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Robust fuzzy logic power system stabilizer based on evolution and learning

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ABSTRACT

A robust fuzzy logic power system stabilizer (FLPSS) based on evolution and learning is proposed in this paper. A hybrid algorithm that combines learning and evolution is developed whereby each one complements other's strength. Parameters of FLPSS are encoded in chromosome (individual) of genetic algorithm (GA) population. Population of FLPSS in GA learns to stabilize electromechanical oscillations in power system at an operating point, as the best fitness becomes large steady value during successive generations. Operating region of FLPSS is enlarged by learning more operating points over the operating domain. Best FLPSS drawn from last generation is saved as designed FLPSS. Effectiveness of the proposed method is validated on a single machine infinite bus (SMIB) power system. Promising optimal stabilizing performance with designed FLPSS for considered power system is obtained at wide range of operating points.

1. Introduction

Most of today's power systems are composite owing to interconnected utilities. Electromechanical oscillations of small magnitude and low frequency (0.1–3.0 Hz) often persist in the power system for a long period of time. Main cause of electromechanical oscillations is insufficient damping in the power system. Power system stabilizers (PSSs) are often incorporated in the power system to boost damping via modulation of generator excitation [1]. PSS generate a supplementary stabilizing signal that is added to excitation control loop of generating unit to produce extra damping. Conventional PSS (CPSS) is a lead-lag network [2]. The CPSS has made a great contribution in enhancing power system dynamic stability. Design of CPSS parameters is based on linearized model of power system at nominal operating point; there it can provide decent performance. However, power systems are highly non-linear with configurations and parameters changing with different operating conditions. CPSS design based on linearized model of the power system at nominal operating point does not result satisfactory and optimal performance for a practical operating environment [3–5]. Attempts have been made to design CPSS parameters to enlarge its operating region for robust performance. CPSS parameters are designed by using linearized models of power system so as to place closed loop poles in a desired sector in the left half of the s-plane using multi-objective optimization [6–9] or Lyapunov based method [10]. Other methods for design of robust PSS includes H^{∞} based method [11] and sliding mode control methods [12–15]. The H^{∞} based method require extensive computation in frequency domain and results higher order PSS. In sliding mode control, robustness is achieved at the cost of increased control activity (chattering). Moreover, output feedback techniques [16,17] are reported that enables to place closed loop poles arbitrary in the left half of s-plane. Periodic output sampling (POS) feedback [18,19] and fast output sampling (FOS) feedback techniques [20–22] are used to design PSS gains using linearized models of power system at wide range of operating points. In FOS method, output is sampled at faster rate than input is changed whereas, in POS method output is periodically sampled to construct control signal.

On the other hand, recent advances in technology have lead to intelligent and learning PSS design methods using artificial neural networks [ANNs] [23–25], fuzzy logics [26–43] and stochastic methods like GA [44,45]. These methods enable to design a PSS by including non-linearity and parameter uncertainty of power system and provide optimal stabilizing performance for wide range of operating conditions. ANN based PSS design methods uses gradient algorithm for learning its parameters either with input/output data [23] or online [24,25] at different operating points of power system. In fuzzy logic based PSS design, rules are either defined with expert knowledge about power system under consideration [26–35] or its parameters synthesized [36] or learned online [36–43] are reported. Online learning (adaptive) method uses a

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separate controller (PSS) and an identifier network, stability of closed loop system depends closely on performance of these networks. Generally adaptive PSS have poor performance during learning phase unless they are properly initialized. Continuity of objective function is prerequisite for gradient algorithm used in such entrainment. Moreover, it has possibility of solution being trapped at local optimal point; consequently global optimal solution may not be attained.

Although, online learning methods offer flexibility of PSS parameters being adapted whenever new operating condition arrives. Nonetheless, if fixed parameters PSS is designed with enlarged operating region then it may eliminate need for its online learning. Design of fixed parameters based fuzzy logic PSS (FLPSS) for enlarged operating region of power system is reported [45]. Coarse rule base is defined by partition of unity circle into six sectors in Z-plane. The parameters of FLPSS [45] are obtained using GA at nominal operating point of power system. In this paper a more robust FLPSS design for power system using a hybrid algorithm (genetic learning (GL)) that combines evolution and learning is proposed. Hybrid algorithm combining evolution and learning improved performance when used for iterated prisoner's dilemma [46] and many other machine learning tasks [47–51]. GL allows acquisition of new knowledge and its integration into existing one thus updating knowledge base of FLPSS. Afterwards FLPSS uses knowledge base efficiently in a complex real world operating environment. Novelty of proposed design method is that it partitions the input space in a flexible way and results FLPSS design with fewer fuzzy rules, contributing optimal stabilizing response at wide range of operating conditions.

Rest of this paper is organized as follows. In Section 2, proposed method is explained. Elements of FLPSS design based on evolution and learning are described in Section 3. Simulation results obtained from case study of single machine infinite power system are discussed and compared with other methods in Section 4. Conclusions and future scope are presented in Section 5.

2. Robust FLPSS design based on evolution and learning

Evolutionary algorithms (EAs), like genetic algorithms (GAs), evolutionary programming (EP), particle swarm optimization (PSO), and Ant colony optimization (ACO) are used in many optimization and machine learning tasks [44–51]. Generally EA work with population of members (individuals). Every EA encompasses mechanism of fitness assignment to each member, selection of better fit members and genotype variation to produce off-springs. Specific features of EA are inbuilt parallelism, ability to work with coding of parameters of real world optimization problem. It uses only fitness information of population members, can work with discontinuous fitness (objective) function and able to search global optimal solution in large search space. It starts with randomly initialized population of its members. Among EA, genetic algorithms (GAs) are most popular as it mimics the operations involved in natural genetics. Genetic algorithms are based on Darwin's theory of "Survival of fittest". Members of population containing better fitness to the environment have more probability of being copied to next generation. GA evolves new population members (offsprings) for next generation using its operators i.e. reproduction, crossover and mutation. GA searches the solutions for improved fitness value during successive generations [44].

Main task of learning system (agent) is to acquire the knowledge and reorganize or update the existing one to accommodate new knowledge. Though, learning causes large variance in performance among learning agents as a result of diverse learning experiences and susceptible to premature convergence. Nevertheless, evolution facilitates information exchange across learning agents allowing knowledge acquired via learning to propagate future generations. Hybrid algorithms combining learning and evolution have following advantages: (i) it stabilizes and reduces performance variance across learning agents; (ii) learning may be used to guide evolution for attaining convergence to most favorable strategy. A hybrid algorithm combining learning and evolution complements one another's strength and compensate for each other's weakness. Existing work showed that EA is extremely successful in discovering effective strategies that adapt well to specific environment only. Consequently to cover immense diverse environment learning should be performed incrementally. Hybrid algorithm utilizing synergy between learning and evolution empowers to acquire better performance.

Hybrid algorithms combining evolution and learning addressed in the literature are memetic algorithms (MAs) [46–50] and knowledge acquisition with a swarm-intelligence approach (KASIA) [51]. Two widely used forms of MA are Baldwinian [46] and Lamarckian [46,47] models. In Baldwinian model, offspring do not inherit learned abilities from parents but simply experience as added ability to learn skills (phenotype characteristics) that are acquired by their parents. In Lamarckian model of MA, desirable skills acquired by parents during their lifetime learning (genotype characteristics) are passed down to offspring inheriting skills directly. In memetic algorithms, learning cycle is placed inside to that of evolutionary cycle. The aim of memetic algorithms is to fine tune the solution obtained by evolutionary algorithm. Proposed approach is rather different from that of memetic algorithms. Learning cycle is exterior to evolutionary cycle in the proposed method. The aim is to extend the operating region of learning agent (FLPSS) for huge diverse environment. An evolutionary cycle completes when the best fitness of population reaches large steady value during successive generations, learning current operating environment. A learning cycle completes when all operating environments are incrementally learned.

Design of robust FLPSS with genetic learning (GL) is proposed in this paper. Core issue considered is adaptation of control strategy of FLPSS for diverse environment (operating conditions) to ensure robust performance. A worthy control strategy results stabilizing response for extended duration covering enlarged operating domain. A flexible structure of FLPSS to use any number of fuzzy rules is proposed. Its parameters are encoded in a chromosome to represent a complete FLPSS, like Pittsburgh approach [51]. A random population of FLPSS is initialized at start of GA. Initially it does not encompass any knowledge regarding stabilizing behavior of power system. Two inputs to FLPSS i.e. slip (per unit speed deviation) of generator and its rate signal are considered. Output of FLPSS is a voltage signal used to modulate the excitation voltage of that generator. Each FLPSS in GA population is evaluated for a trial at an operating point of power system and its fitness is calculated with defined fitness function. GA searches the solutions for improved fitness value during successive generations. GA population of FLPSS learns to stabilize generator shaft oscillations in power system at an operating point, as the best fitness becomes large steady value during successive generations. Operating region of FLPSS is extended by allowing learn incrementally at more operating points of power system. Genetic evolutions propagate knowledge learned by FLPSS regarding stabilizing behavior up to last generation. Best FLPSS in last generation is saved as designed FLPSS.

Fig. 1 shows procedure for genetic learning (GL) of FLPSS. Parameters of GA i.e. crossover probability Pc, mutation probability Pm, population size and maximum generations are initialized. A random population of FLPSS is initialized. Real number coded chromosome string is used instead of binary coding to achieve computational efficiency in the proposed method. Real values in chromosome represent specifications of membership functions in