IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 27, 2020, accepted April 15, 2020, date of publication May 20, 2020, date of current version August 17, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2995716

A Hierarchical Teaching-Learning-Based Optimization Algorithm for Optimal Design of Hybrid Active Power Filter

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This work was supported in part by the National Natural Science Foundation of China under Grant 61503177, Grant 81660299, and Grant 61863028, in part by the China Scholarship Council through the State Scholarship Fund (CSC) under Grant 201606825041, in part by the Science and Technology Department of Jiangxi Province of China under Grant 20161ACB21007, Grant 20171BBE50071, and Grant 20171BAB202033, and in part by the Education Department of Jiangxi Province of China under Grant GJJ14228 and Grant GJJ150197.

ABSTRACT Hybrid active power filter (HAPF) has been widely used to suppress harmonics in the electric power system. However, selecting HAPF parameters accurately remains a primary challenge faced by researchers. To optimize HAPF parameters and reduce the harmonic pollution, this paper proposes an improved teaching-learning-based optimization algorithm, namely HTLBO. In HTLBO, a self-study strategy based on Lévy-Flight is developed to avoid the population falling into local optima. Furthermore, in the teaching phase, all learners are divided into three hierarchies according to their learning ability, and learners at different hierarchies learn from different teachers respectively. While in the learning phase, each learner learns not only from a better individual but also from a worse individual. The above hierarchical teaching strategy and improved learning strategy effectively balance the exploration tendency and exploitation tendency of the algorithm. In addition, a competitive mechanism based on dynamic clustering is proposed to ensure the vitality of the entire population. The performance of HTLBO is verified by identifying the parameters of two classical HAPF topologies. Experimental results present that compared with the other nine well-established meta-heuristics algorithms, HTLBO achieves outstanding performance, especially in terms of accuracy and reliability.

INDEX TERMS Hybrid active power filter (HAPF), harmonic pollution (HP), hierarchical learning, meta-heuristics, teaching-learning-based optimization (TLBO).

I. INTRODUCTION

The electric power system is part of the most important foundations for the construction of modern society. However, with the rapid development of the global economy and the improvement of living standards, the global demand for electricity is drastically increasing. Non-linear power electronic equipment is extensively used in various industries and produced substantial harmonic pollution (HP). The level of harmonic distortion in the distribution network has risen significantly, caused distortions in the voltage and current waveforms, and brought great harm to the electric power system. Thus, harmonic pollution has become one of the major problems that needed to be solved urgently.

Recently, a considerable literature has grown up around the theme of harmonic suppression [1]–[5]. The methods of harmonic suppression in literature could be mainly classified into two categories: active harmonic control and passive harmonic suppression. The first type of method is to optimize the power electronic equipment which produces harmonics and tries to produce as little or even no harmonics as possible. The second type of method is to remove harmonics by installing some filtering devices in the power system. The former is difficult to realize because of its high cost and difficult operation. Thus, the main measure for harmonic suppression in the power grid is to install filters [6].

There are three types of filters commonly used to harmonic suppression: Passive Power Filter (PPF), Active Power Filter (APF), and Hybrid Active Power Filter (HAPF).

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

Among them, PPF has been a feasible way since its low cost, simple structure, and easy implementation. But unfortunately, the performance of PPF is vulnerable to the power grid impedance. Besides, the PPF is easy to resonate with the system, and the filtering effect is not as perfect as APF. On the contrary, APF is flexible in control and fast in response, it can overcome the shortcomings of traditional PPF, but it is still difficult to be widely used because of its small capacity and high cost. Therefore, how to balance the performance and cost has long been a controversial topic in wide range fields of filter design. Recently, researchers have shown enormous interest in HAPF. HAPF adequately combines the advantages of APF and PPF, it filters out the main low-order harmonics through the passive branch, while the remaining few high-order harmonics are processed by APF. Due to its low cost and significant filtering effect, a growing body of literature has recognized the importance of HAPF [7]–[9].

All three types of filters are applied to the treatment of harmonic pollution. Furthermore, it is worth mentioning that meta-heuristic technology plays a vital role in the design of the filters described above. In 2005, F. Cupertino proposed a new technique based on Genetic Algorithm (GA) to optimize the simulation model parameters of a parallel active power filter system, and the overall performance of the system is improved greatly [10]. In 2009, Y.-P. Chang *et al.* designed a large-scale passive harmonic filter under rich harmonic current sources by using the nonlinear time-varying evolution particle swarm optimization technique (PSO-NTVENN) [11]. In 2011, D. Rachid and S. Slimane applied the ant colony optimization (ACO) algorithm to research the passive filters sizing issue in an electric network and achieved satisfactory results [12]. Besides, W. Jian *et al.* tried to the optimization application of the GA in switch harmonic filter and experimental results show that switching harmonics can be effectively suppressed [13]. In 2015, a modified bat algorithm is developed by N.-C. Yang *et al.* to solve PPF design problems, which availably suppressed critical harmonics and improved power factor [14]. In 2016, A. K. Tiwari *et al.* applied the ACO to the HAPF design, and the results indicate that the HAPF designed by the ACO algorithm is feasible [15].

However, to the best of our knowledge, there is still much less research about the application of meta-heuristic technology in HAPF design in contrast to PPF and APF. What's more, in these few studies, most of the optimal design models of HAPF are expressed by multiple objectives [6], [15]. Obviously, it increased the computational difficulty and cost. Under these circumstances, P. P. Biswas *et al.* proposed a single objective function based on the analysis of two commonly used HAPF topologies, consisting of total voltage harmonic distortion (VTHD) and total current harmonic distortion (ITHD), which reduced the difficulty of HAPF design [16]. However, according to the theory of no free lunch [17], no algorithm can solve all optimization problems. Therefore, it is necessary to develop a new meta-heuristic algorithm for this scheme to obtain the optimal HAPF parameters.

Teaching-Learning-Based Optimization (TLBO) is a novel algorithm proposed by Rao *et al.* [18]. The algorithm has two phases: teaching phase and learning phase, and it finds the optimal solution by simulating the teaching process between the teacher and students in the class. In the teaching phase, all students follow the teacher to learn while students discuss with each other in the learning phase. Because of its advantages of simple structure and few control parameters, TLBO algorithm is extensively used in scientific research and industry, such as economic dispatch [19], robot design [20], plasma arc cutting [21], iris recognition [22], trajectory planning [23], fuzzy clustering [24], generation control [25], fault detection [26], and shop scheduling [27].

Nevertheless, as a young algorithm, there is still much room for improvement especially in terms of global search capability and accuracy. Considering this situation, some scholars have improved TLBO according to different strategies. J. Liu *et al.* introduced the competition-based initialization strategy, preview process, and remedial training strategy into the original TLBO algorithm, which improved the convergence speed of the algorithm [28]. S. Li *et al.* proposed a new teaching strategy and a new learning strategy to achieve better performance in terms of accuracy and reliability [29]. Besides, X. Qu *et al.* effectively enhanced the search ability of standard TLBO by introducing an adaptive teaching factor, a multi-meme learning strategy, and the conservation of information incentive operators [30].

Unfortunately, as far as we know, the TLBO algorithm and its proposed variants still fail to accurately identify the parameters of the two HAPF topologies. In this case, a Hierarchical Teaching-Learning-Based Optimization algorithm (HTLBO) is proposed in this paper, which aims to take advantage of meta-heuristics into the design of HAPF. In the original TLBO algorithm, all learners only learn from the best individual, that is, the teacher. On the one hand, it improves the exploitation ability of the algorithm. But on the other hand, it will cause the population vulnerable to fall into local optimal solutions. Thus, HTLBO adopts a novel self-study mechanism based on Lévy-Flight, this mechanism can generate the self-learners. The self-learners do not receive outside information and thus are not affected by the teacher. When learners stagnate in local optima, self-learners can guide them to escape from the local optima in time. Furthermore, according to the learning ability of different learners, HTLBO adopts different hierarchical teaching strategies to teach the learners. The learners at each hierarchy learn from different teachers, which further balances the exploitation and exploration trend. Similarly, we have also improved the original learning strategy in the learning phase. Thus, each learner not only learns from a better individual but also learns from a worse individual, which aims to make full use of the knowledge of the whole population and improve the overall knowledge level. Besides, the whole population is divided into the teaching-learning group and the self-study group. The teaching-learning group is divided into three hierarchies: good, medium, and poor. Before the iterative process, the hierarchy of all individuals is dynamically adjusted according to their objective function values. This competitive mechanism ensures the vitality and sustainability of the entire population. Through the above strategies, the overall performance of HTLBO is effectively improved.

The proposed HTLBO algorithm aims to accurately and reliably extract the parameters of HAPF and minimize harmonic pollution. To verify the effectiveness of the algorithm, we compared the HTLBO with nine other well-known metaheuristics algorithms. Comprehensive experimental results indicate that HTLBO shows great competitiveness in terms of accuracy and reliability.

The main contributions of this work are described below:

1) A self-study mechanism based on Lévy-Flight is introduced into the original TLBO algorithm to improve the global search capability.

2) Both teaching and learning strategies in the original TLBO algorithm have been improved. In the teaching phase, a hierarchical learning mechanism is proposed to improve teaching efficiency. Besides, each learner learns from individuals with different levels in the learning phase. It efficiently promotes the balance between global exploration and local exploitation.

3) A new cluster strategy is proposed for dynamically adjusting the hierarchy of all individuals according to the objective function values, ensuring the vitality of the entire population.

4) The effectiveness of HTLBO is extensively evaluated on two typical HAPF topologies to accurately identify the corresponding parameters.

5) By comparing with other well-established metaheuristics algorithms, the performance of the HTLBO algorithm is verified. That means HTLBO can be an excellent alternative to parameter selection in HAPF design.

The remainder of this paper is organized as follows. In Section II, two popular HAPF topologies and their objective function are given. Section III introduces the original TLBO and Lévy-Flight algorithms. Section IV develops the HTLBO algorithm in detail. Section V discusses the case studies of HAPF. Section VI discusses the comparison and analysis results of HTLBO with the other nine algorithms. Finally, the conclusion and future work are provided in Section VII.

II. HYBRID ACTIVE POWER FILTERS MODEL

In the literature [16], two popular HAPF topologies are studied. In addition, a single objective function is formulated to minimize harmonic pollution in a system consisting of a non-linear source and non-linear loads. They are respectively described as follows.

A. CIRCUIT ANALYSIS

'APF in series with shunt passive filter' (series topology structure) and 'combined series APF and shunt passive filter' (parallel topology structure) are two popular HAPF topologies in the electric power system, the configuration legends

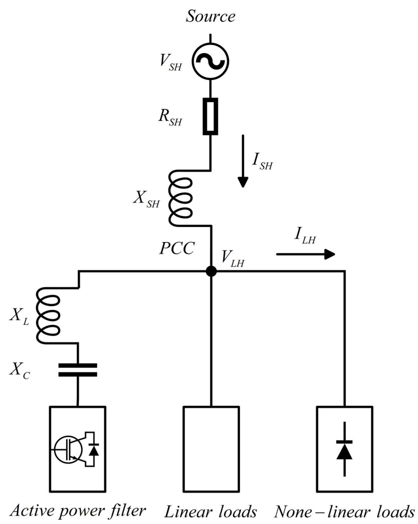


FIGURE 1. APF in series with shunt passive filter (series topology structure).

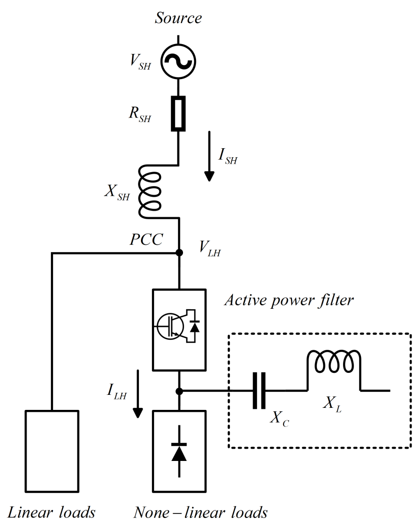


FIGURE 2. Combined series APF and shunt passive filter (parallel topology structure).

without indicating the interface transformer are shown in Fig. 1 and Fig. 2 respectively. In the first configuration, harmonic currents are injected into the passive filter by the active filter to cancel load harmonics. Besides, the fundamental source voltage is applied to the shunt passive filter, thus reducing the voltage rating of the APF [31]. In the second configuration, series APF supplies harmonics by offering high impedance, and the harmonic current is forced to flow to the passive filter, thus allowing reduce the current rating of the APF. In both two types of HAPF structures, the passive filter consists of a set of tuned filters or a single tuned filter that meets the system requirements. The symbols X_L and X_C denote inductance and capacitance reactance respectively, to represent the passive filters. Moreover, the point of common coupling (PCC) is defined as the point where linear loads are connected to the power system.

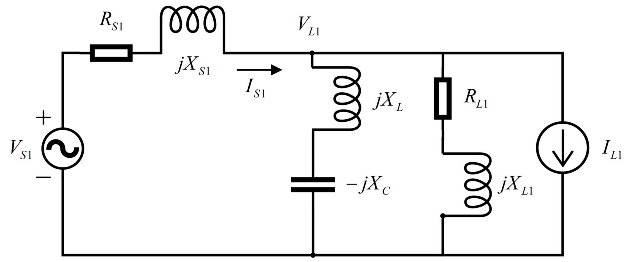


FIGURE 3. Single-phase equivalent circuit at fundamental frequency (H = 1).

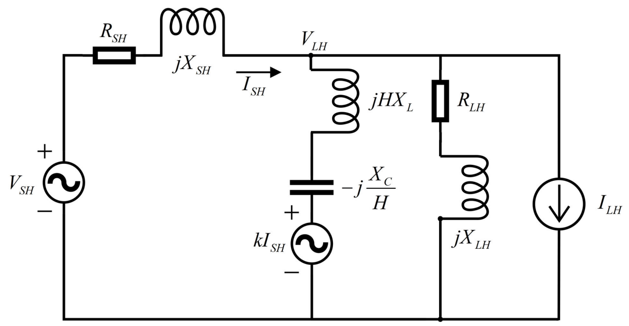


FIGURE 4. Single-phase equivalent circuit for series topology structure at harmonic frequencies (H ⩾ 2).

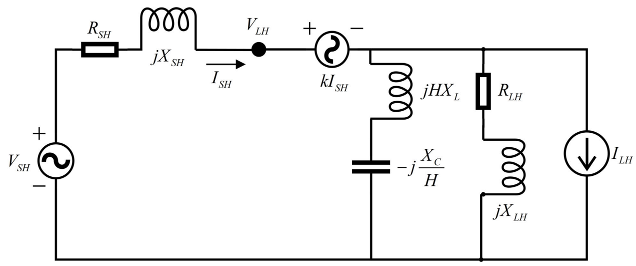


FIGURE 5. Single-phase equivalent circuit for parallel topology structure at harmonic frequencies (H ⩾ 2).

Fig. 3 shows the single-phase equivalent circuit applicable for both two HAPF configurations at fundamental frequency [32]. Here the index '1' of the parameter indicates the parameter value at the fundamental frequency. As can be seen from Fig. 4 and Fig. 5, the single-phase equivalent circuits of the two configurations are different in harmonic frequency. Because the position of APF and its response to the supply harmonics are different. Generally, APF is deemed as a controlled voltage source (V_{AF}) and here $V_{AF} = kI_{SH}$, what this means is that the voltage harmonic waveform injected at its terminals is proportional to the harmonic component of the supply current (I_{SH}). k is the filter gain, it provides zero impedance at fundamental frequency, which means that the active filter component uses as a virtual harmonic resistor [33].

This study set out to reduce harmonic pollution by optimizing the three parameters i.e. k, X_L and X_C when both source and load are non-linearities. Current non-linearities and source harmonic voltage are accounted in I_{SH} and V_{SH} respectively, and those of load are accounted in I_{LH} and V_{LH}.

In the literature [33], the Thevenin voltage sources representing the utility supply voltage and the harmonic current source representing the nonlinear load are expressed as:

$$v_S(t) = \sum_H v_{SH}(t) \tag{1}$$

$$i_L(t) = \sum_H i_{LH}(t) \tag{2}$$

The H-th harmonic source impedance is:

$$Z_{SH} = R_{SH} + jX_{SH} \tag{3}$$

The H-th harmonic load impedance is:

$$Z_{LH} = R_{LH} + jX_{LH} \tag{4}$$

The load admittance is:

$$Y_{LH} = G_{LH} - jB_{LH} \tag{5}$$

Analysis of the equivalent circuit in Fig. 4 for the series topology structure, yields following equations for compensated utility supply current and load voltage respectively at harmonic 'H⩾2'.

$$I_{SH} = \frac{A + jB}{C + jD} \tag{6}$$

$$V_{LH} = \frac{E + jF}{C + jD} \tag{7}$$

Analysis of the equivalent circuit in Fig. 5 for the parallel topology structure, yields the following equations for compensated utility supply current and load voltage respectively at harmonic 'H⩾2'.

$$I_{SH} = \frac{A + jB}{C + jD'} \tag{8}$$

$$V_{LH} = \frac{E + jF'}{C + jD'} \tag{9}$$

where,

$$A = V_{SH}R_{LH} - I_{LH}X_{LH}\left(HX_L - \frac{X_C}{H}\right) \tag{10}$$

$$B = V_{SH}\left(X_{LH} + HX_L - \frac{X_C}{H}\right) + I_{LH}R_{LH}\left(HX_L - \frac{X_C}{H}\right) \tag{11}$$

$$C = R_{TLH} + kR_{LH} - (X_{LH} + X_{SH})\left(HX_L - \frac{X_C}{H}\right) \tag{12}$$

$$R_{TLH} = R_{SH}R_{LH} - X_{SH}X_{LH} \tag{13}$$

$$D = X_{TLH} + kX_{LH} + (R_{LH} + R_{SH})\left(HX_L - \frac{X_C}{H}\right) \tag{14}$$

$$X_{TLH} = R_{LH}X_{SH} + R_{SH}X_{LH} \tag{15}$$

$$\begin{aligned} E &= V_{SH}\left[kR_{LH} - X_{LH}\left(HX_L - \frac{X_C}{H}\right)\right] \\ &\quad + I_{LH}X_{TLH}\left(HX_L - \frac{X_C}{H}\right) \end{aligned} \tag{16}$$

$$\begin{aligned} F &= V_{SH}\left[kX_{LH} + R_{LH}\left(HX_L - \frac{X_C}{H}\right)\right] \\ &\quad - I_{LH}R_{TLH}\left(HX_L - \frac{X_C}{H}\right) \end{aligned} \tag{17}$$

$$D' = X_{TLH} + kX_{LH} + (k + R_{LH} + R_{SH})\left(HX_L - \frac{X_C}{H}\right) \quad (18)$$

$$F' = V_{SH}\left[kX_{LH} + (k + R_{LH})\left(HX_L - \frac{X_C}{H}\right)\right] - I_{LH}R_{TLH}(HX_L - \frac{X_C}{H}) \quad (19)$$

A further review of equations (6) and (8) indicates that compensated utility supply harmonic current, and I_{SH} is inversely related to gain k. For the active filter, on the one hand, it acts as an 'obstructing resistor' which impedes the harmonic current produced by source non-linearities V_{SH}. On the other hand, it also acts as a 'damping resistor' to harmonic current I_{LH}, and can totally attenuate the resonance between the source impedance and the shunt passive filter [32]. Besides, Other system parameters are shown below:

$$DPF = \frac{P_{L1}}{V_{L1}I_{S1}} = \frac{G_{L1}V_{L1}}{I_{S1}} \quad (20)$$

$$PF = \frac{P_L}{V_L I_S} = \frac{G_{L1}V_{L1} + \sum_{H\geq 2} G_{LH}V_{LH}^2}{\sqrt{(I_{S1}^2 + \sum_{H\geq 2} I_{SH}^2)(V_{L1}^2 + \sum_{H\geq 2} V_{LH}^2)}} \quad (21)$$

where DPF and PF represent the compensated load displacement power factor and compensated load power factor, respectively. Besides, the subscript '1' in this formula represents the power factor.

$$P_{LOSS} = I_{S1}^2 R_{S1} + \sum_{H\geq 2} I_{SH}^2 R_{SH} \quad (22)$$

where P_{LOSS} is transmission loss and the transmission efficiency can be calculated as:

$$\eta = \frac{P_L}{P_L + P_{LOSS}} \quad (23)$$

Compensated voltage and compensated utility supply current are given by:

$$VTHD = \frac{\sqrt{\sum_{H\geq 2} V_{LH}^2}}{V_{L1}} \quad (24)$$

$$ITHD = \frac{\sqrt{\sum_{H\geq 2} I_{SH}^2}}{I_{S1}} \quad (25)$$

Finally, the formula for calculating harmonic pollution is as follows:

$$HP = \sqrt{VTHD^2 + ITHD^2} \quad (26)$$

B. OBJECTIVE FUNCTION

This article optimizes the HAPF design from the perspective of selecting three best parameters: k, X_C, and X_L to reduce harmonic pollution. The range of these parameters can be shown:

$$\begin{cases} 0 \leq k \leq 20 \\ 0 \leq X_C \leq 20 \\ 0 \leq X_L \leq 1 \end{cases} \quad (27)$$

Moreover, considering compliance with IEEE Standard 519-2014 [34] based on system voltage level and system short circuit ratio. The allowable ranges for $VTHD$ and $ITHD$ are respectively as follows:

$$\begin{cases} VTHD \leq VTHD_{lim} \\ ITHD \leq ITHD_{lim} \end{cases} \quad (28)$$

where $VTHD_{lim}$ = limitation on $VTHD$ and $ITHD_{lim}$ = limitation on $ITHD$ as per IEEE 519-2014. Thus, the objective function complying with the above conditions is given as:

$$HP_{APP} = abs(VTHD_{lim} - VTHD) + abs\,(ITHD_{lim} - ITHD) \quad (29)$$

While meeting IEEE standards for individual harmonics, the optimization objective is formulated as:

$$\text{Maximize '}HP_{APP}\text{' subject to } PF = PF_{goal} \pm \varepsilon$$

where PF_{goal} is the desired power factor, and it is set to 95% in this work. To facilitate the iterative process, a small error value ε is introduced, and its value is set to 1%. Note that the objective function input to be minimized is '$-HP_{APP}$'. In addition, the algorithm can evaluate the objective function value only when all harmonic levels meet the limitations. Otherwise, this set of experimental data will be considered unqualified and the objective function value will be set to 100.

III. RELATED WORKS

A. ORIGINAL TLBO ALGORITHM

At present, teaching-learning-based optimization (TLBO) has received considerable interest because of its simple structure and fast convergence rate [18]. This algorithm finds the optimal solution by simulating the teaching process of teachers and the communication process between students. The best individual in the population is called the teacher, and the other individuals are called learners.

In the teaching phase, the new value of the i-th learner (x_i^{new}) is updated as follows:

$$x_i^{new} = x_i^t + rand(0, 1) \cdot (x_T - T_F \cdot x_M^t) \quad (30)$$

$$x_M^t = \frac{1}{N_p}\sum_{i=1}^{N_p} x_i^t \quad (31)$$

where N_p represents the number of learners in the class, x_T is the best learner regarded as the teacher, and x_M^t is the average of all individuals at t-th iteration. T_F is a teaching factor and its value is set to either 1 or 2. Besides, $rand(r_1, r_2)$ denotes a random number between r_1 and r_2.

It should be noted that after each iteration, the value of each learner needs to be finally determined according to the following formula:

$$x_i^{t+1} = \begin{cases} x_i^t, & \text{if } f(x_i^t) < f(x_i^{new}) \\ x_i^{new}, & \text{if } f(x_i^t) \geq f(x_i^{new}) \end{cases} \quad (32)$$

where $f(x)$ represents the objective function value of x. In other words, choose the better one between x_i^t and x_i^{new} to keep it after each iteration.

In the learning phase, each learner can communicate with the learner x_j^t that is randomly selected from the class, which can improve their own knowledge level. The update formula for each learner is as follows:

$$x_i^{new}=\begin{cases}x_i^t+rand\,(0,1)\cdot\left(x_i^t-x_j^t\right), & \text{if } f(x_i^t)<f(x_j^t)\\ x_i^t+rand\,(0,1)\cdot\left(x_j^t-x_i^t\right), & \text{if } f(x_i^t)\geq f(x_j^t)\end{cases} \tag{33}$$

Like the teaching phase, the value of each learner is finally determined by the formula (32).

B. LÉVY-FLIGHT ALGORITHM

Lévy-Flight strategy is a stochastic search mode proposed by Lévy [35], and it is based on the foraging behavior of animals in nature. In most cases, Lévy-Flight moves a short distance. But occasionally, long-distance jumps are performed, which improves the ability to escape from the local optimal solution. The Lévy-Flight distribution can be defined as:

$$L\acute{e}vy\,(x)=0.01\cdot\frac{rand\,(0,1)\cdot\sigma}{|rand\,(0,1)|^{\frac{1}{\beta}}} \tag{34}$$

$$\sigma=\left[\frac{\Gamma\,(1+\beta)\cdot sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\cdot\beta\cdot 2^{\left(\frac{\beta-1}{2}\right)}}\right]^{\frac{1}{\beta}} \tag{35}$$

$$\Gamma(x)=(x-1)! \tag{36}$$

where β is a constant, which is taken as 1.5 in this paper. Besides, $rand\,(0,1)$ represents a random number between 0 and 1.

IV. HTLBO ALGORITHM

Extensive research has shown that TLBO has a strong exploitation ability, but its performance in exploration is not satisfactory, especially on the issue of HAPF design in this work. It still faces the challenges of poor global exploration ability and is easily trapped in local optima. In the iterative process of TLBO, all learners are gradually attracted to the teacher (x_T) in the teaching phase. With the number of iterations increasing, a great number of individuals will cluster together around the teacher. Further, the positions of all individuals are very close so that the value of $x_i^t-x_j^t$ tends to 0. The difference between x_T and x_M^t is negligibly small. That is to say, the distance all individuals move during the iteration is almost negligible. Once a substantial number of learners are trapped into local optima, it will be difficult to escape from the local optima, making all individuals gather at one point. In other words, if there is a deviation in the knowledge disseminated by the teacher at the beginning, it will cause all learners to learn in the wrong direction. At the same time, there are no other better teachers to guide them, all learners will learn the erroneous knowledge. Besides, in the learning phase, the information exchange between learners further accelerates the dissemination of wrong information. In the end, all learners and the teacher have the same level of knowledge, but can hardly learn better knowledge.

In view of the above analysis, this paper proposes a novel HTLBO algorithm to balance the global exploration and local exploitation capability of TLBO.

A. DYNAMIC CLUSTERING MECHANISM

In the original TLBO, all learners learn from the best individual (Teacher x_T) and population mean value x_M^t. However, as we all know, different people have different learning abilities, even part of people can acquire knowledge by self-study. Therefore, teaching students in accordance with their aptitude may be a better choice.

Based on the above considerations, we divide all N_p individuals into two groups, the first group is called the teaching-learning group, and the second group is called the self-study group. The teaching-learning group uses an improved hierarchical teaching strategy and improved learning strategy to update individuals' positions, focusing on local exploitation processes, and seeking better solutions near the current optimal solution. Correspondingly, the self-study group uses the Lévy-Flight strategy to update positions and concentrating on global exploration. Specifically, the individual in the teaching-learning group is called the learner, and the individual in the self-study group is called the self-learner.

For the individuals in the self-study group and the teaching-learning group, their identity is not fixed at each iteration but dynamically adjusted according to their objective function values, which ensures the vitality of the population. For the two groups, the individual numbers are divided as:

$$\begin{cases}N_{TL}=\frac{2}{3}N_p\\ N_{SS}=\frac{1}{3}N_p\end{cases} \tag{37}$$

where N_{TL} and N_{SS} represent the number of individuals in the teaching-learning group and the self-study group, respectively. Note that all individuals are sorted by objective function value before iteration, the first two-thirds are elected to the teaching-learning group and the latter one-third are elected to the self-study group.

B. HIERARCHICAL TEACHING STRATEGY

To further balance the exploration and exploitation tendencies of the algorithm, different learners adopt different methods to learn in the teaching phase. All learners are divided into three hierarchies i.e. good, medium, and poor according to their objective function values, and learners at different hierarchy follow different three teachers to learn. These three teachers are from the highest-level individuals in the three hierarchies respectively. In general, most students have an average learning ability. Thus, the number of learners in each hierarchy is as follows:

$$\begin{cases}N_{Good}=\frac{1}{4}N_{TL}\\ N_{Medium}=\frac{1}{2}N_{TL}\\ N_{Poor}=\frac{1}{4}N_{TL}\end{cases} \tag{38}$$

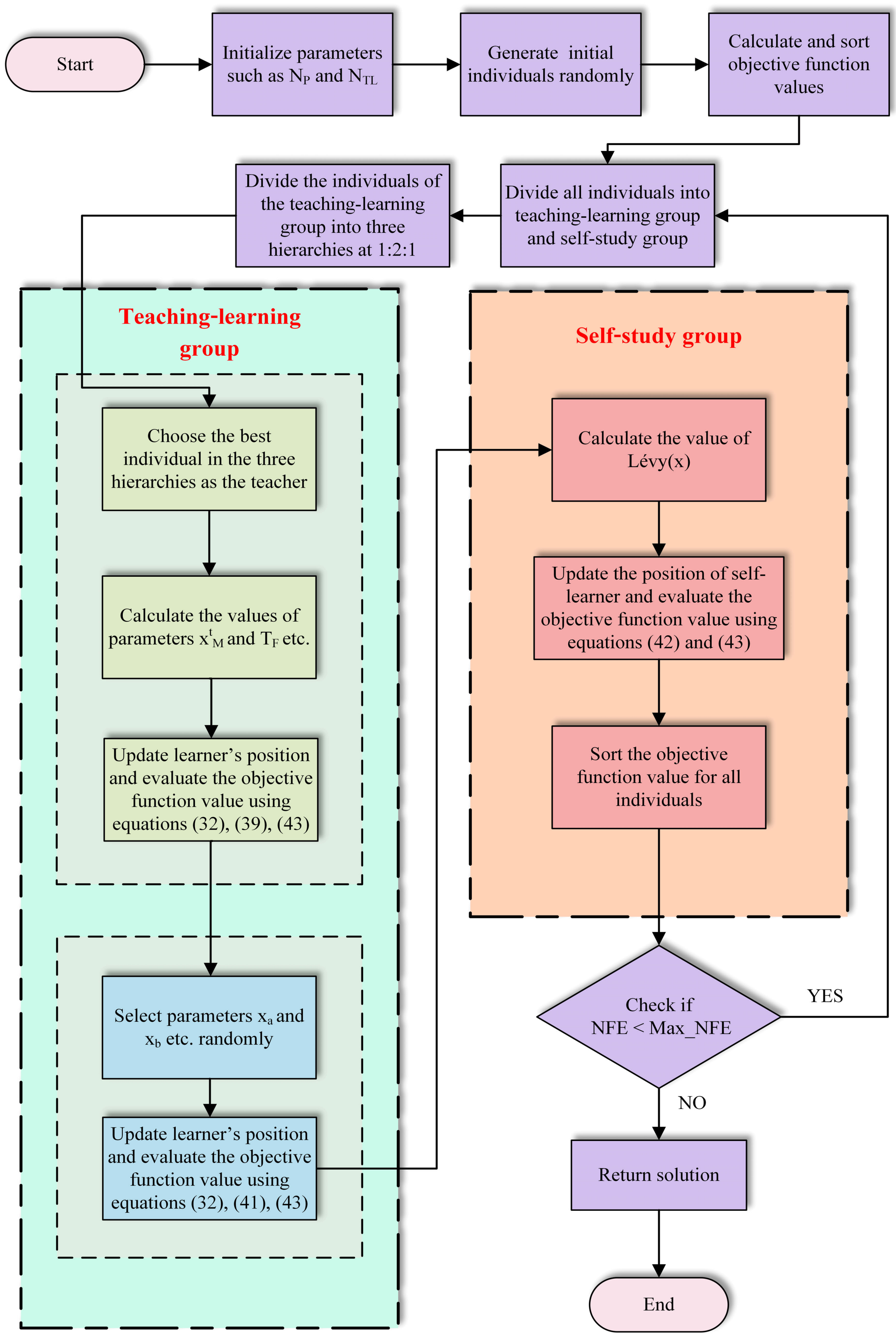


FIGURE 6. The flowchart of HTLBO.

Algorithm 1 "HTLBO Algorithm"

Initialize HTLBO parameters;
Randomly generate initial population;
Calculate and sort the objective function values of the initial population;
While (termination criteria does not hold) **do**
/* **Dynamic clustering mechanism** */
Divide individuals with objective function values at the top two-thirds into the teaching-learning group, and the rest are assigned to self-study groups;
Divide the teaching-learning group into three hierarchies: good hierarchy, medium hierarchy, and poor hierarchy according to the objective function values;
/* **Teaching-learning group** */
for $i = 1 : N_p * (2/3)$
  /* **Improved teaching strategy** */
  Choose three teachers according to (40) and calculate the value of x_M^t;
  Update the learner's position according to (39);
  Use (43) to modify the location of individuals out of range;
  Evaluate objective function values and determine whether to update the position;
  /* **Improved learning strategy** */
  Select parameters x_a, x_b randomly;
  Update the learner's position according to (41);
  Use (43) to modify the location of individuals out of range;
  Evaluate objective function values and determine whether to update the position;
End for
Reordering and grouping according to individual's objective function value;
/* **Self-study group** */
for $i = N_p * (2/3) + 1 : N_p$
  Calculate the value of $L\acute{e}vy\,(x)$;
  Update the individual's position according to (42);
  Use (43) to modify the location of individuals out of range;
  Evaluate objective function values;
End for
NFE = NFE + 1;
End while

where N_{Good}, N_{Medium}, and N_{Poor} represent the number of learners with good, medium, and poor learning abilities, respectively. Since the N_p is taken to be 30 in this work, N_{Good} and N_{Poor} equals 5, N_{Medium} equals 10.

Before each iteration, we sort all 30 individuals according to the objective function value from worst to best, then the top 20 were assigned to the teaching-learning group. In addition, the i-th learner during the t-th iteration uses x_i^t to express. The improved teacher process is given as:

$$x_i^{new} = \begin{cases} x_i^t + rand(0,1)\cdot\left(x_{TGood} - T_F \cdot x_M^t\right), & 1 \le i \le 5 \\ x_i^t + rand(0,1)\cdot\left(x_{TMedium} - T_F \cdot x_M^t\right), & 6 \le i \le 15 \\ x_i^t + rand(0,1)\cdot\left(x_{TPoor} - T_F \cdot x_M^t\right), & 16 \le i \le 20 \end{cases} \tag{39}$$

where x_{TGood}, $x_{TMedium}$ and x_{TPoor} are teachers of three hierarchies. Their values are as follows:

$$\begin{cases} x_{TGood} = x_1^t \\ x_{TMedium} = x_6^t \\ x_{TPoor} = x_{16}^t \end{cases} \tag{40}$$

Unlike the original TLBO algorithm, T_F equals 1 or 2. In the proposed algorithm, T_F is a random number between 0 and 2 to improve population diversity. At the same time, in order to avoid all individuals gathering in local optimal, for the latter half of the learners, whether the newly created position is better or worse, they are updated. On the contrary, for the first half of the learners, like the original TLBO algorithm, it is updated only when the newly generated position is better, that is, using formula (32) for judgment. On the one hand, this measure makes the whole group escape from the local optimal solution when the teacher's guidance is wrong, on the other hand, it can keep the current optimum solution.

C. IMPROVED LEARNING STRATEGY

During the learning phase of the TLBO algorithm, each learner learns only from another individual randomly. In order to enable learners to communicate with each other more deeply, in the improved teaching phase, each learner randomly learns from an individual better than it and an individual worse than it. The improved learning process is formulated as follows:

$$x_i^{new} = x_i^t + 0.5 \cdot rand\,(0,1) \cdot \left(x_a - x_i^t\right) + 0.5 \cdot rand\,(0,1) \cdot \left(x_i^t - x_b\right) \tag{41}$$

where x_a means that among all N_p individuals, a randomly selected individual whose objective function value is lower than or equal to x_i^t, and the objective function value of x_b is higher than x_i^t. Through the learning phase, the teaching-learning group can obtain useful information from the outside world (self-study group), thus avoiding falling into local optima. Besides, like the learning phase, for the first ten individuals, if x_i^{new} is better than x_i^t, then accept it. But for the last ten individuals, all individuals update their positions.

D. SELF-STUDY STRATEGY

For all individuals in the self-study group, i.e. self-learners, using the Lévy-Flight strategy, that is, formula (34) and (42) to update the positions. Guiding individuals to move in a promising direction, and effectively preventing the teaching-learning group from falling into local optima.

$$x_i^{new} = x_i^{new} + L\acute{e}vy\,(x) \tag{42}$$

TABLE 1. Case studies of an industrial plant.

Parameters	Series topology structure				Parallel topology structure			
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
$R_{S1}(\Omega)$	0.02163	0.02163	0.02163	0.02163	0.02163	0.02163	0.02163	0.02163
$X_{S1}(\Omega)$	0.2163	0.2163	0.2163	0.2163	0.02163	0.2163	0.2163	0.2163
$R_{L1}(\Omega)$	1.7421	1.7421	1.7421	1.7421	1.7421	1.7421	1.7421	1.7421
$X_{L1}(\Omega)$	1.696	1.696	1.696	1.696	1.696	1.696	1.696	1.696
$V_{S1}(KV)$	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40
$V_{S5}(\%V_{S1})$	0.00	2.00	4.00	4.00	0.00	2.00	4.00	4.00
$V_{S7}(\%V_{S1})$	0.00	1.50	3.00	3.00	0.00	1.50	3.00	3.00
$V_{S11}(\%V_{S1})$	0.00	1.00	2.00	3.00	0.00	1.00	2.00	3.00
$V_{S13}(\%V_{S1})$	0.00	0.50	1.00	1.20	0.00	0.50	1.00	1.20
$I_{L5}(\%I_L)$	40.00	40.00	40.00	40.00	40.00	40.00	40.00	40.00
$I_{L7}(\%I_L)$	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00
$I_{L11}(\%I_L)$	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
$I_{L13}(\%I_L)$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

In addition, for all the above strategies, if individuals exceed the boundary, the HTLBO algorithm processes as follows:

$$x_{i,j}^t = \begin{cases} x_{j_{min}}, x_{i,j}^t < x_{j_{min}} \\ x_{j_{max}}, x_{i,j}^t > x_{j_{max}} \end{cases} \tag{43}$$

where $x_{i,j}^t$ indicates the value of the j-th dimension of the individual. $x_{j_{max}}$ and $x_{j_{min}}$ represent the upper and lower boundaries of the corresponding dimension, respectively.

Finally, the flow chart of the proposed HTLBO algorithm is described in Fig. 6, and the "HTLBO Algorithm" gives the pseudo code.

V. CASE STUDIES

We employed the proposed HTLBO to identify the parameters of two HAPF configurations discussed in Section II, and Table. 1 shows the parameters of eight classic cases in industrial production. The first four cases correspond to configuration 1, and the last four cases correspond to configuration 2. All these parameters are the same as those in references [16] and [32]. For case 1 to case 3 and case 5 to case 7, the inductive three-phase loads are 5100 KW and 4965 KVAR. The 60-cycle supply bus voltage is 4.16 KV (2400 voltage line-to-neutral). The short-circuit capacity is 80 MVA. For case 4 and case 8, the data come from a factory with a total three-phase apparent load of (5100+j4965) KVA at a 4.16 KV line-to-line voltage. The system short-circuit capacity is also 80 MVA. In addition, it is assumed that the source and load harmonics are time-invariant in all cases; the load and source resistance is independent of frequency, that is, $R_{LH} = R_L$ and $R_{SH} = R_S$. It should be noted that, in this study, PF_{goal} and ε are selected as 95% and 1% respectively. Besides, both $VTHD_{lim}$ and $ITHD_{lim}$ are set to 5%.

TABLE 2. Parameter settings of different algorithms.

Algorithms	Years	Parameter Settings	References
HTLBO	/	$N_p = 30$	/
TLBO	2011	$N_p = 30$	[18]
ITLBO	2019	$N_p = 30$	[29]
DE	1997	$N_p = 30$ F = 0.5, CR =0.9	[36]
LSHADE	2017	$N_p = 100$ $b = 1$	[16]
MFO	2015	$N_p = 30$	[37]
DELMFO	2018	$N_p = 30$ CR=0.7 σ=0.15, ∂=0.6	[38]
WOA	2016	$N_p = 30$, $b = 1$	[39]
DA	2015	$N_p = 30$	[40]
SSA	2017	$N_p = 30$ $c_1 = 2e^{-\left(\frac{4l}{L}\right)^2}$	[41]

VI. THE RESULTS AND ANALYSIS OF EXPERIMENT

In this work, Harmonic Pollution (HP) is directly linked to the objective function. We minimize the objective function value to obtain the three best HAPF design parameters. The objective function and the boundary range of the parameters are given in Section II. In order to verify the performance of the HTLBO on the issue studied in this paper, nine other well-established meta-heuristics algorithms are compared in this section. They are the standard Teaching-Learning-Based Optimization (TLBO) [18], Improved Teaching-Learning-Based Optimization (ITLBO) [29], Differential Evolution (DE) [36], SHADE with a linear population size reduction method (LSHADE) [16], Moth-Flame Optimization

TABLE 3. The statistical results of different algorithms for series topology structure.

Case no.	Algorithm	Harmonic Pollution (in %)				Wilcoxon rank-sum test	Pass rate
		Min	Mean	Max	Std. dev.		
Case 1	HTLBO	**0.236**	**0.236**	**0.240**	**0.001**		100%
	TLBO	**0.236**	0.329	0.462	0.103	≈	100%
	ITLBO	**0.236**	0.286	0.493	0.102	≈	100%
	DE	**0.236**	0.418	0.493	0.117	+	100%
	LSHADE	**0.236**	0.244	0.493	0.045	+	100%
	MFO	**0.236**	0.418	0.493	0.117	+	100%
	DELMFO	**0.236**	0.344	0.493	0.127	≈	100%
	WOA	**0.236**	0.260	0.417	0.052	+	100%
	DA	**0.236**	0.389	0.498	0.124	+	100%
	SSA	**0.236**	0.296	0.493	0.074	+	100%
Case 2	HTLBO	**2.714**	**2.752**	2.808	0.013		100%
	TLBO	2.752	2.876	2.952	0.095	+	100%
	ITLBO	2.752	2.784	2.952	0.074	+	100%
	DE	2.752	2.881	2.952	0.096	+	100%
	LSHADE	2.752	**2.752**	**2.752**	**0**	≈	100%
	MFO	2.739	2.920	2.956	0.075	+	100%
	DELMFO	2.752	2.830	2.952	0.098	+	100%
	WOA	2.728	2.754	2.778	0.014	≈	100%
	DA	2.744	2.911	2.984	0.080	+	100%
	SSA	2.749	2.787	2.954	0.073	+	100%
Case 3	HTLBO	**5.672**	**5.672**	**5.676**	**0.001**		100%
	TLBO	**5.672**	5.851	5.888	0.078	+	100%
	ITLBO	**5.672**	5.832	5.888	0.095	+	100%
	DE	**5.672**	5.839	5.888	0.090	+	100%
	LSHADE	**5.672**	5.826	5.904	0.098	+	100%
	MFO	**5.672**	5.865	5.965	0.076	+	100%
	DELMFO	**5.672**	5.832	5.888	0.095	+	100%
	WOA	**5.672**	5.747	6.090	0.112	+	74.19%
	DA	**5.673**	5.862	5.897	0.071	+	100%
	SSA	**5.672**	5.788	5.914	0.110	+	100%
Case 4	HTLBO	**6.340**	**6.340**	**6.340**	**0**		100%
	TLBO	**6.340**	6.396	7.010	0.137	+	100%
	ITLBO	**6.340**	6.352	6.595	0.052	+	74.19%
	DE	**6.340**	6.360	6.978	0.113	+	100%
	LSHADE	**6.340**	6.364	6.597	0.053	≈	87.10%
	MFO	**6.340**	6.569	6.978	0.293	+	41.94%
	DELMFO	**6.340**	6.361	6.660	0.079	+	100%
	WOA	**6.340**	6.400	6.735	0.116	+	58.07%
	DA	**6.340**	6.542	6.982	0.292	+	83.87%
	SSA	**6.340**	6.342	6.359	0.004	+	90.32%

Algorithm (MFO) [37], Double Evolutionary Learning Moth-Flame Optimization (DELMFO) [38], Whale Optimization Algorithm (WOA) [39], Dragonfly Algorithm (DA) [40], and Salp Swarm Algorithm (SSA) [41]. Note that LSHADE is a competitive algorithm recently proposed and demonstrated outstanding performance on the HAPF design issues. Besides, ITLBO is one of the latest TLBO-based improved algorithms proposed in 2019. For the above algorithms, their parameter settings are given in Table. 2. The experiment was repeated 31 times independently using the MATLAB software (Version: R2016a) to assure the reliability of our statistical results. Furthermore, the maximum fitness evaluation (FE) number of all algorithms is unified set to 50,000 in each run. All comparative experiments were executed on a desktop PC with an Intel Core i5-7300HQ processor @ 2.50 GHz, 8GB RAM, under the Windows 10 64-bit OS.

A. EXPERIMENTAL RESULT OF SERIES TOPOLOGY STRUCTURE

The experimental results of all algorithms in series topology structure are shown in Table. 3, including the minimum HP values (Min), the mean HP values (Mean), the maximum HP values (Max), the standard deviation of HP values (Std. dev.), and pass rate. It is worthwhile to mention that the pass rate

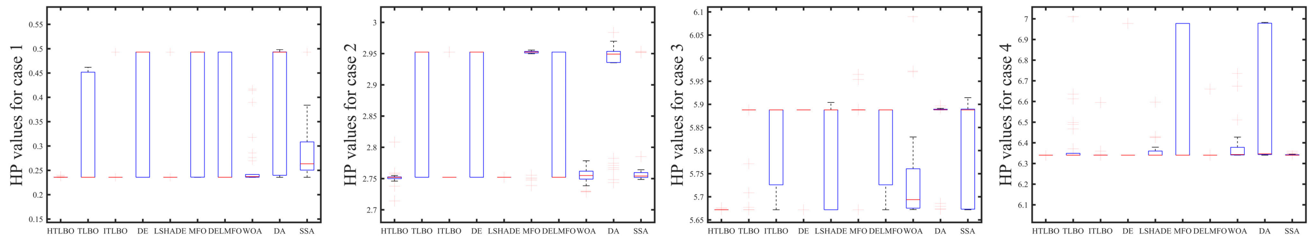


FIGURE 7. Boxplots of ten algorithms for series topology structure (case 1 to case 4).

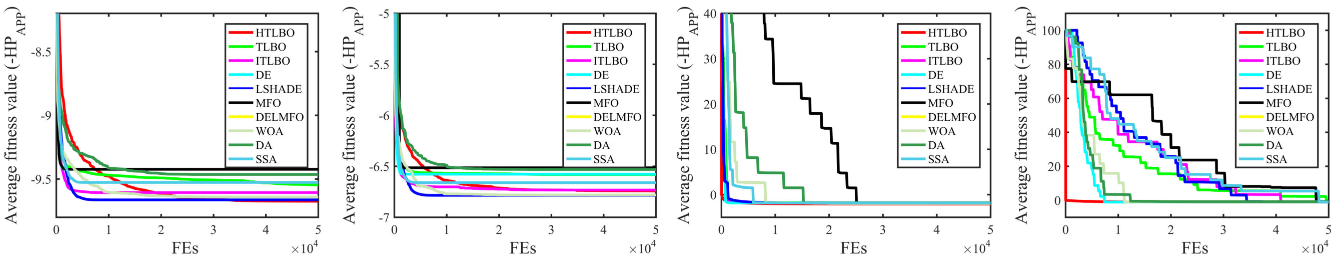


FIGURE 8. Convergence curves of ten algorithms for series topology structure (case 1 to case 4).

is calculated based on the number of times an algorithm has obtained the solution which meets HAPF design requirements out of 31 runs. Furthermore, we conduct the Wilcoxon rank-sum examination at 5% significant level to decide about the significance of the results. Sign "+" denotes that HTLBO owns notably better than the compared algorithm, and sign "≈" indicates that HTLBO almost the same as the compared algorithm. In the above evaluation indicators, the Min represents the accuracy while the Mean denotes the average accuracy; Std. dev. and pass rate reflect the reliability of the estimated parameters. For unqualified solutions, note that we did not include them in the statistical results, except for the pass rate. Moreover, the overall best results of HP among the ten algorithms are highlighted in boldface respectively.

From Table. 3, it can be observed that all algorithms get the minimum HP value in case 1, case 3, and case 4. However, in case 2, only HTLBO achieves the minimum HP value among all compared algorithms. For the mean HP value, HTLBO shows the best performance in all four cases. Furthermore, with regard to the standard deviation, the proposed HTLBO algorithm ranks first in case 1, case 3 and case 4, and LSHADE ranks first in case 2. In terms of the pass rate, all algorithms achieve a 100% pass rate in case 1 and case 2. But it is a pity that WOA has only about three quarters pass in case 3; only HTLBO, TLBO, DE, and DELMFO have a 100% pass rate in case 4. From the results of Wilcoxon rank-sum examination, the advantages of the proposed HTLBO algorithm are further confirmed.

In addition, Fig. 7 gives the boxplots for all compared algorithms to clearly show the distribution of HP values in 31 independent runs. The red line represents the average value and the symbols "+" indicates the outlier. As is evident, HTLBO demonstrates its distinctive competitive advantages in terms of accuracy and reliability. In case 1, case 3 and case 4, all HP values obtained by HTLBO aggregate near the mean. Although in case 2, the HP value fluctuates slightly, HTLBO can reach the accuracy that other algorithms do not possess.

Considering the convergence performance, the convergence characteristics curves of ten algorithms are illustrated in Fig. 8 with the average objective function values. As can be seen from the figure clearly, HTLBO acquires a satisfactory convergence speed on all cases.

Compared with nine other competitive algorithms, the above analysis shows the effectiveness of the proposed HTLBO in HAPF parameter selection with series topology structure, especially in terms of accuracy, average accuracy, and robustness.

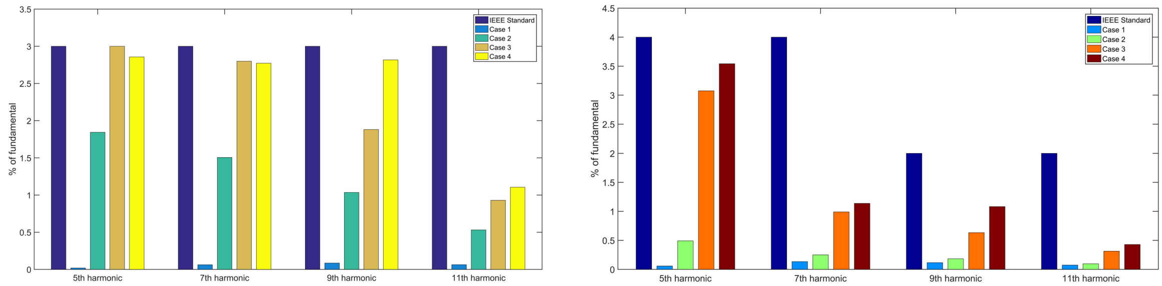
Finally, Table. 4 summarizes the best optimization results of all four cases obtained by HTLBO, including the three-parameter values and useful harmonic distortion values. Furthermore, Fig. 9 gives the individual harmonic contents for the four cases. It is obvious that all harmonics are within limits (28). Experimental results demonstrate that the higher the gain is, the better the compensation is when both the source fundamental impedance and system load without changing. In addition, as *VTHD* and *ITHD* increase, harmonic pollution shows a significant increasing trend. Higher utility distortion leads to lower gain K and X_L tends to be 0. It indicates that the APF with a low-rated voltage source in series with the PPF does not need additional switching filters.

B. EXPERIMENTAL RESULT OF PARALLEL TOPOLOGY STRUCTURE

Table. 5 gives the experimental results of all algorithms in parallel topology structure. Clearly, the proposed HTLBO algorithm shows better accuracy, average accuracy, and reliability than the other nine compared algorithms. Moreover, we

TABLE 4. Results of case studies for series topology structure.

Parameters	Optimization results using HTLBO algorithm			
	case 1	case 2	case 3	case 4
$X_C(\Omega)$	2.7097	2.6865	2.6156	2.6187
$X_L(m\Omega)$	103.98	78.56	0.00	0.00
$K(\Omega)$	20.00	20.00	9.75	8.47
$PF(\%)$	95.00	95.00	95.00	95.00
$DPF(\%)$	95.00	95.03	95.14	95.18
I_S(A)	753.85	753.56	752.94	752.68
V_L(V)	2430.09	2430.76	2431.90	2432.12
$\eta(\%)$	99.30	99.30	99.30	99.30
P_{LOSS}(kW)	12.29	12.28	12.26	12.25
$ITHD(\%)$	0.200	0.588	3.307	3.898
$VTHD(\%)$	0.125	2.650	4.608	5.000
HP (%)	0.236	2.714	5.672	6.340



(a) Compensated individual harmonic of load voltage (V_{LH}).　(b) Compensated individual harmonic of supply current (I_{SH}).

FIGURE 9. Compensated individual harmonic of various cases for series topology structure.

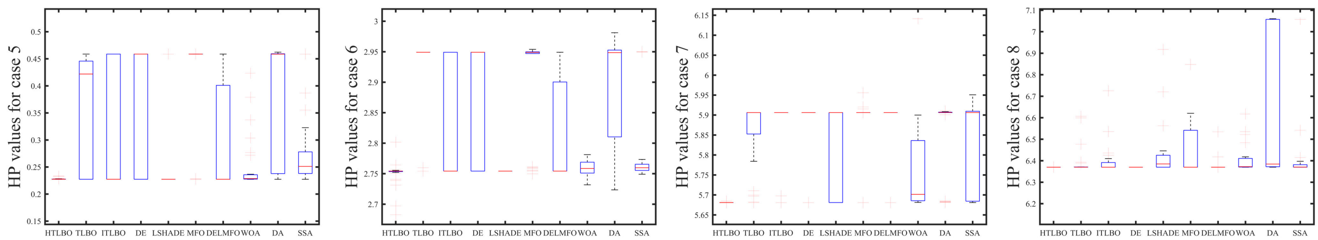


FIGURE 10. Boxplots of ten algorithms for parallel topology structure (case 5 to case 8).

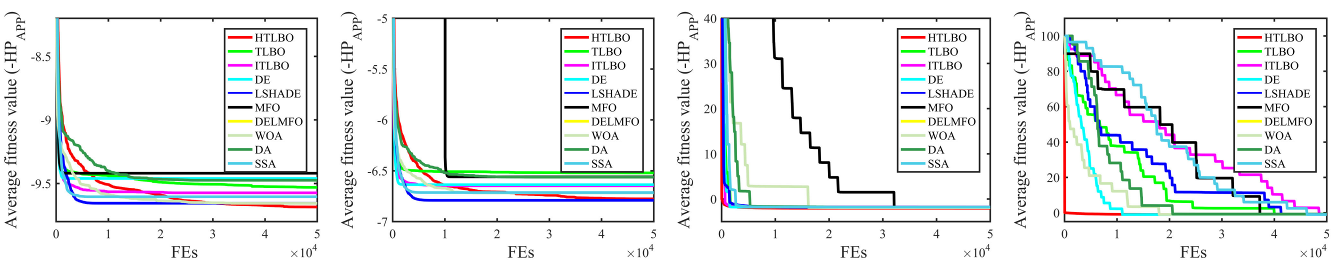


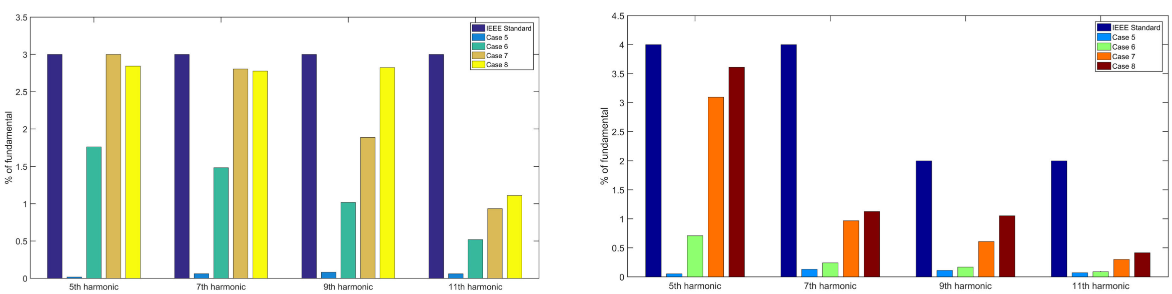
FIGURE 11. Convergence curves of ten algorithms for parallel topology structure (case 5 to case 8).

conduct the comparisons between the ten algorithms on Wilcoxon rank-sum test, the results further demonstrate that HTLBO provides the best overall performance.

Boxplots and average convergence curves for each algorithm are given in Fig. 10 and Fig. 11, respectively. Similar to the results of the series topology structure, the HTLBO

TABLE 5. The statistical results of different algorithms for parallel topology structure.

Case no.	Algorithm	Harmonic Pollution (in %)				Wilcoxon rank-sum test	Pass rate
		Min	Mean	Max	Std. dev.		
Case 5	HTLBO	**0.227**	**0.228**	**0.233**	**0.001**		100%
	TLBO	**0.227**	0.340	0.459	0.109	+	100%
	ITLBO	**0.227**	0.309	0.459	0.111	≈	100%
	DE	**0.227**	0.392	0.459	0.105	+	100%
	LSHADE	**0.227**	0.250	0.459	0.068	≈	100%
	MFO	**0.227**	0.422	0.459	0.085	+	100%
	DELMFO	**0.227**	0.287	0.459	0.101	≈	100%
	WOA	**0.227**	0.249	0.423	0.047	+	100%
	DA	**0.227**	0.382	0.462	0.106	+	100%
	SSA	**0.227**	0.273	0.459	0.061	+	100%
Case 6	HTLBO	**2.683**	**2.750**	2.802	0.019		100%
	TLBO	2.754	2.930	2.949	0.057	+	100%
	ITLBO	2.754	2.844	2.949	0.096	+	100%
	DE	2.754	2.855	2.949	0.097	+	100%
	LSHADE	2.754	2.754	**2.754**	**0**	≈	100%
	MFO	2.750	2.906	2.954	0.080	+	100%
	DELMFO	2.754	2.805	2.949	0.085	+	100%
	WOA	2.732	2.758	2.781	0.014	+	100%
	DA	2.723	2.901	2.981	0.087	+	100%
	SSA	2.749	2.778	2.950	0.056	+	100%
Case 7	HTLBO	**5.680**	**5.681**	**5.685**	**0.001**		100%
	TLBO	5.681	5.682	5.906	0.080	+	100%
	ITLBO	5.681	5.892	5.906	0.053	+	100%
	DE	5.681	5.870	5.906	0.083	+	100%
	LSHADE	5.681	5.827	5.906	0.107	+	100%
	MFO	5.681	5.879	5.956	0.077	+	100%
	DELMFO	5.681	5.877	5.906	0.076	+	100%
	WOA	5.681	5.765	6.141	0.113	+	70.97%
	DA	5.681	5.863	5.910	0.089	+	100%
	SSA	5.681	5.828	5.951	0.111	+	100%
Case 8	HTLBO	**6.370**	**6.370**	**6.370**	**0**		100%
	TLBO	**6.370**	6.391	6.607	0.061	+	93.55%
	ITLBO	**6.370**	6.398	6.752	0.073	+	87.10%
	DE	**6.370**	**6.370**	**6.370**	**0**	+	100%
	LSHADE	**6.370**	6.431	6.918	0.125	+	80.65%
	MFO	**6.370**	6.475	6.848	0.153	+	32.26%
	DELMFO	**6.370**	6.377	6.534	0.031	+	93.55%
	WOA	**6.370**	6.406	6.617	0.066	+	74.19%
	DA	**6.370**	6.572	7.060	0.307	+	67.74%
	SSA	**6.370**	6.404	7.057	0.125	+	96.77%



(a) Compensated individual harmonic of load voltage (V_{LH}). (b) Compensated individual harmonic of supply current (I_{SH}).

FIGURE 12. Compensated individual harmonic for various cases with parallel topology structure.

algorithm achieves competitive results, especially in the latter two cases, HTLBO reaches a striking convergence rate.

Finally, Table. 6 summarizes the best optimization results obtained by HTLBO, including the three-parameter values and useful harmonic distortion values. Besides, Fig. 12 gives

TABLE 6. Results of case studies for parallel topology structure.

Parameters	Optimization results using HTLBO algorithm			
	case 5	case 6	case 7	case 8
$X_C(\Omega)$	2.7101	2.6684	2.6147	2.6188
$X_L(m\Omega)$	104.41	60.41	0.00	0.00
$K(\Omega)$	20.00	19.77	10.30	8.84
$PF(\%)$	95.00	95.00	94.98	95.00
$DPF(\%)$	95.00	95.03	95.13	95.18
$I_S(\mathrm{A})$	753.85	753.54	753.05	752.68
$V_L(\mathrm{V})$	2430.09	2430.71	2431.97	2432.11
$\eta(\%)$	99.30	99.30	99.30	99.30
$P_{LOSS}(\mathrm{kW})$	12.29	12.28	12.27	12.25
$ITHD(\%)$	0.193	0.772	3.311	3.946
$VTHD(\%)$	0.121	2.569	4.615	5.000
HP (%)	0.227	2.683	5.680	6.370

the individual harmonic contents for all cases, it can be seen that all harmonics meet HAPF design requirements. Combining the results of HAPF optimization design for two topologies, it is worth mentioning that they are very similar. A reasonable explanation is that both two HAPF topologies have the same equivalent circuit at the basic frequency. Although the equivalent circuits at harmonic frequencies are different, the parameters I_{SH} and V_{LH} play a decisive role in the two topologies. However, the other HAPF parameters have less influence.

VII. CONCLUSIONS AND FUTURE WORK

This paper proposes a novel Hierarchical Teaching-Learning-Based optimization algorithm (HTLBO) to exactly estimate the parameters of hybrid active power filter (HAPF) with two different topologies. In HTLBO, all individuals are divided into the teaching-learning group and the self-study group. In the teaching-learning group, learners are divided into good, medium, and poor hierarchies according to the objective function value; learners with different levels learn from different teachers in the teaching phase to avoid falling into local optimal. In the learning phase, all learners learn not only from a better individual but also from a worse individual. Furthermore, we also borrow the Lévy-Flight strategy from the references [35] for the self-study group to improve the exploration ability. Through these strategies, the exploitation and exploration of the proposed HTLBO are effectively balanced so that the proposed algorithm can accurately and reliably identify the best HPAF parameters and significantly reduce harmonic pollution.

In the future, HTLBO will be used to solve more optimization problems in engineering design and other fields. In addition, some other strategies will be developed to further optimize the performance of the proposed HTLBO algorithm.

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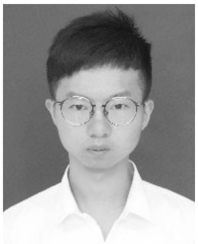

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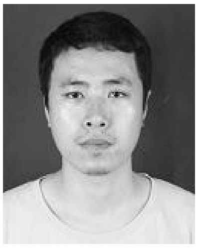

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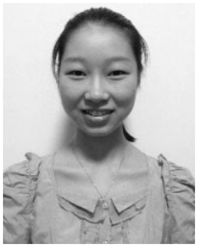

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