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Tunicate Swarm Algorithm-Neural Network for Adaptive Power System Stabilizer Parameter

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ABSTRACT

Tunicate Swarm Algorithm (TSA) is a metaheuristic method that imitates the life of the tunicate. It occurs during navigation and foraging using jet propulsion and swarm behavior. A feed-forward neural network (FFNN) is a neural network that is often used, and applied. computational methods have been widely used to optimize FFNN weights in order to produce better output. This paper proposes a compound algorithm based on a tunicate swarm algorithm to optimize an FFNN. It is applied to power system stabilizers. The proposed method is compared with other algorithm methods such as the feed-forward (FFNN), cascade forward backpropagation (CFBNN), focused time delay (FTDNN), and distributed time delay (DTDNN). The proposed method has the ability to improve the output of FFNN methods. The proposed method has the average ability to reduce the overshoot of the speed by 35.17% and the undershoot of the rotor angle by 15.36%. In addition, the proposed method has better capabilities than the comparison method. The results of the experiment show that the use of the submitted algorithm has preferable adaptability and performance than the other methods.

Keywords: Feed-forward neural network; Metaheuristic; Neural network; Power system stabilizer; Tunicate Swarm Algorithm

1. Introduction

Progress in economic and technological development is followed by demand for electric system requirements. The electrical network is a collection of non-linear and complex systems that is influenced by the increase in load changes. The main key in a reliable power system operation is to keep the synchronous generator running at its work point and able to meet load demands according to the available capacity. Synchronous machines do not handly go down of swing under regular forms. If a machine swing tends to increase or decrease, synchronizing induces it to perform normally. A condition often

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occurs when the synchronization from the generator is less reliable and has a little influence on the system, causing a generator to lose synchronization. Meanwhile, changes in load are followed by an imbalance between supply and demand. This results in the generator having to try to stay in sync to adapt to new operating conditions. Some disturbances often occur in the form of major disturbances such as disconnection of the generator from the system, network outages, or small and random load changes that occur in regular conditions. Oscillations often follow disturbances. Oscillations can be damped by leading to new operating conditions. This is called a stable system.

Oscillations that often occur and have a large impact are low frequencies in the 0.2-2 Hz range [1]. The equipment used in solving the sway stability obstacle is the power system stabilizer (PSS). The PSS is able to increase damping so that it can reform the achievement of the power system.

Conventional PSS has a design using control theory. Power system modeling is assumed to be linear around nominal operation. The PSS variable is assumed and assigned to get the best performance. In fact, the power system has a nonlinear character and operation that varies over a wide range. This is a weakness of conventional PSS which cannot provide optimal performance with complex problems. This is exacerbated by the configuration of an electrical system that turns frequently. It also requires attention in the PSS adjustment in maintaining its best performance [2].

In recent years, methods using artificial intelligence have begun to be used with the aim of optimizing PSS variables such as particle swarm optimization (PSO) [3-5], taboo search [6], genetic algorithm [7-9], Biogeography-Based Optimization [10-12], bat algorithm [13-15], world cup optimization algorithm [16], Harmony Search Algorithm [17-20], Fuzzy [20-22] and neural networks [23-26].

Research on the power system stabilizer is a popular area. Although many studies have presented research in the power system stabilizer area, there is still plenty of room to explore for the best performance. This paper has main contributions, namely:

1) Application of the newest and promising method of metaheuristics, namely the Tunicate Swarm Algorithm. The method was presented by Kaur et al in April 2020. In a study conducted by Kaur et al, it was found that the TSA method had the best performance compared to the Spotted Hyena Optimizer (SHO) method, Gray Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), Multiverse Optimizer (MVO), Sine Cosine Algorithm (SCA), Gravitational Search Algorithm (GSA), Genetic Algorithm (GA), and Emperor Penguin Optimizer (EPO) [27]. Based on research by Kaur et al, this paper is using the TSA method to optimize the feed-forward neural network method. The proposed method is called TSA-FFNN. The proposed method is used to adjust the power system stabilizer.
2) The focus of this research is to measure the output performance of the rotor speed and angle in a single machine.
3) Accuracy and potential are presented by conducting in-depth comparisons using several methods, namely feed-forward (FFNN), cascade forward backpropagation (CFBNN), focus time delay (FTDNN), and distributed delay time (DTDNN).

2. Materials and Methods

2.1 Tunicate Swarm Algorithm

Tunicate Swarm Algorithm is an algorithm that duplicates tunicate colonies. This animal is a group of marine animals which live on docks, rocks or the bottom of boats. To most people, they look like tiny blobs of color. The tunicate can be seen from afar because it is capable of producing bright blue-green light or bioluminescence.

Tunicates have two ends that have different functions; an open end, which is used as a propulsion such as jet propulsion using atrial siphons, and a closed end. Tunicates move by relying on fluid bursts [27]. This burst is so powerful that it can move tunicates vertically in the ocean. This animal has a shape in the millimeter scale. Tunicates have the expertise to find food sources in the sea when there is no food source information. Tunicates have the readiness to recognize food. This is called jet propulsion and swarm intelligence

Mathematical modeling of the first behavior of the tunicates, namely the propulsion of the jet, must meet three conditions: to prevent disputes between tunicates, to shift the potential tunicate locatoin, and to close on the potential tunicate. On the other hand, the swarm behavior has a function to update the existence of other seekers in order to find the best optimal solution.

2.1.1 Keep away the conflict among tunicate

To dodge the clash between tunicates, the new search agent position calculation (T) can be modeled as follows in Eq. (2.1).

$$\vec{T} = \frac{\vec{H}}{\vec{M}}, \tag{2.1}$$

$$\vec{H} = r_2 + r_3 - \vec{W}, \tag{2.2}$$

$$\vec{W} = 2 \cdot r_1, \tag{2.3}$$

where gravity force is $\vec{H}$ in Eq. (2.1) and Eq. (2.2). The movement of water advection in the deep sea is $\vec{W}$ in Eq. (2.2) and Eq. (2.3). r_1, r_2 and r_3 are disorder grade that have a range [0, 1]. $\vec{S}$ in Eq. (2.4) is the colony strength between the tunicates. $\vec{M}$ describes the social compels between search agents.

$$\vec{S} = \lfloor V_{\min} + r_1 (V_{\max} - V_{\min}) \rfloor, \tag{2.4}$$

where $V_{\min}$ and $V_{\max}$ reflect the beginning and lower speeds to create social contact. The variables $V_{\min}$ and $V_{\max}$ have work values 1 and 4.

2.1.2 Shifting to the position of the best tunicate

If conflict between tunicates can be avoided, the tunicates will approach the best tunicates.

$$\overrightarrow{X_{fs}(n)} = \left| \overrightarrow{X_s} - r_{and} \cdot \overrightarrow{X_p(n)} \right|, \tag{2.5}$$

where the distance between the food source and tunicate is $\overrightarrow{X_{fs}}$ in Eq. (2.5), n is the current iteration**.** The location of the food source is $\overrightarrow{X_s}$. Vector $\overrightarrow{X_p(n)}$ shows the location of the tunicate. A disordered grade in space [0, 1] is r_{and}.

2.1.3 Assemble with the best tunicate

Tunicate can update its position towards the best tunicate**.** It is related to the position of food source

$$x(t) = \begin{cases} \overrightarrow{X_s} + \vec{T} \cdot \overrightarrow{X_{fs}}, & \text{if} \quad r_{and} \geq 0.5, \\ \overrightarrow{X_s} - \vec{T} \cdot \overrightarrow{X_{fs}}, & \text{if} \quad r_{and} < 0.5, \end{cases} \tag{2.6}$$

where $x(t)$ in Eq. (2.6) is the updated position of tunicate with respect to the position of food source $\overrightarrow{X_s}$.

2.1.4 Swarm behavior

Optimal solutions are the best kept and other tunicates positions are updated by searching for the best tunicate positions**.** The tunicate crowd behavior can be formulated as follows in Eq. (2.7).

$$\overrightarrow{X_p(n)} = \frac{\overrightarrow{X_p(n)} + \overrightarrow{X_p(n+1)}}{2 + r_1}. \tag{2.7}$$

The tunicate position will determine the last position in a random area. The key points of the turnicate swarm algorithm are:

- Parameters $\vec{T},\vec{H}$ and $\vec{W}$ guard and support a specified search space and avoid conflict between tunicates.
- It is hoped that the exploration and exploitation phase will get a better value by using vector variations $\vec{T},\vec{H}$ and $\vec{W}$.
- The group behavior of the TSA algorithm can be observed from jet propulsion and tunicate colony behavior.

2.2 Feed forward neural networks

Neural Networks are designs that try to replicate several of the fundamental information execution methods proposed in the brain. The advantages of neural networks are high-level computing applications, the ability to learn and generalize (generalization is to produce the appropriate output for input), ability for non-linear problems, and adaptability [28]. ANN has an advanced neural network and a feedback neural network. Feed-forward networks have the characteristics of a simple network structure and are easy to implement [29]. The network is developed from several neurons in each layer which are connected by weighting intermediaries. Neurons from related units in the previous layer, the weighted input which is summed by the refractive unit is passed to a single neuron. The function of bias is to adapt the input to a practical and possible range. The Model of FFNN is illustrated in Fig. 1.

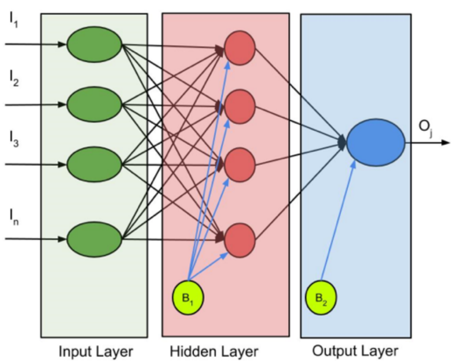

Fig. 1. Conceptual model of a feed-forward neural network.

Output is the sum of the weighted and biased inputs that have passed through the transfer function. The Formula Processing can be seen in Eq. (2.8) and Eq. (2.9). Output is processed by going through the next layer weight. This process is repeated until it matches the algorithm specified.

$$O_i(t) = \sum_{j=1}^{n} W_{jn} I_n(t) + b_1, \tag{2.8}$$

$$O_j(t) = f(O_i(t)) = \frac{1}{1+\exp^{O_i}}. \tag{2.9}$$

Neural network weighting optimization is to get the best weight to achieve a higher classification in terms of accuracy.

The mean square error (mse) is taken to assess the fallacy. The MSE formula can be seen in Eq. (2.10).

$$MSE = \sum_{i=1}^{n} (\text{target}_i - O_i)^2. \tag{2.10}$$

2.3 Power system stabilizer

The power system stabilizer (PSS) has the function of adding attenuation to the system to avoid electromechanical oscillations caused by minor disturbances. A PSS in general has three important components, namely gain, washout and phase compensation. The block unit of a PSS can be seen in Fig. 2. In a conventional PSS, gain is still used and requires good resetting capability when operating conditions change.

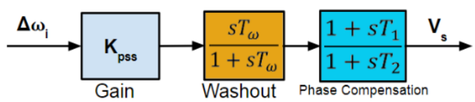

Fig. 2. PSS Block Diagram.

The conventional PSS consists of a K_{pss} gain unit related to a high-pass filter with a time constant $T\omega$ and a lead-lag compensated phase unit with time T_1 and T_2. PSS output (V_s) in Eq. (2.11) is the input added to the excited system. The input of PSS represents the synchronous speed deviation from the system $\Delta\omega_i$.

$$V_s = K_{pss} \cdot \frac{sT\omega}{1+sT\omega} \cdot \frac{1+sT_1}{1+sT_2} \cdot \Delta\omega_i \qquad (2.11)$$

3. Results and Discussion

The generator is modeled in the Heffron-Phillips model**.** The model can be seen in Fig. 3. It includes K1-K6, well-known Heffron-Phillips variables. T_m is input torque and V_{ref} is the reference voltage of the AVR. The rotor speed and the rotor angle are ω and δ. The transient and steady state internal voltage of the armature are $E_q^{'}$ and E_{fd}.

In the mechanical loop, K_A is DC gain and T_A is time constant of the AVR. K_D and $2H = M$ indicate the damping factor and rotor inertia. $T_{do}^{'}$ is the direct axis open circuit time constant. K_A is DC gain. T_A is time constant of the AVR.

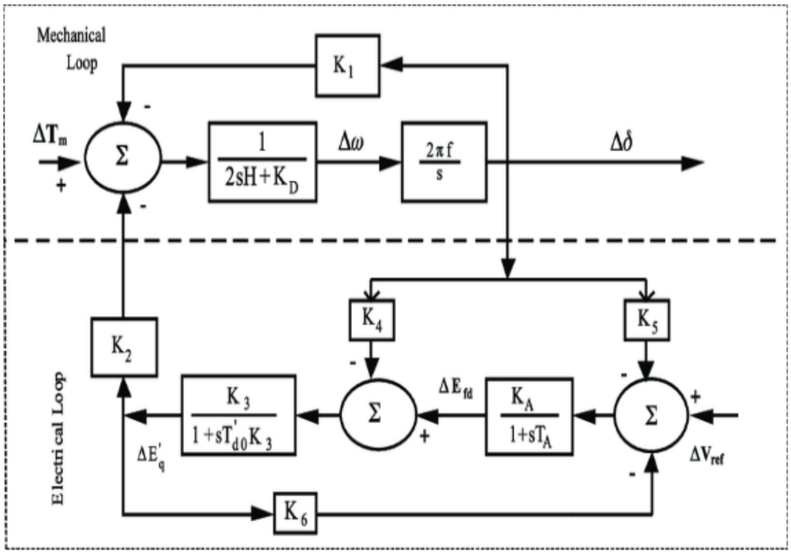

Fig. 3. Heffron–Phillips block diagram for SMIB power system [30].

Fig. 4 is the assembly of TSA with FFNN for setting PSS in a single machine. In this paper, the training data is using the output speed and rotor angle of the system as input for FFNN. At the start of the processing in the TSA session, the random weighting values were derived from the FFNN. The random weight value is optimized using the TSA method**.** The output will be the strength weight for FFNN.

Verification and validation are employed to assess the achievement of the submitted method. TSA-FFNN was measured by comparing the results of the speed and rotor angle. The methods used for comparison are FFNN, CFBNN, FTDNN, and DTDNN. In this paper, the neural network setting is using 4 hidden layers. The number of iterations is limited to 1000 in order to avoid overfitting. Meanwhile, the training method used Levenberg Marquardt which has advantages in speed and stability. The loading variation is also used to examine the capability of the submitted algorithm. In this study, the load variation uses light loads (20%), medium loads (60%), and loads close to full load (90%). The first step is knowing the variables required for the TSA method. This is to get the optimal value. The results from the TSA will be used to obtain the best FFNN variable. Based on research from Kaur et al, which used 30 and 50 tunicate populations with 100 iterations, this study is adding the population data below the data, namely using a population of 10. This is used to test the convergence of the curve.

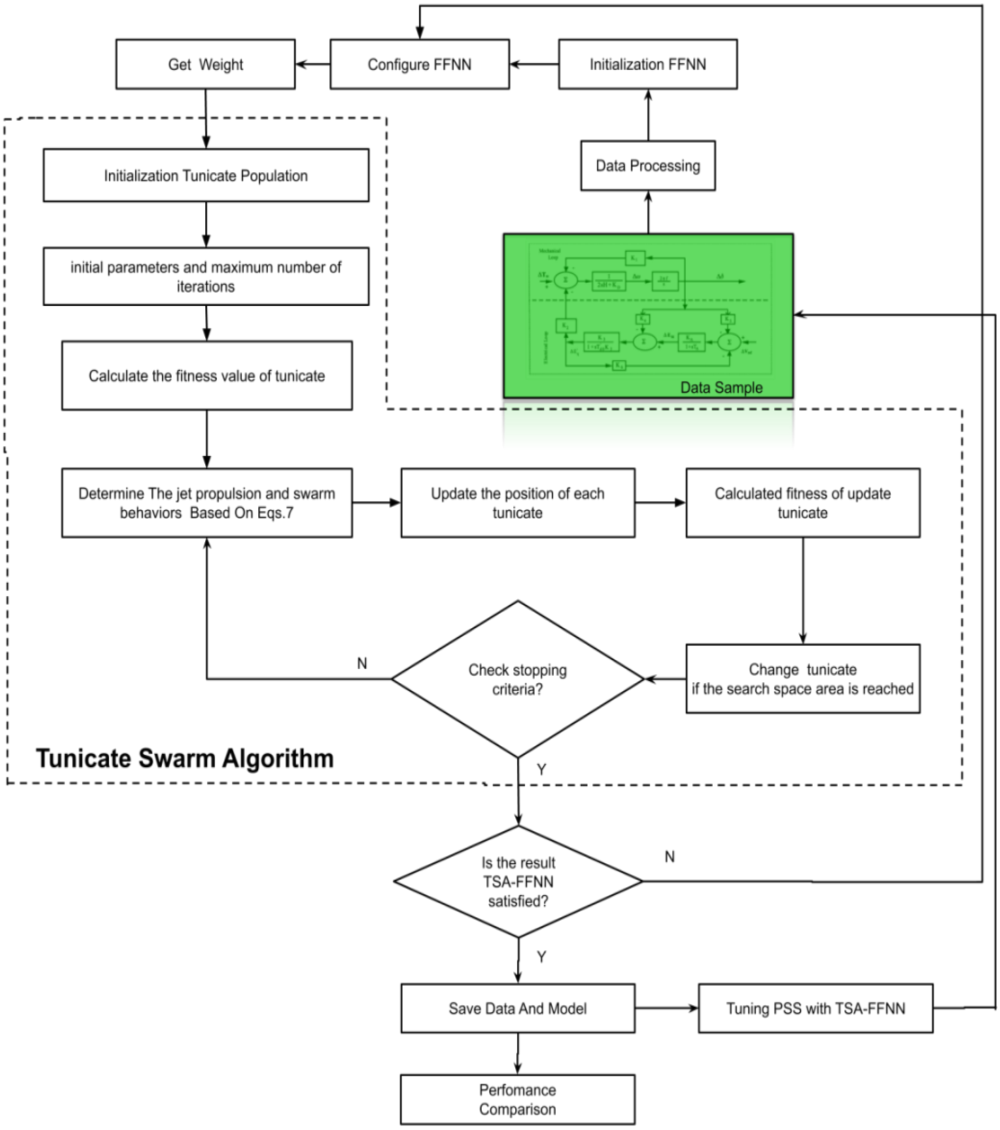

Fig. 4. The TSA-FFNN Flowchart.

The results are shown in Fig. 5. Details of the use of the TSA method can be seen in Table 1. The best value is obtained with a tunicate population of 50. Once the TSA parameter has been obtained it is used for training the FFNN. Table 2 shows complete details of the TSA parameters used.

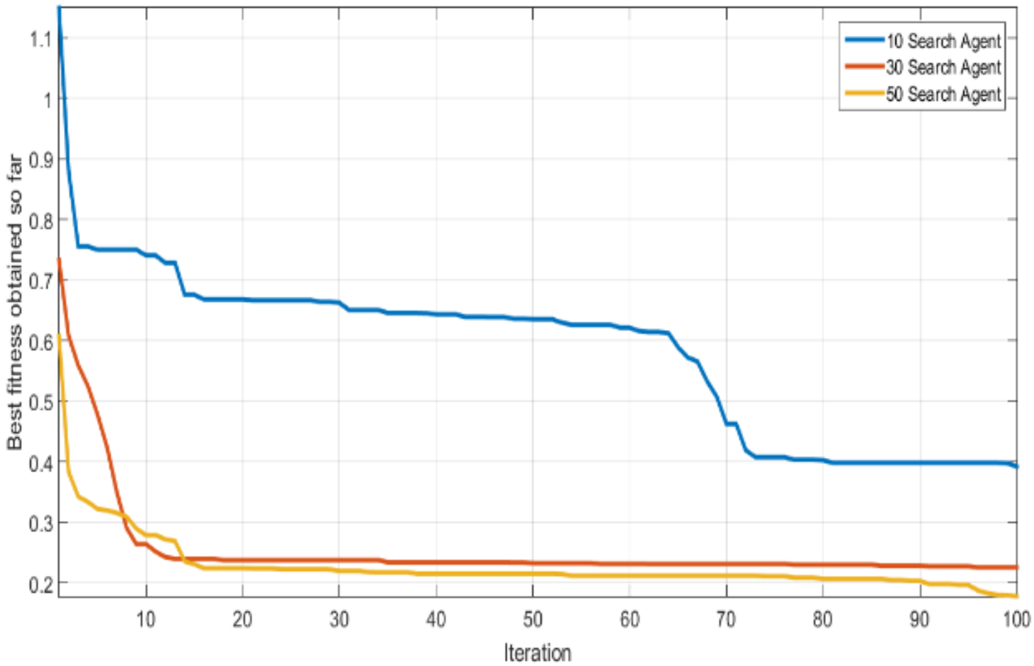

Fig. 5. Convergence Curve Of Tunicate for TSA-FFNN.

Table 1. Parameter values for various population TSA.

Population Tunicate	Rise Time	Settling Time (s)	Peak	Best Fitness
10	68.5930	76.0741	1.1495	0.3922
30	7.1213	34.4710	0.7333	0.2255
50	28.3982	96.2053	0.6075	0.1777

Table 2. Parameter of TSA.

Algorithm	Parameter	Value
TSA	Upper And Lower Limit	[-0.5,0.5]
	Maximum number of iterations	100
	Population of Tunicate	50

The loading variation is used to test the ability of the PSS modeling that applies the TSA-FFNN method. The case 1 is to give 20% loading to the system. The response to the speed and rotor angle can be seen in Fig. 6 and Fig. 7. Detailed results from case 1 can be seen in Table 3. In Table 3, the proposed method has overshoot of a speed response value with 0.1660. The value is the best performance comparing with other methods. The second-best value is the application of conventional methods which has a value with 0.1988. The TSA-FFNN method has 16.5% better performance than conventional methods. Meanwhile, the TSA-FFNN method has the best performance of undershoot rotor angle. This value is -1.5772. It is followed by the use of conventional methods with -1.6763. The lowest value is obtained by the DTDNN method with -1.9408.

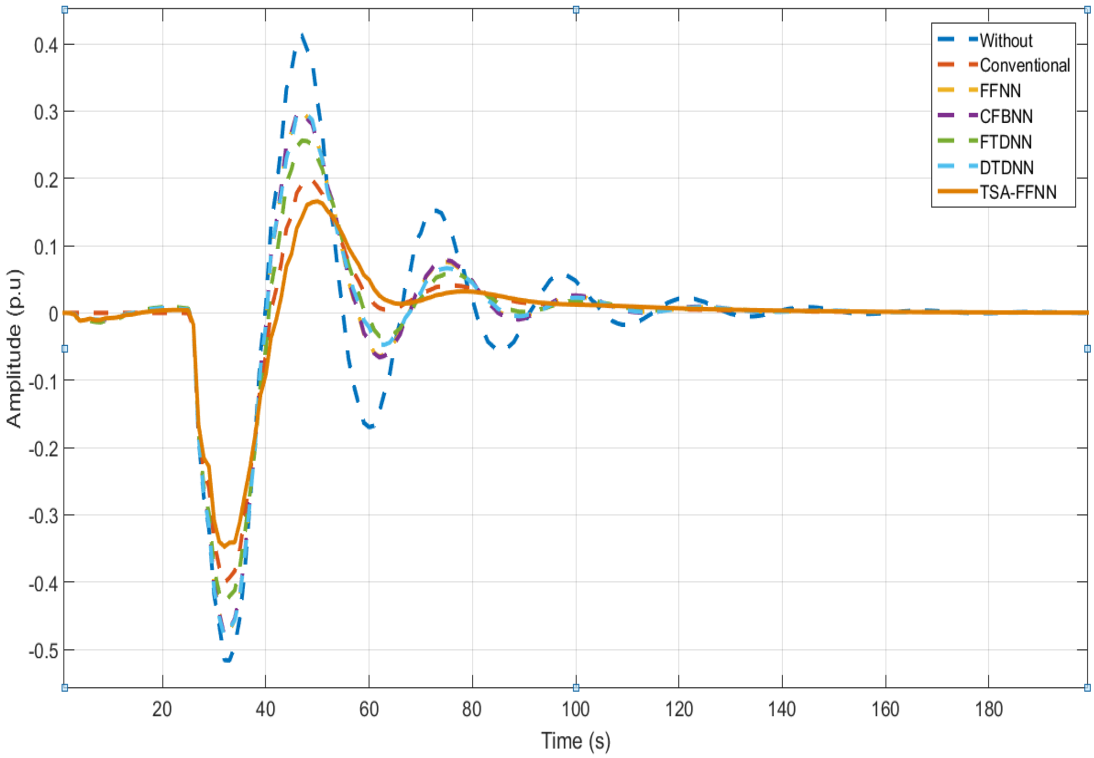

Fig. 6. Speed with 20 % Load.

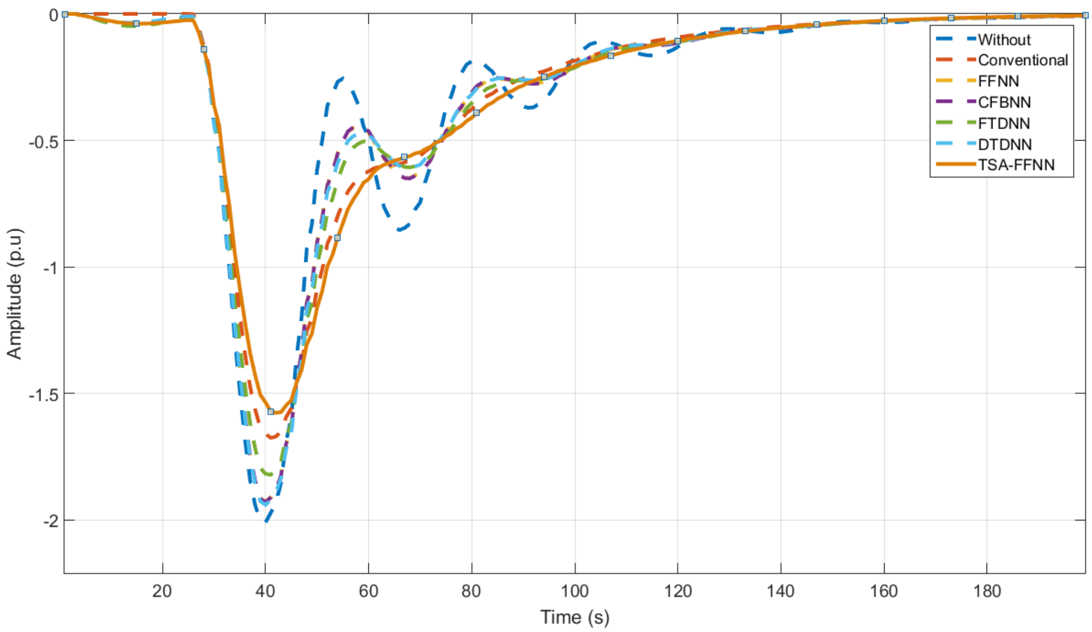

Fig. 7. Rotor Angle with 20 % Load.

Table 3. PSS With 20 % of Load.

Methods	Speed Response				Rotor Angle Response		
	Under Shoot	Over Shoot	Rise Time (s)	Settling Time (s)	Under Shoot	Rise Time (s)	Settling Time (s)
Conventional	-0.4012	0.1988	0.0054	110.7963	-1.6763	0.5191	145.2667
FFNN	-0.4811	0.3011	0.1720	107.2049	-1.9292	1.5021	147.0082
CFBNN	-0.4797	0.2997	0.1732	106.9809	-1.9301	1.6084	147.1597
FTDNN	-0.4316	0.2562	0.1519	109.1226	-1.8221	1.1943	148.1122
DTDNN	-0.4818	0.2986	0.1817	107.1667	-1.9408	1.8207	146.6075
TSA-FFNN	-0.3473	0.1660	0.2305	117.8808	-1.5772	1.1475	150.2386

Experiment 2 is to give 60% loading to the system. Fig. 8 and Fig. 9 are the results of experiment 2. It can be seen in waves from the TSA-FFNN method. The waves are sloping compared to other methods. Details of case 2 can be seen in Table 4.

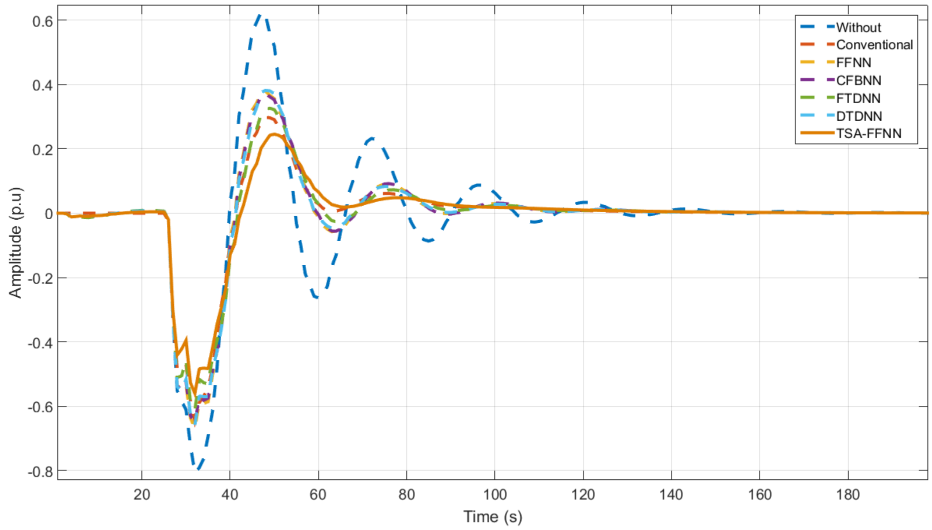

Fig. 8. Speed with 60 % Load.

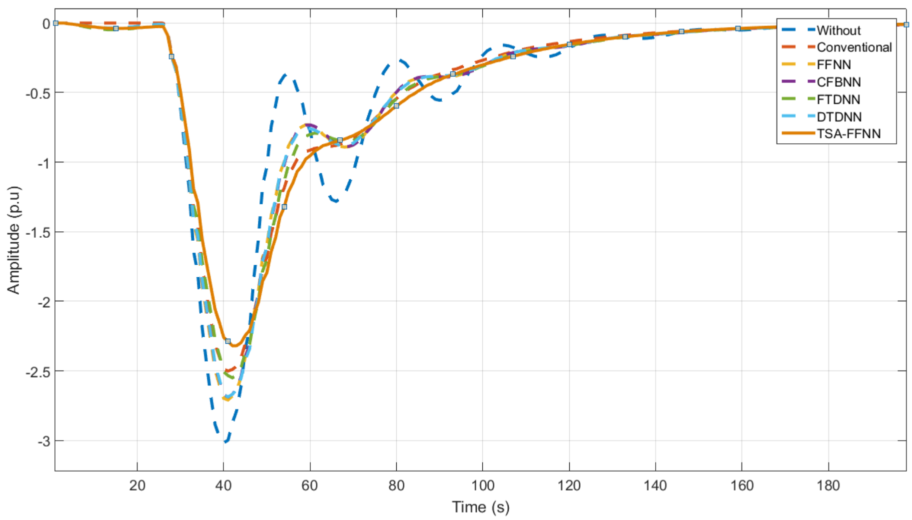

Fig. 9. Rotor angle with 60 % Load.

Table 4. PSS With 60% of Load.

Methods	Speed Response				Rotor Angle Response		
	Under Shoot	Over Shoot	Rise Time (s)	Settling Time (s)	Under Shoot	Time Rise (s)	Time Settling(s)
Conventional	-0.6457	0.2984	0.0054	108.6542	-2.5016	0.1665	143.9857
FFNN	-0.6693	0.3794	0.2533	107.9757	-2.7096	2.1331	146.9509
CFBNN	-0.6549	0.3724	0.2600	107.9826	-2.6885	2.2132	147.3345
FTDNN	-0.6113	0.3260	0.2232	110.0022	-2.5499	1.9220	148.5396
DTDNN	-0.6583	0.3814	0.2772	108.0680	-2.6869	2.3795	147.1166
TSA-FFNN	-0.5602	0.2456	0.3364	115.2298	-2.3203	1.9272	149.3650

In Table 4, the lowest value for overshoot of the speed response, 0.3814, is obtained by the DTDNN method. The best value is achieved by the proposed method with 0.2456 and followed by the conventional method with 0.2984. The method proposed in case study 2 has 17.69% better ability than the conventional method. Meanwhile, the lowest value for the undershoot rotor angle belongs to the FFNN method. The value is -2,7096. The TSA-FFNN method has the best value on the undershoot of rotor angle. This value is 16.77% better than the conventional method which is second best.

In case 3 with 90% loading assigned to the system, the measurement is to determine the system response when given a load nearby to 100% full load. The results of the speed and rotor angle can be seen in Fig. 10 and Fig. 11.

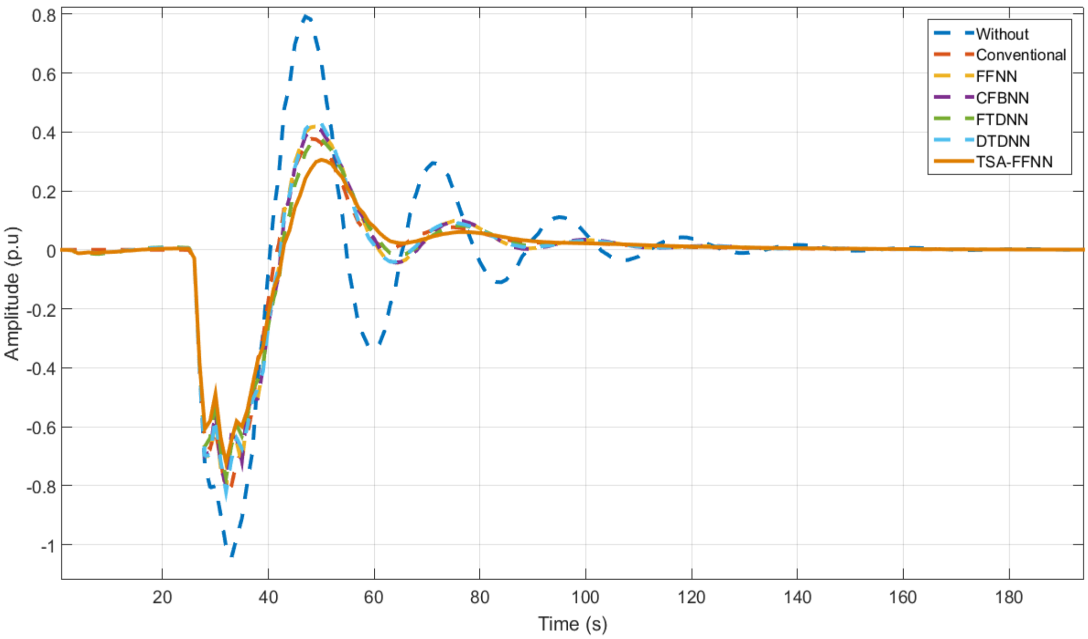

Fig. 10. Speed with 90 % Load.

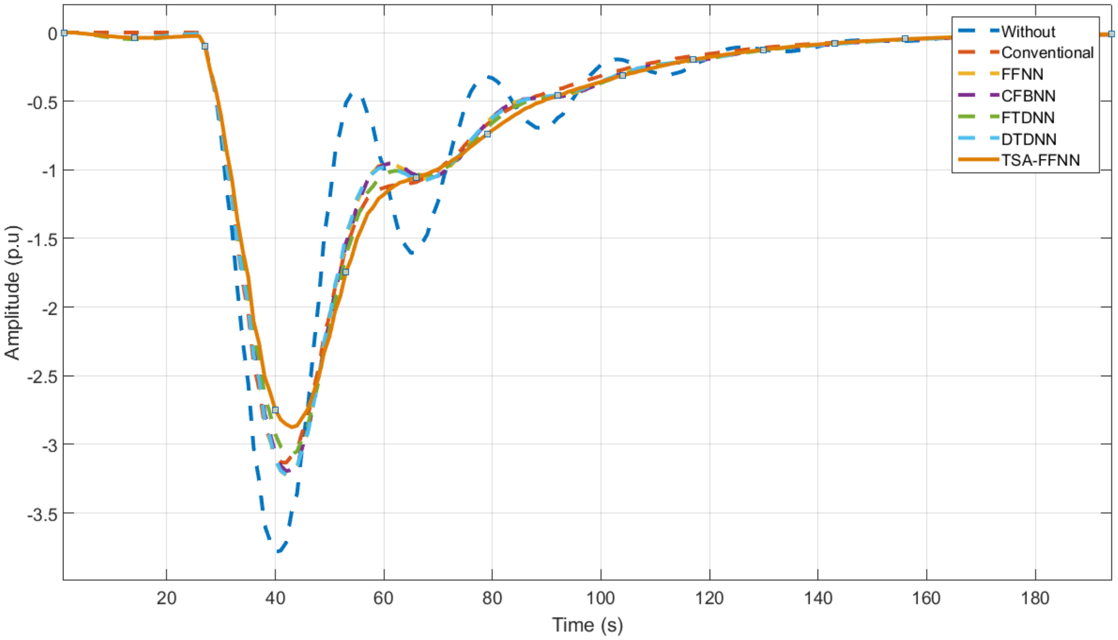

Fig. 11. Rotor angle with 90 % Load.

Table 5. PSS With 90% of Load.

Methods	Speed Response				Rotor Angle Response		
	Under Shoot	Over Shoot	Rise Time (s)	Settling Time (s)	Under Shoot	Rise Time (s)	Settling Time (s)
Conventional	-0.8171	0.3768	0.0086	106.6638	-3.1336	0.1750	140.7572
FFNN	-0.8121	0.4186	0.3052	107.4492	-3.2253	2.4394	145.0699
CFBNN	-0.8009	0.4133	0.3137	107.4591	-3.1943	2.5386	145.4819
FTDNN	-0.7742	0.3757	0.2684	108.8626	-3.0737	2.1785	146.2465
DTDNN	-0.8211	0.4354	0.3343	107.3687	-3.2207	2.7557	145.0275
TSA-FFNN	-0.7226	0.3055	0.4030	112.4465	-2.8748	2.2282	146.2570

Table 5 shows the results for case 3. The worst value for overshoot of the speed response is in DTDNN with 0.4354. The best value is from the TSA-FFNN, which is followed by conventional methods. The TSA-FFNN method has 18.92% better ability than conventional methods. Meanwhile, the worst value for undershoot of the rotor angle is in the FFNN method with -3.2253. The best score is obtained by the TSA-FFNN method followed by the FTDNN method. The TSA-FFNN method has 6.5% better ability than the FTDNN method

4. Conclusion

This paper aims to comprehensively review the tunicate swarm algorithm (TSA) literature to improve the performance of a feed-forward neural network (FFNN) and compare its performance. Its objective is to acquire the best completion for oscillation attenuation in the power system by testing in a single machine. The proposed method has better results than the comparison method in the load test of 20% , 60% and 90% . In this study, the application of the TSA method used to improve the performance of FFNN has the benefit of increasing the ability of FFNN. It can be seen that the value of the overshoot speed by FFNN in case study 1 decreased by

44.67%, case study 2 decreased by about 35.27%, and case study 3 decreased by about 26.59%. Meanwhile, the value of the undershoot rotor angle by FFNN in case study 1 decreased by about 20.84%, case study 2 decreased by about 14.36%, and case study 3 decreased by about 10.87%. In addition, the proposed method has good adaptability with load changes. The weakness of the proposed method is that the experiment is using a simple system. So, the proposed method needs to be tested on a more complex system and non-linear issues to determine its performance further.

References

[1] Rogers G, Power System Oscillations: Springer Science & Business Media; 2012.

[2] Ekinci S, Demiroren A. Modeling, simulation and optimal design of power system stabilizers using ABC algorithm. Turk. J. Elec. Eng. & Comp. Sci., 2016;24: 1532-46.

[3] Wang D, Ma N, We M, and Liu Y. Parameters tuning of power system stabilizer PSS4B using hybrid particle swarm optimization algorithm. Int Trans Electr Energ Syst 2018;28:e2598. https://doi.org/10.1002/etep.2598.

[4] Jagadeesh P and Veerraju MS. Particle swarm optimization based power system stabilizer for SMIB system. International Conference on Emerging Trends in Engineering, Technology and Science (ICETETS), Pudukkottai, 2016;1-6.

[5] Soni PB, Saxena A and Gupta V. A Minimax Polynomial Approximation Objective Function Approach for Optimal Design of Power System Stabilizer by Embedding Particle Swarm Optimization. TELKOMNIKA Indonesian Journal of Electrical Engineering 2015;14(2); 191-8.

[6] Abido MA, Abdel-Magid YL, Eigenvalue assignments in multimachine power systems using tabu search algorithm. Comput. Electr. Eng 2002;28:527-45.

[7] Kharrazi A. Tuning of power system stabilizer in Single Machine Infinite Bus (SMIB) using genetic algorithm and Power Factory Modal Analysis. Australasian Universities Power Engineering Conference (AUPEC), Wollongong, NSW 2015;1-6.

[8] Jebali M, Kahouli O, and Abdallah HH. Power system stabilizer parameters optimization using genetic algorithm. 5th International Conference on Systems and Control (ICSC), Marrakesh 2016;78-83.

[9] Lokman HH, Moghavvemi M, Haider AFA, Muttaqi KM, Velappa GG. Optimization of power system stabilizers using participation factor and genetic algorithm. International Journal of Electrical Power & Energy Systems 2014;55;668-679. https://doi.org/10.10-16/j.ijepes.2013.10.026.

[10] Gholinezhad J, Ebadian M and Aghaebrahimi MR. Coordinated design of PSS and SSSC damping controller considering time delays using biogeography-based optimization algorithm. 30th International Power System Conference (PSC), Tehran 2015;1-7.

[11] Wang Z, Zuo J, Qiu W, Zou W, Fan M. Application of Biogeography-Based Optimization for Tuning Multimachine Power System Stabilizer Parameters. 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE), Shenzhen, China 2020;787-93.

[12] Kasilingam, G, Pasupuleti J, Bharatiraja, C, Adedayo Y. Single Machine connected Infinite Bus system tuning coordination control using Biogeography: Based Optimization algorithm. FME Transactions, 2019; 47(3):502-10.

[13] Sambariya DK, Prasad R, Robust tuning of power system stabilizer for small signal stability enhancement using metaheuristic bat algorithm. International Journal of Electrical Power & Energy Systems 2014;61:229-38.

[14] Ali ES. Optimization of Power System Stabilizers using BAT search algorithm, International Journal of Electrical Power & Energy Systems 2014;61:683-90.

[15] Chaib L, ani Choucha A, Arif S. Optimal design and tuning of novel fractional order PID power system stabilizer using a new metaheuristic Bat algorithm, Ain Shams Engineering Journal 2017;8(2):113-25.

[16] Madadi A, Razmjooy N, Ramezani M. Robust Control of Power System Stabilizer Using World Cup Optimization Algorithm. International Journal of Information, Security and Systems Management 2016;5(1):519-26.

[17] Sambariya DK, Prasad R. Optimal Tuning of Fuzzy Logic Power System Stabilizer Using Harmony Search Algorithm. Int. J. Fuzzy Syst 2015;17: 457-70.

[18] Hameed KA, Palani S. Robust Design of Power System Stabilizer using Harmony Search Algorithm, Automatika 2014;55(2):162-9.

[19] Jonglak P, Ngamroo I. Adaptive Power System Stabilizer Design Using Optimal Support Vector Machines Based on Harmony Search Algorithm, Electric Power Components and Systems 2014;42(5):439-52.

[20] Bhati PS, Gupta R. Robust fuzzy logic power system stabilizer based on evolution and learning. Int J Electr Power Energy Syst 2013;53:357-66.

[21] Saoudi K, Harmas MN. Enhanced design of an indirect adaptive fuzzy sliding mode power system stabilizer for multi-machine power systems. Int J Electr Power Energy Syst 2014;54:425-31.

[22] Ghasemi A, Shayeghi H, Alkhatib H. Robust design of multimachine power system stabilizers using fuzzy gravitational search algorithm. Int J Electr Power Energy Syst 2013;51:190-200.

[23] Rana MJ, Shahriar MS, Shafiullah M. Levenberg–Marquardt neural network to estimate UPFC-coordinated PSS parameters to enhance power system stability. Neural Comput & Applic 2019;31:1237-48.

[24] Masrob MA, Rahman MA, George GH. Design of a neural network based power system stabilizer in reduced order power system. IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, 2017;1-6.

[25] Farahani M, Ganjefar S. An online trained fuzzy neural network controller to improve stability of power systems, Neurocomputing 2015;162:245-55.

[26] Ansari JA, Memon AP, Shah MA. Probabilistic Feedforward Neural Network Based Power System Stabilizer for Excitation Control System of Synchronous Generator 2015;8(2):70-4.

[27] Kaur S, Awasthi LK., Sangal AL, Dhiman G. Tunicate Swarm Algorithm: A new bio-inspired based metaheuristic paradigm for global optimization, Engineering Applications of Artificial Intelligence 2020;90:103541.

[28] Aribowo W, Muslim S, munoto, Suprianto B, Kartini UT, Asto Buditjahjanto IGP. Tuning of Power System Stabilizer Using Cascade Forward Backpropagation. 2020 Third International Conference on Vocational Education and Electrical Engineering (ICVEE), Surabaya, Indonesia, 2020;1-5.

[29] Xue Y, Tang T, Liu AX. Large-Scale Feedforward Neural Network Optimization by a Self-Adaptive Strategy and Parameter Based Particle Swarm Optimization. in IEEE Access 2019;7:52473-83.

[30] Aribowo W. An Adaptive Power System Stabilizer Based On Focused Time Delay Neural Network. Jurnal Teknosains, 2018;7(1):67-73.