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# Optimization of static inter-phase controller using joint particle swarm and neural network algorithm for damping power system fluctuations

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**Abstract**
With the advent of new developments in the field of power electronic circuits technology, the use of power stabilizer has been commonplace in controlling the power system fluctuations to eliminate fluctuations and stabilize system stability. The primary use of these devices is to increase the capability of systems to transmit power. In-phase controller (IPC) is one of the Flexible Alternating Current Transmission System (FACTS) devices used to transfer power between individual lines. IPC, although potentially, capable of independent control of active and reactive power or transmission lines, has not been able to emerge as a result of phase-shifting transmissions (PSTs). The major problem with IPC is the ability to control active and reactive power, while its control range is also limited. This limitation comes from the fact that the IPC uses PST as phase shifters. Accordingly, a rational solution to address the major disadvantages of the IPC could be to find better alternatives for PST. In this paper, the Voltage Switch Convertor (VSC) option is proposed as an appropriate candidate, and a new structure based on Static IPC (SIPC), considering Pourhossein *et al.*, and Mondal *et al.*, has been proposed. In the simulation, a controller based on the neural network trained by the PSO algorithm for the nonlinear system. Simulation results showed the proper functioning of the PSO-based Neural Network (PSONN) controller in our proposed tuning model, reducing the velocity fluctuations against disturbances.

**Keywords:** power control between phase, fluctuations, neural network controller, particle clustering algorithm

## Introduction

In examining and analyzing power systems, problems with shortening, the short circuit lead to destructive effects. The use of SIPC has been suggested to reduce and resolve such problems. SIPC can act as an error limiter and can also isolate the voltage in the network. Therefore, using SIPC, it is possible to control the level of short-circuit current and the resulting damage. SIPC is used to prevent network voltage drop over time, as well as, quickly recover and provide reactive power to the network. One of the advantages and uses of SIPC is the flow control of the line throughput in the normal operating conditions of the network. Therefore, with regard to the above, using SIPC not only restricts the short circuit, but also improves the ability to pass through the fault condition by controlling the inverters. SIPC is also able to control the line throughput in normal operating conditions. In this paper, the nonlinear state space equations for the proposed SIPC-coupled power system are presented in accordance with the reference system model by Pourhossein *et al.*, and Mondal *et al.*, then the space-space equations are modeled around the point of reference inspired by the reference paper. In the next step, the phase compensation controller is designed for the best point using the neural network algorithm and its improvement with the particle pool algorithm and is used in the nonlinear system.

The ability of the power system to maintain stability is largely based on electromechanical oscillations by controlling the power system. Electromagnetic oscillations are inherent phenomena in interconnected power systems that limit the stability of the system by expanding power systems, and especially by connecting these systems with weak pressure lines, to the stability of the static state. It may be necessary on some power systems to use one or more methods simultaneously for system stability. But in any case, the proposed methods should have economic justification. The simplest and cheapest way to increase the damping in a power system is to use PSS in the generator [1-3]. Over the past three decades, many studies have been carried out on electromagnetic oscillations to improve the stability of a small signal using auxiliary suppressor controls. Various methods have been proposed for designing PSS [4]. In recent years, use of evolutionary algorithm in power electronic circuit is evident [4, 5], also the design of sustainable power system devices has been considered using intelligent methods such as fuzzy control, artificial neural networks and inspirational methods for biosphere phenomena [7-10]. To strengthen the control and development of network transmission capacity, the use and use of power controllers and electronic devices is used. These devices are used in mana mode to increase the capacity of power transmission lines in terms of their heat capacity, power transfer control, voltage level stabilization and in the dynamic state to improve transient stability and mild fluctuations in energy transmission systems [11-25]. But with the use of electronic components of power in these devices, they can be used as a system stabilizer. FACTS hardware technology is an important tool for full utilization of the transmission facilities in an emergency and without reducing security of the system [12-17]. One of the types of FACTS devices is the Power Interface (IPC) controller. IPC, although potentially capable of independent control of active and reactive power or transmission lines, has not been able to emerge from the PST via transmissions. The major problem with the IPC is the lack of ability to control active and reactive power, while the control range is limited. This limitation comes from the fact that the IPC uses PST as phase shifters. Accordingly, a rational solution to address the major disadvantages of the IPC could be to find better alternatives for PST. In this thesis, the voltage source converter (VSC) option has been proposed as an appropriate candidate, and a new structure based on voltage source converter (IPC) static (SIPC) for IPC has been proposed [26-28]. This new structure is achieved by replacing two serial voltage source transducers with two phase transitions in the IPC building, respectively. These converters are subscribed to the DC bus, and are further controlled in order to operate in exactly the same fashion as an ideal Phase Angle Regulator (PAR) [26-28]. To train neuronal neural network controller, a post-propagation error method is used, and for multilevel neural network controller training, the post-propagation error method is used to speed up the convergence and improve the dynamic performance of power systems. Then, in order to further improve the damping of the oscillations, the nerve network is designed by the PSO algorithm and its training is fully described [29, 30]. By simulating the SIPC-equipped two-machine power system, the results are illustrated by the use of a lag or lead controller, and in the next section simulation results are shown using a simple neural network controller, and with lead controller function. Then the phase is compared. Finally, the PSO algorithm on the neural network is used to optimize it. A comparison between the performance of the simple neural network controller and the neural network trained by the PSO algorithm is performed to improve the dynamic and transient stability, which simulation results show better performance of controlling the trained neural network by the PSO algorithm. Stability in power systems is divided into three categories: Steady state stability, dynamic stability and transient stability [31]. Steady stability goal is the ability of the system to maintain stability after a very turbulent event. In terms of dynamic stability, the system's ability to maintain new conditions after fluctuations caused by a low-frequency turbulence is considered. In the study of steady and dynamic stability, the linear model is used because the range of turbulence is small. The stability study of this model is quite similar to any other linear system. A linear system in the state of the environment is stable if all of the system's specific values have a negative real part. So the discussion of dynamic stability in power systems is not a complicated issue [31]. The purpose of transient stability is the ability of the system to maintain new conditions after fluctuations caused by a high-frequency turbulence. Changes in load or in the structure of the production or transmission system due to error or keying are examples of large disturbances [31]. One of the devices that compensates reactive power is shunt in the power circuit. SVC is used to solve the stability problems and limit voltage variations and several other applications, but it does not have the ability to control active power. The SVC uses thyristor switches to quickly disassemble reactors or parallel capacitors [32-34]. Its high regulation and high speed SVC has made it one of the most powerful devices in controlling transient voltage conditions compared to older shunt compensators. SVC also plays an important role in reducing the power fluctuations, improving transient stability, and reducing system power losses with optimal reactive power control. The most important structure of the SVC is a capacitor coupled with a controllable controller by the thyristor, the general illustration of which is shown in the following. The controller element is a thyristor that operates at an angle of 90 to 180 degrees corresponding to the capacitor voltage [32-34].

## 2. IPC specifications

The first IPC system has been introduced newly [26-28]. It is a serial power controller, in fact, one of the main reasons for the development of the IPC was to reach a controller that could overcome the constraints of high short-circuit levels and necessarily based on the main frequency components of the power system. For this reason, in the simple building, there are trace elements such as inductors, capacitors, and phase shifting transducers (PSTs). Figure 1 shows a circuit model of sample IPC according to Pourhossein [27].

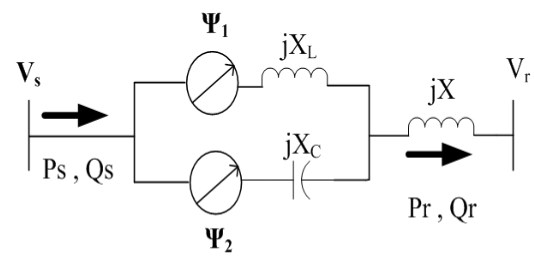


**Fig 1:** IPC circuit model [27].

Hardware is comprised of two types of inductive and Capacitive branches. The system is equipped with SIPC system. the dual power system used in this thesis includes two 1000 MVA and 5000 MVA synchronous generators connected to each other by a 700 km transmission line. The power system model is shown in figure 2.

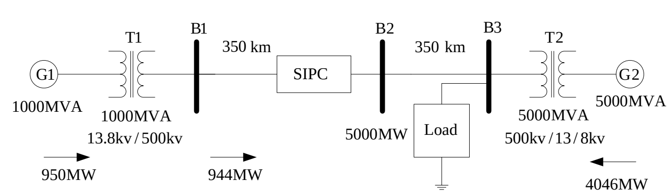


**Fig 2:** Schematic model of power system using SIPC

In accordance with the reference model, we used simulation and algorithms to simplify the comparison of the same model. In figure 2, PSS is installed on both generators and SIPC is located between the bus 1 and the bus 2.

## 5. Formulation

In the power system model, the mechanical fluctuation mode is depicted under the heading of the damping and synchronizing torque with the control loops applied to it. The linear model of a SIPC-equipped power system in a state of the art can be considered as follows.

$$y = C\bar{z} + D\bar{u}_s\,,\quad \dot{\bar{z}} = A\bar{z} + B\bar{u}_s \qquad (1)$$

In this equation, $\bar{z}$ is vector of state variables. $\bar{u}_s$ and $y$ ,vector of input or output variables are the function of the power system's output, respectively. $\Delta\omega$ and impairment. In this case, $\bar{u}_s$ is the vector of the SIPC input signal as $\Delta m_1, \Delta m_2, \Delta\delta_1, \Delta\delta_2$ . As vector z appears as follow:

$$\bar{z} = \begin{bmatrix}\Delta\delta & \Delta\omega & \bar{x}^T\end{bmatrix}^T \qquad (2)$$

Where $\Delta\delta$ , $\Delta\omega$ , respectively, the angle of the load and the generator speed, and the vector $\bar{x}$ is state variables in the equation. Therefore, the matrices A and B come in the form below.

$$B = \begin{bmatrix} 0 \\ -\bar{B}_2 \\ \bar{B}_3 \end{bmatrix} \qquad (3)$$

$$A = \begin{bmatrix} 0 & \omega_b & 0 \\ -k & -d & \bar{A}_{23} \\ \bar{A}_{31} & \bar{A}_{32} & \bar{A}_{33} \end{bmatrix}, \qquad (4)$$

As $\omega_b$ is in $rad/\sec$ in the base frequency of the system is in the form. $(-k)$ Displays the network synchronization effect normalized to the inertia of the machine. The interaction and mode of oscillation of the machine are determined by $(-k)$ and $(-d)$, which show the effects of synchronization and scattering independently of any other variable. For any mode of oscillation $\lambda_0$ or electromechanical poles with a median frequency $\omega_0$ may oscillate. State variables can be arranged in such a way that the median angle $\Delta\delta$ and velocity $\Delta\omega$ of the first and second state variables are displayed as a result of the system.

$$\begin{bmatrix} \Delta\dot{\delta} \\ \Delta\dot{\omega} \\ \dot{\bar{x}} \end{bmatrix} = \begin{bmatrix} 0 & \omega_b & 0 \\ -k & -d & \bar{A}_{23} \\ \bar{A}_{31} & \bar{A}_{32} & \bar{A}_{33} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \bar{x} \end{bmatrix} + \begin{bmatrix} 0 \\ -\bar{B}_2 \\ \bar{B}_3 \end{bmatrix} \Delta u_s$$

$$y = \begin{bmatrix} C_1 & C_2 & \bar{C}_3 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \bar{x} \end{bmatrix} \qquad (5)$$

The natural frequency of oscillation is obtained from the relation ($\omega_n = \sqrt{\frac{K_1\omega_b}{M}}$), $\omega_0 \approx \omega_n$ .

## 6. General Understanding with Neural Networks

Artificial neural networks are a very simple adaptation of biological neural networks. In general, artificial neural networks can be considered as a piece of hardware, or imagined as a mathematical model. In general, this dissertation is referred to as artificial neural networks called neural networks. Neural networks with their ability to deduce results from complex data can be used to extract patterns and identify the various trends that are very difficult for humans and computers to identify. The benefits of neural networks include the following: [28].

### 6.1 Use of the neural network as a moderator controller

Today, neural networks are used extensively to solve complex problems, such as dynamic problems. In this paper, two stages of the neural network are used as a moderator controller. In the first stage, a multilayer perceptron neural network is used. Educational data is used to train the power oscillator to mitigate the power fluctuations, which is obtained by using a power system equipped with a post-phase-pre-phase power suppressor controller and the teaching method is an error correctional post-propagation training method, which is explained in the next section. In the second phase, the PSO algorithm is used to control controller for better and more robust controller than power fluctuations. At this stage, in order to apply this method, a real-system simulator system should be designed to determine the magnitude and type of the power fluctuation error in the next step in the current time step. The power system simulator is selected from the neural network, which is used to design and train it from a power system equipped with a post-phase pre-phase controller, as in the previous step.

## 7. Neural network controller design with training of PSO algorithm

The particle swarm optimization algorithm is based on particle intelligence. A solution to the problem of optimizing the search space or modeling social behavior when there are goals. The PSO algorithm is a social search algorithm modeled on social behavior of bird or fish species. Initially, this algorithm was used to explore the patterns governing the simultaneous flying of birds and the sudden change in their paths and the optimal shape change of birds. The PSO algorithm was first described in 1975 by James C. Kennedy, a social psychologist, and Russell C. Ebertard, an electrical engineer [29]. They initially intended to use a social model and existing social relationships to create a kind of computational intelligence that does not require specific individual abilities. Their first simulation, conducted in 1995, led them to simulate the behavior of birds to find seeds. The initial ideas of the method of bird communities have been formed based on the interest that has been created for the graphical simulation of the interesting and unpredictable flight behavior of birds. Birds have the ability to fly together at the same time, shifting abruptly and at the same time in an optimal form. All these issues are addressed in mathematical simulation, and in solving the optimization problems in the PSO. In PSO, each member of a community is called a particle. These particles are all in a multidimensional space and interact with each other. Change the position of each particle based on its own experience and its knowledge and its neighbors. So, at first, we must define the neighborhood in a community, and also how we communicate the particle, so that we can understand how the algorithm works.

In a d-tuple searching space the position and velocity of a particle $i$ are denoted as $X_i = [x_{i1}, x_{i2}, ... x_{id}]$ and $V_i = [v_{i1}, v_{i2}, ... v_{id}]$. Our fitness function is to evaluate every particle to figure out the best solution $P_i = [p_{i1}, p_{i2}, ... p_{id}]$ it may find and the best solution $P_g$ for the whole swarm at time $t$, and the position and velocity are updated with the equations (6),(7). $P_g$ is the optimum solution.

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_1 [p_{ij} - x_{ij}(t)] + c_2 r_2 [p_{gj} - x_{ij}(t)] \quad (6)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1), \quad j = 1, ..., d \quad (7)$$

Where $\omega$ denotes the inertia weight factor, $c_1, c_2$ denote positive accelerators, and $r_1, r_2$ are random numbers uniformly distributed in interval [0, 1]. The role of inertia weight $\omega$ is considered to be crucial for convergence, and is to control the impact of the previous history of velocity on the current velocity. Thus it regulates the tradeoff between global and local exploration for the swarm. A large $\omega$ makes the searching escape from local minima and facilitates global searching, while small $\omega$ facilitates local searching and converge. When the particles get trapped in local optima the inertia weight is augmented, and when they are dispersive the weight is decreased. The velocity interval $[v_{min}, v_{max}]$ and position interval $[x_{min}, x_{max}]$ are to restrict the searching in the required domain.

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 (xpbest_i\,(t)\_X_i(t)) + c_2 r_2 (xgbest_i\,(t)\_X_i(t)) \quad (8)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (9)$$

Weight $w$ creates a balance in local search and general search in the algorithm. The appropriate selection makes the algorithm less repeatable to reach the optimal point. During the implementation of the PSO algorithm, the coefficient $w_k$ decreases from 0.9 to 0.4, based on the following relation, in which the $iter$ number of the current repetition and $iter_{max}$ the maximum number of repetitions.

$$w_k = w_{max} - [\frac{w_{max} - w_{min}}{iter_{max}}] \times iter \quad (10)$$

**Table 1:** BPSO Parameters

| Value | Parameters |
|---|---|
| 25 | Population |
| 50 | Iteration |
| 2 | $C_1$ - $C_2$ |
| 6 | Max speed |
| -6 | Min speed |
| 0-1 | Inertia |

Regarding to the above objectives, the simplest target function that can be considered for the PSO algorithm is the function.

$$\text{Fitness} = \frac{1}{\alpha(m_1)^2 + \beta(\Delta\omega_k)^2 + c(\Delta\omega_{k+1} - \Delta\omega_k)^2 + \xi} \quad (11)$$

The coefficients $\alpha, \beta, c$ used in the target function are normalized to normalize the signals used in the function and also have an almost identical effect on the value of the function, and the coefficient $\varepsilon$ used to avoid the infinite amount of the function is used. The four SIPC control parameters $m_1, m_2, \delta_1, \delta_2$ can be used to control oscillations and generate electric torque and be considered as controller output.

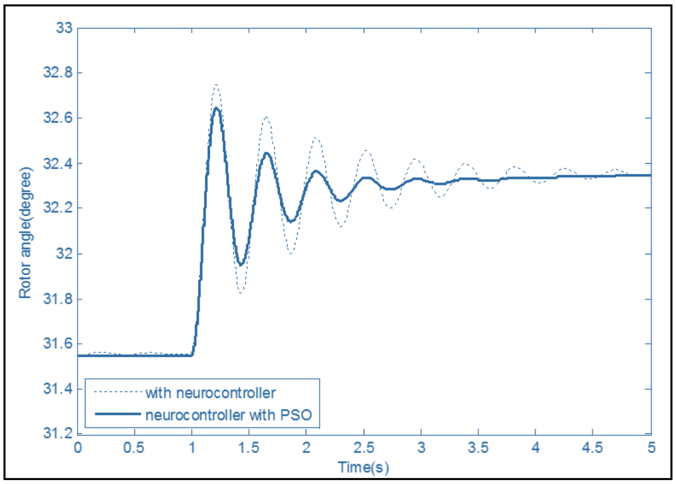


**Fig 3:** comparison of neuro controller and PSONN, light load.

Comparison of rotor angular response of two controllers of simple neural network Neural network trained by PSO in light load conditions.

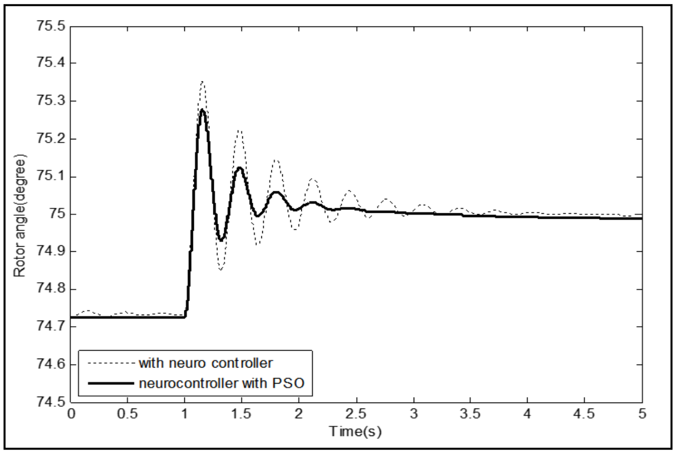


**Fig 4:** comparison of neuro controller and PSONN, overload

Comparison of the rotor angle response of two controllers of the simple neural network Trained neural network with PSO under overload conditions Since the aim of controlling the use of neural networks is faster swinging, hence a comparison between the performance of the perceptron neural network controller and the neural network controller with the PSO.

## 8. Conclusion

The simulation results show that the neural network controller which uses the PSO algorithm to optimize the parameters is better than the PSO controller and the lead and lag controller. The superior performance of joint neural network controller and PSO compared to the other two controllers is approached with dynamic parameters. By comparing the results of the simple controller and the PSONN controller, dynamic fluctuations are controlled. Also particular improvement in transient stability is reached, provides better and faster performance. Also, using SIPC, system stability is much better than before. These results indicate the optimal performance of the controllers designed in this simulation.

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