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An Optimized Neural Network Based On Chimp Optimization Algorithm For Power System Stabilizer

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***Abstract*—The Chimp Optimization Algorithm (ChOA) is a new metaheuristic method based on the life and colony of chimps in nature. A chimp can have an infinite number of colonies and tasks. Each individual has a task that leads to the colony's goal, which is to find prey. This study will propose applying the chimp optimization algorithm used to improve the neural network's performance, which is used to tune the power system stabilizers (PSS). Tests were carried out by using a single machine. In this study, the neural network used is a feed-forward backpropagation neural network. Measuring the performance of the proposed method is to compare it with other methods. From the experiment, the proposed method can reduce the average overshoot and undershoot velocity values by 12.75% and 31.49%, respectively. The results showed that the proposed method, namely ChOA-FFBNN, has the best performance and is adaptive.**

Keywords— chimp optimization algorithm, neural network, power system stabilizer, artificial intelligence, metaheuristic.

I. INTRODUCTION

An electric power system operates in a steady state. Someday, maybe, you will be disturbed. The disturbance is caused by switching operations, disconnected generators, sudden loading, short circuits, and others that disturb the balance between the mechanical input and the generator's electrical output. This situation will affect the stability of the generator and can result in reduced system synchronization.

Dynamic stability of the electric power system is the stability of the electric power system due to small load changes. Small changes in load will cause changes in the speed of the generator rotors and the generator terminal voltage. As a result, the generator rotor speed will swing around synchronous speed, and the generator voltage will swing around the nominal value. However, a generator is stable when the rotor speed returns to synchronous speed, and the voltage converges to a specific value around the nominal value after a fault (load change). In other words, the stability of the power system is described as steady-state and transient stability [1].

The conventional PSS design is based on linear control techniques. This encourages the power system to be modelled around the work point. As a result, PSS models and variables are set to get the best performance. On the other hand, the power system has a nonlinear character and varying operating conditions. This causes the conventional PSS, which adheres to variable settings, to not perform best in all operating conditions. In addition, conventional PSS takes longer to process [2].

Integer controllers have so far dominated conventional theory. In recent years, the theory of fractional calculus has developed. Fractional calculus theory gives its colour in a flexible control system. Several studies on PSS with conventional methods such as PID [3-4] and FOPID [5-6] are starting to gain a place.

Rapid technological developments have led to a shift in mindset in solving problems. A computerized mindset is at the forefront of solving it—likewise, computer technology in optimizing PSS control. The method helps in designing an adaptive PSS. Adaptive can accept parameter uncertainty and nonlinear power systems. In addition, an adaptive PSS must give the best performance in all conditions [7].

Some of the latest PSS research leads to artificial intelligence, such as metaheuristics and neural networks. Several popular metaheuristic methods are used to solve various engineering problems. A metaheuristic method is to duplicate physical or biological phenomena, which can be divided into four main categories, namely: physics-based, evolution-based, swarm-based, and human-based methods.

Several metaheuristic methods are used in research on PSS, such as the whale optimization algorithm [8-11], genetic algorithm [12-13], cuckoo search algorithm [14], Teaching Learned Based Optimization [15], and Gray Wolf Optimization [16-17]. Meanwhile, several studies on PSS apply the neural network method [18-20].

This research will discuss PSS tuning using the hybrid Chimp Optimization Algorithm (ChOA)-neural network method. ChOA is one of the metaheuristic methods of the Swarm Intelligence-based Algorithms (SIAs) category. Swarm Intelligence-based Algorithms (SIAs) are methods derived from the natural behaviour of animals such as whales, ants, bees, salps, and dragon-fly [21].

The research will train neural networks using ChOA, which is applied to the power system stabilizer. Several metaheuristic algorithms have been applied in conducting training in neural networks, but the local optima problem is a very interesting area to study. Furthermore, validation and verification of the performance of the proposed method will be compared with other methods.

II. Literature Review

A. Chimp Optimization Algorithm

The metaheuristic method has become an alternative means of solving various problems in the engineering field. The development of increasingly complex problems has made the metaheuristic method very popular. Multiple advantages of metaheuristic methods, such as modest construction and contexture local optimum deflection flexibility, The Chimp Optimization Algorithm is a metaheuristic method including Swarm Intelligence-based Algorithms (SIAS) derived from the natural behaviour of animals, birds, insects, whales, and their colonies.

Chimpanzee colonies are fission-fusion communities. This community is not static but dynamic. The size of this community often changes in the number of members over time. Each individual in this community operates in all areas. Each chimp has its character in the algorithm for exploring the search space. They have individual abilities and intelligence. They will carry out their duties as part of a group. Individual abilities are useful under different conditions.

The Chimp colony has four types of duties, namely driver, barrier, hunter, and attacker. These are to sustain hunting. The driver must follow the prey without having to chase it. A barrier will block the advance of prey by erecting a barrier. The chaser will chase the prey without having to attack. The attacker predicts the escape path of the prey in the covered area. The movements of each type of chimp can model the eye. The appropriate ChOA specifications are established [21].

1. Driving and chasing the prey

Prey will be hunted in the exploration and exploitation phase. Mathematical modelling for driving and chasing prey is eq, (1) and (2):

$$a = \left|b.x_{prey} - m.x_{chimp}\right| \tag{1}$$

$$x_{chimp}(t+1) = x_{prey}(t) - c.a \tag{2}$$

$$c = 2.\mathrm{f}.\mathrm{r}_1 - \mathrm{f} \tag{3}$$

$$b = 2.\mathrm{r}_2 \tag{4}$$

Where the coefficient vectors are b,c, and m. A chaotic parameter that symbolizes the influence of chimp sexual motivation on the hunting process is m. Important points that must be paid attention to understand the effective individual in ChOA :

- Group of individuals can update f. A chimp can explore the search space with different competencies
- Different competencies and dynamically build global and local searches are in balance
- Individual colonies with nonlinear competence for the function f so that ChOA can effectively solve complex optimization problems.
- Individual colonies that can adjust to solve larger optimization problems

2. The exploration phases

Chimp's behaviour in attack can be modelled in 2 approaches: 1. A chimp will explore the prey area (driver, barrier, chasing), and 2. A chimp will surround the prey area. Finally, the attacker will manage the hunt. In the first iteration, the prey position is assumed to be the same as the chaser position. At the same time, the positions of drivers, barriers, and pursuers are updated according to the attackers' positions. So, by using four parameters, another chimp can update its position by referring to the best position. The following eq defines this approach. (5) to (7):

$$a_{attacker} = |b_1.x_{attacker} - m_1.a| \ , \ a_{barrier} = |b_2.x_{barrier} - m_2.a|$$

$$a_{chaser} = |b_4.x_{chaser} - m_3.a| \ , \ a_{driver} = |b_4.x_{driver} - m_4.a| \tag{5}$$

$$x_1 = x_{attacker} - c_1.a_{attacker} \ , \ x_2 = x_{barrier} - c_2.a_{barrier}$$

$$x_3 = x_{chaser} - c_1.a_{chaser} \ , \ x_4 = x_{driver} - c_4.a_{driver} \tag{6}$$

$$x(t+1) = \frac{x_1+x_2+x_3+x_4}{4} \tag{7}$$

3. The exploitation phase

The chimp will end the hunt when the prey stops moving and the chimp starts attacking its prey. If the position is a random value between [-1,1], the new chimp position will be between the current and prey positions. ChOA is prone to local minimums even though it already has four parameters: driver, blocking, chasing, and prey. Because it requires other variables in the exploitation stage, this avoids the trap of a local minimum. In the ChOA method, the chimps scatter to find and move together to attack their prey. Variable c is used as a mathematical model of this behaviour.

$$|c| > 1 \ \ push\ the\ chimp\ to\ branch\ off\ from\ the\ prey$$
$$(keep\ away\ from\ local\ optima\ traps) \tag{8}$$

$$|c| < 1 \ \ push\ chimps\ to\ gather\ at\ prey\ area$$
$$(global\ optima). \tag{9}$$

The variable of b is a random variable in the range of [0, 2]. In eq. (4), The variable gives random weights for prey to build up (b > 1) or decrease (b < 1) the effect of prey's location in the definition of the distance in Eq. (7). In reality, variable b assigns a random weight to the prey, which makes the prey difficult to hunt.

We improved the exploitation phase using the social incentive.

In a chimp colony, there will be chaos if the chimp leaves his hunting duties at the hunting stage. They will try to snatch the desired hunting meat. Chaotic conditions at this final stage can be modelled using chaotic maps. Chaotic maps are used to improve ChOA performance. This process also assigns random values (μ)starting with 0.7.

$$x(t+1) = \begin{cases} x_{prey} - c.a \ \ , if\ \mu < 0.5 \\ Chaotic\_value \ \ , \ if\ \mu > 0.5 \end{cases} \tag{10}$$

B. Neural Network

The neural network method has a biological topology that is inspired by the work of human nerves. Neural networks have been used extensively in all different fields. This is due to its ability to adapt rules and learn from data and create network models that can be used for identification,

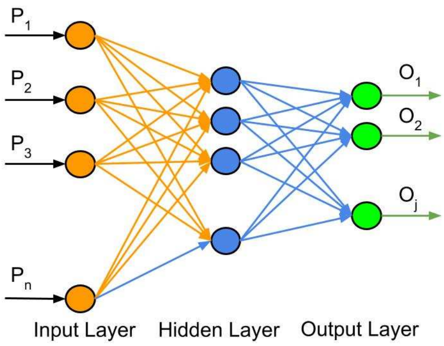

Fig. 1. FFBNN Topology [22]

classification, image recognition, and forecasting. Neural networks have capabilities that other methods do not have. Namely, they can carry out network simulations and modelling, which are useful for further work. One of the popular variants of the neural network is the feed-forward back propagation neural network (FFBNN).

The FFBNN algorithm is also often applied for control because it has regular interconnections. During the training process, the output will give an alarm when there is an error. So, it can be minimized. In addition, FFBNN has the advantage of adding weight to the hidden layer. FFBNN can solve complex problems, both linear and nonlinear. The FFBNN topology consists of input, hidden, and output units. FFBNN has a two-way capability, namely the forward direction, which is used to calculate the output, and the back direction, which is used to calculate the error. The FFBNN topology can be seen in Figure 1.

Input data (P_n) will be processed in the hidden unit by giving weight (W_{ij}) to each input variable. Input data is multiplied by the weight. Each input data will be added with the bias (b_1) in each layer. Meanwhile, the activation function is also used at each layer.

$$A_1(t) = \sum_{i=1}^{j} W_{ij} P_n(\mathrm{t}) + bias_1 \tag{11}$$

$$A_2(t) = f\big(A_1(t)\big) = \frac{1}{1+exp^{A_1}} \tag{12}$$

$$C_1(t) = \sum_{j=1}^{k} W_{jk} A_2(\mathrm{t}) + bias_2 \tag{13}$$

$$O_1(t) = f\big(C_1(t)\big) = \frac{1}{1+exp^{C_1}} \tag{14}$$

The output gets a target pattern that matches the input pattern. The calculation of error information is obtained by multiplying the derivative of the activation function carried out in backpropagation.

$$\delta_k = (t_i - O_1) f'(C_1) \tag{15}$$

The corrections of weight can be used to correct new weights W_{ijk},

$$\Delta W_{jk} = \alpha \cdot \delta_k \cdot A_2 \tag{16}$$

Where α = Learning Rate, which normally ranges from 0.1 to 0.5. The learning rate variable widely influences the strength of the training process.

C. Power System Stabilizer

The generator control consists of two parts, namely automatic voltage regulators (AVR) and power system

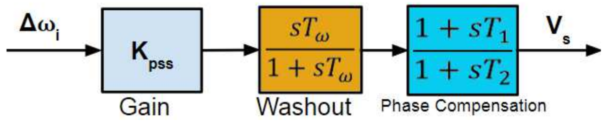

Fig. 3. PSS Block Diagram

stabilizers (PSS). Both AVR and PSS have functions to maintain generator stability [23]. AVR functions to regulate the terminal voltage at a predetermined value. PSS has the function of providing the excitation system's damping torque to the generator. This is to avoid electromechanical oscillations that occur at low frequencies.

PSS has three main components, namely the gain, which has the function of supplying sufficient gain value to the system to dampen oscillations. The washout is used as a high-pass filter. And the phase component is useful for increasing the lagging phase that occurs in the system.

The conventional PSS, which is popularly used, is shown in Figure 2. The transfer function can be seen in eq.17. The conventional PSS consists of a K_{iss} gain block connected to a high-pass filter with Time constant $T\omega$ and a lead-lag compensated phase block with time constants T1 and T2. PSS output (V_s) is the signal added to the exciting system. The PSS signal input is the synchronous speed deviation from $\Delta\omega_i$

$$V_s = K_{pss} . \frac{sT\omega}{1+sT\omega} . \frac{1+sT_1}{1+sT_2} . \Delta\omega_i \tag{17}$$

III. RESULTS AND DISCUSSION

Figure 3 is the application of ChOA and FFBNN for tuning PSS in a single machine. The first step is to model the generator in the Heffron-Phillips. The simulation results from the modelling are the speed and rotor angle. This is used as input to the FFBNN. The random initial value of the weighting

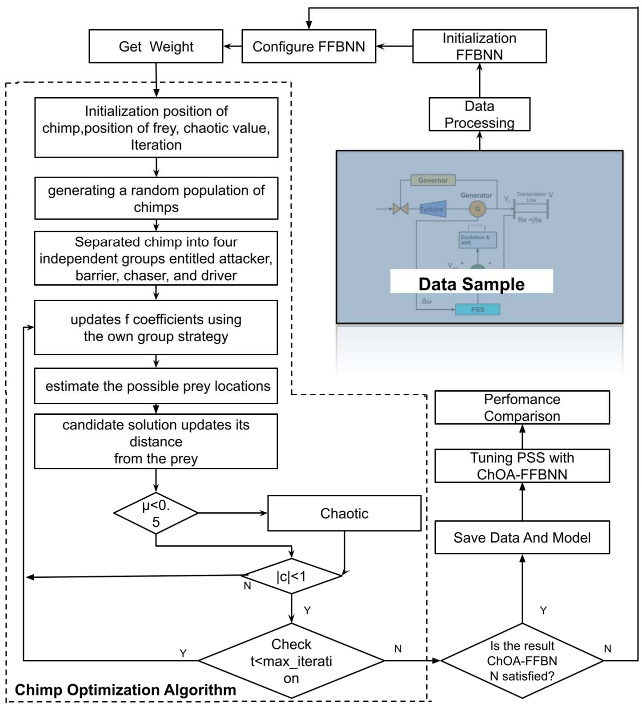

Fig. 2. The ChOA-FFBNN Flowchart

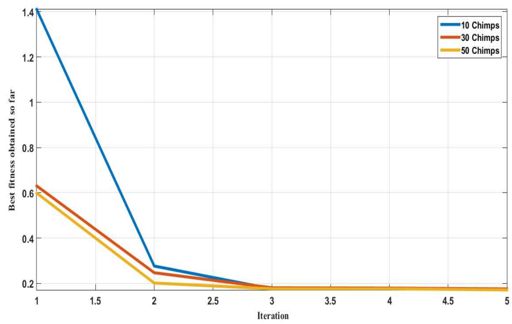

Fig. 6. Convergence Curve Of Search Agent for ChOA-FFBNN

sample is taken, which is processed using ChOA. The results will be the potential weight for FFBNN.

To measure the performance of the ChOA-FFBNN, the proposed method is compared with the Feed-forward Backpropagation Neural Network, Cascade Forward Backpropagation (CFBNN), Focused time-delay neural network (FTDNN), and distributed time-delay. Neural network (DTDNN). The number of hidden layers from the comparison method is four. The neural network is set up with 1000 iterations and uses the Levenberg Marquardt training method. In addition, to measure the performance, also use several variations of cases. The first case is using a load of 10%. The second case uses a 50% load. The third case uses a 90% load. The coding is using the Matlab application. The focus of the research is on the speed deviation in a single machine.

ChOA parameters with the specified variables must be set, and the optimal value is determined. This is to find the best parameter that can be used for setting the variable of FFBNN. The chimp population used is 10, 30 and 50. Figure 4 is the result of 100 iterations of the chimp population 10, 30 and 50. In Table I, it can be seen that the best chimp value is owned by a population of 50. The value of the settling time is 2.87, and the peak value is 0.5989.

TABLE I. PARAMETER VALUES FOR VARIOUS POPULATION

Population Chimp	Rise Time	Settling Time	Peak
10	1.7562	3.7683	1.0402
30	1.3313	3.1759	0.6304
50	0.8614	2.87	0.5989

ChOA parameter has been obtained. The next is to use these parameters for training FFBNN. Table II is a complete detail of the ChOA parameters used.

TABLE II. PARAMETER OF CHOA

Algorithm	Parameter	Value
ChOA	Upper And Lower Limit	[-1.5,1.5]
	Maximum number of iterations	100
	Population Chimp	50

PSS modelling, which is the result of implementing the ChOA-FFBNN, is tested using load variations.

A. Case 1 With 10 % Loading

Case 1 is 10% loading. The system is given a light load, and the effectiveness of the PSS used is measured. Figures 5 and 6 are the speed and rotor angle results with a loading of 10%.

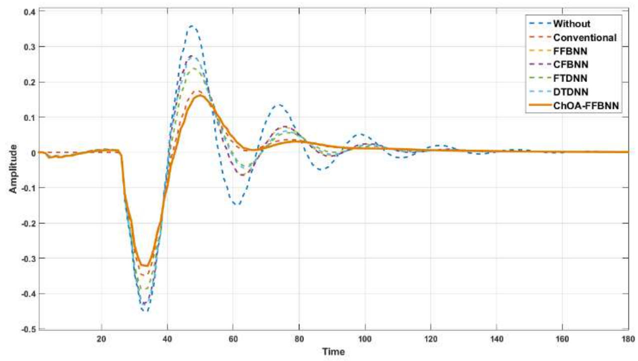

Fig. 4. The speed with 10 % load

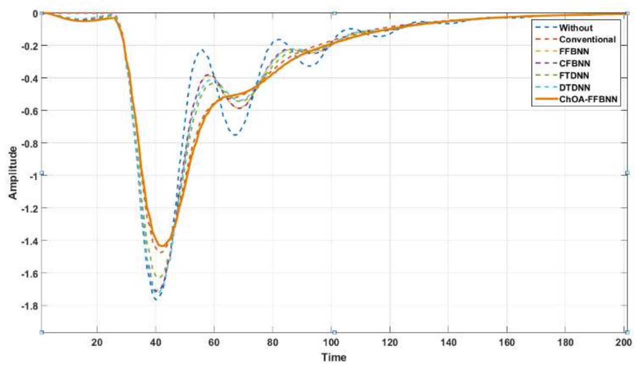

Fig. 5. Rotor Angle with 10 % load

In Case 1, ChOA-FFBNN can reduce the overshoot of the speed by 7.47% and the undershoot of the speed by 33.95% compared to the conventional method. The worst value of the speed overshoot is the CFBNN method. The value is 0.273. Meanwhile, the worst value for undershoot speed is the conventional method. The value is -0.432. The proposed method can reduce the rotor angle by 2.64% compared to the conventional method. Detailed results from case 1 can be seen in Table 3.

B. Case 2 With 50 % Loading

Experiments with a load of 50%, the results of the ChOA-FFBNN method obtained the best speed and rotor angle. Undershoot and overshoot of the speed can be reduced by 9.03% and 9.156%. Meanwhile, the undershoot rotor angle value can be reduced by 3.89% compared to the conventional method. Undershoot and overshoot of the speed can be reduced by 9.03% and 9.156%. Meanwhile, the undershoot rotor angle value can be reduced by 3.89% compared to the conventional method. The worst undershoot and overshoot values of speed are CFBNN and DTDNN. The value is by 6.7% and 33.3%. The Complete results of case 2 can be seen in Table 4.

C. Case 2 With 80 % Loading

The undershoot and overshoot values of the speed can be reduced by 7.37% and 9.87%. Meanwhile, the undershoot rotor angle value can be reduced by 4.78% compared to conventional methods. The undershoot and overshoot worst of speed value is DTDNN. The value is 2.17% and 19.76 % worse than the conventional method. The proposed method can reduce the undershoot by 4.782% compared to the conventional method on the rotor angle.

On the other hand, the worst undershoot value is the FFBNN method. The value is 4.76% worse than the conventional method. Table 5 is the PSS result with several method variations with 80% loading to the system.

IV. CONCLUSION

This study aims to measure the use of the hybrid method, namely the chimp optimization algorithm and feed-forward backpropagation neural network. The hybrid method is applied to the power system stabilizers (PSS) installed in a single machine system. Validation and verification are carried out by comparing the proposed method with other methods. In addition, the proposed method is also tested on systems under different loadings. The research results show that the proposed method has the best value. From 3 experiments using 3 cases, the proposed method has the ability to improve the performance of the FFBNN. The average overshoot and undershoot values of the speed can be reduced by 12.75% and 31.49%.

Meanwhile, the undershoot of the rotor angle can be lowered by an average of 12.63%. The ChOA-FFBNN hybrid method has the advantage of being adaptive, effective, and efficient when applied to PSS installed on a single-machine system. In this study, the proposed method, namely ChOA-FFBNN, was tested on a simple system and linear conditions. It is necessary to carry out test cases on more complex systems and nonlinear circumstances to find out more about performance capabilities.

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