

OPTIMAL DESIGN OF SVC-PI CONTROLLER FOR DAMPING IMPROVEMENT USING NEW COMPUTATIONAL INTELLIGENCE APPROACH

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ABSTRACT

This paper presents an optimal design of a Static Var Compensator (SVC) for damping improvement of a Single Machine Infinite Bus (SMIB) system. In this study, SVC is installed to improve the angle stability of a synchronous generator. A new computational intelligence approach using Mutated Particle Swarm Optimization (MPSO) technique is implemented. The study involves the optimization of the proportional gain, K_P and interval gain, K_I parameters of PI controller. Results are based on damping ratio as an objective function. Results based on MPSO technique are compared with other widely used optimization techniques. From the results, it is found that the proposed technique is very effective to reduce the damping problem which indicates that stability has been achieved.

Keywords: *Small Signal Stability, Damping Ratio, Particle Swarm Optimization, Evolutionary Programming, Artificial Immune System*

1. INTRODUCTION

Small signal stability analysis is a study of the dynamic stability limits of synchronous machines resulted from poorly damped rotor oscillations under small perturbations [1-2]. Such disturbances that occur on the system become a very important topic and were thoroughly discussed in [3-10]. The dynamic performance of the machine can be improved by suitable control methods.

Flexible Alternating Current Transmission Systems (FACTS) technologies have been used widely for power systems applications. Static Var Compensator (SVC) is one of FACTS devices that is connected in shunt with the system. Although it is designed to support bus voltage by controlling reactive power, SVC is also capable of improving the angle stability of the system. Many techniques have been proposed for the damping controllers for SVC to improve the angle stability of the synchronous machines oscillations mode. Some techniques have been explored by means of the lead lag controllers [7], proportional-integral (PI) controllers [8] and proportional-integral-derivative (PID) controllers [9].

Computational intelligence techniques have been widely used in solving power system stability problems. Amongst the popular techniques are

Evolutionary Programming (EP), Particle Swarm Optimization (PSO), and Artificial Immune System (AIS). These algorithms are heuristic population-based search methods that used both random variation and selection. In this paper, new technique which combined PSO and EP technique called as Mutated PSO (MPSO) is proposed. It brought about the performance of PSO in searching the optimal solution with faster computation time.

This paper presents an efficient technique to determine the optimal parameters of SVC-PI damping controller in solving angle stability problems. The fixed-gains of PI controller are determined using MPSO technique and it was compared with EP, PSO and AIS optimization techniques.

2. TRAINING OF ANN PARAMETERS

In this paper, a single machine to infinite bus (SMIB) system model, as shown in Fig. 1 is considered.

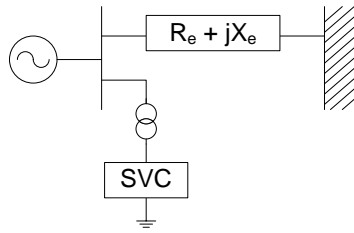


Fig. 1. SMIB system model with static var compensator (SVC)

The SVC is placed in the middle of the transmission line which is generally considered to be the ideal site. The equations which represent the SMIB system without SVC is given by:

$$\frac{\Delta\omega}{\Delta t} = \frac{\Delta T_m - K_1\Delta\delta - K_d\Delta\omega - K_2\Delta E_q}{2H} \quad (1)$$

$$\frac{\Delta\delta}{\Delta t} = \omega_0\Delta\omega \quad (2)$$

$$\frac{\Delta E_q}{\Delta t} = -\frac{K_3K_4\Delta\delta + \Delta E_q - K_3\Delta v_f}{T_3} \quad (3)$$

$$\frac{\Delta v_f}{\Delta t} = -\frac{K_AK_5\Delta\delta + K_AK_6\Delta E_q + \Delta v_f}{T_A} \quad (4)$$

where T_m is the mechanical torque, K_D is the damping torque coefficient, H is the inertia constant, K_A and T_A are the circuit constant and time constant of the exciter oscillation system respectively. ω_0 is equal to $2\pi f_0$. In equation (1)-(4), the dynamic characteristics of the system are expressed in terms of $K_1 \sim K_6$ and T_3 which are related with some variables such as electrical torque, rotor speed, rotor angle and exciter output voltage.

Fig. 2 presents a simplified Phillips-Heffron block diagram model of the SMIB system with SVC-PI controller. This model is used to emulate the eigen values calculation which indicate the angle stability condition. The structure of SVC-PI controller, which is designed to improve the damping torque of the SMIB system, consists of SVC and PI controller parameters, expressed in terms of K_V , T_V , K_P and K_I . K_V and T_V are the circuit constant and time constant of the SVC system, respectively. K_P and K_I are the proportional gain and interval gain of the PI controller, respectively. Both values of K_P and K_I parameters should be kept within the specified limits.

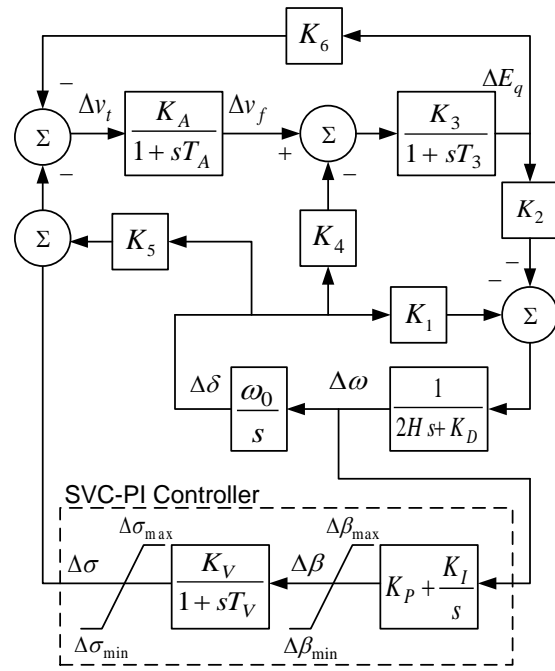


Fig.2. Phillips-Heffron block diagram model of the SMIB system with SVC-PI controller

In this study, the PI controller parameters are searched for the optimal computation value by the proposed MPSO algorithm. From the Phillips-Heffron block diagram model of Fig. 2, the following mathematical relationship is developed:

$$\dot{X} = A \cdot X + B \cdot U \quad (5)$$

where

$$A = \begin{bmatrix} -\frac{K_D}{2H} & -\frac{K_1}{2H} & -\frac{K_2}{2H} & 0 & 0 & 0 \\ \omega_0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -\frac{K_3K_4}{T_3} & -\frac{1}{T_3} & \frac{K_3}{T_3} & 0 & 0 \\ 0 & -\frac{K_AK_5}{T_R} & -\frac{K_AK_6}{T_R} & -\frac{1}{T_R} & -\frac{1}{T_R} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{T_V} & \frac{K_V}{T_V} \\ K_7 & -\frac{K_PK_1}{2H} & -\frac{K_PK_2}{2H} & 0 & 0 & 0 \end{bmatrix} \quad (6)$$

$$X = [\Delta\omega_r \quad \Delta\delta \quad \Delta\psi_{fd} \quad \Delta E_{fd} \quad \Delta\sigma \quad \Delta\beta]^T \quad (7)$$

$$B = \left[\frac{1}{2H} \quad 0 \quad 0 \quad 0 \quad 0 \quad \frac{K_P}{2H} \right]^T \quad (8)$$

$$U = [\Delta T_m] \quad (9)$$

X and U are the state vector and input signal vectors respectively. A and B are matrices of real constants. Matrix A is expressed in constants form $K_1 \sim K_6$ and T_3 . These constants except K_3 , are function of the operating load and the excitation levels in the generator [8]. Detail calculation of constants $K_1 \sim K_6$ and T_3 can be found in [3].

The generator, transmission line, exciter and SVC parameters of the SMIB system are as follows:

Generator parameters:

$$H = 2.0, T_{d0}' = 8.0, X_d = 1.81, X_q = 1.76, X_d' = 0.30, R_a = 0.003, K_{sd} = K_{sq} = 0.8491, E_t = 1.0 \angle -36^\circ.$$

Transmission line parameters:

$$R_e = 0.0, X_e = 0.65, X_L = 0.16.$$

Exciter and SVC system parameters:

$$K_A = 100, T_A = 0.05, K_V = 10, T_V = 0.05.$$

where T_{d0}' is the open circuit field time constant, X_d and X_q are the d -axis and q -axis reactance of the generator, respectively. R_a and X_d' are the armature resistance and transient reactance of the generator, respectively. K_A and T_A are the circuit constant and time constant of the exciter, respectively. R_e and X_e are the resistance and reactance of the transmission line respectively. X_L is the load reactance, K_{sd} and K_{sq} are the d -axis and q -axis of synchronizing torque coefficients respectively and E_t is the terminal voltage.

3. COMPUTATIONAL INTELLIGENCE TECHNIQUES

Computational intelligence technique is proposed in this study due to its capability in achieving optimal solution with comparable computation time. In this paper, four techniques: Evolutionary Programming (EP), Particle Swarm Optimization (PSO), Artificial Immune System (AIS) and new Mutated PSO (MPSO) are discussed.

3.1 EVOLUTIONARY PROGRAMMING (EP)

The Evolutionary Programming (EP) uses the models of biological evolutionary process to obtain the solution for complex engineering problems. Based on the natural process of biological evolution, the search for an optimal solution using EP is accomplished in a parallel method in the parameter search space. In the EP algorithm, the population has n candidate solutions with each candidate solution is an m -dimensional vector, where m is the number of optimized parameters. The EP algorithm can be described as [11]:

a) Step 1 (Initialization): Generation counter i is set to 0. Generate n random solutions ($x_k, k=1, \dots, n$). The k^{th} trial solution x_k can be written as $x_k = [p_1, \dots, p_m]$, where the l^{th} optimized parameter p_l is generated by random value in the range of $[p_l^{\min}, p_l^{\max}]$ with uniform probability. Each individual is evaluated using the fitness J . In this initial population, minimum value of fitness, J_{\min} will be searched, the target is to find the best solution, x_{best} with the fitness, J_{best} .

b) Step 2 (Mutation): Each parent x_k produces one offspring x_{k+n} . Each optimized parameter p_l is perturbed by Gaussian random variable $N(0, \sigma_l^2)$. The standard deviation σ_l specifies the range of the optimized parameter perturbation in the offspring. σ_l can be written as follows:

$$\sigma_l = \beta \times \frac{J(x_k)}{J_{\max}} \times (p_l^{\max} - p_l^{\min}) \quad (10)$$

where β is a search factor, and $J(x_k)$ is the fitness equation of the trial solution x_k . The value of optimized parameter will be set at certain limit if any value violates its specified range. The offspring x_{k+n} can be described as:

$$x_{k+n} = x_k + [N(0, \sigma_1^2), \dots, N(0, \sigma_m^2)] \quad (11)$$

where $k=1, \dots, n$

c) Step 3 (Statistics): The minimum fitness J_{\min} , the maximum fitness J_{\max} and the average fitness J_{ave} of all individuals are calculated.

d) Step 4 (Update the best solution): If J_{\min} is bigger than J_{best} , go to Step 5, or else, update the best solution, x_{best} . Set J_{\min} as J_{best} , and go to Step 5.

e) Step 5 (Combination): All members in the population x_k are combined with all members from the offspring x_{k+n} to become $2n$ candidates. Matrix size would be $[2n \times k]$ from its original size $[n \times k]$, where k is the number of control variables. These individuals are then ranked in descending order, based on their fitness as their weight.

f) Step 6 (Selection): The first n individuals with higher weights are selected as candidates for the next generation.

g) Step 7 (Stopping criteria): The search process will be terminated if one of the followings is satisfied:

- It reaches the maximum number of generations.
- The value of $(J_{max} - J_{min})$ is very close to 0.

If the process is not terminated, the iteration process will start again from Step 2. The flow chart of EP is shown in Fig. 3.

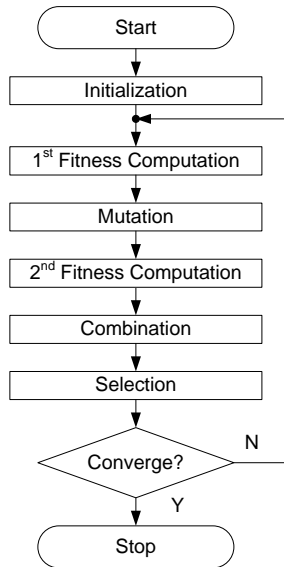


Fig. 3. Flow chart of EP

3.2 PARTICLE SWARM OPTIMIZATION (PSO)

Particle Swarm Optimization (PSO) was introduced by Dr. Russ Eberhart and Dr. James Kennedy in 1995[13],[14]. Similar to EP, PSO is an evolutionary based optimization technique, which imitates the behavior of birds flocking and fish schooling. The technique is initialized with a population of random particles where each particle is a candidate solution. The particles fly through the problem space by following the current optimum particles. Then, it searches for optimal solution by updating positions of each particle. In this paper, the PSO algorithm works as follows:

- a) Step 1 (Initialization): The velocity v_i and position x_i of N particles ($i=1, \dots, N$) are randomly created to form initial population. Similar to EP, each particle is evaluated using the fitness J . In this initialization process, J_i is set as personal best fitness $J_{i,p}$ for i^{th} particle. The maximum fitness of all particles, J_{max} is set as the global best fitness J_g . The position x_i for $J_{i,p}$, J_{max} and J_g is set as the personal best

position p_i , position with maximum fitness p_m and global best position g , respectively.

- b) Step 2 (Update the velocity and positions): At j^{th} iteration, the velocity and position of i^{th} particle is updated according to the following equations:

$$v_i(j) = \omega v_i(j-1) + c_1 r \{p_i(j-1) - x_i(j-1)\} + c_2 r \{g(j-1) - x_i(j-1)\} \quad (12)$$

$$x_i(j) = v_i(j) + x_i(j-1) \quad (13)$$

where, ω is the inertia weight, c_1 and c_2 are the acceleration coefficients, and r is the random function in the range $[0,1]$.

- c) Step 3 (Calculate fitness): The new J , J_{max} and the minimum fitness of all particles J_{min} are calculated.
- d) Step 4 (Update the best positions): p_i and g are updated when the following conditions are met:
- If $J_i > J_{i,p}$, set J_i as $J_{i,p}$, and set x_i as p_i . Else, the value of $J_{i,p}$ and p_i are maintain.
 - If $J_{max} > J_g$, set J_{max} as J_g , and set p_m as g . Else, the value of J_g and g are maintained.
- e) Step 5 (Stopping criteria): The search process will be terminated if one of the followings is satisfied:
- It reaches the maximum number of generations.
 - The value of $(J_{max} - J_{min})$ is very close to 0.

If the process is not terminated, the iteration process will repeat again from Step 2. The flow chart of PSO is shown in Fig. 4.

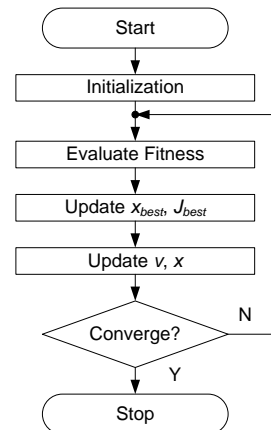


Fig. 4. Flow chart of PSO

3.3 ARTIFICIAL IMMUNE SYSTEM (AIS)

Artificial Immune System (AIS) and EP share many common aspects as optimization techniques. EP based on the natural evolution model, while AIS tries to benefit from the characteristics of a human immune system. Basic algorithm for AIS-based optimization works as follows [3], [15]:

- a) Step 1 (Initialization): During initialization, n random solutions ($x_k, k=1, \dots, n$) are generated which represent the control parameters and determine the fitness, J .
- b) Step 2 (Cloning): Population of variable x will be cloned by 10. As a result, the number of cloned population becomes $10n$. Each individual of cloned population is evaluated using the J . Minimum value of fitness, J_{min} will be searched; the target is to find the best solution x_{best} with best fitness J_{best} .
- c) Step 3 (Mutation): Each individual clone is mutated. The mutation equation can be described as equation (10) and (11).
- d) Step 4 (Ranking process): The population of mutated clones in Step 3 is ranked based on fitness. The first n individuals with higher weights are selected along with their fitness as parents of the next generation. The generation counter will be set to $i=i+1$ and algorithm will start again from Step 2.

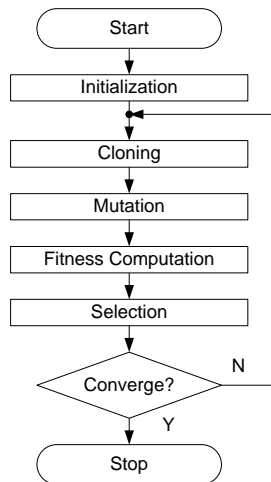


Fig. 5. Flow chart of AIS

- e) Step 5 (Stopping criteria): The search process will be terminated if one of the followings is satisfied:

- It reaches the maximum number of generations.
- The value of $(J_{max} - J_{min})$ is very close to 0.

If the process is not terminated, the iteration process will repeat again from Step 2. The flow chart of AIS is shown in Fig. 5.

3.4 MUTATED PARTICLE SWARM OPTIMIZATION (MPSO)

Mutated Particle Swarm Optimization (MPSO) is a combination of EP and PSO techniques. MPSO improves the computation time without decreasing the search for optimal solution performance. MPSO works as follows:

- a) Step 1 (Initialization): Initial population of N particles is generated randomly for v_i and x_i , and each particle is evaluated using J .
- b) Step 2 (Velocity and positions update): At j^{th} iteration, the velocity and position of i^{th} particle is updated according to the equation (12) and (13).
- c) Step 3 (Calculate fitness): The new J, J_{max} and J_{min} are calculated.
- d) Step 4 (Best and global positions update): p_i and g are updated when the following conditions are met:
 - If $J_i > J_{i,p}$, set J_i as $J_{i,p}$, and set x_i as p_i . Else, the value of $J_{i,p}$ and p_i are maintained.
 - If $J_{max} > J_g$, set J_{max} as J_g , and set p_m as g . Else, the value of J_g and g are maintained.
- e) Step 5 (EP process): If the number of iteration, j is reached, the number of iteration for EP process j_{EP} proceed to step 6. If not, go to Step 9.
- f) Step 6 (Mutation): Each position x_i produces one offspring $x_{new,i}$ perturbed by a Gaussian random variable $N(0, \sigma_i^2)$. σ_i is given by equation (10). The offspring x_{k+n} can be described as equation (11). The new fitness $J_{new,i}$ for every new offspring is then calculated. Velocity of new offspring is equal to the old one.
- g) Step 7 (Combination): All x_i are combined with all $x_{new,i}$ to become $2n$ candidates. These individuals are then ranked based on J as their weight.
- h) Step 8 (Selection): The first n individuals with higher weights are selected along with their

velocity, positions and fitness. J_{min} and J_{max} of the first n individuals are calculated. The counter will be set to $j_{EP}=j_{EP}+5$.

- i) Step 9 (Stopping criteria): The search process will be terminated if one of the followings is satisfied:
- It reaches the maximum number of generations.
 - The value of $(J_{max} - J_{min})$ is very close to 0.

If the process is not terminated, the iteration process will repeat again from Step 2. The flow chart of MPSO is shown in Fig. 6.

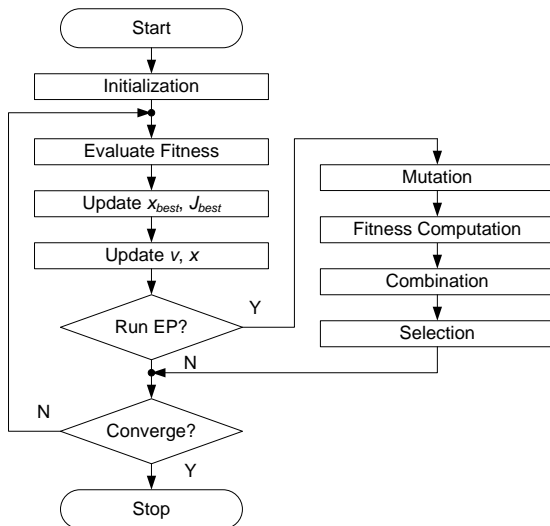


Fig. 6. Flow chart of MPSO.

3.5 PARAMETER SELECTION

All the four optimization techniques have several parameters to be considered. In this study, the value of searching factor β in equation (6) is set to 0.01. This value is considered in EP, AIS and MPSO optimization techniques. For the value of inertia weight ω in equation (8) used in PSO and MPSO, this linearly decreasing parameter is set to the following equation:

$$w = w_{ini} - \frac{w_{ini} - w_{fin}}{iter_{max}} * iter \quad (14)$$

where $iter_{max}$ is the maximum iteration number, $iter$ is the current iteration number, w_{ini} and w_{fin} are the initial and final weight, respectively. In this study, the value of w_{ini} and w_{fin} are set to 0.9 and 0.4[13]. For the acceleration coefficients c_1 and c_2 in the equation (8), this value is set to 1.

All the four techniques also influenced by the number of populations or particles used in the optimization process. The algorithm will stuck at local minimum due to too small number of populations, while too large number of populations will result to slow convergence. For this study, the number of populations or particles is set to 20 as suggested by Shivakumar *et al.* [14].

3.6 OBJECTIVE FUNCTION

The implementation of SVC controller in the SMIB system will accelerate the oscillations damping and minimize the power angle deviation after a disturbance. In order to compute the optimal value of PI controller parameters of SVC, an objective function based on damping ratio effectiveness has been formulated as in equation (15)[14].

$$J = \min(\xi_i) = \min\left(-\frac{\sigma_i}{\sqrt{\sigma_i^2 + \omega_i^2}}\right), \xi_i \in \xi_{em} \quad (15)$$

where, σ_i and ω_i are the real and imaginary part of the i^{th} eigenvalue at the loading condition, respectively. ξ_{em} is a set of damping ratio of electromechanical modes of oscillation. Therefore, the design problem can be formulated as:

$$\text{Maximize } (J) \quad (16)$$

Subject to

$$K_P^{max} \leq K_P \leq K_P^{min}$$

$$K_I^{max} \leq K_I \leq K_I^{min}$$

With the proposed approach, optimum proportional K_P and integral gain K_I settings of the PI controller were searched using MPSO, PSO, EP and AIS for different operating cases simultaneously.

4. RESULTS AND DISCUSSION

In this paper, simulation studies of an SMIB power system with SVC are carried out to tune the value of proportional gain, K_P and integral gain, K_I of PI controller. In this simulation, value of K_P and K_I are optimized until maximum value of fitness J is achieved with selected value of K_P and K_I . From this, two optimized parameters, two system responses, speed deviation, $\Delta\omega(t)$ and angle deviation, $\Delta\delta(t)$ are produced. Cases have been investigated based on the variation of P and Q values of the load buses.

4.1 CASE A

In this case, the performance of SVC with conventional based PI controller (C) is compared to SVC with EP based PI controller (EP), SVC with AIS based PI controller (AIS), SVC with traditional PSO based PI controller (PSO) and SVC with MPSO based PI controller (MPSO). Three different loading conditions are simulated:

- i. Case A1 (P = 0.4 p.u., Q = 0.3 p.u.)
- ii. Case A2 (P = 0.4 p.u., Q = -0.4 p.u.)
- iii. Case A3 (P = 1.0 p.u., Q = 0.75 p.u.).

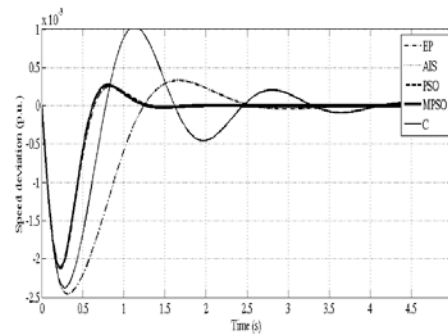
Table 1. Comparison of the Conventional, EP, AIS, PSO and MPSO SVC-PI for Case A.

Cases	Tech.	K_p	K_I	J	Time
A1	EP	1.681	13.507	0.535	3.52s
	AIS	1.686	13.515	0.534	2.84s
	PSO	0.868	10.536	0.601	6.05s
	MPSO	0.822	10.351	0.606	2.93s
	C	1.678	11.178	0.249	-
A2	EP	0.988	3.662	0.484	4.57s
	AIS	0.990	3.677	0.484	2.39s
	PSO	0.704	2.081	0.511	3.32s
	MPSO	0.699	2.062	0.511	2.86s
	C	0.379	0.669	0.176	-
A3	EP	0.663	8.282	0.688	3.42s
	AIS	0.667	8.291	0.688	3.92s
	PSO	0.543	8.008	0.768	3.15s
	MPSO	0.567	8.084	0.752	2.47s
	C	0.207	5.744	0.188	-

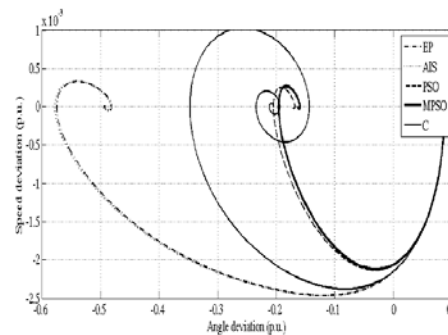
The results for fitness profiles and computation time using C, EP, AIS, PSO and MPSO for Case A are tabulated in Table I. Four computational intelligence based techniques have shown high value of optimized fitness, J results. All values are larger than 0.5 compared to the conventional based technique which gives value of J smaller than 0.3. This indicates that all computational intelligence techniques managed to produce high fitness values which implied that angle stability has been improved. From the overall results, PSO and MPSO dominated the highest value of J . PSO and MPSO techniques give 0.6013 and 0.6057 for Case A1, 0.5111 and 0.5109 (Case A2), and 0.7679 and 0.7519 (Case A3), respectively. It can be concluded that both PSO and MPSO optimized almost the same value of J . On the other hand, the simulation computation time for EP, AIS and PSO based techniques show inconstant results.

Most of the time taken for the results to compile for these three techniques is larger than 3 seconds; with the highest time taken is PSO for Case 1A of 6.05 seconds. Only MPSO technique manages to obtain the computation time less than 3 seconds for all the 3 cases. This implies that MPSO performed faster than other techniques.

The responses of speed deviation and phase plan are shown in Fig. 6~Fig.8. From the responses, it shows that EP and AIS based techniques have similar results. The speed deviation and phase plan for both techniques are very close. The same results are also obtained for PSO and MPSO based techniques in Case A1 and Case A2. Responses for both techniques are counterfeit. From the responses of all cases, PSO and MPSO techniques improve the damping capability of SVC by tuned the PI controller so that the speed deviation becomes stable within shorter time compared to EP, AIS and the conventional one. From the phase plane responses, PSO and MPSO give shorter and smaller curves compared to other three results. This indicates that angle stability improvement has been achieved.

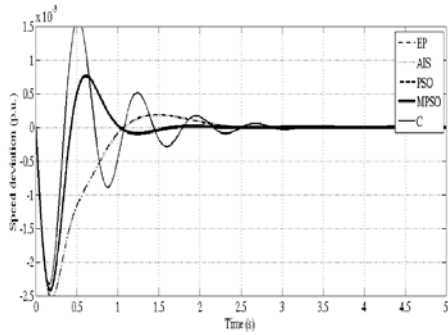


(a) Speed deviation

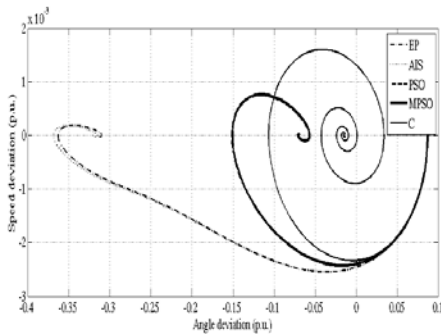


(b) Phase plan

Fig. 6. Response for Case A1.

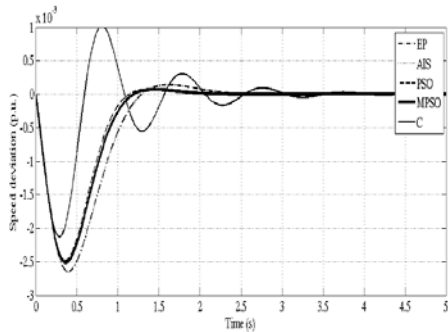


(a) Speed deviation

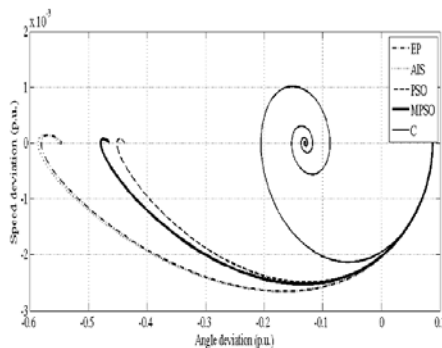


(b) Phase plan

Fig. 7. Response for Case A2.



(a) Speed deviation



(b) Phase plan

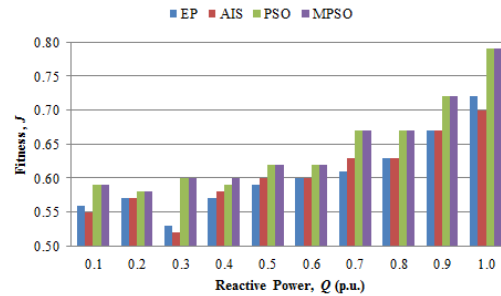
Fig. 8. Response for Case A3.

4.2 CASE B

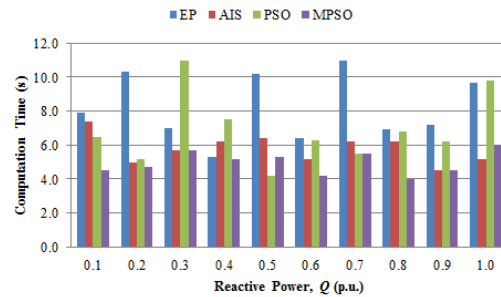
In Case B, comparison of EP, AIS, PSO, MPSO and conventional based PI controller for SVC system are conducted in the large range of loading conditions. The following two different loading conditions are simulated:

- i. Case B1 ($P = 0.4$ p.u., $Q = 0.1$ p.u.~1.0 p.u.)
- ii. Case B2 ($P = 0.1$ p.u.~1.0 p.u., $Q = 0.75$ p.u.).

The results for fitness profiles and computation time using C, EP, AIS, PSO and MPSO for Case B1 are shown in Fig. 9. Fig 9 (a) shows the graph of fitness vs. reactive power. As reactive power increased from 0.1 p.u. to 1.0 p.u., optimal fitness profile J for all four techniques are increasing, which indicate the improvement of angle stability. In all conditions, PSO and MPSO exhibited the best optimized J as compared to EP and AIS.



(a) Fitness vs. Reactive Power

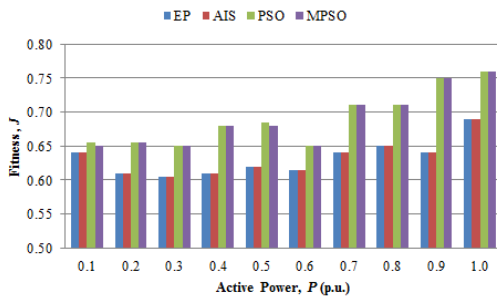


(b) Computation Time vs. Reactive Power

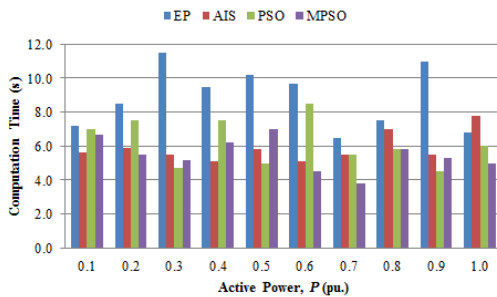
Fig. 9. Fitness profiles and computation time for Case B1.

The graph of computation time vs. reactive power for Case B1 is shown in Fig. 9 (b). Computation time is measured in second. Out of the four techniques, MPSO exhibits the shortest time

range, i.e. between 4 to 6 seconds. From the result, AIS has the time range between 4 to 8 seconds, EP gives 5 to 11 seconds and PSO gives 4 to 12 seconds. The longest computation time is obtained using PSO technique at $Q = 0.3$ p.u. condition, with the value of 11.53 seconds. On the other hand, the shortest computation time is conducted using MPSO at $Q = 0.8$ p.u., with the value of 3.92 seconds. As compared to the other three techniques, the proposed MPSO technique gives the best fitness within minimal computation time.



(a) Fitness vs. Reactive Power



(b) Computation Time vs. Reactive Power

Fig. 10. Fitness profiles and computation time for Case B2.

The results for C, EP, AIS, PSO and MPSO for Case B2 are shown in Fig. 10. Similar to Case B1, PSO and MPSO share almost the same value of J which is higher compared to EP and AIS for all conditions. For computation time, MPSO has the range between 4 to 7 seconds. AIS gives 5 to 8 seconds, EP gives 6 to 12 seconds and PSO gives 4 to 9 seconds. EP technique has been recorded to have the longest computation time of 11.72 seconds, while MPSO has been highlighted as technique to achieve the shortest computation time of 3.80 seconds. From the result, it shows that the proposed

MPSO technique gives the best solution and computation time as compared to EP, AIS and PSO.

5. CONCLUSION

This paper has presented new computational intelligence approach, termed as MPSO techniques based PI controller for SVC system in angle stability improvement scheme. The proposed technique has been designed to optimize the value of fixed-gain K_P and K_I of PI controller. Results obtained from the study indicated that MPSO is capable to search for optimal results which are comparable with PSO performance and outperformed EP and AIS methods in terms of giving better K_P and K_I values which are responsible for angle stability performance. MPSO also manages to perform faster in computation time compared to the other three techniques.

6. ACKNOWLEDGMENT

The authors would like to acknowledge The Research Management Institute (RMI) UiTM, Shah Alam and Ministry of Higher Education Malaysia (MOHE) for the financial support of this research. This research is jointly supported by Research Management Institute (RMI) via the Excellence Research Grant Scheme UiTM with project code: 600-RMI/ST/DANA 5/3/Dst (164/2011) and MOHE under the Exploratory Research Grant Scheme (ERGS) with project code: 600-RMI/ERGS 5/3 (14/2011).

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