lamps.

The expression of γ is based on the Sigmoid function. As shown in Fig. 2, γ has a range of 0-0.5 and the rising trend gradually slows down. This indicates that whether the ε_{RMES} increases or decreases, the threshold φ will change in the same trend and there will be no mutation.

As described in this chapter, the flow of our proposed prediction model is shown in Fig. 3.

III. EXPERIMENT AND DATA ACQUISITION

This section mainly describes the design of the experimental setup, and collects the data related to the harmonic emission characteristics of LED lamps. A portion of the data will be visualized and analyzed.

A. LED LAMPS DRIVER CIRCUIT

There are many kinds of driving circuits for LED lamps, according to different topological structures and conversion principles they can be divided into constant current diode driving circuit, resistance current limiting driving circuit, resistance capacitance buck driving circuit, linear driving circuit, buck constant current driving circuit etc. The buck constant current drive circuit is separated into Passive Power Factor Correction (PPFC) and Active Power Factor Correction (APFC) according to the different Power Factor Correction (PFC) circuits. Currently, the most common LED drive circuits mainly include resistance-capacitance buck drive circuit and buck constant current drive circuit [5], [31].

Resistance capacitance buck drive circuit is widely used in LED with its simple circuit structure and wide voltage range. Its typical topological structure is shown in Fig. 4, where capacitor C_1 is responsible for step-down; R_1 is charge discharge resistor for C_1; C_2 and C_3 are used to filter the rectified pulsating DC voltage into a stable DC voltage. R_2 is a protection resistor, which can prevent the impact of the surge current when the LEDs are switched on, and after step-down, the voltage on R_2 is small, so although there will be extra loss, the loss is relatively small. RV is a varistor, whose function is to discharge the instantaneous pulse high voltage in the input power supply to the ground, so as to protect the LED from the instantaneous high voltage breakdown.

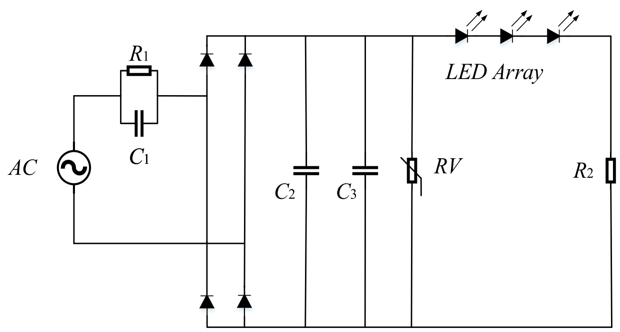


FIGURE 4. Typical topology of resistance capacitance buck drive circuit.

The buck constant current drive circuit adds a constant current control circuit to the structure of the resistance-capacitance step-down drive circuit, so that the current is not affected by the fluctuation of input voltage. The topological structure is shown in Fig. 5.

We can see from Fig. 4 and Fig. 5 that the circuits of these two structures will make a phase angle between the AC side current and the fundamental voltage. Due to the existence of voltage stabilizing filter capacitor in DC side, a large amount of harmonics will be injected into AC side during operation. If the voltage contains background harmonics, it will further influence the phase, active power, and power factor.

B. HARMONIC MEASUREMENT PROCEDURE

In order to collect the data required by the current harmonic distortion rate prediction model and verify the influence of different driving circuits on current distortion. we tested 10 LED lamps from different manufacturers, including various common LED drive circuits. For ease of illustration,

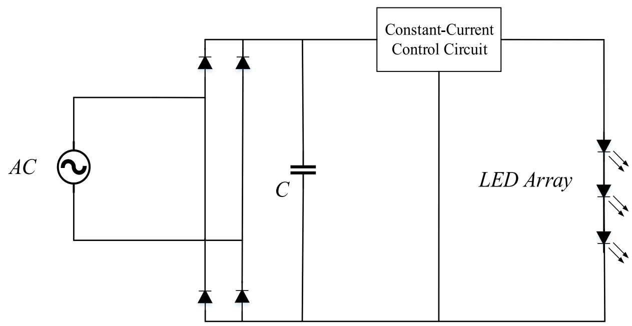


FIGURE 5. Typical topology of buck constant current drive circuit.

TABLE 1. Technical data for the test lamps.

Trade Name	Nominal Power P (W)	Luminous Flux (lm)	Equivalent to Incandescent P (W)	Life Span (hour)
A4	4	350	32	10000
A4.8	4.8	500	40	8000
A6.5	6.5	600	48	15000
B5	5	400	40	8000
C3	3	250	25	15000
C4	4	350	40	15000
C7.5	7.5	650-750	60	15000
D3.3	3.3	250	25	15000
D5.5	5.5	470	40	15000
E9	9	806	60	25000

each brand and its power are identified with a combination of letters and numbers. The basic technical parameters are shown in Table 1.

Set up an experimental setup according to Fig. 6 to obtain accurate data on the harmonic components of the LED lamp current. The setup consists of five components: Fluke 435 power quality analyzer, voltage regulator, LED lamp under teste, illuminance meter and personal computer for data processing. The voltage regulator adjusts the voltage within the allowable voltage range of the LED lamps. We use Fluke 435 to measure the current harmonic distortion rate, current value, K factor and other parameters of the LED lamps under different input voltage levels. It should be mentioned that when measuring the harmonic data under the nominal voltage, each lamp needs to be kept on for 10 minutes to avoid the interference of accidental factors [4]. The collected data are analyzed by Power Log 430-II and MATLAB software.

The variation trend of harmonic current content in different types of LED lamps under nominal voltage is shown in Fig. 7, which indicates that some of the tested LED lamps produce high levels of harmonics, such as A4.8, B5 and C7.5. These three types of lamps do not use any filter, so the total distortion rate is more than 105%. According to the International Electrotechnical Commission IEC61000-3-2, all lighting loads belong to Class C loads. Among them, the harmonic emission limit of lamps with power below 25W should meet the following requirements: The third harmonic current should not exceed 86% of the fundamental while

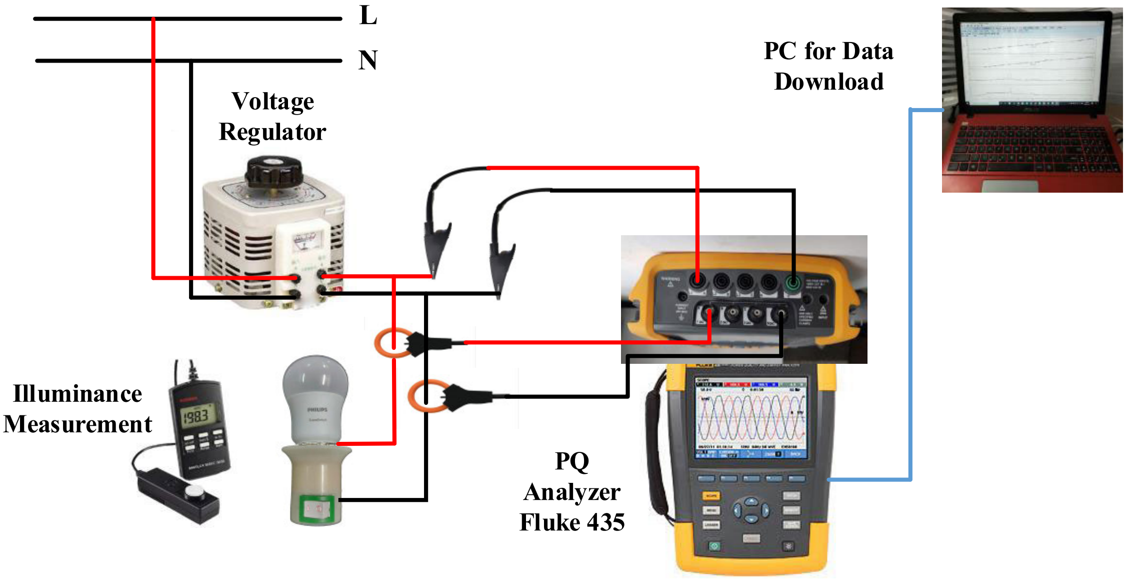


FIGURE 6. Harmonic measurements experimental setup.

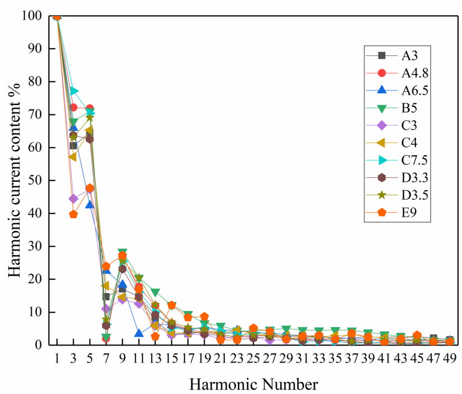


FIGURE 7. Comparison of harmonic current content of different LED lamps.

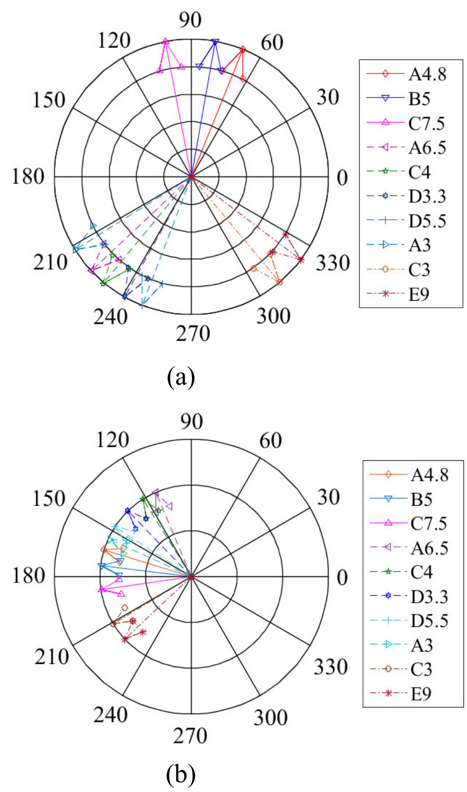


FIGURE 8. (a) Phase angle of all LED lamps for third harmonic current. (b) Phase angle of all LED lamps for fifth harmonic current.

the fifth harmonic should not exceed 61%, it means that the total harmonic distortion of the current should not exceed 105% [32], Therefore, these three types of lamps are beyond the acceptance scope of IEC61000. Besides, the total THD of A3, A6.5, C4, D3.3 and D5.5 range from 83%-100%. The driving circuits used in these 5 types of lamps are all buck constant current type. The best performance of harmonic distortion is C3 and E9, the distortion rate of the two lamps is 70%. The corresponding experimental uncertainty was within 2%.

The initial phase distribution of each harmonic of different types of LED lamps are collected and analyzed when the fundamental voltage crosses zero. The initial phase distribution of the 3rd and 5th harmonic currents of each LED lamp is shown in Fig. 8.

As we can see from Fig. 8, the driving circuit will affect the initial phase distribution of current, and the phase angle distribution of different types of driving circuits is quite different. For the three LED lamps with resistance-capacitance buck circuit, the third harmonic phase is concentrated between 60°-120°, the fifth harmonic is distributed around 180°. For LED lamps whose drive circuits are buck constant current drive circuit, the third harmonic is concentrated in the third quadrant, and the fifth harmonic is concentrated in 110°-160°. C3 and E9 using PFC technology, which are relatively close in phase distribution and the third harmonic

TABLE 2. The correlation coefficient between the parameters and THDi.

	Correlation Coefficient	Phase Voltage	THDu	RMS Current	Fundamental Current	Current Phase	Illumination	K-Factor	Harmonic Power	Temperature
THDi	Pearson	0.623	-0.417	-0.126	-0.464	0.242	-0.444	0.228	0.135	0.095
	sig	0.000	0.054	0.010	0.000	0.000	0.057	0.000	0.006	0.726
	Spearman	0.580	-0.419	-0.123	-0.453	0.254	-0.442	0.279	0.679	0.296
	sig	0.000	0.055	0.012	0.000	0.000	0.059	0.000	0.000	0.266

phase is significantly different from the previous two types of lamps. In summary, we suggest when many LED lamps are needed, different drive circuits of LED lamps can be selected to achieve the purpose that mutual cancellation of different phase harmonics.

IV. SIMULATION AND ANALYSIS OF LED LAMPS CURRENT HARMONIC DISTORTION RATE PREDICTION MODEL

A. DATA PREPROCESSING AND FEATURE EMGINEERING

Through the experiments in Section III, we have collected data on up to 111 dimensions including voltage, current, current phase angle, K-factor, power, frequency and current distortion rate for the fundamental and each harmonic. At the same time, the illuminance of each lamp under tested was measured with an illuminance meter and used infrared thermometer to record the temperature of every LEDs change during the experiment. Selecting the appropriate input data among so many features can help to reach the upper limit of the algorithm's performance. Therefore, this subsection reduces the impact of unhealthy data on prediction performance and speeds up the model convergence through data pre-processing, feature fusion, and feature engineering.

We use correlation analysis in statistics to select the parameters related to current harmonic distortion rate. The specific method is to calculate Pearson Correlation Coefficient and Spearman Rank Correlation Coefficient, which could be calculated by (18) and (19) separately. Both coefficients can reflect the correlation, and the values range is $[-1, 1]$, the larger the absolute value, the stronger the correlation, and the symbols indicate the direction of the correlation [33], [34]. The results of correlation analysis are shown in Table 2

$$r = \frac{\sum\left(X-\bar{X}\right)\left(Y-\bar{Y}\right)}{\sqrt{\sum\left(X-\bar{X}\right)^2\sum\left(Y-\bar{Y}\right)^2}} \tag{18}$$

$$r_s = 1-\frac{6\sum d^2}{n\left(n^2-1\right)} \tag{19}$$

where, d is the difference between the ranks of each pair of observations after ranking the two variables respectively, and n is the number of all observation pairs.

As can be seen from table 2, although the two correlation coefficients show that THDu and illumination are negatively correlated with THDi, neither of them has passed the significance test, so these two parameters will not be included in the input of the prediction model. Since this paper studies small household LEDs, the influence of temperature can be ignored to a certain extent. Because the power of the tested LED lamps is below 9w, and LED is a cold light source, its working process does not generate high temperature like an incandescent lamp, so the heat generated is small. Besides, the tested LEDs were used indoors, the change of indoor temperature difference was not obvious. Other parameters passed the correlation test, so, the inputs to the predictive model includes: Phase voltage, fundamental voltage, current through LED lamps, fundamental current, current phase angle, K-factor and harmonic power.

From the data, there is a large scale gap between the each other. In order to reduce the decline of modeling accuracy triggered by order of magnitude, all input and output data are normalized into decimal numbers between [0, 1] in this paper.

$$\dot{x} = \frac{x-x_{\min}}{x_{\max}-x_{\min}} \tag{20}$$

where, $\dot{x}$ is the normalized data of a sample parameter and x is the sample parameter; $x_{\max}$ and $x_{\min}$ are the maximum and minimum values in the sample respectively.

B. SIMULATION AND ANALYSIS

1) SIMULATION PARAMETERS SETTING

The power quality analyzer we use can record data every 5 seconds. After eliminating duplicate data, we obtained 714 groups of data through experiments. When performing neural network training, the training set and test set are generally divided into 3:2 or 4:1. After training, the model is tested with these two scales separately, and the test results showed that when the 3:2 allocation is performed, the prediction accuracy is 1.4% lower than the 4:1 allocation on average. This is due to the fact that neural networks require more data for feature learning, and the overall amount of data in this paper is small, therefore more data needs to be divided into training sets. So, after randomly arranging each set of data, we selected the first 564 groups as training samples and the remaining 150 groups as test samples to test the performance of the algorithm.

The parameters of each algorithm are set as follows: The kernel function of GRNN algorithm is Gaussian RBF kernel function, the radial basis expansion coefficient (SPREAD) is obtained by MEA optimization, and the maximum iteration number is set to 1000; the population size of MEA algorithm is 200, the size of sub population is 20, the number of superior Sub-populations and temporary Sub-populations is 5, and the maximum number of iterations is set to 20; The improved

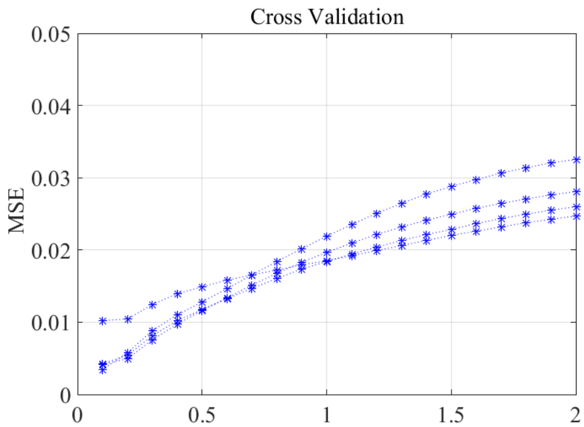


FIGURE 9. Cross validation optimization.

AdaBoost algorithm has 10 learners, the iteration times of each learner is 200, and the initial threshold is set to 0.1.

2) SIMULATION RESULT

The SPREAD value is first optimized by using MEA. According to the introduction of the Section II, the individual fitness function is determined by CV optimization. CV optimization curve is shown in Fig. 9. Then the similartaxis and dissimilation of MEA are performed. The specific operation process is shown in Fig. 10.

In Fig. 10, each pair is a group:

- From Fig. 10 (a) we can observe that after several similartaxis, each Sub-population has matured. There was no change in Sub-population 2, because no better individuals were found around the center of the Sub-population.
- Compared with Fig. 10 (a) and (b), after the superior Sub-population and temporary Sub-population were mature, Sub-populations 1 and 2 in the temporary Sub-population had higher scores than those in the superior Sub-population 2, 4 and 5. Therefore, it was necessary to implement dissimilation operation and add three new Sub-populations to temporary Sub-population.
- In the same way, the two populations in (c) and (d) were analyzed, and it was found that the number 2 in temporary Sub-population was better than number 4 in superior Sub-population, so the dissimilation was continued.
- After similartaxis again, Fig.10 (e) and (f) show that the best individual performance (score 7.1) in the temporary Sub-population was also lower than that of the individual in superior Sub-population who with the lowest score (score 7.6). At this time, the optimal individual in the superior Sub-population was the best individual in this MEA optimization, and it output the best SPREAD after decoding.

The improved AdaBoost algorithm proposed in this paper is used to integrate the MEA-GRNN, and the prediction results of the model are shown in Fig. 11.

As can be seen from Fig. 11, Our proposed algorithm predicts the THDi variation range of LED lamps is matched with the actual situation basically. The error is small, and some fluctuating distortion rates can be more accurately predicted. Through calculation, the accuracy of this model is 95.48%. A comparison with other models is shown in Fig. 12.

Fig.8 depicts that the THDi of LED lamps distribute between 30%-110% basically. The distribution curve of the predicted value is broadly consistent with the change trend of the measured value, which indicate that these four models can be applied for effective prediction. But when the distortion rate is at the upper and lower limits of the variation range, the predicted results using the AdaBoost ensemble algorithm are closer to the actual value. From the image point of view, the prediction results of MEA-GRNN before and after using AdaBoost algorithm are relatively similar, so it is necessary to conduct specific error analysis in the next section.

3) ERROR ANALYSIS

We use Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Median Absolute Deviation (MAD) and Accuracy as error indicators for analysis. The formulas for the four indicators are given in equations (21) - (24). MAE reflects the average absolute error between the network predicted value and the actual value. The smaller the value of MAE, the smaller the prediction error and the better the fitting effect of the model. The MAD is the median absolute error, which is better than the standard deviation for handling outliers in the data set, and can greatly reduce the impact of outliers on model evaluation. The error index of each model is shown in Table 3.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\left(y_{\mathrm{i}} - \hat{y}_{\mathrm{i}}\right)\right| \tag{21}$$

$$MAD = median(\left|y_1 - \hat{y}_1\right|, \cdots, \left|y_{\mathrm{n}} - \hat{y}_{\mathrm{n}}\right|) \tag{22}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{\mathrm{i}} - \hat{y}_{\mathrm{i}}\right)^2} \tag{23}$$

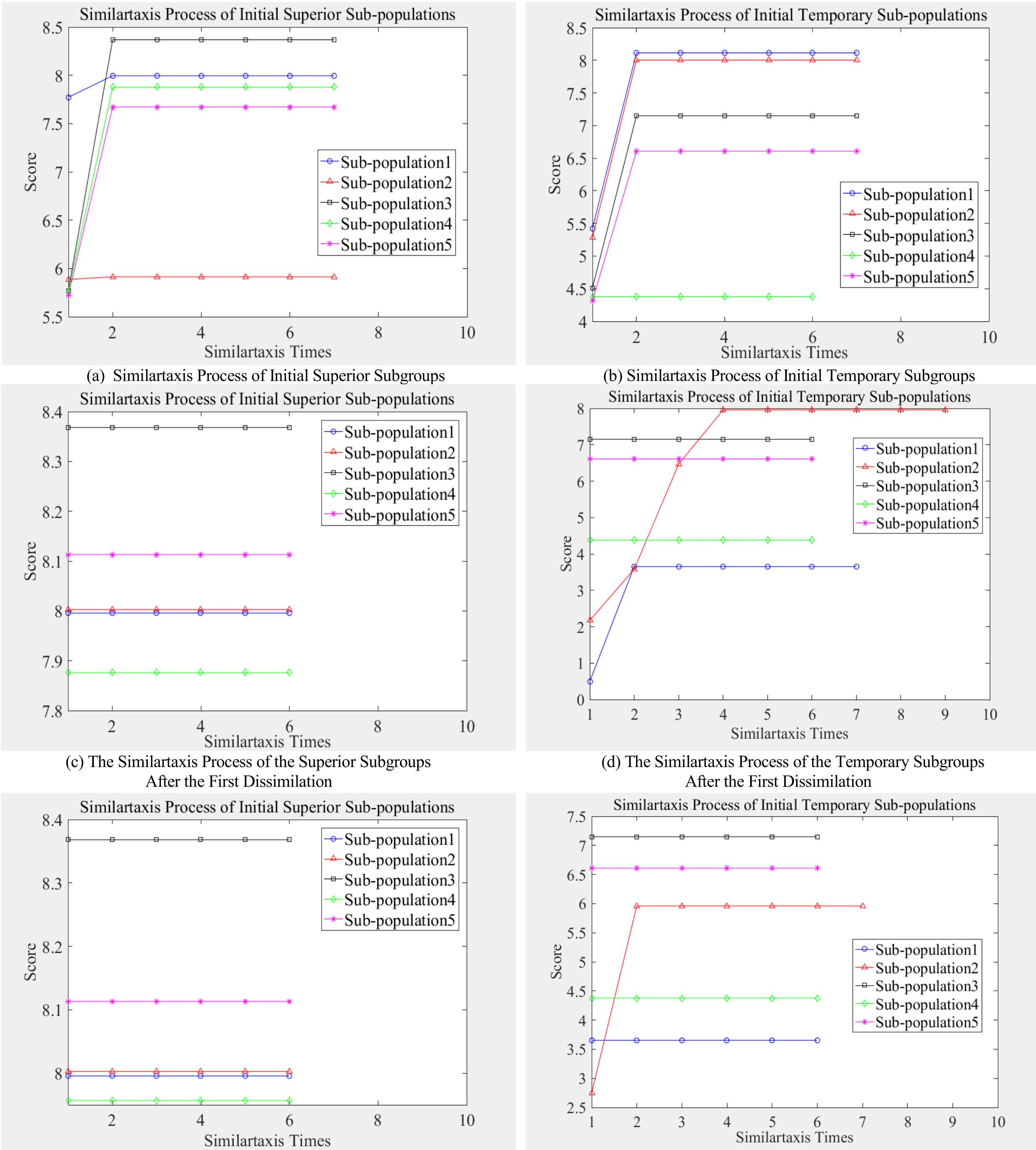
$$Acc = (1 - \frac{\left|y_{\mathrm{i}} - \hat{y}_{\mathrm{i}}\right|}{|y_{\mathrm{i}}|}) \times 100\% \tag{24}$$

where, y_{i} is the network forecast data and $\hat{y}$ is the real data.

TABLE 3. Comparison with different evaluation index.

Error Index	BP	GRNN	MEA-GRNN	Ada-MEA-GRNN
RMSE	0.2818	0.3477	0.1517	0.1483
MAE	0.0501	0.1231	0.0468	0.0385
MAD	0.0347	0.1114	0.0317	0.0201
Accuracy (%)	88.74	86.60	93.96	95.48

From Table 3, we discovered that the GRNN improves significantly in accuracy and RMSE after using MEA, which illustrating the MEA effectively improves the prediction ability of the model. After applying AdaBoost algorithm, RMSE



(a) Similartaxis Process of Initial Superior Subgroups

(b) Similartaxis Process of Initial Temporary Subgroups

(c) The Similartaxis Process of the Superior Subgroups After the First Dissimilation

(d) The Similartaxis Process of the Temporary Subgroups After the First Dissimilation

(e) The Similartaxis Process of the Superior Subgroups After the Second Dissimilation

(f) The Similartaxis Process of the Temporary Subgroups After the Second Dissimilation

FIGURE 10. (a)-(f) The process of similartaxis and dissimilation.

is further reduced and the accuracy is improved by 1.52%. It means that AdaBoost algorithm fully considers the influence of different training data on the model accuracy, and effectively combines the prediction results of each model.

In order to further verify the generalization ability of this method, the input is reduced from 7 dimensions to 4 dimensions. That is, when only voltage, fundamental voltage, RMS current and fundamental current are retained as inputs, error analysis of each model is carried out.

The Table 4 described that even if the input features are reduced, the prediction accuracy of our model is only reduced by 1.78%, which is 10.57% and 8.76% higher than that of GRNN and BP neural network, respectively. RMSE is also the smallest among all models. This indicates that the overall error of the method in this paper is smaller than other models, besides, the improved AdaBoost algorithm effectively enhances the generalization of the prediction model.

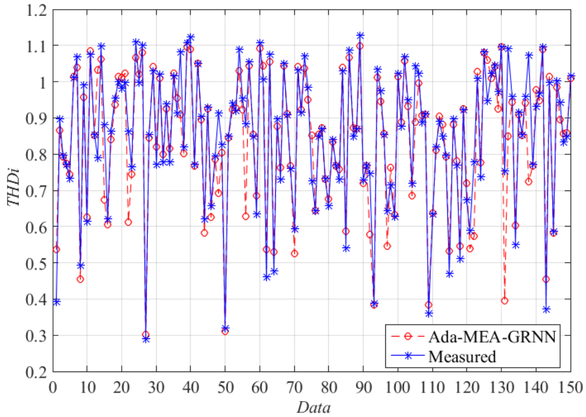


FIGURE 11. Ada-MEA-GRNN prediction results.

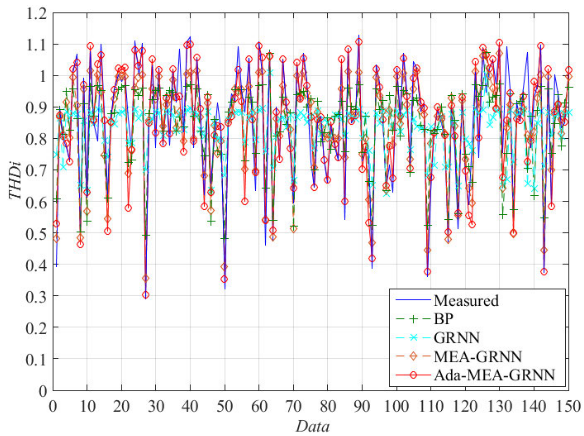


FIGURE 12. BP, GRNN, MEA-GRNN, and ours model evaluations.

TABLE 4. Comparison with different evaluation index (4 Inputs).

Error Index	BP	GRNN	MEA-GRNN	Ada-MEA-GRNN
RMSE	0.3298	0.3546	0.1895	0.1660
MAE	0.0938	0.1296	0.0570	0.0572
MAD	0.0836	0.1109	0.0502	0.0463
Accuracy (%)	84.94	83.13	91.27	93.70

V. CONCLUSION

In this paper, we studied the harmonic characteristics of commonly used LED lamps, and the harmonic parameters of LED lamps with different driving circuits are collected through design experiments. The experimental results show that all LED lamps will produce harmonics, and the THDi of the tested lamps is between 30% and 110%. The phase angle of the harmonic current generated by different drive circuit lamps is also different. The phase angles are distributed in 60°-120°, 210°-250° and 300°-330° respectively, which means that the harmonic partial cancellation can be achieved by designing and combining LED lamps with different drive types.

In addition, this paper researches the integration algorithm and optimization algorithm in machine learning. Proposed an adaptive factor method to improve the threshold selection in AdaBoost algorithm, and optimized GRNN through MEA. An Ada-MEA-GRNN prediction model was finally established, then, we use the data collected from the experiment for model training and performance evaluation, the following conclusions can be drawn:

1) MEA successfully optimized the selection of SPERAD values in GRNN, making the predictions accuracy of MEA-GRNN model was 7.36% higher than that of unoptimized GRNN, and RMSE decreased by 0.196.

2) Considering the differences between data generated by different lamps, the AdaBoost algorithm is applied to integrate the weak predictors based on different training data, which further improves the prediction accuracy of the prediction algorithm. The accuracy is 95.48%, and its RMSE, MAE, MAD are also the smallest among the models.

3) We use the sigmoid-based adaptive factor to improve AdaBoost algorithm, which avoided performance degradation due to improper threshold selection.

4) By reducing the dimension of input data, we found that our proposed prediction model has good generalization ability. The prediction accuracy is only reduced by 1.78%, it is 10.57% and 8.76% higher than that of GRNN and BP. In the future, this model can be integrated into smart meters to monitor harmonic sources. In addition to the harmonic field, this method can also provide a reference for other fields to establish prediction models.

In the future, we will consider how to enrich this research by studying the harmonic characteristics of LEDs and CFLs when used in combination. To build a more universal forecasting model using multi-source data.

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