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Maiden Application of Skill Optimization Algorithm on Cascaded Multi-Level Neuro-Fuzzy based Power system Stabilizers for Damping Oscillations

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Abstract- Power system oscillation is a significant threat among interconnected power systems that may lead to instability. The success of oscillation damping is primarily responsible for a modern power system's safe operation. However, the development of damping controllers is a multimodal optimization problem with constraints which challenges the traditional optimization algorithms. This paper critically examines damping schemes and controller stability analyses to find solutions to these issues and improve the performance of a Multi-Machine Power System (MMPS). This paper reveals the technique of improving power system stability by employing the Skill Optimization Algorithm (SOA) to optimize the gains of the conventional Sower System Stabilizer (PSS) and the Neuro-Fuzzy inputs-output scaling parameters. This study aims to propose a Multi-Level Neuro-Fuzzy Power System Stabilizers (MLNFPSS) to reduce the instability of a Multi-Machine Two-Area Power System (MMTAPS) under fault conditions. The simulations were run on a MMTAPS considering a transmission line fault in the middle. The analysis leads to the deduction that the proposed MLNFPSS response is more efficient than conventional PSS under symmetrical three-phase faults. The terminal voltage of the SOA based MLFPSS has undershoot, overshoot and settling time of 0.986s, 1.182s, 3.5s compared to the CPSS which had undershoot, overshoot and settling time of 0.8998s, 1.253s, 11.5s . Thus, the SOA based MLNFPSS was settled 69.56% taking only 3.5seconds faster than CPSS taking 11.5 seconds. All control strategies have been executed, and the simulation results have been assessed using MATLAB 2016b/Simulink.

Keywords Multi-machine, stability, multi-level Neuro-Fuzzy controller, PSS, SOA.

1. Introduction

Power system stability is defined as the speed with which an electric power system returns to normal functioning after a physical disruption. The structure of electric power systems are rapidly expanding and include numerous components, including transformers, loads, transmission lines, generators, and controllers. These devices' interference with one another complicates the system's design and makes it susceptible to instability issues. The three stability issues are rotor angle stability, voltage stability, and frequency stability. The interconnected synchronous generators' ability to run synchronized under normal operating conditions, after a large and a small disturbance depends on rotor angle stability [1]. To adequately serve the loads, the system must adapt to changing conditions in response to minor disturbances such as a change in load. The failure of large generators, transmission lines, or short circuits causes significant disturbances. The system will revert to a new equilibrium operating point if it remains stable. On the other hand, if a generator loses synchronization, the system becomes unstable. Blackouts and minor outages may thus result from instability in one area [1, 2]. Small signal rotor angle stability is divided into four modes: local, inter-area, control, and torsional. Inter-area modes are defined in the system by swinging arranged machines in one region against another. When two or more groups of a faithfully attached generator are interconnected by a long weak transmission line waving against each other, an inter-area oscillation is produced [3].

The first developed PSS were static phase lead compensators installed before the regulator exciter to provide additional stabilizing signals to compensate for the excitation system's significant phase lag [1-4]. However, a more intelligent and reliable strategy is needed for loading conditions that change quickly. Fuzzy systems, artificial neural networks, SOA, and other algorithms based on so-called "intelligent control" have advanced their implementations in power systems control due to technological and theoretical advances in these methodologies. Kothari et al. [4] have looked at how to design a sliding mode stabiliser for a power system with a changeable structure that achieves the needed Eigen values amid a flurry of literatures that followed new trends in PSS. Hariri and Malik [5] have investigated the neural network's learning capacity to develop a PSS that could trap the equilibrium state in local minima. However, neural networks can only be used if training data is available; this means that the learning process may take a while. Thus, using neural networks and fuzzy logic controllers can be combined to extend PSS studies. Hoang and Tomosovic [6] have developed the seven membership functions, 7*7=49 fuzzy rules-based power system stabilizer. As a result, the authors modified the eleven membership function, resulting in 11*11=121 Rules that can resist the complex dynamic framework. An evolutionary programming algorithm was used by Abido and Abdel-Magid [7] to determine the optimum values for a conventional lead-lag Power system stabilizer. In order to fine-tune the strength of the discontinuous component of the control signal used by the sliding mode controller, Saleem et al. [8] show how linear state feedback may be applied to a sliding surface with an integral term. Douidi et al. [9] suggested fuzzy logic and direct adaptive power system stabilization techniques. An adaptive indirect fuzzy was created by Ibrahim et al. [10]. The stabilization of MMPS was added to the adaptive fuzzy approach by Sharma et al. [11].

The performance of devices is directly dependent on their parameters, and the values of these parameters influence the device's dynamic response. They are challenging to solve because they are driven by dynamic and nonlinear equations of state, and establishing their precise answer is difficult and, in certain cases, even impossible using conventional mathematical techniques. In these instances, meta-heuristic methods are utilised to identify the optimal parameter or one that is very close to optimal. The genetic algorithm, the Firefly Optimization Technique (FFO), the Grey Wolf Optimization technique (GWO), the Particle Swarm Optimization (PSO), the Bacteria Foraging Algorithm (BFO), the Flower Pollination Algorithm (FPA), and the Whale Optimization Algorithm (WOA) are some of the computational algorithms used for tuning controller gains [5–11]. Furthermore, The SOA, a recently created computational algorithm, has been applied to other field of study. However, the MLNFPSS based on SOA that would enhance the gains of a traditional Proportional Derivative with Filter (PDF) and the input-output scaling factors of Neuro-Fuzzy controllers is not explored in literature. The following are the contribution of the proposed paper:

i. Development of novel MLNFPSS for applying the dynamic power system stability

ii. Application of SOA to optimize the PDF and Neuro-Fuzzy controller parameters.

iii. Comparison of the suggested optimum Multi-Level Neuro-Fuzzy (MLNF) controller's dynamic performance with the traditional PSS controllers when a symmetrical three-phase fault in the centre of a transmission line is considered.

iv. Implementation of the controller design in MATLAB /Simulink and evaluate the performance of the controllers in an interconnected power system.

2. Literature Review

PSS was a notion that was initially presented by De Mello and Concordia in 1969 [12]. The PSS is the principal dampening method for power system stability, and it is also the most cost-effective [13, 14]. The theory behind synchronous machines suggests that the excitation voltage may be adjusted in order to influence the amount of power that is generated by the machine. Installing the PSS will allow the provision of an additional input signal to the excitation system of the synchronous generator. This is the primary objective of the installation. PSS contributes an extra synchronising torque that is phase-locked with the speed deviation. As a direct consequence of this, the steadiness of the system is restricted, and the growing oscillations are dampened. Researchers from a variety of institutions provided an explanation for power system stability by installing and building PSS for Single-Machine(SM) [15, 16] and MMPS [17, 18]. The PSS scheme's damping efficiency is contingent upon its having been designed correctly [17]. In most cases, if the PSS is designed correctly, it will be useful not only in damping local modes of oscillation but also in damping inter-area modes of oscillation [12, 17].

Ghandakly and Idowu [18] introduced a Decentralised Model Reference Adaptive Controller (DMRAC) for building PSS. This controller makes use of both exciter loops and governor loops in a coordinated way, which results in an improvement in the system's overall damping. The Lyapunov function of energy served as the foundation for the adaptive legislation [18]. For the design of the PSS, Chen and Malik [19] used the framework of, which included system perturbation for a wide variety of operations as well as parametric stability. Following a similar course of action led to the development of a number of other design concepts [20–23], the majority of which were combinations of already established designs.

It is possible to draw the conclusion that there has been a significant advancement in the notion of designing PSS. This section demonstrates the design idea of a modern-day power supply system that is applied in contemporary power systems that make use of renewable energy sources. These systems are modern and sophisticated. In a nutshell, both PID-based and intelligent-based PSS are being utilised in this process. The given study demonstrated that there is potential for future research in PSS to concentrate on the use of machine learning and artificial intelligence. The performance of devices is directly reliant upon their parameters, and the values of these parameters will impact the dynamic reaction of the device. They are difficult to solve because they are governed by dynamic and nonlinear equations of state, and determining their precise answer is difficult and, in certain instances, even impossible by employing traditional mathematical procedures. In these situations, meta-heuristic algorithms are being utilised in order to locate the ideal parameter, or one that is quite near to being optimal. They achieved success in one circumstance, but they were not successful in others. Due to the fact that they are able to adapt, variable structures with intelligent control offer simplified control in addition to a high level of assurance about their stability [24]. These characteristics are not accessible through the use of traditional methods for locating parameters. Optimizing the controller settings for damping schemes [25, 26] has been accomplished through the use of a wide variety of optimization strategies over the course of the past several decades. Some of the other algorithms explored in very recent years are Augmented Grey Wolf Optimization Algorithm(AGWO) [31], Barnacles Mating Optimizer Algorithm [32], Harris Hawk Optimisation Algorithm (HHO) [33], Sine Cosine Optimisation Algorithm (SCO) [35], Modified Whale Optimisation Algorithm (MWOA) [36], Levenberg Marquardt (LM) algorithm [37], Lightning Search (LS) Algorithm [38], Harmony Search Algorithm [42], Collective Decision Optimisation Algorithm (CSO) [44], Hankel Singular Value Approach [45], Artificial Bee Colony Optimisation Algorithm (ABC) [46], Tabu Search (TS) [50], Simulated Annealing [51], Differential Evolutionary Algorithm (DEA) [52], Immune Algorithm (IA) [53]. Table 1 shows the findings from the most recent literature on optimization for Power system stabilizers for damping oscillators.

Table 1. Recent literature on optimization for PSS for damping oscillations in MMPS

SI. No.	Author	Reference	Year	Proposed method	Findings	Drawbacks
1	Aliyo Sabo et al.	[27]	2022	Interval Type-2 Fuzzy Sliding surface Type real coded GA	To improve damping control, the optimal tuning of sliding surface parameters has been viewed as an optimization problem involving the minimization of Integral Time Square Error using a Real Coded Genetic Algorithm. In a two-area, four-machine, 11-bus IEEE benchmark system, the proposed Fuzzy controller was evaluated.	Though a novel controller was used, the optimization algorithm selected wasn't ideal. There are many more efficient algorithm compared to real coded GA.
2	B Saleem et al.	[28]	2022	Neuro fuzzy FFA	The simulation result for eigenvalue analysis with NFC stabiliser produces stable eigenvalues that increased system damping by more than 0.1 with lower overshoots and time to rise via the suggested NFC process than with the traditional FFA-PSS. Similarly, the generator transient reaction's and depending on time to settle were enhanced by 64.66 and 28.78% with the suggested NFC procedure than with FFA-PSS. The typical PSS was found to be complex in design, parameter optimization, and LFO control.	Although a novel controller was employed, the chosen optimization algorithm was not optimal. There are numerous more efficient algorithms than actual coded GA.
3	Aliyu Saho et al.	[29]	2021 2	back-propagation algorithm based Neuro Fuzzy Wavelwt controlller	This research presents an ANRWC technique to improve power system stability. The suggested approach uses recurrent Gaussian for antecedent and wavelet for subsequent sections.	Though a novel controller was used, the optimization algorithm selected wasn't ideal. There are many more efficient algorithm compared to back propogated algorithm.
4	KM Sridivya et al.	[30]	2021	FFA algorithm	On WSCC multi-machine test systems, PSS's optimal design and auxiliary regulation of power fluctuations for IPFC were tested using a linear model. The IPFC model was compared to the FFA-PSSs controller using time-domain simulations and quantitative analysis.	Though a novel controller was used, the optimization algorithm selected wasn't ideal. There are many more efficient algorithm compared to FFA algorithm.
5	Devarapalli	[31]	2021	AGWO Algorithm	Static Synchronous Compensator (STATCOM), and PSS controllers which are designed in coordinations with the help of an	the optimization algorithm selected wasn't ideal. There are

	R et al.				unique hybrid augmented AGWO-PSO is presented here. A Multi-Objective Function(MOF) has been constructed. Eigenvalue analysis and the damping nature that are subject to perturbation have been presented under various loading conditions.	many more efficient algorithm compared to AGWO-PSO. Furthermore, there is scope of using Neuro Fuzzy controller
6	Devarapalli R et al.	[32]	2021	BMO algorithm	In comparison to the conventional approaches, the newly developed algorithm successfully moved the system poles to the left side of the s-plane, which resulted in an improvement to the system's stability.	A neuro-fuzzy controller hasn't been explored. The optimization algorithm selected wasn't ideal. There are many more efficient algorithm compared to BMO algorithm.
7	Devarapalli R et al.	[33]	2021	HHO-PSO	In this study, a proposal is made for the hybridization of a recently suggested HHO algorithm with the conventional PSO algorithm. The results of these investigations have recommended a particular method for the efficient damping of power network oscillations.	The paper hasn't utilised the most recent and most efficient SOA. Furthermore, a multi level Neuro Fuzzy PSS is not considered.
8	Devarapalli R et al.	[34]	2020	GWO	The suggested approach is validated and it is compared to other methods that are considered to be state-of-the-art. 23 benchmark functions are used for the validation purpose. A mathematical model of a MMPS has been developed, and the dynamics of the power system components have been taken into consideration.	No research has been done on a neural Fuzzy controller. Additionally, the most recent and effective SOA
9	Devarapalli R et al.	[35]	2020	GWO-SCO Algorithm	The research of the system has been conducted under a fault situation that is capable of self-clearing, and the complete analysis has been given by doing an analysis of the eigenvalues.	No analysis of a neurofuzzy controller has been done. Additionally, SOA, which is the most modern and effective, hasn't been used.
10	Sahu PR et al.	[36]	2019	MWOA	The newly suggested MWOA strikes an appropriate balance between the WOA's exploration and exploitation stages. The controller is put through its paces with SM infinite bus system and a MMPS.	No analysis of a neurofuzzy controller has been done. Additionally, SOA, which is the most modern and effective, hasn't been used.
11	Dasu B et al.	[37]	2019	WOA	The proposed method is put to the test on two benchmark MM test systems, namely a three-generator nine- bus system and a two- area four- generator inter connected system, both of which function under a variety of different operating conditions.	A neuro Fuzzy controller hasn't been analysed. Furthermore, the most recent and most efficient, SOA hasn't been utilised.
12	Rana MJ et a.	[38]	2019	LM	In this study, they used a training algorithm based on the Levenberg—Marquardt (LM) method. Under different loading conditions, the eigenvalues of the systems generated by an ANN-tuned PSS coordinated with UPFC and a fixed-gain conventional PSS coordinated with UPFC are compared.	This paper utilised th ANNA nnd Neuro Fuzzy based controllers. But the paper only presented a single level neuro fuzzy controller.
13	Rajbongshi	[39]	2019	LS	The investigation into the impact of the combined controlling action of Interline Power Flow Controller(IPFC) and PSS is	The Neuro Fuzzy controller hasn't been utilised in this paper.

	R et al.				performed. It leads to the revelation that the integration of the same improves the system dynamics effectively than the individual inclusion of IPFC and PSS.	Furthermore, it doesn't utilise the most efficient Optimisation algorithm.
14	Devarapalli R et al.	[40]	2019	HHO	The suggested method performs an analysis on the damping natured given to the system states when they are subjected to perturbations as well as the eigenvalues of the system. The system is studied under a variety of loading situations, and the suggested method is evaluated in comparison to other algorithms.	Although HHO optimization is used in this study, as of 2019, the SOA has shown to be far superior to HHO optimization. Additionally, a Neuro-Fuzzy controller may be added.
15	Devarapalli R et al.	[41]	2019	HHO	In order to remark on the performance of the system while using the suggested technique, an eigenvalue analysis as well as performance characteristics of system states during disturbances are described below.	In this paper, HHO optimization is utilised but since 2019, the SOA clearly demonstrates it's superiority over the Harris Hawk Optimisation.
16	Bagheri et al.	[42]	2018	HS	Thyristor-Controlled Series Capacitor (TCSC) and the Static Variable Compensator (SVC) have been taken into consideration in this design. Within the context of this model, the harmony search method, also known as HSA, is utilised for the purpose of doing fine tuning on the fuzzy PI.	In this paper, compared to previous papers, a fuzzy control is used for the first time for PSS. But, the paper didn't consider a Mulit Level Neuro Fuzzy PSS.
17	Thu WM et al.	[43]	2018	PSO	In order to evaluate the practicability and efficacy of the proposed MRAS-PSS under the influence of network uncertainties, a number of simulations in the nonlinear and time-domain domains are carried out.	In this paper, only three different operating circumstances has been presented.Furthermore, it hasn't utilised more efficient optimization techniques.
18	Dey P. et al	[44]	2018	CDO	PSS parameters are optimised for the goal function, which include eigenvalues and damping ratios of the electromechanical modes that are gently damped throughout a wide range of operating circumstances. Additionally, the most advantageous spots for installing PSS have been identified.	The paper hasn't shown how the proposed algorithm is better than the ones in literature. Furthermore, it hasn't utilised neuro fuzzy techniques.
19	Herrera JD et al..	[45]	2017	HSV approach	It is able to compute the parameters of both controllers thanks to the linearized system model and the parameter-constrained nonlinear optimization technique. In addition to this, the settings are tuned in such a way as to acquire the gains of both controllers concurrently. After that, the nonlinear simulation is carried out so that the temporal response of the controller may be observed.	The paper hasn't demonstrated how the proposed optimization is better than other optimisation in literature. Furthermore, it hasn't utilised neuro fuzzy techniques.
20	Santra S et al.	[46]	2017	PSO	The PSO-based norm minimization technique is utilised in this approach for the purpose of selecting the weighting function and controller parameters. The H/H 2 MOF has been proposed for use in the controller parameter selection process.	The paper has used a traditional optimization technique. Furthermore, it hasn't utilised the Neuro-Fuzzy techniques which can increase the controller gain even more.

21	Khodabakhshian et al.	[47]	2016	WCA	The results of the simulations performed on the IEEE 39-bus power system validate the effectiveness of the approach that was presented and demonstrate its higher performance in comparison to other methods.	Though the paper used a very suitable optimization algorithm, the paper hasn't utilised Neuro fuzzy techniques and Artificial Neural Networks.
22	Shahgolian et al.	[48]	2016	ABC	The optimization that was performed after a significant amount of turbulence demonstrates that there is significant improvement in the system's stability along with the instant damping of the system's fluctuations in comparison to the state in which optimization was not performed.	The paper hasn't explored the use of Neuro Fuzzy techniques. urthermore, algorithms superior than ABC exists which could be utilised.

Various Algorithms were investigated in previous literature. The SOA is a novel algorithm that has arised and has many advantages over previous algorithms. The advantages and disadvantages of various algorithms are given in Table 2.

Table 2. Advantages and disadvantages of different algorithms

Algorıthm	Major advantage	Major dısadvantage
GA [49]	• Simple to understand and put into practice • Does not require prior understanding of maths	• There is no guarantee of a solution that is optimal • Unable to solve a wide variety of different kinds of complicated optimization issues. • The propensity to converge in the optimal solution for the immediate environment
TS[50]	• Escapes from local minima as well by using the "tabu list"	• A sluggish pace of convergence • The ineffective approach to solving the high-dimensional problem
SA[51]	• Can give a solution even in a huge search area. • Easy to understand and apply • Provides pretty excellent solutions for certain optimization issues	• A sluggish pace of convergence a lack of capacity to find solutions to difficult multifaceted issues • Performance decline in big dimension issues
DEA[52]	• Possesses the ability to solve multidimensional, non-differential, and non-continuous problems;	• Difficult to choose the appropriate control settings • There is no guarantee of the accuracy of the solution.
PSO[53]	• It Converges rapidly; • It is capable of resolving complicated optimization issues in a variety of application areas.	• The unfavorable impact on the solutions brought about by the incorrect selection of control factors • The risk of becoming mired at a particular region's minimum point • Poor performance in high-dimensional as well as multimodal optimization
IA[54]	• It is adept at the search exploration process.	• Poor utilization of the search
SOA[55]	• High Convergence rate • Can solve complex multidimensional problems • It is faster and requires less iterations	• It is a little complex to understand

Overall, the authors noticed that there is a need for algorithms with higher convergence speeds which needs less iteration to be used in the controllers for Power System Stabilizers. Earlier papers [43-48] utilised techniques with conventional methods and haven't utilised Neuro Fuzzy techniques. They used optimization algorithms such as ABC [48], WCA [47], PSO [46], HSV [45], CDO [44], HS [43]. It was in [42] where a neuro-fuzzy controller was first explored. Despite the use of neuro-fuzzy controllers, we noticed that we could increase the overall power system stability by using a novel SOA which has a higher convergence rate than every other algorithm. Furthermore, A utilizing a MLNF cascaded controller would be extremely efficient. Thus, the maiden application of SOA for PSS would lead to high power system stability. Also, the authors noticed that there is a need to conduct research on MLNF cascaded controllers for PSS and providing a comparison of it with ordinary methods. The SOA algorithm based MLNF controllers can also be used to different applications like AGC, LFC for power system stability but in this article, we focused on its application for PSS.

3. Materials and Method

3.1. Proposed Test Model

The two fully symmetrical areas of the MMPS in Figure. 1 are connected by two 230 kV lines, each 220 km long. Two identical 20kV/900MVA rotor synchronous machines acts as thermal plant generators are installed in each area, and each is connected to a transformer (T1, T2, T3, and T4). The parameters of the synchronous machines (M1, M2, M3, and M4) are the same in both areas. However, for all generators in Area 1 and Area 2, the inertia is H = 6.5s and H = 6.175s, respectively. All thermal generating plants have fast static exciters with a 200 gain and the same speed regulators. A generator's capacity is 700 MW for all generators; constant impedance loads are taken for granted for the loads. Areas 1 and area 2 have loads of 967 MW (L1) and 1767 MW (L2), respectively. The 187 MVAR capacitors (C1 and C2) were installed in each area to optimize the load voltage profile and bring it closer to unity. Two tie-lines total 413 MW and one tie-line total 353 MW of transport power from Area 1 to Area 2, respectively.

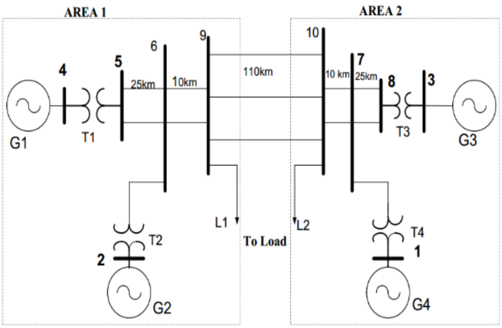

Fig. 1. Four Multi-machine two-area test power systems

3.2. Proposed Method

3.2.1. Fuzzy Logic Controller (FLC)

The FLC theory, a theoretical concept that improves conventional control theories, was first proposed in 1965. FLC is a key tool for solving problems with the power system using mathematical techniques. A substantial body of research has been compiled on FLC applications in order to improve the dependability and resilience of power system control. FLC is a type of logic utilized in human reasoning. However, these systems must be created, modified, and used with adequate care. FLC includes Defuzzification and fuzzy inference systems built on fuzzification rules [12]. Several membership functions are used to convert binary values into fuzzy values. The entire control structure is made clear by the rule base, which is just an if-then rule. The membership functions and rules base need to be modified to build a fuzzy controller with a solid structure. Defuzzification converts fuzzy values into clear ones that plants can use. The fuzzy logic controller receives two scaling factors, Ke1 and Ke2, as inputs and produces Ku as an output. Input and output membership functions must be equally represented to ensure optimal computation performance and memory usage. From the literature review, the triangular membership function is the best among the others. It requires less memory, is simple to implement in real-world scenarios, and is easy to use with a fuzzy interfacing system [9-13].

A crisp quantity (set) becomes a fuzzy quantity by fuzzification (set). The absolute lack of determinism and uncertainty of the many well-known precise and deterministic quantities must be acknowledged. The ability of the variables to be represented by a membership function may have contributed to the development of this uncertainty owing to fuzziness and imprecision. The complete control architecture is explained by the rule base, which is effectively an if-then rule [56]. To design a Fuzzy controller with a clear organizational structure, the Membership functions and rule foundation must be modified. Using the fuzzy inference method is not practicable for these rules because they have been transformed into fuzzy forms. In order to boost the firing power of the rule base, Mamdani FIS was utilized in this work, which employed the well-known "center of gravity" Defuzzification technique [57]. In previous literature for fuzzy controller design, seven membership functions with 7*7=49 criteria were also taken into account. To optimize the heavy-loading power system, nonetheless, it falls short. The authors created 11*11=121 Rules by updating the eleven membership functions to fit the complex dynamic framework.

Defuzzification is the process of transforming ambiguous data into clear ones that plants can use. Two scaling factors, Ki1 and Ki2, are used as inputs and outputs by the fuzzy logic controller. To ensure excellent computation speed and memory efficiency, input and output membership functions must be represented equally [58]. Triangular membership functions are favoured, according to the literature study, since they are easy to create for real-time applications, utilize less memory, and are straightforward to employ with fuzzy interfacing systems (FIS). Therefore, eleven MFs are taken into account for both inputs and outputs. All MFs range in value from -1 to 1, [59–62]. The fuzzy interface system creates logic. The output from each rule foundation is produced by the Mamdani Fuzzy interface system logic. The acronyms for the following terms are: PV (positive very high), PL (positive large), PB (positive big), PM (positive medium), PS (positive small), ZR (zero), NS (negative small), NM (negative medium), NB (negative big), NL (negative large), and NV (negative extremely high) (negative very high). The fundamental block diagram of a fuzzy logic controller is shown in Figure 2. Figure 3 shows the Inputs and output triangular membership function of fuzzy logic controller. The range of all membership functions should be between -1 and 1 as shown in Figure 3 (a) – (c).

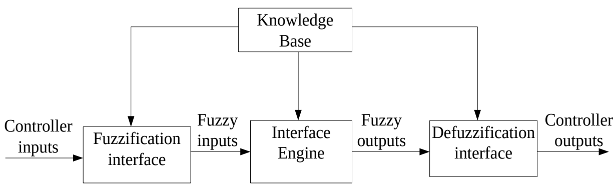

Fig. 2. The block diagram of Fuzzy Logic controller

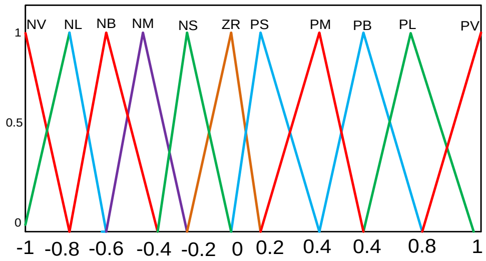

Fig.3 (a). Error input signal (e) of Inputs and output triangular membership function of LFC

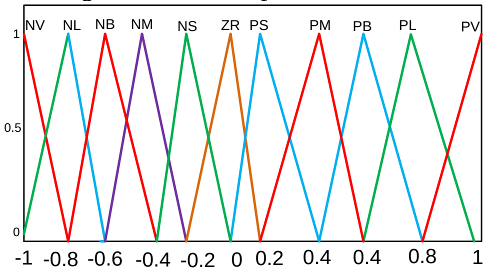

Fig.3 (b). Error derivative input signal (de)

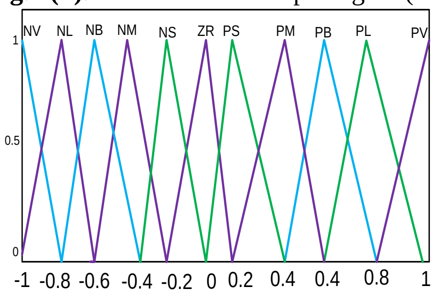

Fig.3 (c). Output signal (u)

3.2.2. Neuro-Fuzzy Controller (FLC)

The benefits of neural networks and fuzzy systems are integrated in the Neuro-fuzzy approach. It develops a model that uses the learning capabilities of neural networks to optimize its parameters and fuzzy theory to express knowledge understandably. The structure of the Neuro-Fuzzy controller is shown in Figure 4. The most effective artificial intelligence technique combines fuzzy logic control and neural networks. The fuzzy logic interface system is represented by the systems model's input and output data pairs [5]. Neuro-fuzzy interface systems have applications in many control applications, signal processing, decision-making, and modelling [9].

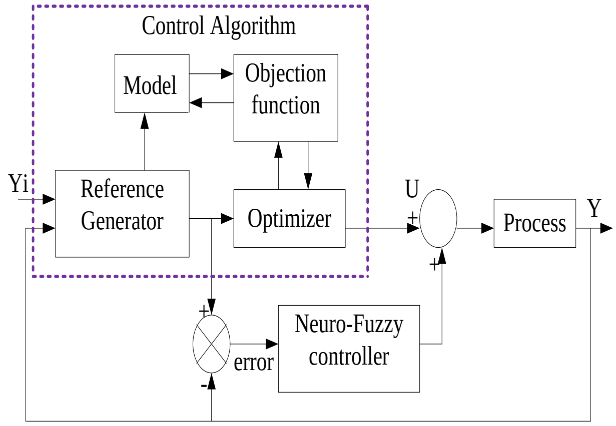

Fig. 4. The structure of Neuro-Fuzzy controller

3.2.3. PDF Controller

Most linear plants use traditional PDF controllers because they are less expensive, more efficient, and have more superficial design structures. The PDF controller is ineffective for higher-order systems with variable parameters and a time delay because of its linear nature. A PDF is a PD controller that uses a low-pass filter on the derivative term to improve system dynamics response. The low-pass filter helps reduce the dynamic system response to high-frequency oscillations. Additionally, each generator comes with initial built-in traditional PDF controllers. The generator is represented by the transfer function

$$G_c(s) = K_p + K_D\left(\frac{1}{1+\frac{s}{N}}\right) \quad (1)$$

Where Kp refers to the controllers proportional gain, KD refers to the controllers Derivative gains and N refers to the derivative filter coefficient.

3.2.4. The Proposed Cascade MLNF-PDF PSS

The suggested cascaded Neuro-fuzzy controller employs Neuro-fuzzy logic control, with Proportional plus derivative (PD) control actions (Eq. 1). According to the equation, the values of e and de affect the Kp and Kd, which are the equivalent proportional and derivative gains of the conventional controller depending on the operating point. The nonlinear Neuro-fuzzy action has variables due to the inputs-output scaling factors gained with the operating point, just like a PDF linear action. When the Neuro-Fuzzy PSS scaling factors (ke, kde, and Ku) are various, the linear proportional-derivative gains (Kp, Kd, N) change dramatically. Figure 5 shows the block diagram of the proposed cascaded MLNPSS.

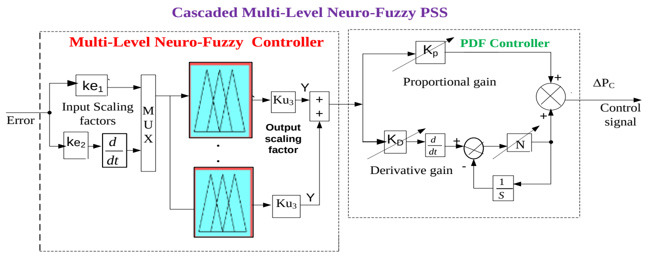

Fig. 5. Block diagram of the proposed cascaded MLNF PSS

3.3. Skill Optimization Algorithm

When the Neuro-Fuzzy PSS scaling factors (ke, kde, and Ku) are various, the linear proportional-derivative gains (Kp, Kd, N) change dramatically. The collaborative development of multi-machine PSSs is frequently presented as an optimization issue. Several optimization algorithms have been described in the literature to handle this kind of problem. A SOA is a novel metaheuristic optimization technique [63-64]. The real source of inspiration for SOA design is human efforts to acquire new skills and improve on those already possessed. A connection exists between the string structure and an SOA's parameters. On the other hand, the SOA skilfully takes advantage of a random search to produce the desired result. The SOA first creates a random population of various strings to select the best response. Each stage determines each agent's fitness value for the following generation of the current population. The Integral of Squared Error (ISE) must be optimized for the objective function. The procedure is repeated until the best and the most thorough response has been found. Figure 5 is shown the flow chart of SOA. In order to optimize the PDF gains and the NLNF controller inputs-output scaling factors subject to minimizing J. It is thought that the number of search agents (n) = 20, population size (100), problem dimension (6), damping coefficient (0.7), and the maximum number of iterations (N) = 30 should be used. The Parameter limits expression for the objective function is illustrated in Eq. (2).

$$\left.\begin{array}{c} K_P,\min \leq K_P \leq K_P,\max \\ K_d,\min \leq K_d \leq K_d,\max \\ N,\min \leq N \leq N,\max \\ K_{1e},\min \leq K_{1e} \leq K_{1e},\max \\ K_{2ed},\min \leq K_{2ed} \leq K_{2ed},\max \\ K_{3u},\min \leq K_{3u} \leq K_{3u},\max \end{array}\right\} \quad (2)$$

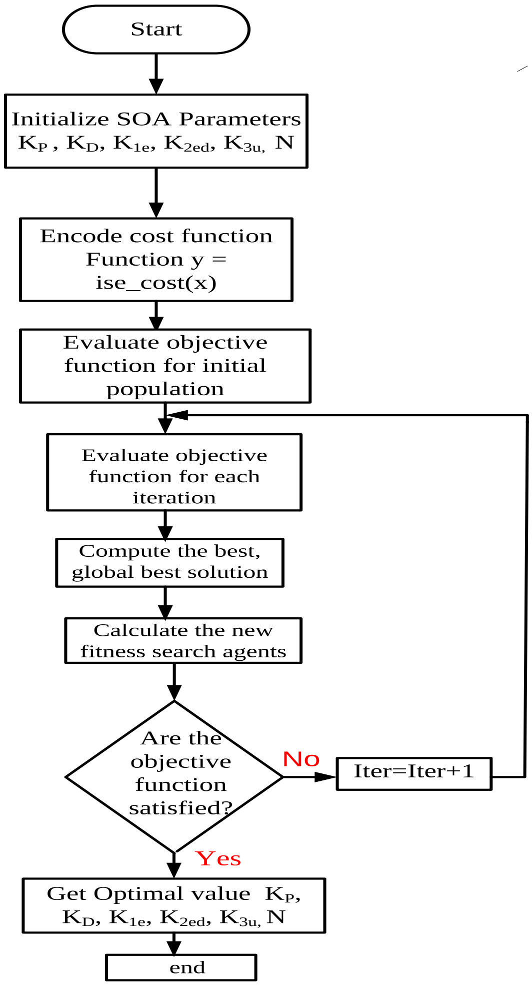

Fig. 6. The flow chart of SOA

The SOA is a population-based technique, and its participants are real people who are always working to advance their knowledge and capabilities. In point of fact, individuals of the SOA population are candidates for solving the optimization problem in question. The values of the problem decision variables may be determined based on the placements of these members in the search space. At the beginning of the algorithm, the placements of SOA members are first determined by a random process. According to the equation, a mathematical model of the SOA population may be constructed using a matrix (Eq. (3)).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix} \quad (3)$$

In this case, X is the population matrix for the SOA, Xi is the ith candidate solution, xi, d is the value of the dth variable that was suggested by the ith population member, N is the number of members of the SOA, and m is the number of variables.

Each individual in the population has the potential to be a part of the solution to the issue. To put it another way, a value for the goal function is calculated by inserting each member into the appropriate variable in the problem.

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{4}$$

As a result, the values that were acquired for the goal function are able to be characterised mathematically using a vector in accordance with Eq (4). In this case, F is a vector containing all of the values that were obtained for the objective function, and Fi is the value that was acquired for the objective function based on the ith candidate solution. When looking at the values that were assessed for the objective function, the value that is considered to be the best identifies the member that is considered to be the best, and the value that is considered to be the worst identifies the member that is considered to be the worst. Given that both the values of the objective function and the members of the population are updated during each iteration, the best and worst members of the population are also changed throughout each iteration of the process.

Exploration and exploitation are the two stages that make up the process of updating the population members in SOA. During the exploration phase, you will simulate the process of acquiring a skill from an experienced professional. During the exploitation phase, you will be mimicking the growth of skills through the efforts and actions of individual users. The update process is carried out in the context of SOA design in two phases: the phase of exploration, which has the goal of doing a global search in the problem-solving space, and the phase of exploitation, which has the goal of conducting a local search. During the exploration phase, SOA was structured such that its members moved in the search space following the instruction of other SOA members rather than travelling simply in the direction of the person who was deemed to be the best. Because of this, the algorithm's exploration capacity is increased, allowing it to more correctly scan the search space and locate the area that was initially ideal. On the other hand, when it comes to the exploitation phase, the algorithm is able to converge to better probable solutions thanks to the local search that is conducted close to each individual member of the population.

3.3.1. The First Phase: Learning from Experienced Individuals (Exploration)

During the first phase, each member of the SOA works toward the acquisition of a skill under the direction of an expert member of the community. The value of the objective function attained by a member of the population is directly proportional to the quality of that individual's contribution to the population as a whole. An SOA member is said to have an expert member when that member's conditions are deemed to be superior to those of the other members based on the value of the objective function. If a member of the SOA has a higher objective function value than any other members of the SOA, then those members are included in the "experts set" for that member. One of these individuals from this group will serve as a mentor to the individual in question after being chosen at random to take on this role. As a result, the specialist who has been chosen to direct the SOA member might not always be the most suitable candidate option. In point of fact, the best possible candidate solution is a non-rotating member of the experts set, applicable to all SOA members. Learning the skill, which refers to the algorithm's capacity for both global search and exploration, leads the members of the population to be steered to different spots in the search space. The expert member is responsible for this. If the new position that is computed for each individual in the population results in an increase in the value of the objective function, then it may be considered acceptable. As a result, the first phase of the update may be described using Eqs. (5) and (6) in accordance with the notions that have been discussed.

$$X_i^{P1}: X_{i,d}^{P1} = x_{i,d} + r \times (E_{i,d} - I \times x_{i,d}), E_i = X_k, \tag{5}$$

Where $F_k < F_i$ and *k* is randomly selected from *{1,2,,N}*, $k \neq i$

$$X_i = \begin{cases} X_i^{P1}, F_i^{P1} < F_i \\ X_i, else \end{cases} \tag{6}$$

Here, X^{P1} is the newly calculated status of the i^{th} candidate solution based on the first phase, x_{P1} is its I i,d d^{th} dimension, F^{P1} is the value of its objective function, E_i is the expert who has been chosen to guide and train the i^{th} member of the population, $E_{i,d}$ denotes its d^{th} dimension, *r* is a random number in the range [0 1], and *I* is a random number.

3.3.2. The Second Phase Focuses on Improving One's Skills via Individual Effort and Practise (Exploitation)

During the second phase, every member of the population engages in independent study and practice in an effort to further develop the capabilities obtained during the first phase. This concept is modelled as local search in SOA with the intention of increasing exploitation in such a way that each member, in the neighbourhood of its position, seeks better conditions to improve the value of its objective function. This is done in such a way that the overall goal is to increase exploitation (which indicates the level of skill). In the same way as the phase before it, the newly computed location in this phase is considered acceptable if it results in an increase in the value of the goal function. Eqs. (7) and (8) are used to provide a mathematical description of the concepts involved in this step of SOA updating.

$$X_i^{P2}: x_{i,d}^{P2} = \begin{cases} x_{i,d} + \frac{1-2r}{t} \times x_{i,d}, r < 0.5 \\ x_{i,d} + \frac{lb_{j+r(}ub_j - lb_j)}{t} \times x_{i,d}, else \end{cases} \tag{7}$$

$$X_i = \begin{cases} X_i^{P1}, F_i^{P1} < F_i \\ X_i, else \end{cases} \tag{8}$$

Here, X^{P2} denotes the newly computed status of the *ith* candidate solution based on the second phase, x^{P2} denotes its d^{th} dimension, F^{P2} denotes the value of its objective function, t denotes the iteration counter, and lb_j and ub_j denote the lower and upper bounds of the j^{th} variable, respectively.

Table 3. Mean values of Evaluation results of Unimodal functions [63-64]

	GA	PSO	GSA	TLBO	GWO	MVO	WOA	TSA	MPA	RFO	SOA
F1	21.26981	0.00051	7.68E-17	4.29E-61	1.3E-100	0.207125	6.5E-82	3.21E-82	5.99E-86	6.46E-84	0
F2	1.569531	0.591161	3.95E-08	4.47E-32	1.8E-58	0.300354	2.2E-175	1.82E-48	2.67E-47	6.78E-46	4.6E-191
F3	2081.245	1393.67	185.0622	1.03E-19	6.47E-29	21.44854	6629.856	3.65E-21	7.73E-23	4.67E-58	0
F4	2.69652	4.39557	1.05E-08	3.98E-25	9.73E-25	0.628421	35.21117	1.01E-05	1.23E-32	1.34E-35	1.9E-181

3.3.3. *The Sequential Object Architecture's Repetition Process*

After all of the members of SOA have been brought up to date based on the first and second phases, the first iteration of SOA has been finished. The algorithm will then proceed to the subsequent iteration, at which point the process of updating will be performed in accordance with Equations (5) to (8). When the SOA has been completely implemented, the output will contain the best potential solution. The flowchart for the SOA is displayed in Figure 6.

Table 3 shows the mean value in the evaluation results of Unimodal functions of different algorithms compared to SOA taken from the work done in [63-64]. From the mean values of evaluation results of unimodal functions, it is clear that SOA is superior compared to every other algorithm in terms of optimization. A similar trend is followed for multimodal functions. In Table 3, the mean values for unimodal functions F1 - F4 is presented demonstrating the superiority of SOA but a similar trend is noticed for higher levels of function beyond F4.

4. Simulation Results and Analysis

4.1. *The Sequential Object Architecture's Repetition Process System Performance Evaluation of CPSS Controllers Considering Symmetrical Three Phase Fault*

The multi-machine two-area ten buses system simulation has been performed with CPSS, and a MLNFPSS have been discussed in this section. First, we investigated the dynamics system performance of the power system with conventional PSS, illustrated in Figure. 7. The dynamic response oscillations are not well damped for all generators. The MLNF technique cascaded of the CPSS is a more robust than CPSS and it significantly damps the oscillations of the studied system, as shown in Figure .8. The SOA adjusts these two controllers by reducing the time-domain. The cost function values in this optimization are subjected to the constraint given Eq. (2). This operation is carried out by adjusting the Neuro-Fuzzy PSS's input-output scaling factors and conventional PSS's gains. The optimum values of the controllers' parameters are illustrated in Table 4.

Table 4. Optimum values of controller gains and scaling factors for various controllers

Gains/scaling factors	CPSS	MLNFPSS
kp1	0.1627	0.251
kd1	0.378	0.0362
kp2	0.494	35.679
kd2	0.221	0.1223
kp3	0.0807	0.0229
Kd3	0.028	0.0264
Kp4	0.2179	0.2483
kd4	0.1285	0.1810
N1	49.85	87.73
N2	60.878	76.33
N3	57.571	88.783
N4	35.679	77.475
k1	-------	0.0931
k2	-------	0.302
k3	-------	0.291
k4	-------	0.212
k5	-------	0.456
k6	-------	0.425
k7	-------	0.271
k8	------	0.0995
k9	-------	0.5966
k10	-------	0.354
k11	-------	0.445
k12	-------	0.476

Figure 7 depicts the system performance investigation of the CPSS of the machine power system when a short circuit fault occurs in the mid of the transmission line. The MMPS has reached a steady state but is not well damped. The CPSS controller requires further development to stabilize the MMPS. Figure 7a represents the active power transfer from area 1 to area 2. The undershoot time is 196ms, the overshoot time is 464ms while the settling time is 4.5s. Figure 7b represents the active power transfer from each generators from generator 1 to generator 4. We can notice that the active power transferred is the same for the generators. The undershoot time is -0.3s, the overshoot time is 0.5s while the settling time is 4.5s. Figure 7c represents the generator speed for each generators from generator 1 to generator 4. Generator 3 and Generator 4 is responsible for the highest value of undershoot and overshoot among the generators. The generators 1 and 2 have lower values of undershoot and overshoot. The undershoot time is 0.983s, the overshoot time is 1.004s while the settling time is 16s. Figure 7d represents the terminal voltage of each generator with time. The terminal voltage undershoot is due to generator 3 and the generator overshoot is due to generator 1. The undershoot time is 0.8998s, the overshoot time is 1.253s while the settling time is 11.5s.

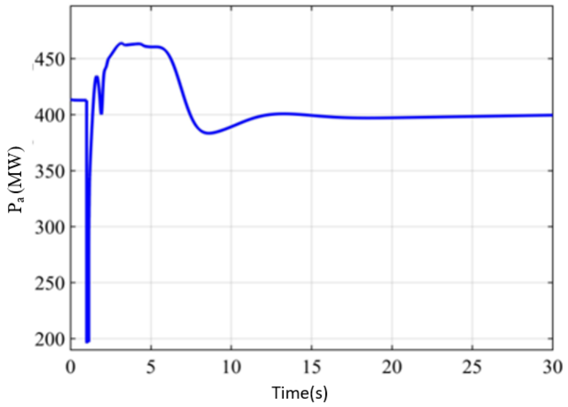

Fig. 7 a. Active power transfer from area-1 to area -2(Pa)

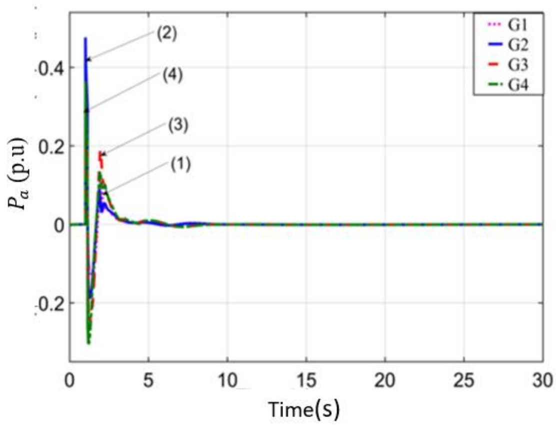

Fig. 7 b. Active power for each generator (Pa)

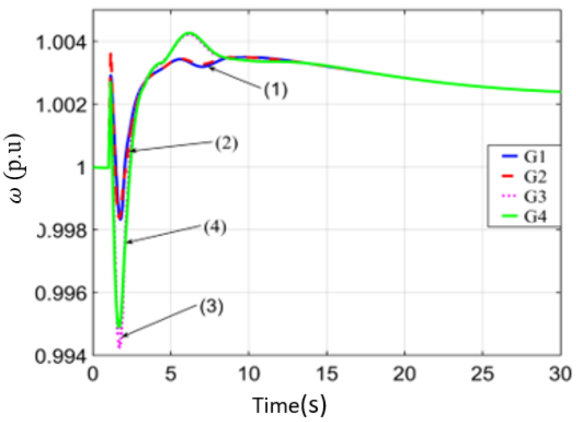

Fig. 7 c. Rotor speed of each generator (ω)

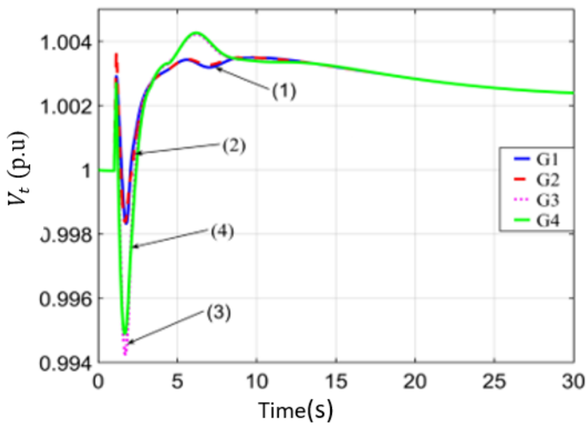

Fig. 7 d. Terminal voltage of each generator (Vt)

4.2. System Performance Evaluation of MLNFPSS Considering Symmetrical Three Phase Fault

A novel MLNFPSS controller has been suggested in this study. It is a cascade of traditional PD with a filter coefficient that mimics the lead-lag correction of a traditional PSS in oscillation frequency. This suggestion has primarily improved the oscillations' damping and robustness against operation points and certain critical parameter variations of a significantly disturbed MMPS. This MLFN based PSS collaborative design was carried out with the help of a newly developed human-based Metaheuristic Optimization technique, SOA, which is fast and capable of finding complex multi-parameter structures of the overall system in general. Dynamic analysis was used to optimize the design, and the time-domain speed integral time squared, ISE, was chosen as the fitness function to minimize. In the case of a four-generator-ten-bus power system, the obtained results demonstrated the superiority of the present MLNF based stabilizer over the classic PSS regarding settling time, overshoots, and undershoots. A complete testing process has been presented in the proposed MLNFPSS by considering a symmetrical three-phase fault in the middle of the transmission line.

Figure 8 depicts the system performance of a MLNFPSS when a symmetrical three-phase fault in the middle of the transmission line is considered. The MMPS requires less settling time and amplitude oscillation to achieve a steady state. The MLNFcascaded controller is more robust than CPSS and significantly damped the oscillations of the studied system. Figure 8a represents the active power transfer from area 1 to area 2. The undershoot time is 242.7ms, the overshoot time is 442.6ms while the settling time is 9s. Figure 8b represents the active power transfer from each generators from generator 1 to generator 4. We can notice that the active power transferred is the same for the generators. The undershoot time is -0.15s, the overshoot time is 0.07s while the settling time is 3.8s. Figure 8c represents the generator speed for each generators from generator 1 to generator 4. Generator 3 and Generator 4 is responsible for the highest value of undershoot and overshoot among the generators. The generators 1 and 2 have lower values of undershoot and overshoot. The undershoot time is 0.998s, the overshoot time is 1.00s while the settling time is 10s. Figure 8d represents the terminal voltage of each generator with time. The terminal voltage undershoot is due to generator 3 and the generator overshoot is due to generator 1. The undershoot time is 0.986s, the overshoot time is 1.182s while the settling time is 3.5s. Table 3 shows the comparison of undershoot, overshoot and settling time of CPSS and MLNFPSS.

When the proposed controller is compared to the traditional PSS, a significant reduction in time is observed and this leads to stabilization of the power system.

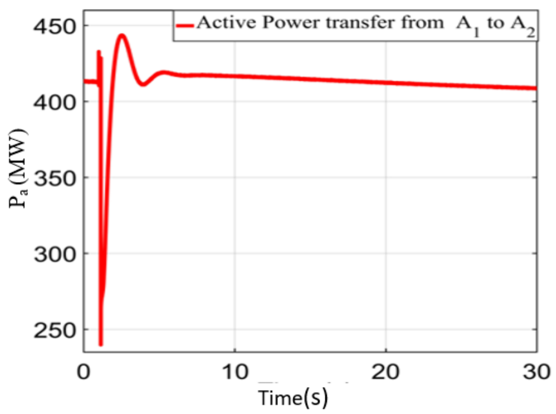

Fig. 8 a. Active power transfer from area-1 to area -2(Pa)

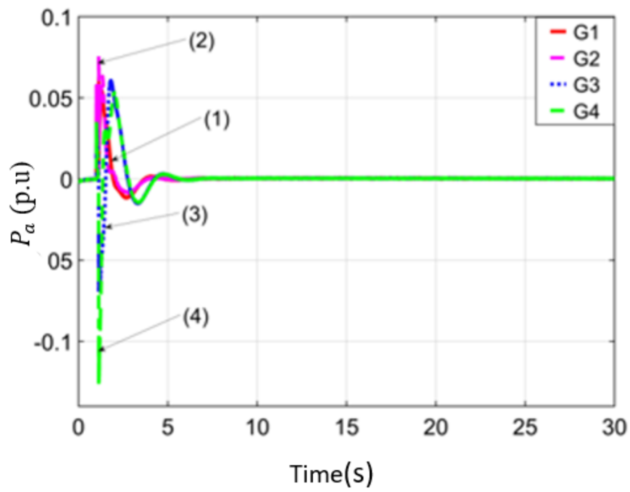

Fig. 8 b. Active power transfer from area-1 to area -2(Pa)

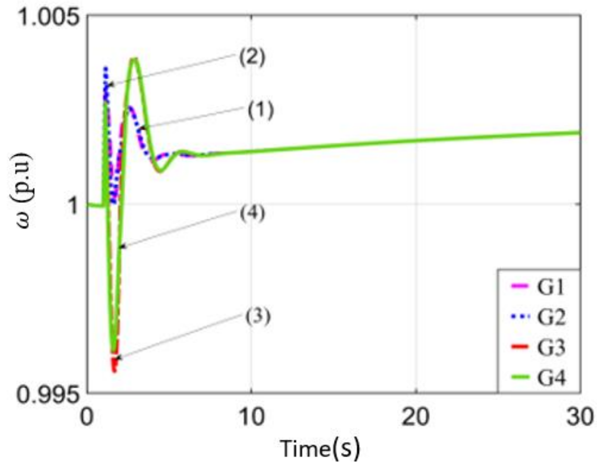

Fig. 8 c. Active power transfer from area-1 to area -2(Pa)

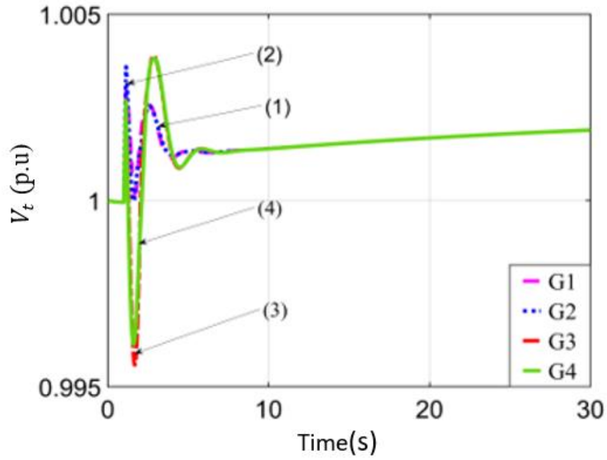

Fig. 8 d. Active power transfer from area-1 to area -2(Pa)

Moreover, the terminal voltages of the generator show that the proposed controller integrated with PSS takes only 3.5 seconds to completely dampen the system oscillations, whereas PSS takes 11.5 seconds to control the system oscillations. The MLNFPSS was settled by 69.56% faster than CPSS. Table 5 demonstrates the comparison of CPSS with MLNFPSS in terms of overshoot, undershoot, and settling time for the various control actions.

Table 5. Comparison of conventional PSS (CPSS) and MLNFPSS

Control action	controllers	undershoot	Overshoot	Settling time(s)
Power transfer from A1-A2(MW)	CPSS	196ms	464ms	14.5
	MLNFPSS	242.7 ms	442.6 ms	9
Active power Pa (p.u)	CPSS	-0.3s	0.5s	4.5
	MLNFPSS	-0.15s	0.07s	3.8
Rotor speed ϖ (p.u)	CPSS	0.983s	1.004s	16
	MLNFPSS	0.998s	1.00s	10
Terminal voltage (V_t) (p.u)	CPSS	0.8998s	1.253s	11.5
	MLNFPSS	0.986s	1.182s	3.5

The work done by Rana MJ et al.[34] first introduced the idea of using neuro fuzzy controller for PSS. The work done by Rajbongshi et al. [35] further explored the use of neuro fuzzy controllers. In this paper, we utilised a MLFNPSS in contranst to a single level NFPSS[5],[9]. Furthermore,, the work done by [34] and [35] used the LM and LS algorithms for optimization while our paper demonstrated the SOA algorithm for optimizing the controller gains. The SOA has been proven to be better in terms of convergence speed and accuracy against GA [45].TS [46], SA [47], DEA[48], PSO [49], IA [50]. We implemented the CPSS [37] and the MLNFPSS. In comparison to the CPSS, which had undershoot, overshoot, and settling times of 0.8998s, 1.253s, and 11.5s, the terminal voltage of the SOA-based MLFPSS has undershoot, overshoot, and settling times of 0.986s, 1.182s, and 3.5s. As a result, the SOA based MLNFPSS was settled 69.56% in only 3.5 seconds as opposed to 11.5 seconds for CPSS. This clearly demonstrates the superiority of the MLNFPSS.

5. Conclusion

In this research, schemes of damping and controller stability assessments are analyzed critically with the goal of improving the performance of a MMPS by finding solutions to the difficulties that currently exist. This article describes a method for enhancing power system stability that makes use of the SOA to improve the traditional PSS gains and the Neuro-Fuzzy inputs-output scaling factors parameters. This method is presented in this article. The purpose of this research was to suggest a MLNFPSS, with the end goal of increasing the degree to which a MMTAPS remains stable in the face of fault circumstances. The simulations were done on a power system with two areas and many machines, with a transmission line problem in the centre of the system. According to the findings, the reaction of the suggested MLNFPSS is more resilient than that of the standard PSS when symmetrical three-phase faults are present. In comparison to the CPSS, which had undershoot, overshoot, and settling times of 0.8998s, 1.253s, and 11.5s, the terminal voltage of the SOA-based MLFPSS has undershoot, overshoot, and settling times of 0.986s, 1.182s, and 3.5s. As a result, the SOA based MLNFPSS was settled 69.56% in only 3.5 seconds as opposed to 11.5 seconds for CPSS. Using MATLAB 2016b/Simulink, each of the control schemes has been put into action, and the outcomes of the simulation have been analysed.

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