Mahdiyeh ESLAMI, Hussain SHAREEF, Azah MOHAMED

University Kebangsaan Malaysia

Application of artificial intelligent techniques in PSS design: a survey of the state-of-the-art methods

***Abstract**. Power system stabilizers (PSSs) are the most well known and efficient devices to damp the power system oscillations caused by interruptions. Low frequency oscillation problems are very difficult to solve because power systems are very large, complex and geographically distributed. Hence, it is necessary to employ most efficient optimization methods to take full advantages in simplifying the problem and its implementation. These optimization methodologies and techniques are widely diverse and have been the subject of ongoing enhancements over the years. This paper presents a survey of literature on the various optimization methods applied to solve the PSS problems.*

***Streszczenie.** System stabilizacji mocy PSS jest powszechnie stosowaną I skuteczną metodą tłumienia oscylacji spowodowanych przerwaniami. Oscylacje niskiej częstotliwości są trudne do eliminacji ze względu na ich złożoność i rozległość przestrzenną. Dlatego warto poszukiwać skutecznych metod optymalizacji metody PSS. Artykuł przedstawia metody optymalizacji wykorzystujące sztuczną inteligencję. (**Wykorzystanie technik sztucznej inteligencji przy projektowaniu systemów stabilizacji mocy systemu energetycznego**)*

Keywords: artificial intelligence techniques, optimization methods, power system stabilizer.
Słowa kluczowe: sztuczna inteligencvja. Metody optymalizacji, stabilizacja w systemach energetycznych.

1. Introduction

With the advent of automatic voltage regulators (AVRs) in the late 1950s, installation of AVRs on power generating units become a common practice. Unfortunately, the high performance of these voltage regulators caused a destabilizing phenomenon on the power system. Most of the problems are associated with the low frequency oscillation in interconnected power systems, especially in the deregulated paradigm. Small magnitude and low frequency oscillation often remained for a long time. To provide fast damping for the system and thus improve the dynamic performance, a supplementary control signal in the excitation system and/or the governor system of a generating unit can be used. As the most cost effective damping controller, power system stabilizer (PSS) has been widely applied to suppress the low frequency oscillation and enhance the system dynamic stability. PSSs contribute in maintaining reliable performance of the power system stability by providing an auxiliary signal to the excitation system.

In last decade, artificial neural network controllers (ANNCs) [1] and fuzzy logic controllers (FLCs) [2] being used as PSSs, have been developed and tested. Unlike other classical control methods, ANNCs and FLCs are model-free controllers; i.e they do not required an exact mathematical model of the controlled system. Moreover, speed and robustness are the most significant properties in comparison to the other classical schemes. But these controllers for the Fuzzy PSS design, so the rules and the membership function of the controller are tuned subjectively, making the design laborious and a time-consuming task. With respect to ANNCs, they have the capability of learning and adaptation, but they work like a 'black-box' and it is difficult to understand the behavior of the network. Despite the existence of various structures of PSSs, the conventional fixed structure lead-lag PSS (CPSS) is still preferred by most of the power system utilities. It may be due to ease of on-line tuning, and the lack of assurance on the stability associated to some variable or adaptive structure methods. To understand the effects of CPSSs with different parameters on the overall dynamic performance of the power system, an extensive investigation was done in [3].

The investigation has illustrated that the satisfactory performance during the system upsets is related to the appropriate choice of the CPSS parameters. The PSSs parameters' tuning problem is one of the optimization issues in power system stability.

Intelligent optimization based methods have been initiated to solve this problem. Two main techniques used for the parameter tuning of the PSS in the power system are sequential tuning and simultaneous tuning. To achieve a set of optimal PSS parameters under different operating conditions, the tuning and testing of PSS parameters must be repeated under different operating conditions of the system. The simultaneous tuning of PSS parameters is generally formulated as a very large scale, nonlinear, non-differentiable optimization problem. This type of optimization problem is very difficult to solve by applying traditional differentiable optimization algorithms. Sequential quadratic programming (SQP) techniques are fast deterministic optimization techniques [4], but they are very sensitive to the choice of initial point. To overcome the above-mentioned problems, many random search methods such as Tabu search (TS) [5], simulated annealing (SA) [6], Ant Colony Optimization (ACO) [7] and Harmony search (HS) [8], evolutionary programming (EP) [9], bacteria foraging optimization (BFO) [10], genetic algorithm (GA) [11], and particle swarm optimization (PSO) [12-14] have been used.

In this work, a serious attempt is made to present a comprehensive analysis of artificial intelligence techniques for designing PSSs, which were recently proposed by various researchers. This includes important mathematical optimization and artificial intelligence (e.g. fuzzy logic, artificial neural network, evolutionary computing, etc.) techniques used in power system optimization problems. In addition, applications of hybrid artificial intelligence techniques in PSSs have also been discussed.

2. Power System Stabilizer (PSS)

Since the 1960s, PSSs have been used to add damping to electromechanical oscillations. The PSS is an additional control system, which is often applied as a part of an excitation control system. The basic function of the PSS is to apply a signal to the excitation system, producing electrical torques to the rotor in phase with speed differences that damp out power oscillations. They perform within the generator's excitation system to create a part of electrical torque, called damping torque, proportional to speed change. A CPSS can be modeled by a two stage (identical), lead-lag network which is represented by a gain K and two time constants T_1 and T_2. This network is connected with a washout circuit of a time constant T_w. The signal washout block acts as a high-pass filter with the time constant T_w that allows the signal associated with the oscillations in rotor speed to pass unchanged. Furthermore, it does not allow the steady state changes to modify the terminal voltages. The phase compensation blocks with time constants T_{1i} – T_{4i} supply the suitable phase-lead characteristics to compensate the phase lag between the input and the output signals. The commonly used structure of the PSS is shown in Fig. 1.

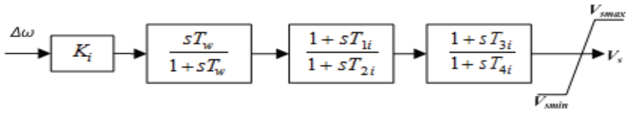

Fig.1. Structure of power system stabilizer

3. Artificial Intelligence Techniques

In the field of power system operations and planning, very sophisticated computer programs are required and designed in such a way that they could be executed and modified frequently according to any variations. Artificial intelligence (AI) is a powerful knowledge-based approach that has the ability to deal with the high non-linearity of practical Systems. AI has a benefit to decrease the mathematical complexity beside the rapid response which can be utilized for transient analysis. AI techniques, which promise almost a global optimum, such as ANN, FL, and Evolutionary Computation (EC), have appeared in recent years in power systems applications as efficient tools to mathematical approaches. Recently, many researchers are concerned with various types of AI techniques to develop efficient PSSs. The real beginning of AI was presented in 1958 [15]. Various optimization methods have been introduced to overcome the power systems' problems, and enormous studies have been published in this area since 1950. This section presents a survey of AI techniques (e.g. ANN, FL, EC, etc.) which are used in power system stabilizer optimization problems.

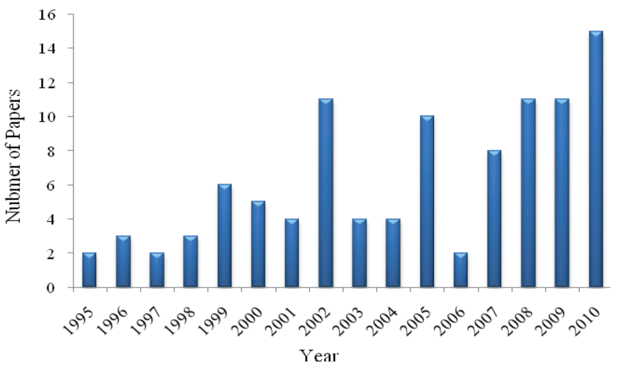

Fig.2. Number of papers published in each year on the subject of PSS

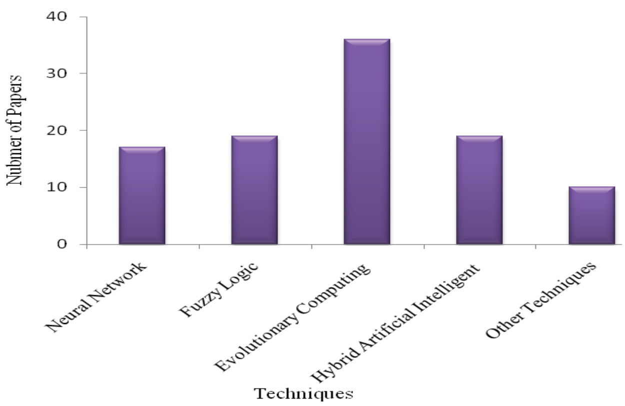

Fig.3. Number of papers published on different Artificial Intelligence Techniques used.

For the aim of this review, a literature overview has been carried out including the IEEE/IET/Elsevier/Springer databases which are the largest abstract and citation databases of research literature and quality web sources. The survey spans over the last 15 years from 1995 to 2010. Fig. 2 statistically illustrates the number of published research papers on the subject of the PSS problem during the last 15 years. Also, the number of publications and the method applied in the specified period are shown in Fig. 3.

3.1 Artificial Neural Network (ANN)

In 1949, Hebb presented the training algorithm and verified how a network of neurons could exhibit learning behavior [16]. This was the starting point of the ANN. ANNs are chiefly classified by their architecture (number of layers), topology (connectivity pattern, feed forward or recurrent, etc.), and learning regime. An ANN is a computational model or mathematical model on the basis of biological neural networks and is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The novel structure of the information processing system is the main component of this paradigm. It is composed of a great number of highly interconnected processing components (neurons) working in unison to overcome the special problems. Like people, ANNs learn by example. The most important advantages of the ANN are: (i) learning ability; (ii) appropriateness and control; (iii) adaptation to the data; (iv) robustness; (v) rapidity. Despite the advantages, some disadvantages of the ANN are: (i) large dimensionality; (ii) choice of the optimal configuration; (iii) selection of training method; (iv) the 'black-box' representation of the ANN (they lack explanation capabilities); and (v) the generation output even if the input data are unreasonable. The feed-forward neural network is the first and arguably simplest type of ANN devised. The information moves in only one direction, forward, from the input to the output through the hidden nodes without any cycles or loops in the network. The most applications of the ANN in the power systems use a multi-layer feed forward network. ANNs are effective tools used for many years for identification and control of complex systems due to the non-linear mapping properties. The ANN, when sufficiently trained, may be used as a controller instead of the CPSS. To achieve best performance, the ANN must be trained for different operating conditions to tune the CPSS parameters. The learning procedures cause interference by the conventional back propagation network under various conditions. To solve this drawback, a modular ANN was proposed instead of a back propagation network [17]. This model consisted of three local expert networks and a single gate network with three layers for each one. The ANN was trained directly from the input and output of the CPSS. The simulation results verified that the modular PSS was more efficient in damping oscillations and achieving good performances.

To develop a neural adaptive PSS, a feed-forward neural network with a single hidden layer was investigated in [18-20]. The proposed neural adaptive PSS includes two sub networks: adaptive neuro-identifier which tracked the dynamic characteristics of the plant, and adaptive neuro-controller to damp the low frequency oscillations. These two sub-networks were trained in an on-line mode utilizing the back propagation method.

Radial basis function network (RBFN) consisted of three layers: input layers, hidden layers, and output layers. The hidden layer was trained at first using an unsupervised learning algorithm to find centers and widths of the radial basis functions for individual pattern units. To find the weights between the pattern units and the output units, the output layer was trained using a supervised learning algorithm [21]. A novel approach for on-line adaptive tuning of PSS parameters using RBFNs was presented by Abido and Abdel-Magid [22]. The proposed RBFN was trained over a wide range of operating conditions and system parameter variations in order to re-tune PSS parameters on-line based on real-time measurements of machine loading conditions. The proposed RBFN based PSS was trained for various operating conditions and system parameter variations. The orthogonal least squares learning algorithm was developed for designing an adequate and parsimonious RBFN model. A very large amount of training was needed in the ANN. Therefore, to solve this problem a self-tuning PSS based on the ANN was presented in [23]. In this approach, the ANN was introduced to tune the CPSS parameters in real-time. A new method was utilized for choosing the number of neurons in the hidden layer.

To improve the transient stability of power systems, a recurrent neural network (RNN) stabilization controller was presented in [24]. The proposed method was used for both the governor and AVR. The weights of the proposed controller were adjusted on-line. The signal output of the first RNN was added to the PSS signal output for excitation control. The signal output of the second RNN was used as a stabilizing signal for the governor system.

ANNs can also be applied as intelligent controllers to control nonlinear, dynamic systems through learning, which can easily accommodate the nonlinearities and time dependencies, though; they need the large training time and large number of neurons to deal with complex problems. To overcome this problem, a generalized neuron-based adaptive PSS was proposed by Chaturvedi and Malik [25-29] because the generalized neuron needed shorter training time and much smaller training data. The stabilizer was trained off-line for a large range of operating conditions and different disturbances and then it was trained online on the power system. In order to enhance the system performance, gain-scheduling scheme was applied to design a PSS. A neural PSS, which was trained using a set of gain-scheduling PSS parameters, was presented in [30]. These parameters previously were calculated using a pole-shifting method for various operating points. It was verified that the stabilizers would be more beneficial for the case when the reactive power was absorbed by the machines. The results showed that the proposed stabilizer achieved the good performance compared with a CPSS.

To improve the damping performance, a probabilistic PSS was proposed using a single neuron model by Ping et al. [31]. The variation of system operating conditions can be tracked by adding supplementary self-adjusted gains to PSSs. In a related work, adaptive critics and ANNs were presented to design a real time digital signal processor (DSP) implementation of an optimal wide area control system (WACS) for a power system [32]. The WACS was implemented on the DSP which was interfaced to the real time digital simulator that simulates the power system. Simulation results exhibited that the damping of inter-area oscillation was increased by adding a PSS to the WACS under different operating conditions and contingencies.

3.2 Fuzzy Logic (FL)

In 1964, Lotfi Zadeh developed FL to address inaccuracy and uncertainty which usually exist in engineering problems [33]. Fuzzy set theory can be considered as a generalization of the classical set theory. In classical set theory an element of the universe either belongs to or does not belong to the set. Therefore, the degree of association of an element is crisp. Membership function is the measure of degree of similarity of any element in the universe of discourse to a fuzzy subset. Triangular, trapezoidal, piecewise-linear, and Gaussian functions are most commonly used membership functions. In a fuzzy set, an infinite number of memberships are allowed. The degree of each membership for each element is indicated by a number between 0 and 1 [21]. The membership function is usually designed by taking into consideration the requirement and constraints of the problem. FL implements human experiences and preferences via membership functions and fuzzy rules. Due to the use of fuzzy variables, the system can be made understandable to a non-expert operator. In this way, FL can be used as a general methodology to incorporate knowledge, heuristics, or theory into controllers and decision makers. The benefits are: (1) accurate representation of the operational constraints of the power systems; and (2) fuzzified constraints will be softer than traditional constraints [34]. FL was first introduced in 1979 for solving power system problems.

To design traditional controllers, it is essential to linearize non-linear systems. After that, control laws are derived based on the new model. These controllers are utilized to control the system. Fuzzy logic controllers (FLCs) are nonlinear. Moreover, FLCs do not need a controlled plant model, and are not sensitive to plant parameter variations. The human experience and knowledge can be applied to design of the controller by using FL. FLCs are rule-based. The rules of the system are written in natural language and translated into FL [35]. A FLC based on a state feedback control system was developed for damping electro-mechanical modes of oscillations and enhancing power system stability [36]. The input signals to the controller were the weighted sum of the mechanical states and the electrical states' weighted sum, while its output signal was added to the conventional fixed-gain proportional-integral controller output signal to give the excitation control signal.

A design process for a fuzzy logic based PSS (FLPSS) was proposed and investigated for a multi-machine power system [37]. Speed deviation of a synchronous generator and its derivative were chosen as the input signals to the FLPSS. A two area, five generator power system was used to illustrate the robustness of the FLPSS. A normalized sum-squared deviation index was used for designing the FLPSS and demonstrating its robustness. A novel input signal based FLPSS was applied in the multi-machine environment [38]. Deviation of active power through the tie line connecting two areas was used as one of the inputs to the FLPSS in conjunction with the speed deviation. The proposed method achieved better dynamic performance compared to a CPSS and FLPSS with a usual speed deviation and acceleration input signals. The cost and scanning time of the approach were reduced because the same signal can be fed to each of the FLPSSs attached with each machine. A new gain scheduling proportional-integral-derivative (PID) stabilizer was presented for excitation control of power systems using FL [39]. The parameters of the proposed stabilizer were tuned on-line using a fuzzy rule base and a fuzzy inferencing mechanism for manipulating the speed error and its derivative. A new global tuning method was presented by Kvasov et al. [40] for a FLPSS in a multi-machine power system in order to damp the power system oscillations. This technique was based on an iterative adaptive efficient partition algorithm. Numerical results showed that the proposed method can find the optimum global solution faster than a conventional GA.

Lu et al. [41] presented a method for designing a FL-based adaptive PSS based on the traditional frequency domain method. Also, a fuzzy signal synthesizer was introduced to obtain adaptiveness. Two linear stabilizers were designed to accommodate two extreme loading cases. A FL mechanism was used to generate one single control signal by properly combining the outputs of the linear stabilizers. The fuzzy controller was optimized using a least squares' error criterion. A model reference adaptive fuzzy controller consisting of a reference model and self-learning fuzzy logic controller and its application as a PSS was described in [42]. Off-line model identification was applied to achieve a dynamic equivalent model for the synchronous machine with respect to the rest of the system. In [43], an indirect adaptive fuzzy-logic PSS (AFLPSS) was presented using the concept of fuzzy basis functions. The power system was modeled using two unknown differential equations with nonlinear parameters which were functions of the state of the system. Lyapunov's synthesis method was applied to adapt the FL systems. Moreover, Elshafei et al. [44] proposed a novel AFLPSS that grasps the merits of adaptive and FL methods and solved their drawbacks. The proposed stabilizer was initialized using the rule-base of a standard FLPSS to ensure a satisfactory performance during the learning stage. The rule-base was then tuned on-line so that the stabilizer could adapt to different operating conditions. The results of the proposed method achieved the acceptable performance using a significantly small rule base as compared to the FLPSS. In [45] an AFLPSS design for damping electro-mechanical modes and enhancing the first-swing synchronous stability margins was presented. The design was based on a multi-zonal PID structure and fuzzy logic variable-gain scheduling to optimize the damping action. The FLPSS was proposed for use in parallel with the CPSS with added simple switching criteria.

In [46-48] a linear matrix inequalities design of a model-based fuzzy static output-feedback PSS was proposed. A power system design model was approximated by a set of Takagi–Sugeno (T-S) fuzzy models to account for nonlinearities, uncertainties, and large scale power systems. The design guarantees robust pole-clustering in a satisfactory region in the complex plane for different operating conditions and disturbances. The simulation results of both single-machine and multi-machine power systems verified the efficiency of the proposed PSS design.

To enhance the dynamic performance of large interconnected power systems, wide-area measurement systems (WAMS) signals have been suggested for design of stabilizers. However, long time-delay during sending and receiving signals may be detrimental to system stability and may degrade system performance. Therefore, to solve this drawback, Dou et al. [49-51] investigated the delay-independent robust control problem based on WAMS via H_∞ fuzzy control method. The nonlinear large interconnected power systems were represented by a set of equivalent T–S fuzzy model. The model was stabilized by using a feedback decentralized control scheme. Ramirez and Malik presented a self-tuned FLPSS to enhance the damping of power system oscillations [52]. The design of the self-tuned FLPSS was based on a simple FL controller that possesses a significantly reduced rule base, a small number of tuning parameters, and was implemented through a simple control algorithm and architecture. The fuzzy tuner was used to non-linearly modify on-line the sensitivity of the simple FL controller to its input variable, which indirectly changes the relative sensitivity of areas of associated input membership functions.

3.3 Evolutionary Computing (EC) methods

Different types of intelligent optimization techniques are used to search for optimal or near optimum solutions for many power system problems, especially for PSSs. These techniques are TS, SA, ACO, HS, BFO, GA and PSO, etc. Fig. 4 shows the number of publications and the method applied to solve the optimization problem on the PSS. This survey included, to the best of our knowledge (based on IEEE/IET/Elsevier/Springer databases), most of the papers that have been published during the past two decades or so.

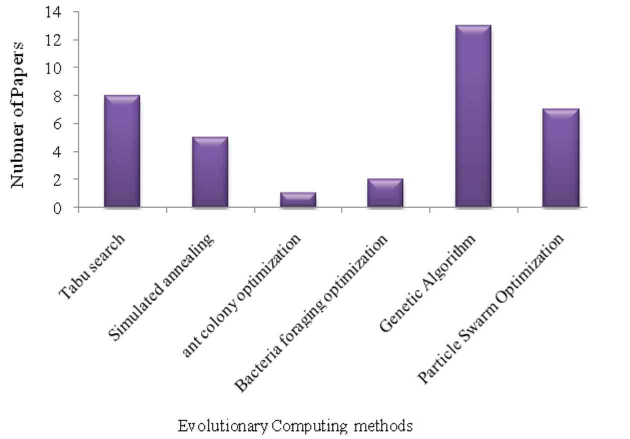

Fig.4. Number of papers published on different evolutionary computing methods used

3.3.1 Tabu Search (TS)

TS is a mathematical optimization method belonging to the class of local search techniques. TS enhances the performance of a local search method by using memory structures. Once a potential solution has been determined, it is marked as "taboo" ("tabu" being a different spelling of the same word) so that the algorithm does not visit that possibility repeatedly. TS is an iterative improvement procedure that can start from any initial feasible solution (searched parameters) and attempt to determine a better solution. As a meta-heuristic method, TS is based on a local search technique with the ability to escape from being trapped in local optima [53-54].

Abido [5] presented the TS algorithm to search the optimal parameters of the conventional lead-lag power system stabilizer (CPSS). This approach provided a good performance when tested on a single-machine-infinite bus (SMIB) and multi-machine power systems with different operating conditions. In addition, application of the TS optimization technique to multi-machine PSS design was presented in [55-57]. The proposed approach employed TS to search for optimal or near optimal settings of PSS parameters that shift the system eigenvalues associated with the electromechanical modes to the left of a vertical line in the s-plane. Incorporation of a TS algorithm in a PSS design significantly reduced the computational burden.

Power system stability enhancement through control of excitation and static phase shifter (SPS) was investigated by Abido and Abdel-Magid [58]. The design problem of excitation and SPS controllers was formulated as an eigenvalue-based optimization problem. Then, a TS algorithm was proposed to search for optimal controller parameters. In [59], a new optimization method of a robust load frequency stabilizer equipped with superconducting magnetic energy storage was proposed. To enhance the robustness of the load frequency stabilizer against system uncertainties such as different load changes, system parameter variations, etc., the multiplicative uncertainty was included in the system modeling. Thus, the robust stability of the stabilized system can be easily guaranteed in terms of the multiplicative stability margin. The configuration of the load frequency stabilizer was practically based on a second order lead/lag compensator with a single feedback input. The control parameters were automatically optimized by a TS algorithm, so that the desired damping ratio of the target inter-area mode and the best multiplicative stability margin were achieved.

3.3.2 Simulated Annealing (SA)

SA is a generic probabilistic meta-heuristic for the global optimization problem of applied mathematics, namely locating a good approximation to the global optimum of a given function in a large search space. It is often applied when the search space is discrete. For certain problems, SA may be more efficient than exhaustive enumeration - provided that the goal is merely to find an acceptably good solution in a fixed amount of time, rather than the best possible solution. The name and inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to enhance the size of its crystals and decline their defects. The heat causes the atoms to become unstuck from their initial positions and wander randomly through states of higher energy; the slow cooling gives them more chances of finding configurations with lower internal energy than the initial one. By analogy with this physical process, each step of the SA algorithm replaces the current solution by a random "nearby" solution, chosen with a probability that depends both on the difference between the corresponding function values and also on a global parameter called the temperature that is gradually reduced during the procedure. The dependency is such that the current solution changes almost randomly when T is large, but increasingly "downhill" as T goes to zero. The allowance for "uphill" moves saves the method from becoming stuck at local optima - which are the bane of greedier methods. The method was independently described by Kirkpatrick et al. in 1983 [60] and by Černý in 1985 [61]. Design of a PSS using the SA heuristic optimization method was presented by Abido [62]. Two different PSSs were described, namely, SA-based PSS (SAPSS) and robust SAPSS (RSAPSS). The proposed approach utilized SA to find for optimal or near optimal settings of RSAPSS and PSS parameters. Moreover, the robustness of the proposed SAPSS and RSAPSS over a wide range of loading conditions and system parameter uncertainties was investigated. Also, Abido [63-65] proposed robust design of a multi-machine PSS using the SA optimization technique. The proposed approach applied SA to search for an optimal parameter setting of a widely used CPSS.

3.3.3 Ant Colony Optimization (ACO) and Harmony search (HS)

In computer science and operations research, the ACO algorithm is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. This algorithm of ant colony algorithms is a member in swarm intelligence methods, and it constitutes some meta-heuristic optimizations [66-67].

A new mixed-integer ant direction hybrid differential evolution (MIADHDE) algorithm was proposed to determine the optimal tuning of PSSs. The MIADHDE was improved from ADHDE by the addition of accelerated phase and real variables. The main idea of ADHDE was to use the ACO to find the proper mutation operator to accelerate the search for the global solution. The MIADHDE algorithm searched for the optimal PSS parameters, which can include remote feedback of speed deviation measurement signals [7].

The HS is an effective modern heuristic optimization algorithm developed in recent years. The HS was applied for tuning of PSS parameters in [8]. Two power systems, i.e. the New England 10-unit 39-bus system and the 64-unit 305-bus Fujian power system, were served for demonstrating the feasibility and efficiency of the developed model and method.

3.3.4 Bacteria Foraging Optimization (BFO)

A novel optimization method was presented by Passino [68] called the BFO algorithm which is based on the foraging strategies of the Escherichia Coli bacterium cells. These strategies are based on the idea of natural selection among animals. In the competition for living, the animals are in a constant battle to win out not only their lives but also their generations. The ones with superior genetic capabilities from within (physiological) and better adaptation to the environmental elements from without can survive. Different animals have different strategies to survive; that is, more efficient strategies are adapted as the poor ones are either eliminated or turned into better ones.

In order to find optimal value of PSS parameters, Mishra et al. [10] proposed the BFO technique. Different operating conditions were considered during the tuning process. Time domain simulations were carried out for multi generator power systems with the proposed approach under different kinds of disturbances. The results show a robust performance of the stabilizer compared to conventional and GA optimization techniques. In [69], BFO is considered for tuning the parameters of both single-input and dual-input PSSs. CPSS and the three dual-input IEEE PSSs (PSS2B, PSS3B, and PSS4B) were optimally tuned to achieve the optimal transient performances. A comparative performance study of these four variants of PSSs was also made.

3.3.5 Genetic Algorithm (GA)

The GA is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. GAs belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover [70].

The GA has been applied by many authors for tuning PSS parameters. Simulation results show activity of GA in tuning PSS parameters with a fixed location [71-72]. However, these PSSs cannot guarantee good damping performance when the location of the stabilizer is changed. Therefore, in [43-74] a simple method is applied to find the optimal locations and the best PSSs parameters simultaneously in multi-machine power systems using GA. Nonlinear simulation and eigenvalues analysis demonstrate the effectiveness of the technique in damping of oscillations under different scenarios. Also, a method to simultaneously tune PSSs in a multi-machine power system was presented using hierarchical GA and parallel micro GA based on a multi-objective function [75].

Abdel-Magid and Dawoud investigated the tuning of PSS using GA. A digital simulation of a linearized model of a single-machine infinite bus power system at some operating point was used in conjunction with the GA optimization process [76]. Optimal multi-objective design of robust multi-machine PSSs using GA was presented by Abido and Abdel-Magid [77]. A CPSS was used in this work. The multi-machine power system operating at various loading conditions and system configurations was treated as a finite set of plants. The stabilizers were tuned to simultaneously shift the lightly damped and un-damped electro-mechanical modes of all plants to a prescribed zone in the s-plane.

It is difficult to use binary representation when dealing with continuous search space with large dimensions. Therefore, the real-coded genetic algorithm (RCGA) was employed by [78-80] to search for optimal PSS and TCSC and SVC-based stabilizer parameters. The eigenvalue analysis and non-linear simulation were carried out for a weak connected power system. The results demonstrated the ability of the proposed stabilizers to improve stability of the system. In [81-82], the RCGA optimization technique was applied to design a robust PSS for an SMIB and multi-machine power system. The design problem of the proposed controller was formulated as an optimization problem and RCGA was employed to search for optimal controller parameters. By minimizing the time-domain based objective function, in which the deviation in the oscillatory rotor speed of the generator was involved; stability performance of the system was improved.

3.3.6 Particle Swarm Optimization (PSO)

PSO is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO does not use the gradient of the problem being optimized, which means PSO does not require the optimization problem to be differentiable as is required by classic optimization methods such as gradient descent and quasi-Newton methods. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time, etc. PSO optimizes a problem by having a population of candidate solution, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae. The movements of the particles are guided by the best found positions in the search-space which are updated as better positions are found by the particles [83-84].

El-Zonkoly et al. [85-86] proposed a PSO technique for tuning parameters of the brushless exciter and lead-lag power system stabilizer. Simulation results demonstrated the activities of the stabilizer in damping of oscillations of multi-machine power systems. A novel evolutionary algorithm-based approach to optimal design of multi-machine PSSs was proposed [87-88]. The proposed method used a PSO technique to search for optimal settings of CPSS parameters. The PSO method was utilized to design a robust PSS by Panda [89]. The design problem was formulated as an optimization problem and PSO was applied to search for optimal parameters. By minimizing the time-domain based objective function, stability performance of the system was improved. The results showed the effectiveness and robustness of the proposed method under wide range of operating conditions and disturbances and their ability to provide efficient damping of low frequency oscillations.

Chaotic optimization algorithms, which have the features of easy implementation, short execution time and robust mechanisms of escaping from the local optimum, is a promising tool for the engineering applications. Therefore, in [90], a chaotic optimization algorithm was introduced for design of the multi-machine PSSs. The robustness of the proposed COA-based PSSs was verified on a multi-machine power system under different operating conditions and disturbances.

3.4 Hybrid Artificial Intelligent Techniques

Two or more AI techniques are applied to create a hybrid intelligent system. Through cooperative interactions, such methods are used in series or in integration to gain successful results. During the last two decades, hybrid systems are applied in engineering applications.

A design method for a new hydro-power plant controller using fuzzy set theory and ANNs was proposed by Djukanovic et al. [91]. The controller was suitable for real time operation, with the aim of improving the generating unit transients by acting through the exciter input, the guide vane, and the runner blade positions. The developed FLC, whose control signals were adjusted using the on-line measurements, can offer better damping effects for generator oscillations over a wider range of operating conditions than conventional regulators. For damping electromechanical modes of oscillation and enhancing power system synchronous stability, a novel neuro-fuzzy hybrid PSS was designed [92]. The hybrid PSS comprised of a front-end conventional analog PSS design, an ANN based stabilizer, and a fuzzy logic post-processor gain scheduler. Moreover, to develop PSS, a fuzzy basis function network (FBFN) was introduced by Abido and Abdel-Magid [93-94]. The proposed FBFN was trained to adapt the PSS parameters based on real-time measurements of the machine loading conditions. The orthogonal least squares learning algorithm was applied for selecting the FBFN structure. In [95] a neuro-fuzzy controller (NFC) with adaptive input link weights (LLWs) was presented and it worked as an adaptive PSS. The control structure of the proposed adaptive neuro-fuzzy PSSs included a neuro-identifier to track the dynamic behavior of the plant and an NFC to damp the low-frequency oscillations. Generally, the input membership functions (IMFs) and consequent parameters (CPs) are adapted in order to increase the performance of the NFC. Therefore, LLWs and CPs were updated online by the gradient descent method.

Optimal tuning of the neuro-fuzzy PSS parameters using GA was discussed in [96-97]. The neuro-fuzzy PSS was implemented as a multilayer perceptron, in which the weights are fuzzy membership functions. Furthermore, in [98] two different PSSs were presented which were designed by making use of neural fuzzy network and GA. In both cases, GAs tuned a CPSS on different operating conditions and then, the relationship between these points and the PSS parameters was learned by the adaptive network-based fuzzy inference system (ANFIS). The ANFIS selected the PSS parameters based on machine loading conditions. Also, Mahabuba and Khan investigated a design process for a robust and adaptive fuzzy neural network-based PSS (RAFNNPSS) [99]. The parameters of RAFNNPSS were tuned by an adaptive neural network. This RAFNNPSS applied an ANFIS network, which provided a natural framework of a multi-layered feed forward adaptive network using a fuzzy logic inference system. In this approach, the hybrid-learning algorithm tuned the fuzzy rules and the membership functions of the RAFNNPSS. Speed deviation of the synchronous generator and its derivative were chosen as the input signals to the RAFNNPSS.

To find the optimal parameters of member functions and desired PSS gains, the TS algorithm was used to SMIB and multi-machine power systems. The results reveal that the proposed fuzzy PSSs had robust and adaptive performances under different operating conditions including three phase faults [100]. Malik [101] proposed a comprehensive study to show the possibility of implementing an adapting controller using different approaches. An Adaptive PSS was designed based on purely analytic methods, purely AI techniques, and a combination of the analytical and AI techniques. All three approaches (i.e. purely analytical, purely AI, and integrated) were used by application to an Adaptive PSS to improve damping and stability of an electric generating unit. A design of fuzzy PSS using an adaptive evolutionary algorithm (AEA) was presented by Hwang et al. [102]. AEA included GA for a global search ability and evolution strategy (ES) for a local search in an adaptive manner when the present generation evolves into the next generation. AEA was used to optimize the membership functions and scaling factors of fuzzy PSS. The proposed method was applied to SMIB and a multi-machine power system.

In procedure plants like thermal power plants, biomedical instrumentation of the popular use of PID controllers can be noted. Proper tuning of such controllers is obviously a prime priority as any other alternative situation will require a high degree of industrial expertise. In order to get the best results of PID controllers, the optimal tuning of PID gains, Craziness based particle swarm optimization (CRPSO) and binary coded GA were the two props used in [103]. These methods were utilized to determine off line, nominal, optimal gains of the PID controller for an AVR. For on-line off-nominal system parameters, Sugeno fuzzy logic was used to get an on-line terminal voltage response. CRPSO demonstrated to be more robust than GA in performing optimal transient performance even under various nominal operating conditions.

The number of variables is based on the complexity of the power system. In a standard fuzzy system, the number of the rules and the complexity of the problem are enhanced exponentially with the number of variables involved. To introduce linear relation between the number of variables and number of rules, the hierarchical fuzzy system can be used. An ANN back-propagation algorithm was applied to select best coefficients of hierarchical fuzzy PSS by Caner et al. [104]. The ANN algorithm was employed to predict load condition of the power system. And according to the predicted load condition the ANN determined selecting optimal parameters of the hierarchical fuzzy controller to get better performance. An indirect adaptive fuzzy controller was proposed by Hussein et al. [105-106] for damping the inter-area modes of oscillation. Compared to the IEEE standard multi-band PSS, indirect adaptive fuzzy-based stabilizers are more efficient because they can cope with oscillations at different operating points. A nominal model of the power system was identified on-line using a variable structure identifier. A feedback linearization-based control law is implemented using the identified model. The gains of the controller were tuned using PSO to ensure system stability. Also, a PSO based multi-stage fuzzy controller was presented for solution of the load frequency control problem in a restructured power system that operated under deregulation based on the bilateral policy scheme [107]. In this approach the control was tuned on-line from the knowledge base and fuzzy inference, which request fewer sources and have two rule base sets. To reduce the design effort and find a better fuzzy system control, membership functions were designed by the PSO algorithm, which has a strong ability to find the most optimistic results.

3.5. Other AI Techniques

A CPSS can improve the steady-state stability margin and enhance the system positive damping, but it has some drawbacks, such as the time-consuming tuning and non-optimal damping in the entire operating process. A proportional-integral (PI) adaptive control law in simple adaptive control (SAC) can overcome these drawbacks. However, it can only be applied to the plants with almost strict positive realness, and the computation of adaptive control law is really complex. A new improved SAC (ISAC) based on a quadratic performance index was proposed [108]. A new PSS can be designed using the ISAC. Bhattacharya et al. [109] proposed a sequential tuning approach based on minimization of the integral squared error technique for tuning of the PSS parameters. The tuning sequence was decided depending on which machine most required stabilization. It was shown that the system damping improved considerably if the tuning was iterated twice. Also, in such cases the tuning sequence was no longer of much relevance and any tuning sequence yielded an equally satisfactory performance. Cai and Erlich used the SQP method for tuning of PSS [110]. The algorithm was based on the linearized power system model and parameter constrained nonlinear optimization technique. Simulation results of multi-machine power systems confirmed the efficiency of this approach. An evolutionary algorithm based approach to multi-machine PSS design was presented by Abido [111]. This approach used the Differential Evolution technique to search for optimal settings of PSS parameters. The performance of the proposed Differential Evolution based PSS under different disturbances, loading conditions, and system configurations was investigated and examined for different multi-machine power systems.

A new method for PSS design using the multi-objective optimization approach named Strength Pareto approach was presented in [112]. This provided an excellent negotiation opportunity for the system manager, manufacturer of the PSS, and customers to pick out the desired PSS from a set of optimally designed PSSs. The proposed approach was implemented and examined in the system comprising an SMIB. In [113], a novel Combinatorial Discrete and Continuous Action Reinforcement Learning Automata (CDCARLA) based approach for optimal design of multi-machine PSSs was presented. The proposed CDCARLA based design approach was a combined procedure of two optimization stages in discrete and continuous spaces for fast convergence and high optimization efficiency.

A nonlinear PSS based on synergetic control theory was introduced in [114]. Synergetic synthesis of the PSS was based fully on a simplified nonlinear model of the power system. Oscillations of small magnitude and low frequency, linked with the electromechanical models in power systems, often persist for long periods of time and in some cases present limitations on the power transfer capability. So, Rigatos and Siano proposed an RPSS as an effective way to damp-out oscillations in electric power systems [115]. The proposed PSS was designed according to Kharitonov's extremal gain margin theory. In order to analyze power system stability in an environment of WAMS, a new steady state stability model with time-varying delay was proposed for power systems [116]. The factors of exciter and power system stabilizer with delay were introduced into the analytical model. To decrease conservativeness of stability analysis, an improved Lyapunov-Krasovskii functional was constructed, and then a new delay-dependent steady state stability criterion for the power system, which overcomes the disadvantages of eigenvalue computation method, was derived.

To relieve the power system engineers from the burden of the complex and time-consuming process of PSS tuning, [117] introduced an automatic process for computerized tuning of PSSs, which was based on an iterative process that used a linear matrix inequality solver to select the PSS parameters. Simoes Costa investigated an integrated technique for PSS design appropriate to multi-machine power systems [118]. The parameters of all stabilizers were jointly determined, so that the dynamic interactions among the system machines were properly taken into account during the design procedure. By imposing output feedback and decentralization as structural constraints on the control problem, the method provided results which are in full agreement with PSS topologies usually employed in practice.

4. Conclusions

This paper presents a bibliographical survey of the work published on the application of different AI techniques applied to solve the problems of power system control. Various AI techniques that tackled the problem are overviewed and classified with their advantages and limitations critically discussed. The paper also provides a general literature survey and a list of published references on the topic aiming to offer the essential guidelines regarding this active research area. This review is undertaken to explore and report that fast and accurate acting controllers developed based on AI techniques are required to maintain system stability and damping of oscillation and provide high-quality performance. Also, various hybrid AI techniques utilized in power system stabilization have been discussed. Furthermore, the following are the significant points of conclusion. AI relies heavily on good problem description and extensive domain knowledge. The ANN and FL suffer from a lack of the formal model theory and mathematical rigors and so are vulnerable to the experts' depth of knowledge in problem definition. Fuzzy theory with its promise of realistic description of PSS problems and the ANN with its promise of adaptive training and generalization deserve scope for further study. By contrast, PSO accesses deep knowledge of system problems by well-established models. PSO is a kind of random search algorithm that simulates the natural evolutionary process by mimicking the social behavior of swarms of birds and insects (particles). Compared with other EC algorithms, like GA, HS, TS, SA, and ACO, it has some advantages, including simple implementation, small computational load, and fast convergence. Therefore, it is efficient for solving many problems for which it is difficult to find accurate mathematical models. Despite these advantages, the PSO algorithm is prone to relapse into local minima and premature convergence when solving complex optimization problems. Also, PSO has much more potential in power system stability and is the latest entry into the AI fields and is getting most of the current attention. PSO needs to be understood in relation to the computation requirements and convergence properties. The application of hybrid systems in power system stabilizer problems is a novel development, which represents a definite future trend in power systems research.

REFERENCES

[1] Segal R., Sharma A., Kothari M., A self-tuning power system stabilizer based on artificial neural network. *Int. J. Elect. Power Energy Syst.*, 26 (2004) No. 6, 423-430.

[2] Talaat H.E.A., Abdennour A., Al-Sulaiman A.A., Design and experimental investigation of a decentralized GA-optimized neuro-fuzzy power system stabilizer. *Int. J. Elect. Power Energy Syst.*, 32 (2010) No. 7, 751-759.

[3] Kundur P., Klein M., Rogers G., Zywno M., Application of power system stabilizers for enhancement of overall system stability. *IEEE Trans. Power Syst.*, 4 (2002) No. 2, 614-626.

[4] Cai L.,Erlich I., Simultaneous coordinated tuning of PSS and FACTS damping controllers in large power systems. *IEEE Trans. Power Syst.*, 20 (2005) No. 1, 294-300.

[5] Abido M., A novel approach to conventional power system stabilizer design using tabu search. *Int. J. Elect. Power Energy Syst.*, 21 (1999) No. 6, 443-454.

[6] Abido M. *Thyristor Controlled Phase Shifter Based Stabilizer Design using Simulated Annealing Algorithm*. in *International Conference on Electric Power Engineering*. 1999. Hungary

[7] Wang S., Chiou J., Liu C., Parameters tuning of power system stabilizers using improved ant direction hybrid differential evolution. *Int. J. Elect. Power Energy Syst.*, 31 (2009) No. 1, 34-42.

[8] Wu D., Huang T., Yang G., Yang Y., Guo W., Lin Z., Wen F. *Optimal parameter coordination of power system stabilizers in multi-machine power systems employing Harmony Search*. in *8th International Conference on Advances in Power System Control, Operation and Management)*. 2010.

[9] Abido M.,Abdel-Magid Y., Optimal design of power system stabilizers using evolutionary programming. *IEEE Trans. Energy Convers.*, 17 (2002) No. 4, 429-436.

[10] Mishra S., Tripathy M., Nanda J., Multi-machine power system stabilizer design by rule based bacteria foraging. *Electr. Power Syst. Res.*, 77 (2007) No. 12, 1595-1607.

[11] Abdel-Magid Y.L.,Abido M.A., Optimal multiobjective design of robust power system stabilizers using genetic algorithms. *IEEE Trans. Power Syst.*, 18 (2003) No. 3, 1125-1132.

[12]Abido M., Optimal design of power-system stabilizers using particle swarm optimization. *IEEE Trans. Energy Convers.*, 17 (2002) No. 3, 406-413.

[13] Eslami M., Shareef H., Mohamed A., Tuning of power system stabilizers using particle swarm optimization with passive congregation. *International Journal of the Physical Sciences*.,17(2010) No. 5, 2658–2663

[14] Eslami M., Shareef H., Mohamed A., Damping of Power System Oscillations Using Genetic Algorithm and Particle Swarm Optimization. *International Review of Electrical Engineering*, 6(2010) No.5, 2745-2753.

[15]McCarthy J. *Programs with common sense*. 1958: Proceedings of the Symposium of the National Physics Laboratory, Her Majesty's Stationery Office, London, UK

[16] Wasserman P.,Meyer-Arendt J., Neural computing, theory and practice. *Applied Optics*, 29 (1990) No. 2503.

[17] Pillutla S.,Keyhani A., Power system stabilization based on modular neural network architecture. *Int. J. Elect. Power Energy Syst.*, 19 (1997) No. 6, 411-418.

[18] Hosseinzadeh N.,Kalam A., A hierarchical neural network adaptive power system stabilizer. *Int. J. Elect. Power Energy Syst.,* 19 (1999) No. 1, 28-33.

[19] Shamsollahi P.,Malik O., Design of a neural adaptive power system stabilizer using dynamic back-propagation method. *Int. J. Elect. Power Energy Syst.*, 22 (2000) No. 1, 29-34.

[20]Shamsollahi P.,Malik O., An adaptive power system stabilizer using on-line trained neural networks. *IEEE Trans. Energy Convers.*, 12 (2002) No. 4, 382-387.

[21] Tsoukalas L.,Uhrig R., *Fuzzy and neural approaches in engineering*. 1996: John Wiley & Sons, Inc. NY, USA.

[22] Abido M.,Abdel-Magid Y., Adaptive tuning of power system stabilizers using radial basis function networks. *Electr. Power Syst. Res.*, 49 (1999) No. 1, 21-29.

[23] Segal R., Kothari M., Madnani S., Radial basis function (RBF) network adaptive power system stabilizer. *IEEE Trans. Power Syst.*, 15 (2002) No. 2, 722-727.

[24] Senjyu T., Morishima Y., Yamashita T., Uezato K., Fujita H., Recurrent neural network supplementary stabilization controller for automatic voltage regulator and governor. *Electr, Power Compon. Syst.*, 31 (2003) No. 7, 693-707.

[25] Chaturvedi D.,Malik O., Generalized neuron-based PSS and adaptive PSS. *Control Eng. Practice*, 13 (2005) No. 12, 1507-1514.

[26] Chaturvedi D.,Malik O., Generalized neuron-based adaptive PSS for multimachine environment. *IEEE Trans. Power Syst.*, 20 (2005) No. 1, 358-366.

[27] Chaturvedi D.,Malik O., Experimental studies of a generalized neuron based adaptive power system stabilizer. *Soft Comput.*, 11 (2007) No. 2, 149-155.

[28] Chaturvedi D., Malik O., Kalra P. *Generalised neuron-based adaptive power system stabiliser*. IEE Proceedings Generation, transmission and Distribution 2004.

[29] Chaturvedi D.,Malik O., Neurofuzzy power system stabilizer. *IEEE Trans. Energy Convers.*, 23 (2008) No. 3, 887-894.

[30] Barreiros J., Ferreira A., Tavares-da-Costa C., A neural power system stabilizer trained using local linear controllers in a gain-scheduling scheme. *Int. J. Elect. Power Energy Syst.*, 27 (2005) No. 7, 473-479.

[31] Ping H., Kewen W., Chitong T., Xiaoyan B., Studies of the improvement of probabilistic PSSs by using the single neuron model. *Int. J. Elect. Power Energy Syst.*, 29 (2007) No. 3, 217-221.

[32] Ray S.,Venayagamoorthy G., A wide area measurement based neurocontrol for generation excitation systems. *Eng. Appl. Artif. Intell.*, 22 (2009) No. 3, 473-481.
[33] Zadeh L., Fuzzy sets*. *Information and control*, 8 (1965) No. 3, 338-353.
[34] Pal S.,Mandal D., Fuzzy Logic and Approximate Reasoning: An Overview. *J. Institution of Electronics and Telecommunication Engineers*, (1991) No. 548–559.
[35] El-Hawary M., *Electric power applications of fuzzy systems*. 1998: Wiley-IEEE Press.
[36] El-Sherbiny M., Sharaf A., El-Saady G., Ibrahim E., A novel fuzzy state feedback controller for power system stabilization. *Electr. Power Syst. Res.*, 39 (1996) No. 1, 61-65.
[37] Lakshmi P.,Abdullah Khan M., Design of a robust power system stabilizer using fuzzy logic for a multi-machine power system. *Electr. Power Syst. Res.*, 47 (1998) No. 1, 39-46.
[38] Mitra P., Chowdhury S., Chowdhury S., Pal S., Lahiri R., Song Y. *Performance of A Fuzzy Power System Stabilizer With Tie Line Active Power Deviation Feedback*. in IEEE Power Systems Conference and Exposition, 2007.
[39] Dash P., Liew A., Mishra B., An adaptive PID stabilizer for power systems using fuzzy logic. *Electr. Power Syst. Res.*, 44 (1998) No. 3, 213-222.
[40] Kvasov D., Menniti D., Pinnarelli A., Sergeyev Y., Sorrentino N., Tuning fuzzy power-system stabilizers in multi-machine systems by global optimization algorithms based on efficient domain partitions. *Electr. Power Syst. Res.*, 78 (2008) No. 7, 1217-1229.
[41] Lu J., Nahrir M., Pierre D., A fuzzy logic-based adaptive power system stabilizer for multi-machine systems. *Electr. Power Syst. Res.*, 60 (2001) No. 2, 115-121.
[42] Abdelazim T.,Malik O., Power system stabilizer based on model reference adaptive fuzzy control. *Electr, Power Compon. Syst.*, 33 (2005) No. 9, 985-998.
[43] Hossein-Zadeh N.,Kalam A., An indirect adaptive fuzzy-logic power system stabiliser. *Int. J. Elect. Power Energy Syst.*, 24 (2002) No. 10, 837-842.
[44] Elshafei A., El-Metwally K., Shaltout A., A variable-structure adaptive fuzzy-logic stabilizer for single and multi-machine power systems. *Control Eng. Practice*, 13 (2005) No. 4, 413-423.
[45] Lie T.,Sharaf A., An adaptive fuzzy logic power system stabilizer. *Electr. Power Syst. Res.*, 38 (1996) No. 1, 75-81.
[46] Soliman M., Elshafei A., Bendary F., Mansour W., LMI static output-feedback design of fuzzy power system stabilizers. *Expert Syst. Appl.*, 36 (2009) No. 3, 6817-6825.
[47] Soliman M., Elshafei A., Bendary F., Mansour W., Robust decentralized PID-based power system stabilizer design using an ILMI approach. *Electr. Power Syst. Res.*, 80 (2010) No. 12, 1488-1497.
[48] Kim S., Kwon S., Moon Y., Low-order robust power system stabilizer for single-machine systems: an LMI approach. *Int. J. Elect. Power Energy Syst.*, 8 (2010) No. 3, 556-563.
[49] Dou C., Jia Q., Jin S., Bo Z., Delay-independent decentralized stabilizer design for large interconnected power systems based on WAMS. *Int. J. Elect. Power Energy Syst.*, 29 (2007) No. 10, 775-782.
[50] Dou C., Jia Q., Jin S., Bo Z., Robust controller design for large interconnected power systems with model uncertainties based on wide-area measurement. *Electr. Eng.*, 90 (2008) No. 4, 265-273.
[51] Dou C., Zhang X., Guo S., Mao C., Delay-independent excitation control for uncertain large power systems using wide-area measurement signals. *I Int. J. Elect. Power Energy Syst.*, 32 (2010) No. 3, 210-217.
[52] Ramirez-Gonzalez M.,Malik O., Self-tuned Power System Stabilizer Based on a Simple Fuzzy Logic Controller. *Electr, Power Compon. Syst.*, 38 (2010) No. 4, 407-423.
[53] Glover F.,Marti R., Tabu search. *Metaheuristic Procedures for Training Neutral Networks*, (2006) No. 53-69.
[54] Rayward V., Osman I., Reeves C., Smith G., *Modern heuristic search methods*. 1996: John Wiley & Sons, England.
[55] Abido M.,Abdel-Magid Y., Eigenvalue assignments in multimachine power systems using tabu search algorithm. *Comput. Electr. Eng.*, 28 (2002) No. 6, 527-545.
[56] Abido M.,Abdel-Magid Y., *Robust design of electrical power-based stabilizers using tabu search*. 2001, IEEE, Power Engineering Society Summer Meeting: Vancouver, BC , Canada p. 1573-1578.
[57] Abido M.,Abdel-Magid Y., *Robust design of multimachine power system stabilisers using tabu search algorithm*, in *Generation, Transmission and Distribution*. 2000, IET. p. 387-394.
[58] Abido M.,Abdel-Magid Y., A tabu search based approach to power system stability enhancement via excitation and static phase shifter control. *Electr. Power Syst. Res.*, 52 (1999) No. 2, 133-143.
[59] Ngamroo I., An optimization technique of robust load frequency stabilizer for superconducting magnetic energy storage. *Energy Conv. Manag.*, 46 (2005) No. 18-19, 3060-3090.
[60] Kirkpatrick S., Optimization by simulated annealing: Quantitative studies. *Journal of Stat. Phys.*, 34 (1984) No. 5, 975-986.
[61] Cerný V., Thermodynamical approach to the traveling salesman problem: An efficient simulation algorithm. *J. optim. theory appl.*, 45 (1985) No. 1, 41-51.
[62] Abido M., An efficient heuristic optimization technique for robust power system stabilizer design. *Electr. Power Syst. Res.*, 58 (2001) No. 2, 53-62.
[63] Abido M., Pole placement technique for PSS and TCSC-based stabilizer design using simulated annealing. *Int. J. Elect. Power Energy Syst.*, 22 (2000) No. 543–554.
[64] Abido M., Simulated annealing based approach to PSS and FACTS based stabilizer tuning. *Int. J. Elect. Power Energy Syst.*, 22 (2000) No. 4, 247-258.
[65] Abido M., Robust design of multimachine power system stabilizers using simulated annealing. *IEEE Trans. Energy Convers.*, 15 (2002) No. 3, 297-304.
[66] Colorni A., Dorigo M., Maniezzo V. *Distributed optimization by ant colonies*. 1992.
[67] Dorigo M., Optimization, learning and natural algorithms. *Unpublished doctoral dissertation, Politecnico di Milano, Dipartimento di Elettronica, Italy*, (1992).
[68] Passino K., Biomimicry of bacterial foraging for distributed optimization and control. *Control Systems Magazine, IEEE*, 22 (2002) No. 3, 52-67.
[69] Ghoshal S.P., Chatterjee A., Mukherjee V., Bio-inspired fuzzy logic based tuning of power system stabilizer. *Expert Syst. Appl.*, 36 (2009) No. 5, 9281-9292.
[70] Goldberg D., *Genetic algorithms in search, optimization, and machine learning*. 1989: Addison-wesley.
[71] Do Bomfim A., Taranto G., Falcao D., Simultaneous tuning of power system damping controllers using genetic algorithms. *IEEE Trans. Power Syst.*, 15 (2002) No. 1, 163-169.
[72] Hasanovic A.,Feliachi A. *Genetic algorithm based inter-area oscillation damping controller design using MATLAB*. in *IEEE Power Engineering Society Summer Meeting*. 2007. IL, USA
[73] Sebaa K.,Boudour M., Optimal locations and tuning of robust power system stabilizer using genetic algorithms. *Electr. Power Syst. Res.*, 79 (2009) No. 2, 406-416.
[74] Sebaa K., Gue guen H., Boudour M., Mixed integer non-linear programming via the cross-entropy approach for power system stabilisers location and tuning. *Generation, Transmission & Distribution, IET*, 4 (2010) No. 8, 928-939.
[75] Hongesombut K., Dechanupaprittha S., Mitani Y., Ngamroo I., *Robust power system stabilizer tuning based on multiobjective design using hierarchical and parallel micro genetic algorithm*. 2005: IEEE Int Conf Power Syst Technol, p. 402-407.
[76] Abdel-Magid Y.,Dawoud M., Tuning of power system stabilizers using genetic algorithms. *Electr. Power Syst. Res.*, 39 (1996) No. 2, 137-143.
[77] Abido M.,Abdel-Magid Y., A genetic-based power system stabilizer. *Electr, Power Compon. Syst.*, 26 (1998) No. 6, 559-571.
[78] Abido M.A., Parameter optimization of multimachine power system stabilizers using genetic local search. *Int. J. Elect. Power Energy Syst.*, 23 (2001) No. 8, 785-794.
[79] Abido M.A.,Abdel-Magid Y.L., Coordinated design of a PSS and an SVC-based controller to enhance power system stability. *Int. J. Elect. Power Energy Syst.*, 25 (2003) No. 9, 695-704.
[80] Abdel-Magid Y.L.,Abido M.A., Robust coordinated design of excitation and TCSC-based stabilizers using genetic algorithms. *Electr. Power Syst. Res.*, 69 (2004) No. 2-3, 129-141.

[81] Panda S.,Ardil C., Real-coded genetic algorithm for robust power system stabilizer design. *International J. Electr. Comput. Syst. Eng.*, 2 (2008) No. 1, 6-14.
[82] Panda S., Patidar N., Singh R., Simultaneous Tuning of Static Var Compensator and Power System Stabilizer Employing Real-Coded Genetic Algorithm. *International J. Electr. Power Energy Syst. Eng*, 1 (2008) No. 240-247.
[83] Kennedy J.,Eberhart R. *Particle swarm optimization*. 1995: Perth, Australia.
[84] Shi Y.,Eberhart R. *A modified particle swarm optimizer*. in IEEE World Congress on Computational Intelligence, 2002, pp. 69-73.
[85] El-Zonkoly A., Optimal tuning of power systems stabilizers and AVR gains using particle swarm optimization. *Expert Syst. Appl.*, 31 (2006) No. 3, 551-557.
[86] El-Zonkoly A., Khalil A., Ahmied N., Optimal tunning of lead-lag and fuzzy logic power system stabilizers using particle swarm optimization. *Expert Syst. Appl.*, 36 (2009) No. 2, 2097-2106.
[87] Shayeghi H., Shayanfar H., Safari A., Aghmasheh R., A robust PSSs design using PSO in a multi-machine environment. *Energy Conv. Manag.*, 51 (2010) No. 4, 696-702.
[88] Shayeghi H., Safari A., Shayanfar H., Multimachine power system stabilizers design using PSO algorithm. *Int. J. Electr. Power Energy Syst. Eng.*, 1 (2008) No. 4, 226-233.
[89] Panda S.,Padhy N., Robust power system stabilizer design using particle swarm optimization technique. *Int. J. Electr. Syst. Sci. Eng.*, 1 (2008) No. 1, 1-8.
[90] Shayeghi H., Shayanfar H., Jalilzadeh S., Safari A., Multi-machine power system stabilizers design using chaotic optimization algorithm. *Energy Conv. Manag.*, 51 (2010) No. 7, 1572-1580.
[91] Djukanovic M., DobrijevicMilan S., Djorde M., Coordinated stabilizing control for the exciter and governor loops using fuzzy set theory and neural nets. *Int. J. Elect. Power Energy Syst.s*, 19 (1997) No. 8, 489-499.
[92] Sharaf A.,Lie T., A neuro-fuzzy hybrid power system stabilizer. *Electr. Power Syst. Res.*, 30 (1994) No. 1, 17-23.
[93] Abido M.,Abdel-Magid Y., A fuzzy basis function network based power system stabilizer for generator excitation control. *Electr. Power Syst. Res.*, 49 (1999) No. 1, 11-19.
[94] Abido M.,Abdel-Magid Y., A hybrid neuro-fuzzy power system stabilizer for multimachine power systems. *IEEE Trans. Power Syst.*, 13 (2002) No. 4, 1323-1330.
[95] Ramirez-Gonzalez M.,Malik O., Power system stabilizer design using an online adaptive neurofuzzy controller with adaptive input link weights. *IEEE Trans. Energy Convers.*, 23 (2008) No. 3, 914-922.
[96] Afzalian A.,Linkens D., Training of neurofuzzy power system stabilisers using genetic algorithms. *Int. J. Elect. Power Energy Syst.*, 22 (2000) No. 2, 93-102.
[97] Awadallah M.,Soliman H., A Neuro-fuzzy Adaptive Power System Stabilizer Using Genetic Algorithms. *Electr, Power Compon. Syst.*, 37 (2009) No. 2, 158-173.
[98] Fraile-Ardanuy J.,Zufiria P., Design and comparison of adaptive power system stabilizers based on neural fuzzy networks and genetic algorithms. *Neurocomputing*, 70 (2007) No. 16-18, 2902-2912.
[99] Mahabuba A.,Khan M., Small signal stability enhancement of a multi machine power system using robust and adaptive fuzzy neural network based power system stabilizer. *Eur. Trans. Electr. Power*, 19 (2009) No. 7, 978-1001.
[100] Cheng Y.,Elangovan S., Enhanced power system stabilizer via integrated tabu-fuzzy knowledge based controller. *Int. J. Elect. Power Energy Syst.*, 25 (2003) No. 7, 543-550.
[101] Malik O., Amalgamation of adaptive control and AI techniques: applications to generator excitation control. *Annual Reviews in Control*, 28 (2004) No. 1, 97-106.
[102] Hwang G., Kim D., Lee J., An Y., Design of fuzzy power system stabilizer using adaptive evolutionary algorithm. *Eng. Appl. Artifi. Intell.*, 21 (2008) No. 1, 86-96.
[103] Mukherjee V.,Ghoshal S., Intelligent particle swarm optimized fuzzy PID controller for AVR system. *Electr. Power Syst. Res.*, 77 (2007) No. 12, 1689-1698.
[104] Caner M., Umurkan N., Tokat S., Üstün S., Determination of optimal hierarchical fuzzy controller parameters according to loading condition with ANN. *Expert Syst. Appl.*, 34 (2008) No. 4, 2650-2655.
[105] Hussein T., Saad M., Elshafei A., Bahgat A., Damping inter-area modes of oscillation using an adaptive fuzzy power system stabilizer. *Electr. Power Syst. Res.*, 80 (2010) No. 12, 1428-1436.
[106] Hussein T., Saad M., Elshafei A., Bahgat A., Robust adaptive fuzzy logic power system stabilizer. *Expert Syst. Appl.*, 36 (2009) No. 10, 12104-12112.
[107] Shayeghi H., Jalili A., Shayanfar H., Multi-stage fuzzy load frequency control using PSO. *Energy Conv. Manag.*, 49 (2008) No. 10, 2570-2580.
[108] Zhang S.,Luo F., An improved simple adaptive control applied to power system stabilizer. *IEEE Trans. Power Electr.*, 24 (2009) No. 2, 369-375.
[109]Bhattacharya K., Kothari M., Nanda J., Aldeen M., Kalam A., Tuning of power system stabilizers in multi-machine systems using ise technique. *Electr. Power Syst. Res.*, 46 (1998) No. 2, 119-131.
[110] Cai L.,Erlich I., Robust power system stabilizer design using particle swarm optimization technique. *IEEE Trans. Power Syst.*, 20 (2005) No. 1, 294 - 300
[111] Abido M., Robust Design of Power System Stabilizers for Multimachine Power Systems Using Differential Evolution. *Comput. Intell. Power Eng.*, 302 (2010) No. 1-18.
[112] Yassami H., Darabi A., Rafiei S., Power system stabilizer design using Strength Pareto multi-objective optimization approach. *Electr. Power Syst. Res.*, 80 (2010) No. 7, 838-846.
[113] Kashki M., Abdel-Magid Y., Abido M., Parameter optimization of multimachine power system conventional stabilizers using CDCARLA method. *Int. J. Elect. Power Energy Syst.*, 32 (2010) No. 5, 498-506.
[114] Jiang Z., Design of a nonlinear power system stabilizer using synergetic control theory. *Electr. Power Syst. Res.*, 79 (2009) No. 6, 855-862.
[115] Rigatos G.,Siano P., Design of robust electric power system stabilizers using Kharitonov's theorem. *Mathematics and Computers in Simulation*, Article in Press (2010) No.
[116] Li T., Wu M., He Y., Lyapunov-Krasovskii functional based power system stability analysis in environment of WAMS. *J. Cent. South Univ. Technol.*, 17 (2010) No. 4, 801-806.
[117] de Oliveira R., Ramos R., Bretas N., An algorithm for computerized automatic tuning of power system stabilizers. *Control Eng. Practice*, 18 (2010) No. 1, 45-54.
[118] Simoes Costa A., Freitas F., Pena H., Power system stabilizer design via structurally constrained optimal control. *Electr. Power Syst. Res.,* 33 (1995) No. 1, 33-40.

***Authors**: Mahdiyeh Eslami, Dr. Hussain Shareef and Prof. Azah Mohamed. Department of Electrical, Electronic and Systems Engineering, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia.*
***Corresponding author:** Mahdiyeh Eslami, E-mail: mahdiyeh_eslami@yahoo.com;*
Dr. Hussain Shareef, E-mail: hussain_ln@yahoo.com,
Prof. Azah Mohamed, E-mail: azah@eng.ukm.my,