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Enhanced leader PSO (ELPSO): A new algorithm for allocating distributed TCSC's in power systems

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ABSTRACT

Allocation of flexible AC transmission systems (FACTS) devices is a challenging power system problem. This paper proposes a new particle swarm optimisation (PSO) variant, called enhanced leader PSO (ELPSO), for solving this problem. This algorithm is capable of solving FACTS allocation problem in a way leading to lower amounts of power flow violations, voltage deviations and power losses with respect to other optimisation algorithms. Distributed thyristor controlled series compensators (D-TCSC's) are used. D-TCSC's are installed at all branches except those with regulating transformers. The reactances of D-TCSC's are found in optimisation process. ELPSO features a five-staged successive mutation strategy which mitigates premature convergence problem of conventional PSO. ELPSO and other optimisation algorithms are applied to IEEE 14 bus and 118 bus power systems for N-1 contingencies and also for simultaneous outage of four branches. The results show that it leads to lower amounts of power flow violations, voltage deviations and power losses with respect to conventional PSO (CPSO) and eight other optimisation algorithms including genetic algorithm (GA), gravitational search algorithm (GSA), galaxy based search algorithm (GBSA), invasive weed optimisation (IWO), asexual reproduction optimisation (ARO), threshold acceptance (TA), pattern search and nonlinear programming (NLP).

Introduction

Line outage contingencies in power systems are likely to result in overloads in branches, voltage deviations in buses and excessive power losses [1–5]. Using FACTS devices is the most common approach for alleviating such consequences [6]. Since overloads are the main concern in line outage contingencies and thyristor-controlled series compensators (TCSC's) are effective in power flow control, they are used for mitigating consequences of line outage contingencies [6]. When FACTS devices are intended to be utilised in a power system, they should be allocated optimally. From optimisation perspective, optimal allocation of FACTS devices is a very complex optimisation problem, because it is highly multi-modal, multi-objective and constrained [7,8]. Heuristic approaches are the most common and efficient approaches for solving FACTS allocation problems [7,9–11]. Among heuristics, particle swarm optimisation (PSO) has some advantages which make it popular in solving FACTS allocation problems [12–15]. The advantages of PSO are as follows.

- It does not require preconditions such as continuity or differentiability of objective functions [7].
- In comparison with most other heuristic optimisation algorithms, it has less control parameters to be tuned by user.
- It provides fast convergence [16].
- Its computational burden is relatively low [17].

Despite all PSO advantages, it suffers from a crucial drawback called premature convergence [18–26], that is, particles tend to converge into local optima instead of the global one. The reasons of premature convergence in PSO are twofold:

- Since all particles of swarm are highly attracted toward the swarm leader, they converge quickly without enough exploration of different regions of search space. Therefore, PSO possesses weak exploration capability that leads to premature convergence [27].
- When the particles converge into a region in search space including a local optimum, they will stagnate and there is no mechanism for jumping out particles from that region [28].

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Due to PSO's premature convergence, in TCSC allocation problem during contingencies, it is not able to find a near-global solution. Therefore, considerable amounts of overloads, voltage deviations and power losses are obtained.

There exist different approaches for mitigating premature convergence in PSO [29–31]. Although these approaches lead to mitigation in premature convergence to some extent, they have some shortcomings that should be addressed.

- The explorative capability is not decreased during the run [32,33].
- In most cases, the mutated object is transferred to the new position whether it leads to a lower objective value or not [34–36].
- In most cases [32,37–41,34–36,42–45], the mutations are applied to positions or velocities of particles, while applying mutation to the leader may enhance the leader and attract all the particles toward better regions of search space (regions with lower objective values).
- They do not provide any mechanism for jumping out particles after stagnation [46–48].

Removing the shortcomings of existing premature convergence mitigation strategies can lead to a more efficient approach for mitigating premature convergence. Therefore, in this research, it is intended to develop a PSO variant addressing the mentioned shortcomings of existing premature convergence strategies. In this research, distributed TCSC's (D-TCSC's) are used. The new proposed PSO variant is expected to outperform existing optimisation algorithms in solving D-TCSC allocation problem during line outage contingencies.

Different optimisation algorithms have been applied to solve FACTS allocation problem in power systems. In [49], real coded genetic algorithm is applied to maximise available transfer capability (ATC) of power systems with static var compensator (SVC) and TCSC. In [50], bacterial foraging optimisation algorithm (BFOA) is applied to maximise power system damping with TCSC. The results show that BFOA outperforms GA.

In [51], artificial bee colony (ABC) as a heuristic algorithm with strong exploration capability is hybridised with sequential quadratic programming (SQP) as an algorithm with strong exploitation capability. This is to benefit from the advantages of both algorithms. The hybrid ABC–SQP is applied to maximise damping of power system with SVC devices. The results showed the superiority of the hybrid ABC–SQP over ABC and GA. In [52], a harmony search algorithm is applied to find optimal location and setting of SVC's and static synchronous compensator (STATCOM) units. The objective is to maximise voltage stability and minimise power losses. In [53], differential evolution (DE) is used to find optimal location and setting of unified power flow controller (UPFC) devices in order to maximise power system security during single contingencies. In [54], gravitational search algorithm (GSA) is used to find optimal setting of UPFC devices in order to minimise fuel cost of generating units. In [55], evolution strategy (ES) is applied to find optimal setting of SVC, STATCOM, UPFC and static synchronous series compensator (SSSC) in order to minimise power losses. In [56], simulated annealing and Tabu Search are applied to find optimal setting of SVC in order to maximise power transfer capability in power system. In [57], optimal location and setting of SVC and TCSC devices are determined via PSO. The objective is to maximise small signal stability. In [58], PSO is utilised to find optimal location and setting of SVC, TCSC and UPFC devices. The objective is to maximise power system loadability and minimise installation cost of FACTS devices.

This paper is organised as follows; in Section 'Enhanced leader PSO (ELPSO)', the proposed PSO variant (Enhanced leader PSO) will be introduced in details. The D-TCSC allocation problem is formulated in Section 'D-TCSC description and problem formulation'. The procedure for applying ELPSO to D-TCSC allocation problem is elaborated in Section 'Procedure of ELPSO application'. The results and analysis of results will be presented in Section 'Results and analysis'. Finally, the conclusions are presented in Section 'Conclusions'.

Enhanced leader PSO (ELPSO)

PSO starts with random initialisation of a swarm of particles in the n-dimensional search space (n is the dimension of problem in hand) [59]. Each particle keeps two values in its memory; its own best experience whose position and objective value are called P_i and P_{best} respectively and the best experience of the whole swarm, named swarm leader, whose position and objective value are called P_g and g_{best} respectively. The position and velocity of particle i is denoted with the following vectors:

$$X_i = (X_{i1}, X_{i2}, \dots X_{id}, \dots, X_{in})$$

$$V_i = (V_{i1}, V_{i2}, \dots V_{id}, \dots, V_{in})$$

At each iteration t, the velocities and positions of particles are updated according to the following equations [60]:

$$V_{id}(t+1) = \omega V_{id}(t) + C_1 r_{1d}(P_{id} - X_{id}) + C_2 r_{2d}(P_{gd} - X_{id}) \tag{1}$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \tag{2}$$

where ω represents inertia weight, C_1 and C_2 are cognitive and social acceleration coefficients respectively. Symbols r_{1d} and r_{2d} represent two random numbers in $[0, 1]$.

In this research, a novel PSO variant called enhanced leader PSO (ELPSO) is developed by addressing the mentioned shortcomings of existing premature convergence mitigation strategies. In ELPSO, at each iteration a five-staged successive mutation strategy is applied to swarm leader. After applying each mutation, if the mutated P_g has better objective value than the current P_g, it takes the position of current P_g. By applying this successive mutation strategy to swarm leader, swarm leader is enhanced, so a more efficient search is done.

At the first stage of the successive mutation strategy, Gaussian mutation is applied to swarm leader as below.

$$P_{g1}(d) = P_g(d) + (X_{max}(d) - X_{min}(d)).\ \text{Gaussian}\ (\text{o},\ \text{h})\ \text{for}\ d = 1, 2, \dots, n \tag{3}$$

where $X_{max}\ (d)$ and $X_{min}\ (d)$ represent upper and lower bounds of decision vectors in dth dimension respectively and h is standard deviation of Gaussian distribution. If the fitness of P_{g1} is better than the fitness of P_g, then P_{g1} takes the position of P_g (better fitness is equal to lower objective).

The standard deviation of the Gaussian distribution is decreased linearly during the run as Eq. (4). This is to ensure that the exploration capability is stronger at initial iterations and it fades out during the run to result in more exploitative capability.

$$h(t+1) = h(t) - (1/t_{max}) \tag{4}$$

where t and t_{max} represent current iteration number and maximum number of iterations respectively.

At the second stage of the successive mutation strategy, Cauchy mutation is applied to swarm leader as below.

$$P_{g2}(d) = P_g(d) + (X_{max}(d) - X_{min}(d)).\ \text{Cauchy}\ (\text{o},\ \text{s})\ \text{for}\ d = 1, 2, \dots, n \tag{5}$$

where s is scale parameter of Cauchy distribution which is decreased linearly during the run as Eq. (6). This is also to ensure that the exploration capability decreases during the run.