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RESEARCH ARTICLE

A Novel Time Synchronization Method for Smart Grid Based on Improved Wolf Colony Algorithm-Cuckoo Search Optimized Fuzzy PID Controller

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ABSTRACT This paper develops a high-precision time synchronization control method based on IEEE 1588 protocol. A novel control technique based on the hybridization of the improved wolf colony algorithm and cuckoo search algorithm (hybrid IWCA-CS) is used to dynamically adjust the fuzzy PID controller parameters to reduce the error of the master-slave clock. To make better performance of the conventional wolf colony algorithm (WCA), it is improved by using the Bloch coordinate encoding to determine the initial population and adding inertial weights to balance the search ability of the algorithm. The proposed hybrid IWCA-CS combines the best attributes of WCA's global search and local search of cuckoo search (CS). In optimizing benchmark function experiments, the proposed hybrid IWCA-CS presents a superior performance compared to other soft computing methods. Furthermore, the hybrid IWCA-CS optimized controllers with different structures are presented to demonstrate its dynamic response characteristics. The results show that IWCA-CS tuned fuzzy PID controller shows the best dynamic performance as compared to PID/PI controllers. And the IWCA-CS based fuzzy PID controller is less sensitive to step load disturbance and parameter changes. Finally, the effectiveness of the proposed time synchronization control method in this paper over published methods is further confirmed by employing in power information collection system (PICS).

INDEX TERMS Smart grid, time synchronization, wolf colony algorithm, cuckoo search, fuzzy PID controller, power information collection system (PICS).

I. INTRODUCTION

It is a comprehensive concept that covers intelligent systems such as smart substations, smart distribution networks, smart energy meters and interactive terminals [1], and different systems should follow a unified time standard. Thus, the time synchronization technology is the significant scheme for achieving this goal, and the quality of the method employed will directly influence the synchronization precision. Research on IEEE1588 (Precision Time Protocol, PTP) [2] has been of utmost attention in recent years. It is pointed out in [3] that the time synchronization accuracy level can reach sub-micro second, which is sufficient to meet the requirements of smart grid applications.

Recently, many scholars have conducted on the researches of time synchronization approach based on IEEE1588. Seo et al. [4] introduced a stochastic model-based direct compensation for interference effects to improve synchronization

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performance. Giorgi et al. [5] analyzed the performance of Kalman-filter based synchronization method, where a state-variable clock model was established based on Allan variance plots, and a kalman-filter-based clock servo is employed in this model. Xu et al. [6] developed a new time synchronization method based on a proportional-integral (PI) clock servo to achieve the frequency compensation. [7] proposed an adaptive parameter PI controller, which has small response time, but the simulation results present some oscillations due to the lack of a derivative controller of the proportional-integral-derivative (PID) controller. In [8], the authors used PID controller in cooperation with wolf colony algorithm for time synchronization. In fact, PID controller is extensively employed in the field of process control due to its basic structure and strong robustness. However, it is difficult to adapt to the time-varying characteristic of the synchronization error by applying fixed parameters [9], [10].

As an intelligent control method, fuzzy control has been highly applied in the system with non-linearity, and can deal with the variations of system parameter [11]. The employment of fuzzy logic in collaboration with PID controller can enhance the performance of controller, and provides a feasible scheme for controller establishment of nonlinear systems [12]. The successful applications obtained with fuzzy logic based PID controller are distributed in the fields of unmanned aerial vehicles [13], power systems [14], [15], [16], [17], micro gas turbines [18], [19]. For example, authors in [16] employed the improved firefly-pattern search optimizing fuzzy PID controller for automatic generation control of power systems with multi-type generation to improve the dynamic performance. In [17], a fuzzy PID control system is designed to perform load frequency control of multi area interconnected power systems. In paper [20], an adaptive clock servo is proposed to improve time synchronization, which uses a fuzzy PI clock servo based on IEEE1588 to reduce the frequency of clock compensation. However, the study on fuzzy PID controller employed in the field of time synchronization is immature, and using self-tuning method to select the fuzzy logic parameters (fuzzy rules, scaling factors, membership functions) is usually inadequate to obtain the optimal parameters resulting in adverse effect on system performance. With development of intelligence algorithm, the optimization technique emerges as the time requires. Recently, many optimization approaches have been successfully applied in the selection of PID controller parameters. For example, the PID controller design for DC motor speed regulation was presented in [21], wherein an improved version of atom search optimization algorithm was used to optimize the parameters of controller. Literature [22] proposed a novel hybrid method using atom search optimization algorithm in cooperation with Nelder-Mead simplex search algorithm to optimize the PID controller of automobile cruise control system. In [23], authors designed an optimal PID controller to control the output voltage of DC-DC buck converter, and the parameters of controller is tuned by the artificial ecosystem-based optimization algorithm incorporating Nelder-Mead simplex method to improve the controller performance. Inspired by that, this paper proposes using the intelligent algorithm to optimize the fuzzy logic parameters.

It can be seen from the literature review that the synchronization precision is prone to be affected by the factors of controller configuration and optimization algorithm used. Therefore, new optimization techniques are always welcomed to address practical problem. Wolf colony algorithm (WCA) is a swarm intelligence algorithm, and has good generalization as employed in the field of optimization. It is an invaluable technique and can present better characteristics than some other optimization algorithms [24]. The performance of WCA is decided by its parameter selection such as initial population, N, distance factor, w, and maximum iteration, k; thereby some researchers developed some modification versions in succession [25], [26], [27]. Nevertheless, few researches have focused on changing the quality of the initial population, and the initial population of WCA is randomly generated, which is not instructive to the algorithm. In light of this, an optimal WCA is designed by integrating two modifications with conventional WCA. Specifically, the improvement of WCA is acquired by using Bloch coordinate encoding to determine the initial population along with adding inertial weights, which can improve the convergence speed and convergence accuracy of WCA. To obtain significant performance applying any optimization algorithm, it is necessary to maintain a balance between development and exploration in the overall search process. As a global search algorithm, WCA can explore in a wide range space, but it usually present poor results if employed only. Cuckoo search (CS) is meta-heuristic algorithm that depends on the nest parasitism in the cuckoo breeding behavior, and the algorithm adopts local random walk strategy [28]. Considering their respective strengths, it is an excellent method to integrate their best attributes. In view of the above, this paper approaches a novel time synchronization method based on hybrid IWCA-CS algorithm optimized fuzzy PID controller parameters to ensure an adaptive control for the frequency of local clock. The contributions of present work are highlighted as follows:

1) The fuzzy PID controller is proposed to replace the traditional PID controller to reduce errors of different clocks as it can handle variations of system parameters, and is applicable to non-linear system.
2) An improved version of WCA using Bloch coordinate encoding method to select the initial population and adding inertial weights, is proposed to enhance the performance of WCA, and the improved WCA is incorporated with CS to tune fuzzy PID controller parameters.
3) The hybrid IWCA-CS tuned fuzzy PID controller is proposed, and its effectiveness is confirmed through comparative experiments.

The organization of the rest of the paper is as follows: Section 2 establishes the problem model. In section 3, the controller structure and objective function are presented. Section 4 introduces the theoretical basis of IWCA, CS and hybrid of IWCA-CS. In section 5, the simulation results are analyzed and verified. Section 6 illustrates concluding remarks.

II. PROBLEM MODELING

IEEE 1588 relies on the time stamp recorded in the process of message transmission. In this mode, a master clock must be specified in the network as reference time, while other devices should place a slave clock to be synchronized with the reference time. Fig. 1 shows the time synchronization process [29]. The time error of master-slave clock is calculated by propagating timestamps in the network to periodically correct slave clock. The implementation process is as follows.

Firstly, the master clock periodically sends the Sync message to the slave clock, and records the sending time T_1. T_1 is stored in following message (Follow_Up), and transmitted to slave clock. The slave clock measures the arrival time T_2. The deviation of master-slave clock is corrected by T_1 and T_2. The time offset is:

$$T_{offset} = T_2 - T_1 - t_{ms} \tag{1}$$

where t_{ms} is the transmission delay of master clock and slave clock. Subsequently, the slave clock sends the Delay_Req message to the master clock and writes the sending time T_3. T_4 is the time when the Delay_Req message arrives at the master clock, and recorded in Delay_Resp message. Then Delay_Resp message is sent back to slave clock. In this process, the transmission delay of master-slave clock is:

$$t_{sm} = T_4 - T_3 + T_{offset} \tag{2}$$

where t_{sm} is the transmission delay of slave clock and master clock. Assuming that the communication links are symmetrical, then

$$T_{Delay} = t_{ms} = t_{sm} \tag{3}$$

$$T_{offset} = \frac{(T_2 - T_1) - (T_4 - T_3)}{2} \tag{4}$$

$$T_{Delay} = \frac{(T_2 - T_1) + (T_4 - T_3)}{2} \tag{5}$$

Finally, the slave clock adjusts its time on the basis of the value of T_{offset} to achieve the time synchronization with the master clock.

In practice, the ideal clock uses the crystal oscillator pulse to compute its time, while the crystal oscillator frequency is easily sensitive to the factors such as ambient temperature, crystal aging, noise and power supply voltage resulting in error generation and the error will accumulate as time proceeds. Therefore, the slave clock is molded as:

$$s(t) = (1 + c) \times t + b \tag{6}$$

where c is the frequency drift and b is the random error similar to Gaussian noise.

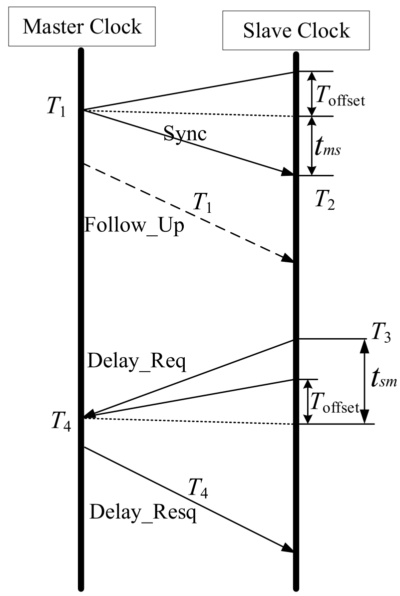

FIGURE 1. IEEE1588 time synchronization process.

III. CONTROLLER STRUCTURE AND OBJECTIVE FUNCTION

In the time synchronization system, there is a time-varying error between the master-slave clock due to difference of crystal oscillator. By adjusting the frequency of slave clock, the error between master clock and slave clock can be reduced, so as to achieve the purpose of time synchronization. However, the error of synchronization system exhibits various dynamic characteristics under the changes of operating conditions and external interference, which limits the application of PID controller. For this reason, the fuzzy logic is used to enhance the dynamic performance of conventional PID controller as fuzzy logic is able to deal with changes of system parameters in real-time via automatically adjusting the PID controller gains. Fig.2 shows the structure of the fuzzy PID controller. And, the time deviation of the master and slave clock (e) and its derivative (ec) are considered as control inputs. The output is fed to a PID with appropriate proportional, integral and derivative gains to get the control signal. k_1 and k_2 are input scale factors of fuzzy logic controller. The composition of the fuzzy logic controller mainly has four elements: fuzzification, fuzzy inference, rule base and defuzzification as given in Fig. 3. In detail, the fuzzification converts the input from the numeric values to fuzzy sets. The fuzzy inference performs logical operations on the fuzzy inputs according to the fuzzy rules. The output of the fuzzy inference has to be converted into an accurate value by defuzzification. Note that the rule base comprises the membership functions and fuzzy rules. Design of a proper fuzzy logic is the core of fuzzy PID controller including the selection of membership functions and fuzzy rules [30].

It can be appeared from the literature review that trapezoidal, bell shaped and triangular membership functions are generally used in fuzzy PID designs owing to their

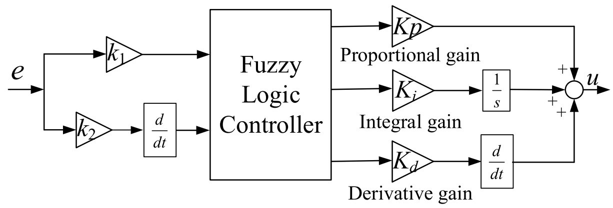

FIGURE 2. Fuzzy PID controller structure.

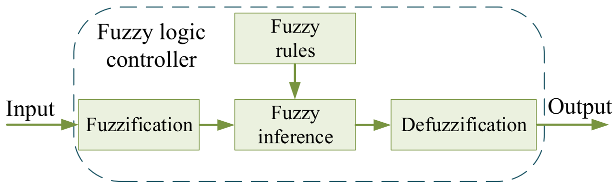

FIGURE 3. Fuzzy logic controller structure.

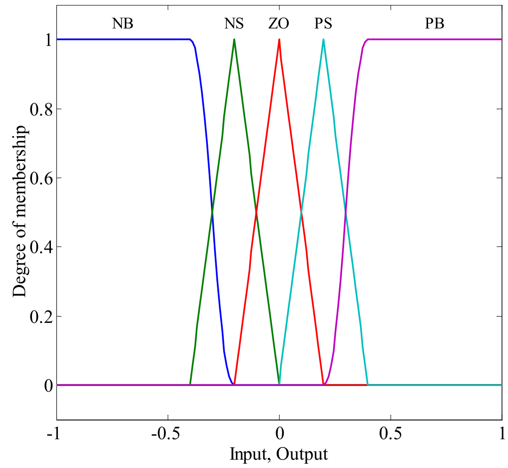

FIGURE 4. Inputs and output membership function.

implementation easily. Within these membership functions, triangular membership function has smaller calculation and higher resolution [31]. Therefore, the triangular membership function is preferred for the input and output of the fuzzy logic in the controller. Five fuzzy linguistic variables such as negative big (NB), negative small (NS), zero (ZO), positive small (PS) and positive big (PB), are applied for separating the input and output of the fuzzy logic controller. Identical membership function is selected for inputs and output of the fuzzy logic controller, as shown in Fig. 4. Furthermore, the fuzzy rules for inputs and output are listed in Table 1. This paper adopts the typical Mamdani fuzzy inference and center of gravity method of defuzzification.

TABLE 1. Fuzzy rules for inputs and output.

e	*ec*				
	NB	NS	ZO	PS	PB
NB	NB	NB	NS	NS	ZO
NS	NB	NS	NS	ZO	PS
ZO	NS	NS	ZO	PS	PS
PS	NS	ZO	PS	PS	PB
PB	ZO	PS	PS	PB	PB

The output of the fuzzy logic controller is supplied to the PID controller. Also, its proportional, integral and derivative are multiplied K_p, K_i and K_d respectively, then the obtained results are added to provide the output of fuzzy PID controller. Obviously, the selection of scales factors (k_1, k_2) and gain factors (K_p, K_i, K_d) determine the output of controller. Selecting these parameters manually may not be the optimal. The improper selection of these parameters has an adverse effect on the system performance. Consequently, the proposed hybrid optimization algorithm in this paper is used to tune these parameters.

Alternatively, several objective functions, namely integral of time multiplied absolute error (ITAE), integral of time multiplied squared error (ITSE) and integral of absolute error (IAE), are used to evaluate the performance of PID controller [32]. Out of these objective functions, the ITAE based objective functions is preferred as it has the significant characteristics of small overshoot and fast settling time. The performance index of the proposed controller is judged by:

$$F = \int_0^{\infty} t|e(t)|^2 dt \tag{7}$$

where $e(t)$ indicates the systematic error of the controller.

IV. PROPOSED OPTIMIZATION METHOD

A. WOLF COLONY ALGORITHM

The wolf colony algorithm was proposed by Yang in 2007 [33], and it is motivated by cooperative hunting way to ensure their survival and reproduction. In the nature, wolf colony relies on a rigid level organization that can guide wolves towards the prey. The wolf colony algorithm is also inspired by an optimization technology based on population iterative and evolutionary search like other swarm intelligent algorithms. Furthermore, the entire predatory behavior of wolves is abstracted as searching, summoning, besieging and prey distribution.

In the implementation of algorithm, the initial position of wolf is randomly generated, and the leader wolf is governed by the wolf closest to the prey. Note that leader wolf is prone to be replaced by the wolf with higher fitness than it in iterations. In addition to leader wolf, q wolves with better fitness are selected to move in h directions. The position of the ith wolf in the jth ($j = 1, 2, \ldots, h$) directions are updated as:

$$x_{id}^{j} = x_{id} + \sin(2\pi \times j/h) \times step_a (1 \le i \le N, 1 \le d \le D) \tag{8}$$

where $step_a$ is the step length, and x_{id} is the position of the ith wolf in the dth dimension. The searching wolves are mainly responsible for finding prey within the range of activities, and then reporting the prey information to leader wolf. After that, the leader wolf calls on the other wolves to get close to the prey, such that:

$$x_{id}^{k+1} = x_{id}^{k} + step_b \times (G_d^k - x_{id}^k)/|G_d^k - x_{id}^k| \tag{9}$$

where $step_b$ is attacking step length, and G_d^k is the position of the leader wolf in the dth dimension at the kth iteration. However, if the leader wolf remains unchanged, the other wolves will go on attacking until the distance between them is less than d_{near}, which can be expressed as:

$$d_{near} = \frac{1}{D \times \omega} \times \sum_{d=1}^{D} (\max_d - \min_d) \tag{10}$$

where ω is the distance factor and $\max_d$ and $\min_d$ are the maximum and minimum of x_{id}. Subsequently all the wolves will beleaguer the prey, and the position is updated by:

$$x_{id}^{k+1} = x_{id}^k + \lambda \times step_c \times (g_d^k - x_{id}^k) \tag{11}$$

where λ is a random number uniformly distributed in the interval [0, 1], $step_c$ is the besieging step, and g_d^k is the position of the prey in dth dimensional space.

Subsequently, the wolf colony assigns the prey according to the principle of more pay for more work, which means that some wolves who work less will be given little food and starve to death. Thus, the M wolves with the worst fitness are removed. At the same time, to preserve the diversity of population, M new intelligent wolves are randomly generated.

B. IMPROVED WOLF COLONY ALGORITHM

It is apparent from the literature [34] that the convergence speed of the algorithm suffers from the quality of the initial population. Therefore, in the present study, using Bloch spherical coordinate encoding to optimize the initial population can overcome the weakness of the randomness for the initial population. Then the inertial weights are introduced into algorithm to improve the convergence accuracy of traditional algorithm. The improvement measures are provided as bellow.

1) INITIAL POPULATION BASED ON BLOCH SPHERICAL COORDINATE

In quantum computing, a qubit with the smallest unit of information is consistent with a point on the Bloch sphere [35]. Thus, the qubits can be expressed in the form of Bloch coordinates as:

$$|\ \Phi\rangle = [\cos\varphi \sin\theta \quad \sin\varphi \sin\theta \quad \cos\theta]^{\mathrm{T}} \tag{12}$$

where $0 \leq \theta \leq \pi$, $0 \leq \varphi \leq 2\pi$, they define a point on the Bloch sphere as shown in Fig. 5.

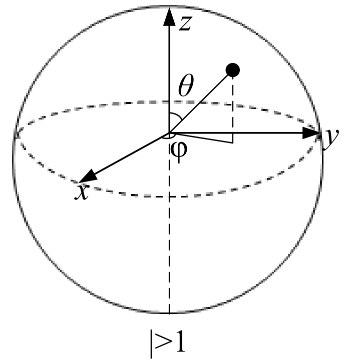

FIGURE 5. Representation of the qubit on Bloch sphere.

Suppose that S_i is the ith solution in the population, and its coding based on Bloch spherical coordinate is:

$$S_i = \begin{vmatrix} \cos\varphi_{i1} \sin\theta_{i1} \\ \sin\varphi_{i1} \sin\theta_{i1} \\ \cos\theta_{i1} \end{vmatrix} \cdots \begin{vmatrix} \cos\varphi_{iD} \sin\theta_{iD} \\ \sin\varphi_{iD} \sin\theta_{iD} \\ \cos\theta_{iD} \end{vmatrix} \tag{13}$$

where $\varphi_{ij} = \pi \times rand$; $\theta_{ij} = 2\pi \times rand$; $i = 1, 2, \ldots, N$; $j = 1, 2, \ldots, D$; N is the number of individuals in the population, and D is the dimension of the optimization space.

Each candidate solution occupies three positions in the space represented by the following three optimal solutions:

$$\begin{cases} P_{ix} = (\cos\varphi_{i1} \sin\theta_{i1}, \ldots, \cos\varphi_{iD} \sin\theta_{iD}) \\ P_{iy} = (\sin\varphi_{i1} \sin\theta_{i1}, \ldots, \sin\varphi_{iD} \sin\theta_{iD}) \\ P_{iz} = (\cos\theta_{i1}, \cos\theta_{i2}, \ldots, \cos\theta_{iD}) \end{cases} \tag{14}$$

The space transformation is that each solution in $[-1, 1]^D$ is converted to the solution space of the optimization problem. Taking the Bloch coordinates of jth qubit in S_i for instance, namely $[\cos\varphi_{ij} \sin\theta_{ij} \sin\varphi_{ij} \sin\theta_{ij} \cos\theta_{ij}]^{\mathrm{T}}$, its corresponding transformation formula is:

$$\begin{cases} x_{ij}^1 = \frac{1}{2}[b_j(1 + \cos b_{ij} \sin a_{ij}) + a_j(1 - \cos b_{ij} \sin a_{ij})] \\ x_{ij}^2 = \frac{1}{2}[b_j(1 + \sin b_{ij} \sin a_{ij}) + a_j(1 - \sin b_{ij} \sin a_{ij})] \\ x_{ij}^3 = \frac{1}{2}[b_j(1 + \cos a_{ij}) + a_j(1 - \cos a_{ij}) \end{cases} \tag{15}$$

where a_j and b_j are the lower and uper limits of jth qubit respectively. Thus, this coding method ensures that each position in Bloch sphere corresponds to three candidate solutions of the optimization problem. In all candidate solutions, N individuals with smaller fitness values are selected as the initial population, which can enhance the traversability of the solution space and improve the diversity of the population.

2) OPTIMIZATION DISTANCE FACTOR W

In the summoning behavior, the distance factor w is inversely proportional to that of the d_{near}. When w is large, the d_{near} becomes small resulting in small search range, and it is easy to fall into the local optimal value. On the contrary, the d_{near} becomes large, which affects the local convergence speed. Therefore, it is necessary to dynamically adjust w to balance the search ability of the algorithm.

$$\begin{aligned} w = w_1 + w_2 \times (\cos(&\frac{2\pi k}{k_{\max} \times (f_{\max}(x_i^k) - f_{\min}(x_i^k))}) \\ &- \sin(\frac{2\pi k}{k_{\max} \times (f_{\max}(x_i^k) - f_{\min}(x_i^k))})) \end{aligned} \tag{16}$$

where $k_{\max}$ is the maximum number of iterations, w_1 and w_2 are inertial weights (w_1, $w_2 \in [0, 2]$). $f_{\max}(x_i^k)$ and $f_{\min}(x_i^k)$ are the maximum and minimum value of the objective function of the ith wolf at the kth iteration, respectively.

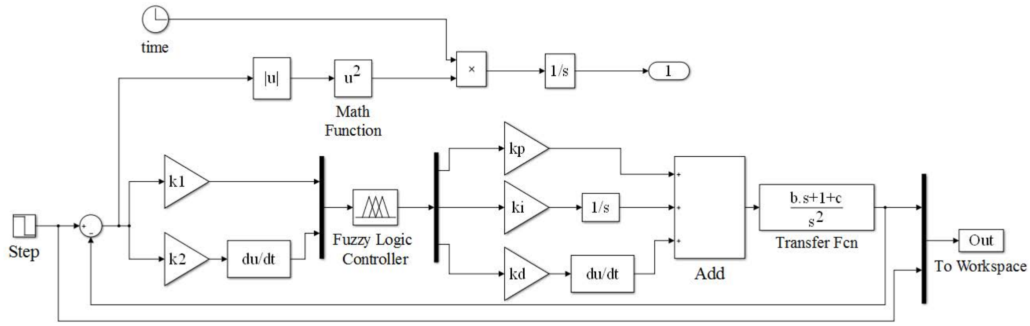

FIGURE 6. Simulink model of time synchronization system.

C. CUCKOO SEARCH ALGORITHM

The cuckoo search (CS) algorithm is a bionic algorithm inspired by the unique breeding behavior of cuckoo population. Cuckoos lay their eggs in the other nests, and the process of cuckoo incubation is complicated. The CS algorithm mainly obeys three principles [36]. Firstly, each cuckoo lays only one egg at a time and places it in a random nest. Then, the nest with the highest quality eggs will be preserved to the next generation. The number of available nests is fixed, and the host discovers the other eggs with the probability P_a. Subsequently, the host will throw away the eggs or builds a new nest.

In the CS algorithm, each egg represents a solution of the optimization problem, and the initial solution is generated randomly. Then, the solution is updated as:

$$x_i^{k+1} = x_i^k + \alpha \oplus levy(\zeta) \tag{17}$$

where x_i^k is the current solution at iteration k, α is the step-size scale factor, $\oplus$ represents the vector product, and ξ is the control factor for Levy flight. The Levy flight is a random walk and its step length meets the heavy-tailed stability probability with infinite variance and infinite mean.

$$levy \sim u = t^{-\xi} \quad (1 < \xi < 3) \tag{18}$$

D. HYBRID IWCA-CS ALGORITHM

In this paper, considering the characteristics of wolf colony algorithm and cuckoo search algorithm, a hybrid optimization technique, namely hybrid IWCA-CS, is proposed. Initially, the conventional wolf colony algorithm is improved by optimizing the initial population and adding inertial weights. Specifically, an encoding method based on Bloch spherical coordinates is employed for generating the initial population to improve population quality. Using inertial weights to dynamically adjust distance factor can improve the convergence performance of the algorithm. In the hybrid IWCA-CS algorithm, initially IWCA is applied, and then CS is applied. The best solution corresponding to the minimum objective function obtained by IWCA is taken as the beginning point of the CS algorithm.

In the hybrid IWCA-CS algorithm, the population of the algorithm is determined by the controller parameters to be optimized. The proposed hybrid algorithm can achieve self-tuning fuzzy PID controller via intelligently searching a group of controller parameters. By constantly adjusting the controller parameters, it is possible for the error to change toward the direction of reduction. Ultimately, the time synchronization between the master clock and slave clock is realized. The flow of the hybrid IWCA-CS algorithm is as follows:

Step 1: WCA and CS parameters initialization.
Step 2: Using Bloch spherical coordinate to generate initial population of IWCA, and calculating their fitness to determine leader wolf.
Step3: The searching wolves performs the walking behavior, until the leader wolf is replaced or the maximum iterations is reached, and then turn to step 4.
Step 4: In the summoning behavior, all the wolves get close to the prey reported by leader wolf according to (9). If there is a wolf with better fitness to replace the leader wolf, the next step is implemented; otherwise, the other wolves will go on attacking until the distance between them is less than default value.
Step 5: Update the position of wolves in the process of besieging prey according to (11).
Step 6: Assign the prey and update the wolf colony.
Step 7: If the termination condition is met, the step 8 is implemented; otherwise, go to step 2.
Step 8: Output the position of leader wolf, that is, the optimal solution of the problem, and select the best solution as the initial points of CS algorithm.
Step 9: Perform CS algorithm for further local search.
Step10: Output the optimal parameters of fuzzy PID controller.

V. EXPERIMENT RESULTS AND ANALYSIS

To test the performance and effectiveness of the proposed time synchronization control method, this paper designs a simulation model using Simulink as shown in Fig. 6. In the considered system, Step module is a step signal module, which generates a step signal with amplitude of 20 μs at time 0, that is, the initial error of master clock and slave clock is 20 μs. The Out module imports the simulation results into

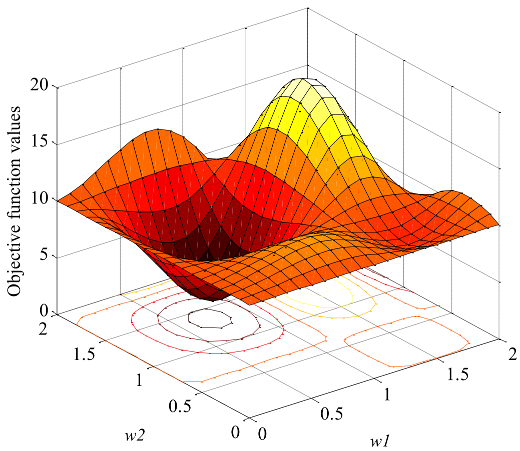

FIGURE 7. The results of different parameters.

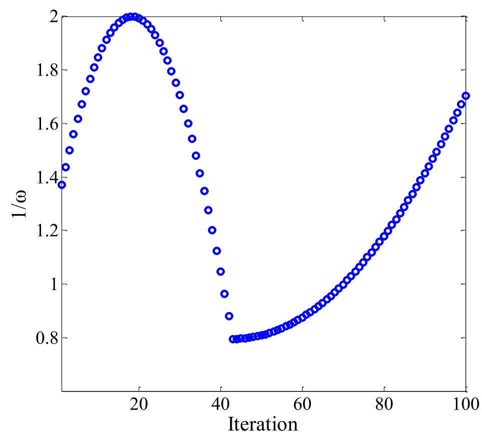

FIGURE 8. The fluctuation range of $1/\omega$.

the Matlab environment for data processing, and the transfer function of slave clock is taken as the control object. In the experiment, the frequency drift, c, is 0.00001, and the random error, b, is replaced by a Gaussian noise with 20 dB signal-to-noise ratio (SNR).

A. PARAMETER SETTINGS

As can be drawn from the descriptions of the hybrid IWCA-CS algorithm, some parameters require to be entered manually as employing the algorithm. In (16), w_1 and w_2 are introduced to dynamically adjust distance factor w. It is vital to select the appropriate parameters to improve the solution accuracy and convergence speed of the algorithm. To comprehend the effect of parameters on the controller, both w_1 and w_2 are set in the same range. Fig. 7 depicts the objective function values under different parameters.

It can be clearly seen from the three-dimensional figure that the optimal performance is obtained with algorithm parameters of $w_1 = 0.6$ and $w_2 = 1.4$. Meanwhile the fluctuation range of parameter w is shown in Fig. 8.

It is obvious from the figure that with the number of iterations increasing, the parameter $1/\omega$ firstly increases in the early stage which can extend the search scope and enhance the global ability of the algorithm. Then $1/\omega$ decreases indicating that the search scope becomes smaller to facilitate fine search and improve the convergence accuracy. In the later stage of the algorithm, the search scope gradually becomes wide to jump out of the local optimum. Therefore, introducing the inertial weights to dynamically adjust distance factor, w, can well balance the search ability of WCA.

B. HYBRID IWCA-CS PERFORMANCE ANALYSIS

By optimizing the test functions employed, the hybrid IWCA-CS optimizer is compared to WCA, CS and particle swarm optimization (PSO) to explain its optimization performance, and the parameters of these algorithms are presented in Table 2. Therein, all the algorithms have the same parameters in the maximum number of iterations and population size. The former is 100, and the other is the product of 10 and data dimension. The test functions involved are listed in Table 3. In addition, the data dimension is set to either 30 or 100. All the simulation experiments are performed on the PC system with a 2.50 GHz CPU and 8 GB RAM and its operating system is Windows 10 (64-bit).

TABLE 2. Parameters of algorithms.

Algorithm	Parameters
IWCA	q=5, h=8, $step_a$=1.5, $step_b$=0.9, ω=500, M=5, w_1=0.6, w_2=1.4
WCA	q=5, h=8, $step_a$=1.5, $step_b$=0.9, ω=500, M=5
CS	Abandonment rate P_a=0.25
PSO	Learning factor c_1=c_2=1.49

TABLE 3. Test functions.

Name	Formula range	Optimum
Sphere	$f_1(x)=\sum_{i=1}^{d} x_i^2$ [−100, 100]	0
Schwefel	$f_2(x)=\sum_{i=1}^{d} \lvert x_i \rvert + \Pi_{i=1}^{d} \lvert x_i \rvert$ [−10, 10]	0
Rastrigin	$f_3(x)=\sum_{i=1}^{d} [x_i^2 - 100*\cos(2\pi * x_i)+10]$[−5.12, 5.12]	0
Zakharov	$f_4(x)=\sum_{i=1}^{d} x_i^2 + (\sum_{i=1}^{d} 0.5x_i)^2 + (\sum_{i=1}^{d} 0.5x_i)^4$ [−100, 100]	0
Griewank	$f_5(x)=\frac{1}{1000}\sum_{i=1}^{d} x_i^2 - \Pi_{i=1}^{d} \cos(\frac{x_i}{\sqrt{i}})+1$[−100, 100]	0

In the experiment, the five algorithms are conducted independently 50 times for each of benchmark function. Here, the comparison results are analyzed primarily from four perspectives: optimum value, worst value, average value and average time consumption. The particulars of experiment result are listed in Table 4.

An analysis of the statistical data in the Table 4 shows that the hybrid IWCA-CS is significantly outstanding in all terms of evaluation indexes when solving the five benchmark functions. Specifically, the hybrid IWCA-CS can find the optimum value of 0 regardless of data dimensions, and its

TABLE 4. Comparison of optimization results.

Function	Algorithm	Optimum (30/100)	Worst value (30/100)	Average value (30/100)	Average running time (s) (30/100)
$f_1(x)$	hIWCA-CS	**0/0**	**0/0**	**0/0**	**6.08/10.58**
	IWCA	**0**/1.0018E-110	3.6701E-98/5.0269E-83	5.8806E-100/9.0135E-90	6.83/11.25
	WCA	3.9069E-85/2.0186E-76	2.0542E-60/6.5073E-54	1.5562E-73/4.3798E-65	15.27/20.16
	CS	7.0127E-67/2.7943E-58	3.2167E-45/1.0437E-39	3.0029E-54/1.9087E-46	30.22/45.12
	PSO	4.1760E-20/8.2697E-18	4.3306E-9/5.0327E-5	3.2173E-15/6.4032E-10	31.49/44.29
$f_2(x)$	hIWCA-CS	**0/0**	**0/0**	**0/0**	**6.10/11.22**
	IWCA	**0**/3.6593E-68	5.5832E-60/2.5096E-55	3.7064E-65/4.3021E-60	7.03/12.58
	WCA	2.8076E-56/9.1184E-45	2.3074E-37/1.8327E-30	3.2075E-50/5.3294E-40	15.90/20.66
	CS	3.7219E-25/5.3092E-20	1.4073E-16/6.2106E-12	8.3021E-19/5.2076E-15	30.78/44.90
	PSO	2.0754E-12/5.6013E-10	4.3336E-6/1.7094E-5	1.3904E-7/4.1743E-7	31.20/43.90
$f_3(x)$	hIWCA-CS	**0/0**	**0/0**	**0/0**	**5.96/11.04**
	IWCA	**0/0**	3.2804E-12/**0**	5.6073E-15/**0**	6.54/11.22
	WCA	**0**/3.6707E-64	8.0264E-53/2.7543E-50	2.7643E-70/8.4031E-56	15.30/20.48
	CS	6.5032E-14/4.5015E-12	0.7315/1.3641	2.6504E-4/0.1749	30.23/43.90
	PSO	3.7651E-10/5.1025E-9	8.3012E-4/2.6739E-3	1.5937E-5/6.9048E-5	31.80/44.79
$f_4(x)$	hIWCA-CS	**0/0**	**0/0**	**0/0**	**7.30/12.59**
	IWCA	**0**/5.2503E-113	8.2147E-98/4.0912E-94	3.0765E-100/8.2405E-95	7.94/13.09
	WCA	9.4327E-50/4.6803E-45	3.2074E-38/6.3026E-36	3.6435E-47/7.3218E-42	15.02/21.03
	CS	5.5032E-15/8.2134e-15	2.1358E-9/0.9032	5.3702E-12/6.3064E-10	30.50/43.78
	PSO	7.0916E-14/2.8045E-12	5.3025E-5/9.0325E-5	4.3890E-7/7.3184E-6	31.78/44.54
$f_5(x)$	hIWCA-CS	**0/0**	**0/0**	**0/0**	**6.12/11.23**
	IWCA	**0/0**	0.3217/0.7057	4.795E-3/0.0023	6.79/12.04
	WCA	7.3296E-54/7.1302E-50	5.8327E-43/8.0367E-40	4.0753E-48/7.0129E-48	15.27/19.96
	CS	3.3372E-21/6.2105E-19	1.9054E-13/4.7317E-11	4.9634E-17/2.0485E-15	30.25/43.76
	PSO	2.5834E-15/6.0851E-14	7.0364E-10/1.8528E-9	6.3256E-12/9.0483E-12	31.37/44.93

time consumption is the shortest of all five test functions as compared to other test optimizers. On the other hand, the minimum time consumption of IWCA, WCA, CS and PSO are 6.54 s/11.22 s, which is calculated by the IWCA optimization $f_3(x)$, and the IWCA can converge to optimal value for both $f_3(x)$ and $f_5(x)$. However, optimal value of WCA is 0 only for function $f_3(x)$ as the data dimension is small, and the computing time increases significantly than IWCA. Therefore, the two improvements in the quality of initial population and introduction of inertia weights are significant for further strengthening the performance of traditional wolf colony algorithm. It is also can be observed that, with the increase of data dimension, the performance of CS and PSO method deteriorate in terms of optimal solution and average running time, which indicates that both methods have poor optimization performance for the benchmark functions.

From the comprehensive analysis above, the hybrid IWCA-CS exhibits excellent performance in optimizing test functions. Therefore, it is employed for the parameters tuning of fuzzy PID controller in this paper.

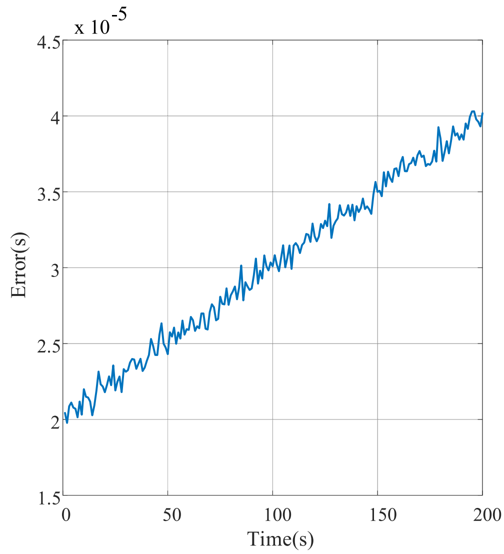

FIGURE 9. The offset errors of master-slave clock before synchronization.

C. APPLICATION OF THE PROPOSED APPROACH

The offset error of master clock and slave clock without adjustment is shown in Fig.9. As can be concluded, the deviation of the initial time between the master and slave clock is 20 μs. With the change of time, the error shows a linear growth trend, and is accompanied by slight jitter owing to the instability of the clock crystal oscillator. To compensate the error of the slave clock with respect to the master clock, the hybrid IWCA-CS is used to optimize the parameters of the fuzzy PID controller to realize the control of time synchronization.

For the successful application of fuzzy PID controller, it is essential to make the adjusting frequency of the controller in good agreement with the sending frequency of the synchronization message to get high synchronization accuracy. Hence, the sending period of the synchronization message must be selected carefully. Multiple IWCA-CS runs are performed to optimize fuzzy PID controller by changing the sending periods, and the error results are shown in Fig. 10.

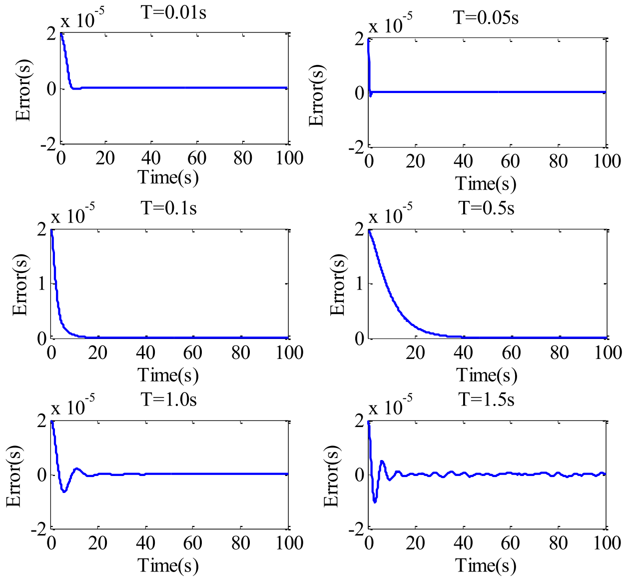

FIGURE 10. The error results under different synchronization periods.

It can be concluded that when the sending period is 0.01 s, the error can keep stable after 10 s. As the period increases to 0.05 s, the convergence speed of the error is the fastest as compared to that of other periods, and the minimum error is obtained at 5 s and then is constant until the simulation ends. Meanwhile, it also can be found that the error fluctuates obviously in the simulation time when the sending period is 1.5 s, and the system error changes around 0.1 μs after 20 s. From the above analysis, the best controller performance is obtained with sending period of 0.05 s, and the time synchronization precision is 0.1 μs, which meets the sub-microsecond synchronization requirement for the smart grid.

In the next step, an optimization method employing improved wolf colony algorithm with above parameters tunes the fuzzy PID controller parameters. To be fair comparison, 100 times are executed for the improved WCA, and the results are given in Table 5. Here, we primarily describe the results from four statistical aspects: maximum, minimum, average and standard deviation of ITAE. It can be observed from Table 5 that the improved WCA outperforms conventional WCA in all evaluation indicators. Finally, the proposed IWCA-CS is leveraged for optimizing fuzzy PID controller parameters, and the results obtained in 100 runs are also presented in Table 5, where it is found that obvious advance in the matter of maximum, minimum, mean and standard deviation are supplied by IWCA-CS compared to improved WCA and original WCA.

TABLE 5. Simulation results under different algorithms.

Algorithm	Max.	Min.	Ave.	Std.
WCA	3.8094	3.1723	3.5826	0.2739
IWCA	3.2103	2.5972	2.9631	0.2504
IWCA-CS	3.0659	2.3117	2.7463	0.1872

To further verify the performance of the fuzzy PID controller, we make a comparison of it with PID and PI controller.

TABLE 6. Itae and parameters under different controllers.

Controller	k_1	k_2	K_P	K_i	K_d	ITAE
PI	-	-	0.7527	0.3406	-	5.4258
PID	-	-	1.6435	0.9033	0.7257	3.9624
fuzzy PID	0.8425	0.3015	1.1791	0.4365	0.1135	2.0317

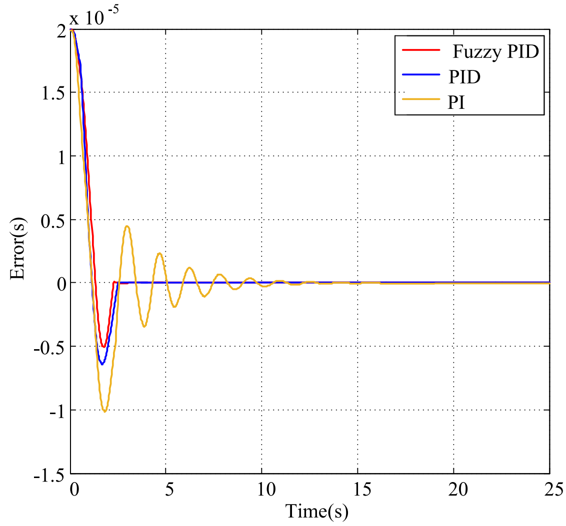

FIGURE 11. Output response curves of different controllers.

From the above analysis, the higher synchronization accuracy is obtained with the sending frequency of 0.05 s. The adjustment frequency of the controllers should be consistent with the above sending period to obtain high accuracy. Therefore, the three controllers are applied with above sending period for comparison. The results are gathered in Table 6, where IWCA-CS optimized PI/PID/fuzzy PID controller parameters along with ITAE are presented. It can be seen from Table 6 that lower objective function values are acquired with proposed IWCA-CS optimized fuzzy PID controller when compared to IWCA-CS optimized PI/PID controllers. Meanwhile, the system dynamic responses of the three controllers are quantified in Fig. 11. It is obvious from the figure that fuzzy PID controller obtain the distinct amelioration in output response as compared to PI and PID controller.

D. ROBUTNESS OF CONTROLLER

In time synchronization system, the crystal oscillator will inevitably be interfered by external disturbance during operation. The ambient interference will change the error of slave clock with respect to the master clock, and restrict the stable and reliable operation of power system. Therefore, it is significant importance to discuss the robustness of the controller.

Robustness of the proposed controller is found by putting in step load disturbance and varying the model parameters. Specifically, a 1% step load disturbance is applied with above designed controller to corroborate its anti-interference ability.

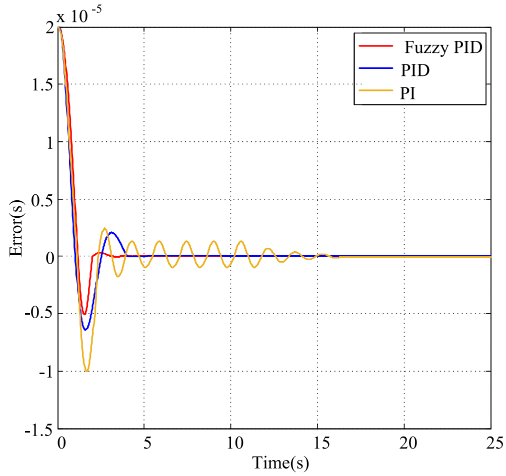

FIGURE 12. Output response curves under load disturbance.

Fig. 12 depicts the dynamic response curve of fuzzy PID controller optimized by hybrid IWCA-CS method under 1% step load disturbance increase. To have a better comparison, the results of PID/PI controller are also presented in Fig. 12.

It is obvious from Fig. 12 that compared with PID/PI controllers, the small overshoot and fast stable time are obtained with the proposed fuzzy PID controller under load disturbance. Therefore, the use of fuzzy PID controller structure can significantly reduce the stable time and enhance the flexibility of the system. Subsequently, by changing the SNR of Gaussian to verify the ability of the controller to tackle the external condition, SNR is selected in the range of ±30%. The evaluation indicators of the above test cases are given in Table 7.

TABLE 7. Sensitive analysis of the proposed fuzzy PID controller under system parameter changes.

Controller	Parameter variation	Change (%)	Overshoot ($\times10^{-5}$)	Settling time (s)	ITAE
Fuzzy PID	b	0	0.5	2.43	2.3276
		+30	0.45	2.51	2.3462
		-30	0.47	2.45	2.3158
PID	b	0	0.65	2.50	3.8731
		+30	1.26	3.25	4.0173
		-30	1.35	3.29	4.1065
PI	b	0	1.00	12.0	5.2219
		+30	2.65	15.25	7.3012
		-30	2.71	15.50	6.9632

It is evident from Table 7 that the performance of the proposed fuzzy PID controller is not easy to be affected by the parameter variations as compared to PID and PI controller. Specifically, the fuzzy PID controller can still keep the performance indicators in terms of overshoot, settling time and ITAE within a reasonable range respect to nominal in all tests. Furthermore, both PID and PI controller are sensitive to the changes of parameter. For example, the performance metrics of PID controller deteriorate with the changes of parameter, resulting in large overshoot, settling time and ITAE. It also can be revealed that the PI controller shows the worst performance when the parameter variations are considered. In a consequence, the fuzzy PID controller based on the hybrid IWCA-CS can get satisfactory performance with varied conditions.

E. IWCA-CS TUNED FUZZY PID CONTROLLER PERFORMANCE ANALYSIS

In this section, for assessment of the proposed IWCA-CS based fuzzy PID controller, the IWCA-CS is compared to the improved WCA, WCA, CS and PSO. In the simulation experiments, five algorithms involved are applied with aforementioned parameters to tune fuzzy PID controller parameters for convergence analysis as the convergence speed of the methods is one of the important indexes for the performance evaluations, and can reflect the optimization degree of the algorithm.

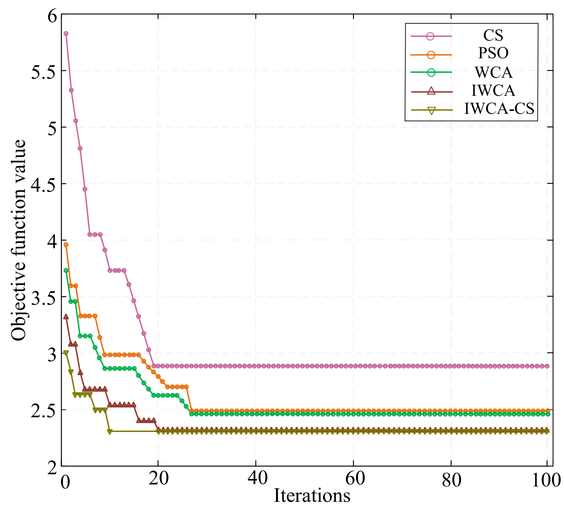

FIGURE 13. Convergence curves of different methods.

Fig. 13 shows the convergence curves of optimization methods tuned fuzzy PID controller. It can be illustrated that the convergence speed and optimization accuracy obtained with proposed IWCA-CS outperforms other compared algorithms. It converges at approximately 10 times the number of objective function evaluations. Although the solution calculated with improved WCA is almost similar to that of the IWCA-CS, it has slower convergence speed, which demonstrates that the improved WCA incorporating CS can make the algorithm converge quickly. In addition, CS algorithm adopting a local random walk and Levy flight strategy is of fast convergence speed, but the poor solution accuracy is presented in convergence curve. Based on the above convergence analysis, the proposed IWCA-CS is extremely effective for tuning FPID parameters: it accelerates convergence and improves the efficiency of the algorithm.

F. COMPRRISON WITH RECENT TIME SYNCHRONIZA-TION METHOD

To illustrate the excellent performance of the proposed hybrid IWCA-CS based fuzzy PID controller, the power information collection system (PICS) in smart grid is considered as test system. The PICS consists of three main elements: master station, data collection terminal and electric meters as given in Fig.14. The time synchronization of PICS adopts layered design. Specifically, the master station is applied for synchronizing the time of collection terminal, then the collection terminal is responsible for setting the time of electric meters. Using time synchronization algorithms can effectively improve the accuracy and efficiency of the power information collection. In this subsection, the proposed hybrid IWCA-CS tuned fuzzy PID controller is employed to synchronize the time of the collection terminal and the electric meters, and the time synchronization between the master station and data collection terminal is not narrated to avoid prolonging discussion. In addition, we make a comparison of it with the wolf colony algorithm-based PID controller [8] and an adaptive fuzzy-PI clock servo [20].

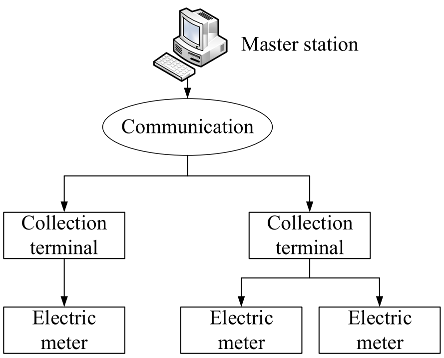

FIGURE 14. The architecture of the PICS.

In the experiment, the time of data collection terminal is regarded as the standard time. The time deviation of the collection terminal and electric meter and its derivative are considered as the inputs of aforementioned controllers. The equipment connection is shown in Fig. 15, wherein the collection terminal is the black device, and the meter is a three-phase fee-controlled smart meter (MLD-6300O). Specifically, the data collection terminal sends timestamp information to the electricity electric meter via PTP protocol at a fixed time interval, and then the electricity meter relies on the timestamp information for accomplishing time synchronization. The simulation time is set to 10 s, and the regulating period of the controller is set as 0.05 s, which means that the electricity meter is tuned every 0.05 s. The comparison results are plotted in Fig.16.

It can be concluded from Fig.16 that the errors calculated by the proposed method in this paper are smaller than that of the other two compared methods. In addition, the average errors of the proposed method, the method in [8] and [20] are -15.23 μs, -5.38 μs, and 0.76 μs, respectively. obviously, the minimum synchronization error is obtained with the hybrid IWCA-CS optimizing fuzzy PID controller. In brief, the proposed hybrid IWCA-CS tuned fuzzy PID controller makes further efforts to improve the time synchronization accuracy, and can meet the requirements of sub-microsecond for smart grid.

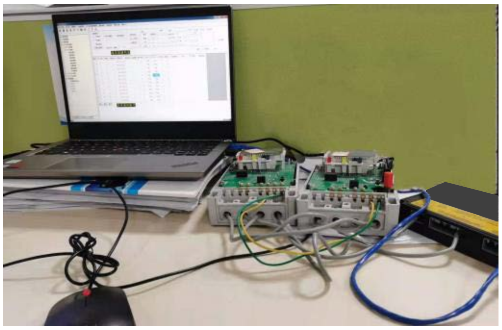

FIGURE 15. Physical equipment connection.

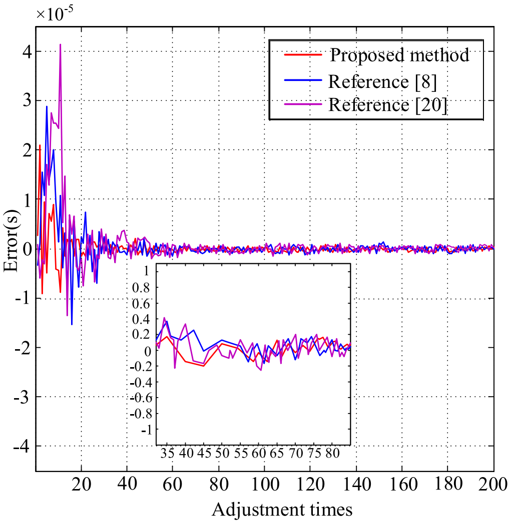

FIGURE 16. Comparison results of four methods.

VI. CONCLUSION

In this study, the time synchronization is considered as a control problem. Depending on the model of master clock and slave clock, an approach by integrating the improved WCA with CS (hybrid IWCA-CS algorithm) tuned fuzzy PID controller is proposed to dynamically adjust the frequency of the slave clock to get higher synchronization precision. The algorithm initialization of the improved WCA version is determined by the method of qubit Bloch coordinate encoding, and the inertial weights are introduced to balance the search ability, and the local search strategy CS is subsequently used to expand the search scope. The hybrid IWCA-CS optimizer is compared to improved WCA, WCA, CS and PSO by discussing five benchmark functions. The simulation results show that the proposed hybrid IWCA-CS method can accurately find the optimal value of test functions in the shortest time. Meanwhile, it is clear that hybrid IWCA-CS tuned fuzzy PID controller presents the best dynamic response when compared to IWCA-CS optimized PI/PID controllers. Then robustness analysis is conducted and it is observed that the proposed IWCA-CS tuned fuzzy PID controller is immune to step load disturbance and system parameter changes. Finally, the proposed time synchronization method is applied in PICS, and the further experiment demonstrates that the time synchronization accuracy of proposed hybrid IWCA-CS tuned fuzzy PID controller outperforms other published time synchronization methods. Therefore, the proposed IWCA-CS based fuzzy PID controller provides a time synchronization method with high precision for smart grid.

The proposed time synchronization control method only realizes the time synchronization between the data collection terminal and electric meter, which is only a part of the time synchronization for the entire PICS. There is still much work to be studied and explored. Further research will be conducted on the other equipment to validate the effectiveness of the proposed method, and the proposed time synchronization method lays a solid foundation for the future investigation research.

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