A new approach for reliability assessment of a static var compensator integrated smart grid

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A New Approach for Reliability Assessment of a Static Var Compensator Integrated Smart Grid

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***Abstract*—This paper presents an algorithm, based on Sequential Monte Carlo Simulation (SMCS), to estimate operational states of components connected to a grid??. The algorithm determine the optimum size and location of Static Var Compensators (SVCs) usingthe Accelerated Quantum Particle Swarm Optimization (AQPSO). The approach maximizes the level of reliability of the smart grid, utilizing voltage regulation. The specific contribution of the paper is that it presents the impact of the integration of SVC over the system reliability that leads to a comprehensive composite system adequacy evaluation for a smart grid environment??.**

Keywords—accelerated quantum particle swarm optimization; Markov Chain; Monte Carlo simulation; reliability assessment; smart-grids; static var compensator

I. INTRODUCTION

The vision of smart grids is becoming transparent with the advances of information and communication technologies. Federal Energy Regulatory Commission (FERC) and the recently founded in the U.S., the Department of Energy (DOE), recognized that one of the trends of this vision prevails on reliability [1]. Therefore, the big challenge is to secure the continuous operation of power systems, meeting high reliability standards.

The power systems are frequently affected by electrical failures that produce an interruption to supply the demand. In order to enhance the generation adequacy for reliability evaluation of an electrical grid, recent investigations [2-4] proposed the incorporation of distributed generation to the electrical grid. However, a line outage produces a bus voltage instability and distributed generations cannot deal with this situation. The problem is extended since other lines will carry more current and some of them may be overloaded. This may produce a load curtailment and an increment in electric power losses. As a solution, an adequate reactive power reserve is expected to maintain system integrity during post-contingency operation [5]. Several techniques to evaluate the reliability of power systems based on reactive power sources have been developed. For instance, [5, 6] present a technique to evaluate system and load point reliability of a power system considering reactive power shortage due to failures caused by reactive power sources such as generators, synchronous condensers and compensators. The authors in [7] introduce a novel concept of including the effect of reactive power failures in Demand Side Management (DSM) reliability studies. Reference [8] investigates the effects of reactive power limits on composite system reliability indices and provides a quantitative measure for reactive power support for power system reliability improvement. It is a fact that these studies offer an improvement in system reliability, nevertheless, a gap on them is that they do not challenge the optimization problem based on size and placement of the var compensator in order to maximize the system reliability.

The field of reliability assessment is dominated by Monte Carlo Simulation (MCS), since it allows a reduction in complexity to determine a solution in comparison to the analytical method. There are several studies that employ it: [9] proposes a method for the reliability evaluation of HVDC systems using the MC technique, with the emphasis on the use of the reliability index distributions, [10] presents a MC hierarchical dynamic reliability model for a dynamic change of component failure rate and [11] presents a reliability assessment to determine the indices loss of energy expectation and loss of load expectation by the employment of Sequential Monte Carlo Simulation (SMCS). The limitation on these investigations is that they do not offer a clear pathway for smart grids since the concept of optimization is not involved. This paper proposes the employment of Static Var Compensators (SVCs) as a contingency measure to increase the reliability of a smart power grid. The operational states for all the components connected to the smart grid (including the SVCs) are determined by using SMCS. In order to maximize the reliability of the system based on the size and placement for SVCs, an Accelerated Quantum Particle Swarm Optimization (AQPSO) is proposed. The combination of SMCS and AQPSO brings a new algorithm that allows to simulate a smart grid and analyze the impact of the integration of SVCs over the power system reliability.

This paper is divided into the following sections: Section II presents the reliability model for a SVC. Section III presents the theory related with MCS and AQPSO. Section IV presents the proposed algorithm. In Section V, the optimization problem is given. In Section VI, the proposed algorithm is tested in a case study. Section VII shows the impact of the integration of SVC over the system reliability that leads to a smart grid environment. Finally, Section VIII brings the conclusion based on the obtained results and the applied approach.

II. Reliability Model for a Static var Compensator

A. Markov Chain: State Space Diagram

The reliability model of some components is not easy to deal with, since sometimes this may involve differential equations. Nevertheless, a simple way to model it is by applying Markov chain, which is a representation of all key states in a diagram connected between them by variables called transition rates. Fig. 1 shows a transition state of a repairable component with two possible states: operational and failure.

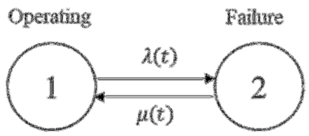

Fig. 1 Space state diagram for repairable component

For components that follow an exponential distribution, the failure rate λ and the repair rate μ are time independent. Then, the mean time to failure ($MTTF$) and the mean time to repair ($MTTR$) can be expressed as [12]:

$$MTTF = 1/\lambda \tag{1}$$

$$MTTR = 1/\mu \tag{2}$$

These formulations are convenient for the reliability evaluation using SMCS.

B. Operational States of a Static Var Compensator

A SVC primarily has three main components : 1. main circuit; 2. auxiliary power supply; and 3. control and protection system. In a reliability context, while more elements involved in a system, it may become less reliable. Hence, applying this criterion to the SVC due to the number of components involved, the contribution of forced outages may be high. Nonetheless, there is an evidence that the SVC have lower failure rates as presented in [13] and for this reason, the SVC was selected in this paper rather than other var compensators.

In order to describe the reliability model for a SVC, the following notation is used: "Up" the system is in operation, "Down" the system is not operating, "A" corresponds to the main circuit, "B" is the control and protection system and "C" is used to describe the auxiliary power supply. Now, applying Markov chain the result is as shown in Fig. 2.

III. Fundamental Algorithms

A. Sequential Monte Carlo Simulation

The generation of random numbers of any distribution or stochastic process to evaluate numerically, indirect or artificial way and estimate their behavior is defined in [12] as Monte Carlo simulation. In SMCS, the state of each component in the system is obtained by sampled, defined by its distribution function. Let the state of a power system be the vector $w = (w_1, w_2, .., w_b)$, where w_s is the state of the s^{th} component, in such a way that:

$$w_s = \begin{cases} 1, \text{Up state} \\ 0, \text{Down state} \end{cases} \tag{3}$$

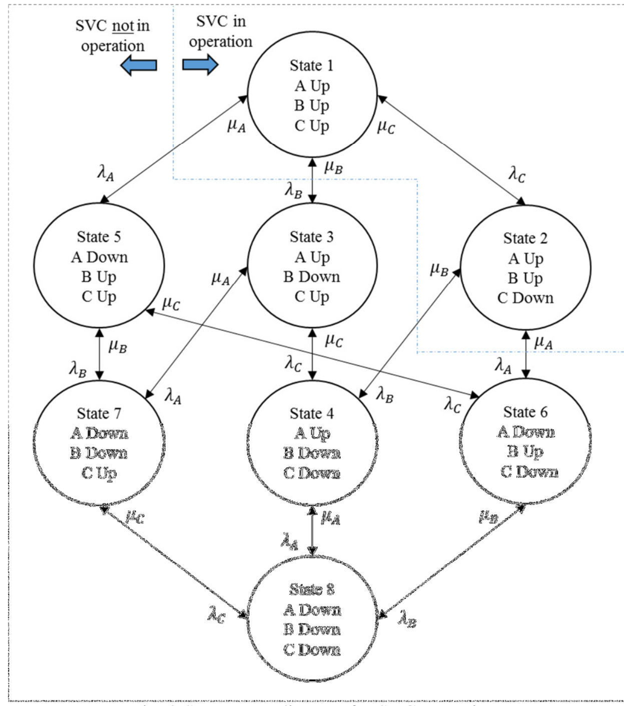

Fig. 2 Space state diagram for SVC operation

The combinations of all components states bring the state space W. Assuming that each system state has the probability $P(w)$ and the experiment function $F(w)$, the mathematical expectation of the experiment function of all system states is given by (4): [14]

$$E(F) = \sum_{w \in W} F(w) P(w) \tag{4}$$

The estimate of the expected value of the test function in terms of the number of sampling NS can be expressed as: [14]

$$\hat{E}(F) = \frac{1}{NS} \sum_{e=1}^{NS} F(W_e) \tag{5}$$

These mathematical formulations are used to describe the SMCS, as shown in Algorithm 1.

Algorithm 1: Pseudocodes for SMCS Algorithm.

1. **Procedure** of SMCS
2. **For** $e = 1$ to NS
3. randomize the states for all components: $w = (w_1, w_2, \ldots, w_b) \rightarrow W_e$;
4. evaluate W_e in experiment function to get $F(W_e)$ and save the value
5. **Endfor**
6. use **(5)** in order to get the estimate of the expected value;

B. Accelerated Quantum Particle Swarm Optimization

Quantum Particle Swarm Optimization (QPSO) is an evolutionary computation technique that unlike classical PSO, it does not employ the concept of velocity to get the optimal solution. Instead, it associates a wave function

$\psi(x,t)$ to each particle, which represents the compress information about the particle that depends on the potential field that lies in. The scenario of the particle is a quantum well.

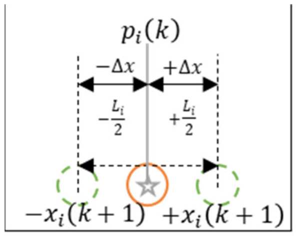

Fig. 3 Moving model of a particle in a quantum well

On the other hand, each particle has a memory of its own best position called personal best $D_i(k)$. However, this is not the only particle since there is a number of particles SS which is greater than one, hence there must be a solution of the whole swarm, called global best $g(k)$. The particle i at search step k initially is in the position $x_i(k)$ and it will move to a position defined by the local attractor $p_i(k)$. Based on a trajectory analysis the authors in [15] proposed a local attractor following the coordinates:

$$\begin{aligned} p_i(k) &= \varphi(k) D_i(k) + (1-\varphi(k)) g(k) \\ \varphi(k) &= c_1 r_1 / (c_1 r_1 + c_2 r_2) \end{aligned} \tag{6}$$

where r_1 and r_2 are random numbers uniformly distributed between [0,1], c_1 and c_2 are the acceleration coefficients, such that $0 \le c_1, c_2 \le 2$.

Since the particle is treated as a quantum particle, its position can be estimated using its time independent wave function. In quantum mechanics, the probability density function is defined as:

$$Q(x) = |\psi(x)|^2 \tag{7}$$

For a particle in a quantum well the probability density function that the particle appears at position Δx_i relative to $p_i(t)$ is [16]:

$$Q(\Delta x_i) = |\psi(\Delta x_i)|^2 = \frac{1}{L_i} e^{-2|\Delta x_i|/L_i} \tag{8}$$

The probability density function give a number between 0 and $1/L_i$. Hence:

$$|\psi(\Delta x_i)|^2 = \frac{1}{L_i} u_i;\; u_i = rand(0,1) \tag{9}$$

Since (8) and (9) are equal, then:

$$u = e^{-2|\Delta x_i|/L_i} \tag{10}$$

Solving for Δx_i:

$$\Delta x_i = \pm \frac{L}{2} \ln\left(\frac{1}{u}\right) \tag{11}$$

where L is a parameter control given by [16, 17]:

$$\frac{L}{2} = \alpha \left| x_i(k) - \frac{1}{SS} \sum D_i(k) \right| \tag{12}$$

A comprehensive representation of the model is given in Fig. 3, from which:

$$\Delta x_i = \pm x_i(k+1) - p_i(k) \tag{13}$$

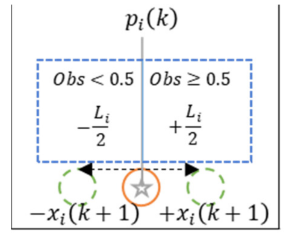

Fig. 4 Updated position of the particle using AQPSO

By replacing (11) and (12) in (13) and solving for $x_i(k+1)$:

$$x_i(k+1) = p_i(k) \pm \alpha \left| x_i(k) - \frac{1}{SS} \sum D_i(k) \right| \ln\left(\frac{1}{u}\right) \tag{14}$$

The position of the particle is in a multi-state (like the Schrödinger cat [18]) and it is not possible to determine the updated position until an observation take place. Given that the position of the particle is $x_i(k)$, at step $k+1$, the particle may appear in the zone $(-x_i(k+1), +x_i(k+1))$. The probability for each state is 0.5 determined by the observation $obs = rand(0,1)$ [16]. The traditional QPSO employs one observer to define the next position of the particle. Nonetheless, in order to accelerate the convergence and enhance the accuracy of the results, this paper proposes to increase the number of observers to an odd natural number U, which is greater than one, in such a way that the set of observers is:

$$\begin{aligned} A \cup B &= \{obs_1, obs_2, \ldots, obs_U\} \\ A = \{\text{all } obs \ge 0.5\};\; B &= \{\text{all } obs < 0.5\} \end{aligned} \tag{15}$$

The number of elements in a set is known as cardinality and its operator is defined as 'card', then the observer is chosen based on the following formulation:

$$\begin{aligned} &if \text{ card}(A) > \text{card}(B) \Rightarrow Obs \ge 0.5 \\ &if \text{ card}(A) < \text{card}(B) \Rightarrow Obs < 0.5 \end{aligned} \tag{16}$$

ALGORITHM 2: PSEUDOCODES FOR AQPSO ALGORITHM.

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Procedure of AQPSO
For i = 1 to swarm size (SS)
    randomize the position of each particle x_i(0);
    D_i(0) = x_i(0);
    Evaluate the objective function O(x_i(0));
Endfor
min O(x_i(0)) → g;
For k = 1 to maximum number of iterations (It)
    For i = 1 to SS
        calculate p_i(k) with (6);
        Get obs based on (16)
        update x_i(k) with (17);
        Evaluate the objective function O(x_i(k));
        If O(x_i(k)) < O(D_i(k))
            D_i(k) = x_i(k);
            If min O(x_i(k)) → g' < g
                g = g'
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            Endif
        Endif
    Endfor
Endfor
```

Then (14) can be written as:

$$x_i(k+1)=\begin{cases} p_i(k)+\alpha\left|x_i(k)-\frac{1}{n}\sum D_i(k)\right|\ln\left(\frac{1}{u}\right), if\ Obs\geq 0.5 \\ p_i(k)-\alpha\left|x_i(k)-\frac{1}{n}\sum D_i(k)\right|\ln\left(\frac{1}{u}\right), if\ Obs< 0.5 \end{cases} \tag{17}$$

A graphical representation of the updated position of the particle is as shown in Fig. 4. The procedure for implementing the AQPSO is given in ALGORITHM 2.

IV. PROPOSED ALGORITHM FOR OPTIMUM RELIABILITY ASSESSMENT

The proposed algorithm has two main parts. The first one called *Algorithm 'OF'*, regards about the evaluation of the objective function. The reliability index adopted for the whole system is the Expected Energy Not Supplied (EENS). In order to estimate, it is necessary to work with the SMCS, so in that way, the operational state of a component at certain time τ can be determined. To represent the operational state, "1" is used to describe that the component is in operation and "0" to describe that the component is in failure. This part of the algorithm starts by defining the maximum number of experiment NS, the time of simulation T and all reliability data related with the power system.

At a time $t=0$, it is assumed that all components are in operation (state "1") and the Energy Not Supplied (ENS) is considered as zero. For the next hour, a random number generation based on their failure distribution function takes place. The data is recorded and before going to the next hour, if there is a component in state "0", to simulate its restoration a random number generation based on the renewal distribution function takes place. This process will be repeated until reaching the time simulation T.

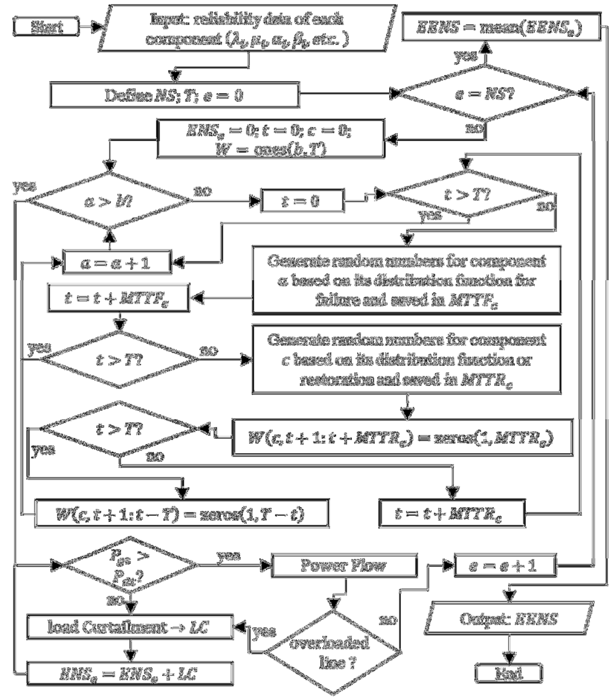

Fig. 5 Algorithm '*OF*' to evaluate the objective function

The next step is to verify if the total generation (P_{gt}) is greater than the total demand (P_{dt}), if it is so no load curtailment (LC) is needed, otherwise a load curtailment takes place and this value will represent the ENS. The load curtailment is based on two criteria [12]: 1. Loads are curtailed at buses which are as close to the elements on outage as possible; 2. loads are classified according to their importance. The least important load should be curtailed first, then the next least important, and at the last the most important load. Continuing with the process, to estimate the currents and voltages on the grid at a time τ, a power flow based on the decoupled Newton Raphson method is performed. The power flow takes as an input just the components that are in state "1". If any constraint is violated or if there is any overloaded line (OL), load curtailment will be applied and added to the ENS, otherwise, the experiment is finished and the value of ENS for experiment e is saved. Finally, the whole process is repeated NS times and the EENS is calculated using (5). More details about the algorithm go to Fig. 5.

The next stage of the proposed algorithm is the optimization problem, which cannot be solved employing basic mathematical methods since it requires of the power flow analysis (which is based on iterative process) to evaluate the objective function. As a result, AQPSO algorithm is applied. Regardless of the fact that this method cannot assure to obtain the global solution, it is able to provide a sufficiently good solution that is close to the global one. The input for the algorithm is the system data such as line voltage, daily power consumption, line impedances etc. Next, the maximum number of iterations It and the swarm size SS is defined.

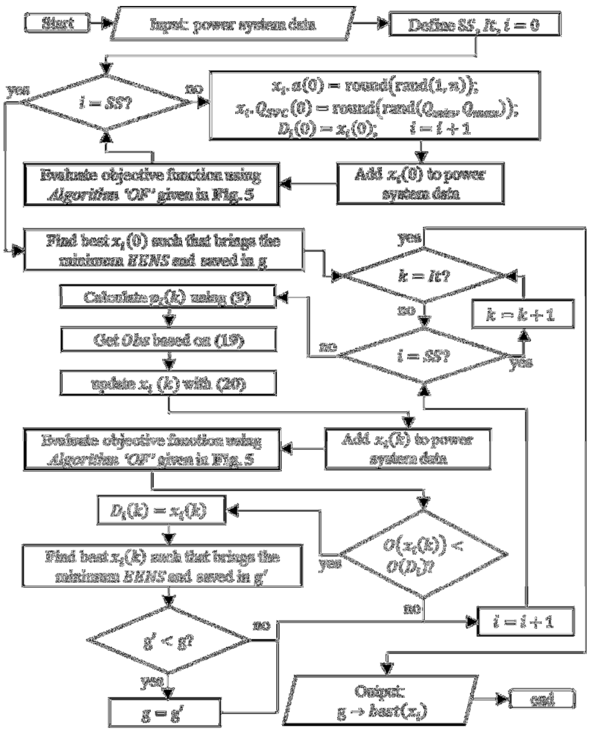

Fig. 6 Algorithm for optimum reliability assessment

The swarm x_i is defined as the combination of the different SVCs installed at bus a with capacity Q_{SVC}. Then, $x_i(0)$ is gotten by the generation of discrete random numbers such that $1 \leq a \leq n$ and $Q_{min} \leq Q_{SVC} \leq Q_{max}$, where n is the total number of buses of the grid and Q_{min} and Q_{max} are the minimum and maximum reactive power that the SVC can supply. Since the analysis is for $k = 0$ then $D_i(0) = x_i(0)$. The next step is to add $x_i(0)$ as part of the power system, then the process described in the *Algorithm OF* (Fig. 5) is used to determine the EENS. g(0) is obtained based on the particle that has the minimum value of EENS. At this point, the first iteration for the AQPSO take place and the particles start moving following (16) and (17). The process is repeated It times and the result is the best $x_i(It)$ that minimize the EENS. For more details about the algorithm, Fig. 6 is presented.

V. Problem Formulation

The main objective of this paper is to maximize the power system reliability by minimizing the EENS. An hourly time-slotted system with slot index t is considered for this formulation. The optimization problem can be defined as:

$$\textit{minimize}\ (\textit{EENS}) \tag{18}$$

Subject to:

$$P_{gen}(t) - \sum_{a=1}^{n} P_{losses}(a,t) = \sum_{a=1}^{n} P_{load}(a,t),\ a = 1,2,\ldots,n \quad , t = 1,2,\ldots,T \tag{19}$$

$$Q_{grid}(t) + \sum_{a=1}^{n} Q_{DSVC}(a,t) - \sum_{a=1}^{n} Q_{losses}(a,t) = \sum_{i=1}^{n} Q_{load}(a,t), \quad a = 1,2,\ldots,n;\ t = 1,2,\ldots,T \tag{20}$$

$$Q_{\min}(a) \leq Q_{SVC}(a,t) \leq Q_{\max}(a), a = 1,2,\ldots,n;\ t = 1,2,\ldots,T \tag{21}$$

$$V_{p.u.\min} \leq \left|V_{p.u.}(a,t)\right| \leq V_{p.u.\max},\ a = 1,2,\ldots,n\ ;\ t = 1,2,\ldots,T \tag{22}$$

$$0 \leq d \leq n \tag{23}$$

The constraints shown in (19) and (20) indicate that the power (active and reactive) carried by the generation must satisfy the load and the electrical power losses. The reactive power produced by an installed SVC is constrained by (21), since it has a minimum and maximum defined power. The constraint given in (22) provides a voltage regulation for each bus. Finally, constraint (23) is employed to control the number d of installed SVC. Note that only one SVC is allowed to be installed per node.

VI. Case Study

The study incorporates the IEEE 24 bus reliability test system [19]. The reliability index used for the whole system performance assessment was the Expected Energy Not Supplied (EENS). Two scenarios are evaluated: no SVCs installed and SVCs installed. To simplify the analysis, the assumptions are: 1. all components are initially operating and their reliability model follows an exponential distribution; 2. reliability model of the SVCs is as described in section II, with the failure and repair rate are as given in Table I; 3. SVCs available is as shown in Table II. 4. Bus voltages must be between 0.95 and 1.05 p.u.

Table I. Failure and repair rate for SVC's components

	λ [failure per year]	$r = 1/\mu$ [repair hours]
Main Circuit [20]	0.0906	1802
Control & protection [13]	0.2100	30
Auxiliary power supply [13]	0.4904	60

Table II. SVC Available

SVC Capacity [MVAr]	5	10	20	30	40	50

VII. Results and Discussion

A. *Scenario 1: No SVCs installed*

This case is used as a benchmark case in order to observe the effects of the installation of the SVCs over the power system reliability. The EENS was estimated using the algorithm described in Fig. 5, resulting 128.816 GWh/year.

B. *Scenario 2: SVCs installed*

To bring the vision of a smart grid, in this scenario the algorithm described in Fig. 6 is used. The optimal size and placement of the SVC are shown in Fig. 7. With the implementation of the SVCs, the EENS is reduced to 71.898 GWh/year, showing an improvement in the power system reliability.

C. Computational efficiency

The results are obtained using a computer with a RAM of 8.00 GB and processor Intel Core i7-6700 of 3.40 GHz. In order to show the efficacy of the proposed algorithm, the same optimization problem is solved using PSO and classical QPSO. In addition, AQPSO with three (AQPSO3), five (AQPSO5) and seven (AQPSO7) observers are used. The convergence and average time simulation per experiment are presented in Fig. 8 and **Error! Reference source not found.**, respectively.

The results reveal that although the PSO possesses the fastest convergence, it has the largest average time simulation. Moreover, the solution is not accurate enough as the other optimizations. On the other hand, the AQPSO3, AQPSO5 and AQPSO7 require more time simulation than the QPSO. This is logical since more observers imply more operations to develop in the simulation. In terms of convergence achievement, AQPSO3 is slower than the QPSO. However, the convergence is enhanced as the number of observer increases. The fastest convergence was achived from AQPSO5 and AQPSO7.

TABLE III. ROBUSTNESS OF THE EMPLOYED ALGORITHMS

Algorithm	Average time simulation per experiment [s]	Convergence iteration
PSO	10.67	34
QPSO	11.04	37
AQPSO3	11.20	36
AQPSO5	11.25	30
AQPSO7	11.26	30

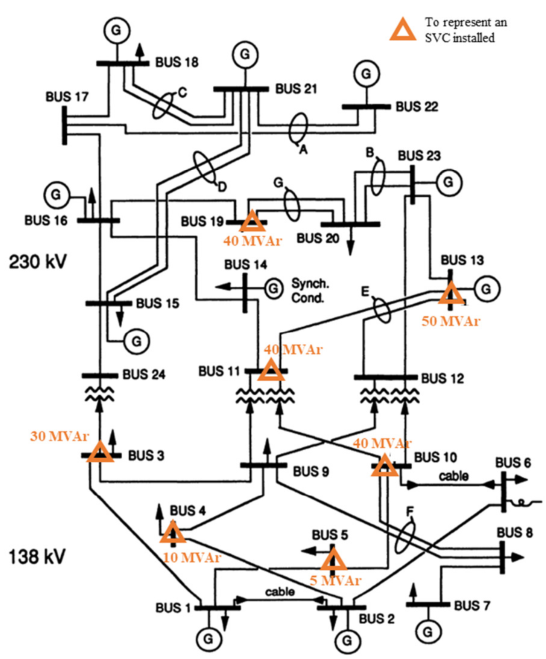

Fig. 7. Optimal size and placement of available SVCs

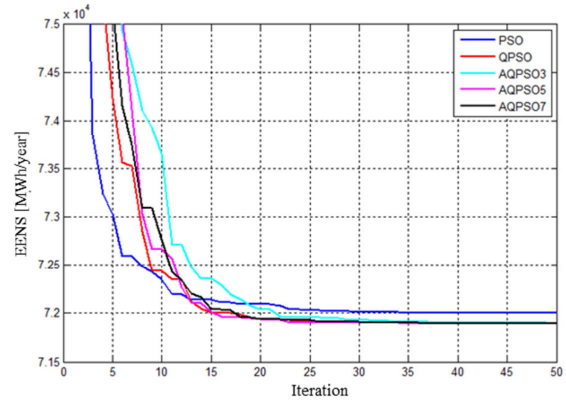

Fig. 8. Convergence of the employed algorithms

VIII. CONCLUSIONS

This paper proposes an approach to maximize reliability of a power system based on optimization of placement and size of SVCs in a smart grid environment. The approach incorporates AQPSO, which proved to be superior in convergence and efficiency in comparison with the conventional QPSO and PSO. The proposed algorithm can also be extended to estimate the cost-benefit of SVCs in a Smart Grid Environment.

REFERENCES

[1] K. Moslehi and R. Kumar, "A Reliability Perspective of the Smart Grid," *IEEE Transactions on Smart Grid,* vol. 1, pp. 57-64, 2010.

[2] G. Khudyakova, "Method of optimal placement of distributed generation sources in order to improve the reliability of power supply," in *2016 57th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON)*, 2016, pp. 1-4.

[3] D. Issicaba, J. A. P. Lopes, and M. A. d. Rosa, "Adequacy and Security Evaluation of Distribution Systems With Distributed Generation," *IEEE Transactions on Power Systems,* vol. 27, pp. 1681-1689, 2012.

[4] S. Guocheng, Z. Jingtao, Z. Xiaoyan, L. Cheng, Z. Yusen, K. Xiangyu*, et al.*, "Reliability analysis method for microgrid with intermittent distributed generations," in *2016 China International Conference on Electricity Distribution (CICED)*, 2016, pp. 1-5.

[5] W. Qin, P. Wang, X. Han, and X. Du, "Reactive power aspects in reliability assessment of power systems," *IEEE Transactions on Power Systems,* vol. 26, pp. 85-92, 2011.

[6] P. Wang, W. Qin, X. Han, Y. Ding, and X. Du, "Reliability assessment of power systems considering reactive power sources," in *Power & Energy Society General Meeting, 2009. PES'09. IEEE*, 2009, pp. 1-7.

[7] P. Soumya and K. Swarup, "Reliability improvement considering reactive power aspects in a smart grid with Demand Side Management," in *Power Systems Conference (NPSC), 2016 National*, 2016, pp. 1-6.

[8] M. Benidris, S. Sulaeman, Y. Tian, and J. Mitra, "Reactive power compensation for reliability improvement of power systems," in *Transmission and Distribution Conference and Exposition (T&D), 2016 IEEE/PES*, 2016, pp. 1-5.

[9] W. Hou, B. Bagen, and A. Gole, "Including reliability index distributions in HVdc system adequacy assessment using Monte Carlo simulation," 2017.

[10] X. Huang, Y. Shen, C. Chen, F. Zeng, and Y. Cao, "Reliability evaluation of microgrid cluster based on Monte-Carlo hierarchical dynamic reliability model," 2015.

[11] Z. Liu, W.-l. Liu, G.-c. Su, H. Yang, and G. Hu, "Wind-solar micro grid reliability evaluation based on sequential Monte Carlo," in *Probabilistic Methods Applied to Power Systems (PMAPS), 2016 International Conference on*, 2016, pp. 1-6.

[12] W. Li, *Reliability assessment of electric power systems using Monte Carlo methods*: Springer Science & Business Media, 2013.

[13] A. Janke, J. Mouatt, R. Sharp, H. Bilodeau, B. Nilsson, M. Halonen*, et al.*, "SVC operation & reliability experiences," in *Power and Energy Society General Meeting, 2010 IEEE*, 2010, pp. 1-8.

[14] X.-F. Wang, Y. Song, and M. Irving, *Modern power systems analysis*: Springer Science & Business Media, 2010.

[15] M. Clerc and J. Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," *IEEE transactions on Evolutionary Computation,* vol. 6, pp. 58-73, 2002.

[16] J. Sun, B. Feng, and W. Xu, "Particle swarm optimization with particles having quantum behavior," in *Evolutionary Computation, 2004. CEC2004. Congress on*, 2004, pp. 325-331.

[17] Z.-L. Yang, A. Wu, and H.-Q. Min, "An improved quantum-behaved particle swarm optimization algorithm with elitist breeding for unconstrained optimization," *Computational intelligence and neuroscience,* vol. 2015, p. 41, 2015.

[18] C. Monroe, D. Meekhof, B. King, and D. J. Wineland, "A" Schrödinger cat" superposition state of an atom," *science,* pp. 1131-1136, 1996.

[19] C. Grigg, P. Wong, P. Albrecht, R. Allan, M. Bhavaraju, R. Billinton*, et al.*, "The IEEE Reliability Test System-1996. A report prepared by the Reliability Test System Task Force of the Application of Probability Methods Subcommittee," *IEEE Transactions on Power Systems,* vol. 14, pp. 1010-1020, 1999.

[20] M. Alvarez-Alvarado and D. Jayaweera, "Reliability Assessment of a Static Var Compensator," in *2017 IEEE Second Ecuador Technical Chapters Meeting (ETCM)*, Salinas-Ecuador, 2017, pp. 1-8.