SWAMI: A SWARM-INTELLIGENT OPTIMIZATION TECHNIQUE FOR VOLTAGE COLLAPSE MITIGATION

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Abstract: In this paper, a voltage collapse optimization system based on comparative studies of swarm-intelligent techniques is proposed for voltage collapse mitigation in power system network. The approach draws inspiration from the idea of utilizing the intelligent behavior of swarm-based artificial machine intelligence technique coined SWAMI for voltage collapse minimization or prevention through dynamic shunt compensation of overloaded power network buses. Several simulation studies have been conducted considering three very popular and successful SWAMI agents – the PSOM, BCOM and ACOM on an IEEE benchmark power network with promising results. Simulation studies showed that the PSOM SWAMI exhibited the most stable response in terms of voltage profile collapse and recovery from voltage collapse state after voltage sensitivity studies. Safe margins of loading and optimal shunt compensations are determined based on the SWAMI techniques.

Keywords: artificial intelligence, optimization, power systems network, shunt compensation, voltage collapse

1. INTRODUCTION

Power systems have over the years shown tremendous improvements in design and in the standardization of the supply from the TRANSCOS to the DISCOS. However, the current challenges of ensuring the stability of such power systems have resulted in extensive research in the field using a variety of techniques that are software or hardware based. Voltage collapse represents one of the primary stability issues affecting power systems and is the result of an extreme level of line faults or excessive overloading in the power system leading to the voltage deviating from the normal or expected ranges. In the context of modern power system stability studies, the voltage collapse prevention or mitigation in dynamic networks represents an approach via simulation or in real time to avert the potential failure of the system and corresponding blackouts; in this research, this is related to the power system network voltage profile improvement in simulation. In order to perform this important function, optimization is used such that the solution space can be found more quickly and more accurately.

Recently, there has been a keen interest to develop modern Artificial Intelligent (AI) optimization solutions for the Voltage Collapse Optimization Problem (VCOP) studies using a variety of evolutionary-swarming techniques [1-4]. Some of the very popular evolutionary-swarming power system optimization solutions include

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the Ant Colony Optimization Method (ACOM) in [5], Particle Swarming Optimization Method (PSOM) in [6] and the Bee Colony Optimization Method (BCOM) technique in [7]. However, due to the stochastic nature of these SWAMI techniques, the tendency to give stable or reliable responses before and after recovery from a voltage collapse state may be impaired.

Thus, it is the object of this paper to identify which one of these optimization techniques can in general perform well considering bus overloading tests for a range of power networks and considering a fixed set of the SWAMI system-specific parameters.

Our primary objective is to determine the permissible MW loading and corresponding MVAR compensation level that should be added to the stressed buses for a recovery from the voltage collapse state to be attained.

This paper is structured as follows: In Section 2, the related works are presented. In Section 3, the methodological aspects of the optimization strategies used in this research study are presented. Section 4 presents the experimental details and discussion of results including the detailed comparative studies of the considered ACOM, PSOM and BCOM for power system voltage collapse studies. Finally, we present the concluding remarks on this study.

2. RELATED WORKS

A number of researches in the field of power system optimization abound in the literature; a recent trend is the use of swarm based solutions for effective power system voltage stabilization and control considering certain system constraints.

In [6], a voltage stability margin called the L-index earlier introduced in [7] was used in a multi-objective minimization optimal power flow problem. Their formulation used a chaotic mutation Stochastic Weight Trade-off (SWT) swarm intelligence technique based on non-dominated sorting particle swarm optimization (SWT-NS-SPO) which was applied to IEEE 30-bus power. Simulation results compared with some existing techniques such as NSGA-II, NSPSO, NS_CPSO etc. showed that NS- SWT-NS-SPO is best as an optimizer.

Jayakansar et al [8] proposed a ranking scheme based on a standard feed-forward back-propagation trained artificial neural network and using L-index for voltage collapse prediction of weak lines of the IEEE 30-bus with Thyristor Controlled Series Capacitor (TCSC) compensation. Standard feedforward neural network was used for matching the input (load variations) with line indexes computed after a variety of load flow simulations.

The results of the analysis showed that the line that gives the most stability improvement i.e. with more number of lines improved can be identified when a step-by-step mutually exclusive installation of the TCSC on the discovered weak lines is used. Chatterjee and Roy [9] proposed a Catastrophic Failure Index (CFI) with signature analysis for early prediction of catastrophic failures of power system due to voltage collapse. Their proposed technique has been applied to the IEEE 30-bus with promising results.

Other methods of VCA include the use of a Genetic Algorithm (GA) based on reactive power dispatch for the minimization of the L-index to improve voltage stability [10], VSM improvement using PSO and Continuation Power Flow (CPF) techniques [11], game theoretic approach for voltage stabilization [12] and the Voltage Collapse Index (VCI) prediction based on the structural characteristics of the L-index [13].

One strong theme amongst the aforementioned researches and similar ones is the use of swarm or evolutionary control agents to modify the power system control variables adaptively which in turn optimally leads to better and more optimal results. However, the list of swarming techniques is endless and more keep on springing up in the field of soft computing; this may be attributed to the idea that there is indeed no universal solution to optimization problems [14].

Though as pointed out in [15], quite a number of swarm-based optimization strategies exist in the literature, there are still some few and very popular ones that stand out in most optimization problems used by academic researchers. In this research study, we concentrate on three very popular and successful SWAMI strategies namely the Particle Swarm Optimizer (PSO), the Bee Colony Optimizer (BCO) and the Ant Colony Optimizer (ACO) as applied to a power system optimization problem.

3. MATERIALS AND METHODS

In this study, the considered swarm optimization techniques - the PSOM, BCOM, and the ACOM are described succinctly (see subsections 3.1-3.3). These models or optimization solutions fundamentally are composed of two key parts:
i) The mode of operation of intelligent agents (agent module) – explorative or exploitative.
ii) The objective, minimization or problem function.

In (i), the method of search or exploitation is introduced at a much higher level to solve the problem of determining appropriate and clearly defined boundaries or/and constraints including the power bounds (load limits) and MVAR compensation bounds (MVAR limits). This is achieved for a number of evolutions or trial runs such that as the agent module tends to the finite number of runs, the solution space or point of convergence is simultaneously reached.

In (ii), the method of fitting the problem to be minimized or maximized is obtained in line with the search operations; this is done at a much lower level. Thus, in the context of this study, the solution of the Voltage Collapse Optimization Problem (VCOP) allows the boundaries (numerical ranges) of the test system loads and injected MVARS for compensation to be dynamically computed by minimizing a reference voltage deviation using the different SWAMI computer programs.

The technique for selecting the best optimizer is also equally presented in sub-section 3.4.

3.1. The particle swarm optimization method (PSOM)

The PCOM is based on the theory of swarming particles proposed earlier by Eberhart [16]. This method follows the fundamental nature of swarming including such important functions as bird flocking, fish pooling, organization of air particles, bee hives and other such metaphor-based natural phenomena. These instances are used to formulate the method of evolving better solutions through modified searches particle swarms.

The emphasis of using the SPOM in the compensation program is to intelligently minimize the voltage deviation cost function with respect to the Voltage Collapse Optimization Problem (VCOP) by exploiting particle velocities and positions.

The PSOM modeling is as provided in Algorithm 1.

Algorithm 1: *The PSOM Algorithm*
The steps for the PSOM algorithm are as follows (i – xii):

i. Initialize the size of the particle swarm say, *n*
ii. Initialize the positions and velocities for all swarm particles randomly
iii. **While** end criterion false **do**
  a. t = t+1
  b. Compute fitness value of each particle
iv. x $x* = \arg\min_{t-1}^{n}\left(f\left(x*(t-1)\right), f\left(x_1*(t)\right), f\left(x_2*(t)\right), \ldots\ldots f\left(x_t(t)\right), \ldots\ldots f\left(x_n(t)\right)\right);$
v. For I = 1 to n
vi. $x_t^{\#}(t) = \arg\min_{t-1}^{n}\left(f\left(x_t^{\#}(t-1)\right), f\left(x_1(t)\right)\right)$
vii. For j = 1 to Dimension
viii. Update the *j-th* dimension value of x_t and v_t
ix. $v_{ij}(t+1) = wvi_j(t) + c_1 r_1\left(x_{ij}^*(t) - x_{ij}(t)\right) + c_2 r_2\left(x_j^*(t) - x_{ij}(t)\right)$
  a. $x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)$
  b. $v_{ij} = sign(vi_j)mn\left(\left|v_{ij}\right|, v_{\max}\right)$
x. End For
xi. End For
xii. End While

3.2. Bee colony optimization method (BCOM)

The BCOM was introduced in 2005 by Karaboga and his team at Eciryes university Turkey and is based on the intelligent swarming nature of honey bees towards food sources [17]. This method follows the intelligent foraging ability of honey bees to source for the best set of food sources [18]. The food sources typically refer to a randomly generated sequence of numerical values of the optimization parameters (called the population set) that must be fitted to an objective function (or fitness function) in the BCO system. The fitness is calculated for every trial run, cycle and for every limit trial of the internally generated solution. Just as in the PSOM technique cost function with respect to the Voltage Collapse Optimization Problem (VCOP), the emphasis of using the BCOM in the compensation program is to intelligently minimize the voltage deviation by exploiting the honey bee search behavior.

The BCOM modeling is as provided in Algorithm 1.

Algorithm 2: *The BCOM Algorithm.*
The steps for the BCOM algorithm are as follows (i - xii):

i. Generate initial population X_i, $i = 1 \ldots, SN$
ii. Evaluate the population
iii. Set cycle to 1
iv. Repeat
v. FOR each employed bee
    a. Produce new solutions v_i by using (1)
    b. Calculate the fitness
    c. Apply a greedy selection process
vi. FOR each onlooker bee
    a. Choose a solution xi depending on a probability say, p_i
    b. Produce new solutions v_i
    c. Calculate the fitness
    d. Apply the greedy selection process
vii. If there is an abandoned solution then:
    a. Replace it with a new solution produced by a scout using (3).
viii. Memorize the best solution achieved so far
ix. cycle = cycle + 1
x. Until cycle = MCN
xi. END FOR
xii. END FOR

3.3. Ant colony optimization method (ACOM)

The ACOM was proposed by Dorigo [19] and uses the concepts of ants intelligent search for food - this method follows from the intelligent swarming behavior of sugar ants in nature. It was developed with the idea that the intelligent food search direction of ants will lead to better solutions to computational science problems. In the context of the VCOP, the ants are motivated towards the direction of high pheromone trail updates as the reference voltage deviations become smaller. The better fitness can be attained at the best parameter and variable settings.

The ACOM modeling is provided Algorithm 3.

Algorithm 3: *The Algorithm for the ACOM technique*
The steps for the ACOM algorithm are as follows (i - xii):

i. Initialize the number of ants say, n
ii. While end criterion false do
    a. t = t+1
    b. For k = 1 to n
    c. ant_k is positioned on a starting node
iii. For m = 2 to problem size
iv. Choose the state according to the probabilistic
v. transition rules
vi. Append the chosen move into $tabu_k(t)$ for the ant_k
vii. End For

viii. Update the trail pheromone intensity for every edge (i, j)

$$\tau_{i,j}(t)=\rho\tau_{i,j}(t-1)+\sum_{k=1}^{n}\Delta\tau_{i,j}{}^{k}(t)\forall(i,j)$$

ix.

$$\Delta\tau_{i,j}{}^{k}(t)=\begin{cases}\dfrac{Q}{L_k(t)} & if\ the\ edge(i,j)\ chosen\ by\ ant_k\\ 0 & otherwise\end{cases}$$

x. Compare and update the best solution
xi. End For
xii. End While

3.4. Power systems voltage collapse simulation model

In this study the considered systems model for simulating the effects of voltage collapse and the subsequent mitigation using swarm intelligence optimizers include a loading model, a load flow model and a compensation model.

1. The loading model captures the test loads needed to stress a given case bus just beyond its limits.
2. The load flow model uses a conventional solver – the Newton Raphson (NR) technique to obtain the system network solution state and the SWAMI algorithms – PSOM, BCOM and ACOM to find the best fitted solution agents or variables. The fitness is determined by an objective function defined in the MATLAB program (see Appendix). Here, the loading is applied till point of collapsing the power network.
3. The compensation model captures the needed injection of MVARS via a theoretical shunt compensation model.

The entire systems approach is provided in Figure 1. The SWAMI search module processing is illustrated using the information funnel filter concept where fitted solutions (e.g. agent 1) form a good solution (MVAR compensation value) and is passed over to the compensator model selection stage.

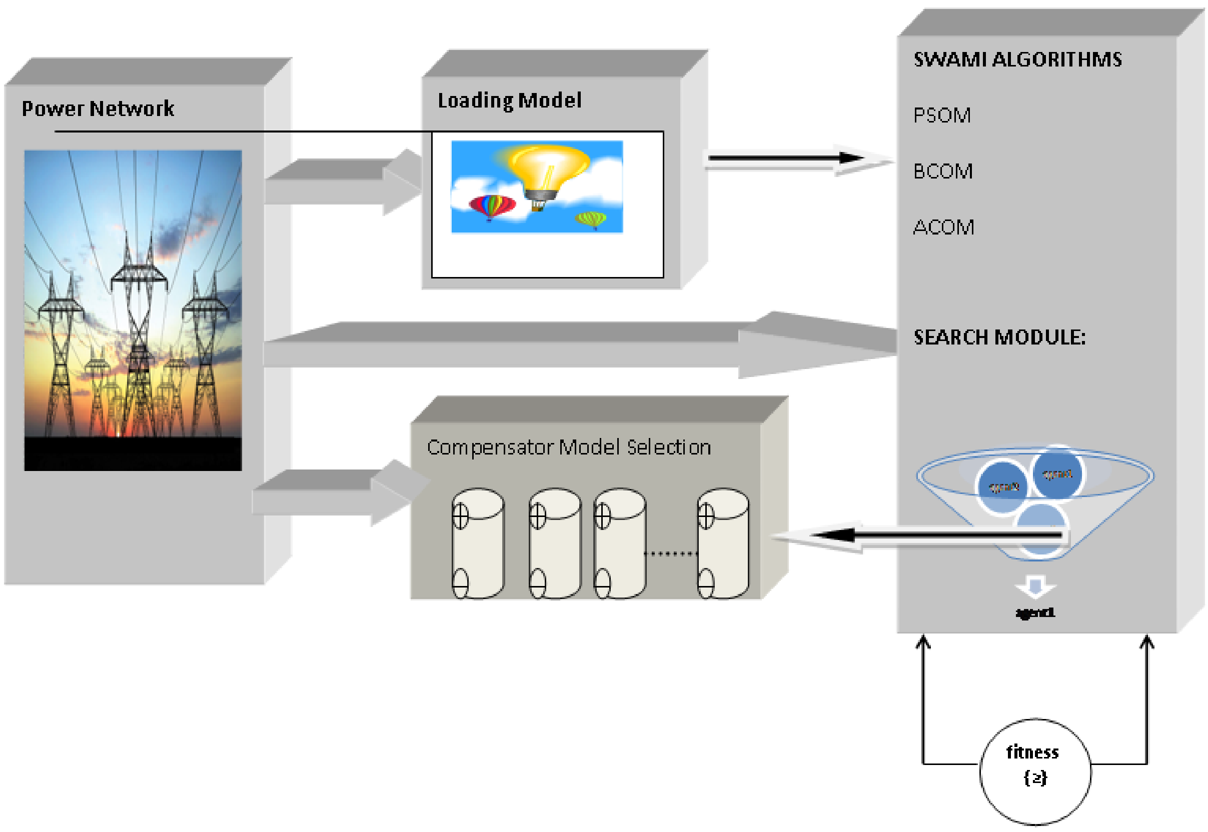

Fig. 1. Pictorial model of a SWAMI voltage collapse mitigation solution; SWAMI agents are indicated by the blue circles.

3.5. Objective function formulation

In optimization problems, it is the convention to define an objective function for which the optimizers try to minimize or maximize. In this study, the objective is stated as follows:

$$Minimize : v_{dev(tot)} = v_{ref} - \sum_{j=1}^{n_{PQ}} v_{PQ}^{j} \tag{1}$$

s.t.:

Equality constraints:

$$P_G - P_D - P_L = 0 \tag{2}$$

$$Q_G - Q_D - Q_L = 0 \tag{3}$$

$$P_{Lj} = |V_i||V_j||Y_{ij}|\left|\sum_{n-1}^{N} \cos(\alpha_{ij} - \delta_i - \delta_j)\right. \tag{4}$$

$$Q_{Lj} = |V_i||V_j||Y_{ij}|\left|\sum_{n-1}^{N} \sin(\alpha_{ij} - \delta_i - \delta_j)\right. \tag{5}$$

and, inequality constraints:

$$P_G^{\min} \le P_G \le P_G^{\max} \tag{6}$$

$$Q_G^{\min} \le Q_G \le Q_G^{\max} \tag{7}$$

$$P_D^{\min} \le P_D \le P_D^{\max} \tag{8}$$

$$V_{bus}^{\min} \le V_{bus} \le V_{bus}^{\max} \tag{9}$$

$$d_{bus}^{\min} \le d_{bus} \le d_{bus}^{\max} \tag{10}$$

$$P_{li}^{\max} \ge P_{li} \tag{11}$$

$$Q_c^{\min} \le Q_c \le Q_c^{\max} \tag{12}$$

where $v_{dev(tot)}$ = Total voltage deviation; v_{ref} = A prespecified voltage reference, set at 1.0.pu; v_{PQ}^{j} = the calculated load (PQ) bus voltage at load bus j for simulation time step, t; n_{PQ} = number of load (PQ) buses; P_G = Real Power of Generator; Q_G = Reactive Power of Generator; P_D = Real Power of Load; Q_D = Reactive Power of Load; P_L = Real Power Losses; Q_L = Reactive Power Losses

4. EXPERIMENTAL RESULTS AND DISCUSSION

The experiments for voltage collapse studies are carried out considering the IEEE benchmark power network – the IEEE 3-machine 6-bus. This power network is used as a baseline for the evaluation and selection of a stable SWAMI technique for subsequent experiments.

The IEEE benchmark power data including network sizes and ranges used in the simulations can be found in Ref.[20]; so we do not replicate them here. The system parameters used for each considered SWAMI technique are provided in the Appendix. A loading and shunt compensation table is provided for both power benchmarks – see Table 1 for the IEEE 3-machine 6-bus; this table provides the trigger load range needed to initiate a voltage collapse situation and an MVAR compensation range; it is indeed an extended range from the one used in Ref. [20]. Thus, for each experiment, the first task for the SWAMI optimizer system is to automatically determine the extent of loading needed to trigger a voltage collapse in the chosen power network considering a given test bus. In addition to this task, the SWAMI system should be able to determine the needed compensation to keep the system to within permissible voltage levels. Simulation studies have been conducted for two of the buses for the considered power network and for 5 trial runs. The results generally portray graphically the voltage state at load buses; it also shows numerically the solved permissible loading and needed shunt injections to stabilize the power system. This method of visualization has been found to be more clearer and easier to interpret by both experts and novice power system operators. The results are provided in the following sub-sections.

Table1. Load range and shunt compensation setting for IEEE 3-machine 6-bus (extended version of Ref. [20]).

Bus.No.	Load Range (MW)	Shunt Compensation Range (MVAR)
4	0 – 1800	0 – 500
5	0 – 2500	0 – 500

4.1. Voltage response results using the IEEE 3-machine 6-bus power network

Initial experimental results of the solved voltages at Bus 4 and 5 considering PSOM, BCOM and ACOM at default no-loading and zero compensation states are shown in Figure 2. This table shows the voltage state when the system is unperturbed. From, the results in Table 1, it is clearly seen that there is no significant difference in the solutions generated by all three class of optimization techniques.

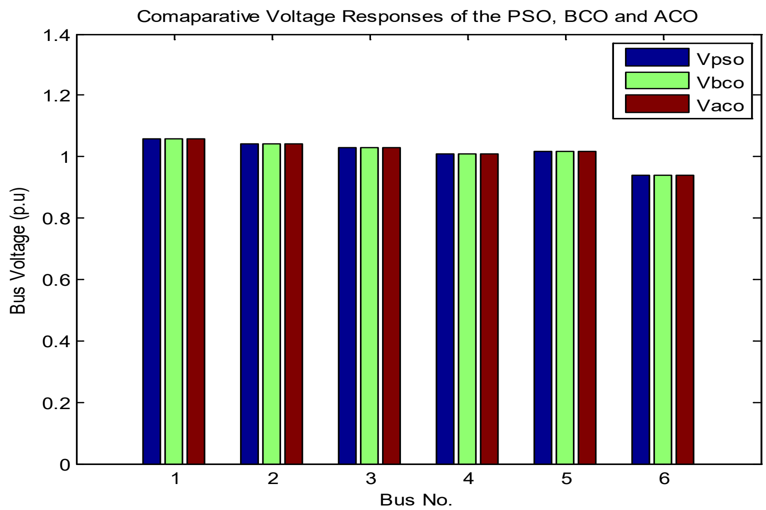

Fig. 2. Solved voltages of the various algorithms, PSO (pso), BCO (bco) and ACO (aco).

Further experiments considering loading without and with compensation for Bus Site 4 are provided in sub-sections 4.1.1 and 4.1.2 respectively; also the case of loading with and without compensations for Bus site 5 are provided in sub-sections 4.1.3 and 4.1.4 respectively. These simulations are all performed for 5 trial runs. Statistical t-tests are performed in sub-section 4.1.5 to validate the performance of the various SWAMI techniques.

4.1.1. Bus loading without compensation at Bus site 4

In these experiments, the load range setting for Bus 4 is defined in accordance with the loading specifications in Table 1. The results for loading at Bus site 4 are as shown in Figure 3 to Figure 5 for the PSO, BCO and ACO SWAMI optimizers respectively.

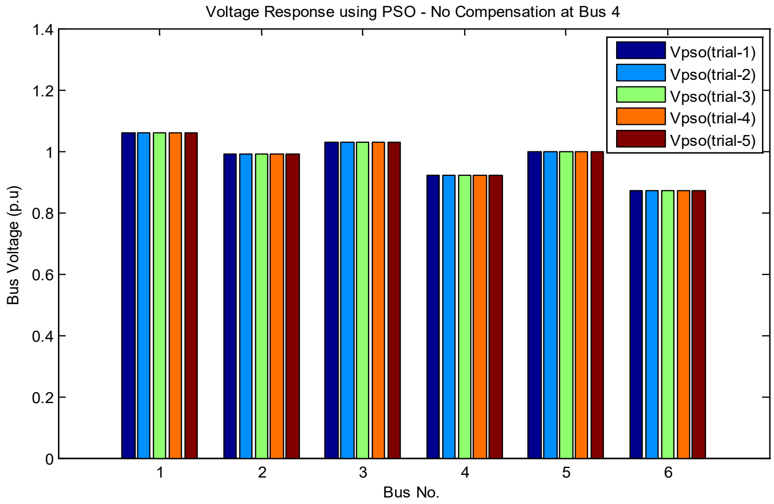

Fig. 3. Solved voltages of the PSO optimizer without compensation (5 simulation trials).

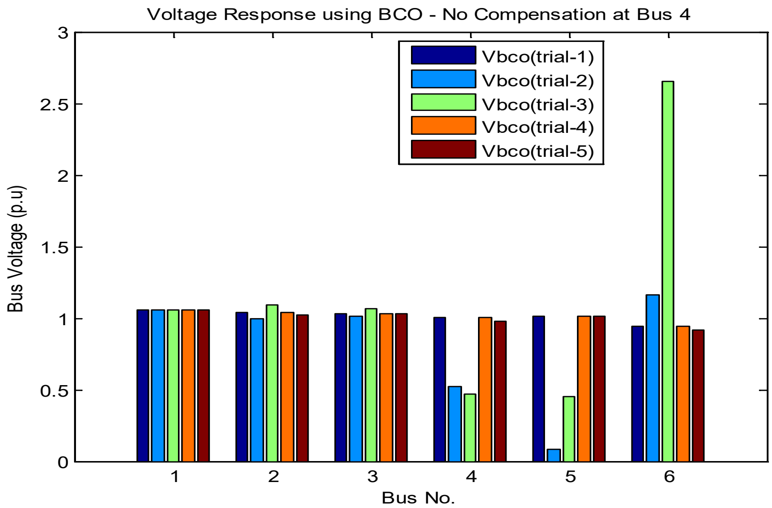

Fig. 4. Solved voltages of the BCO optimizer without compensation (5 simulation trials).

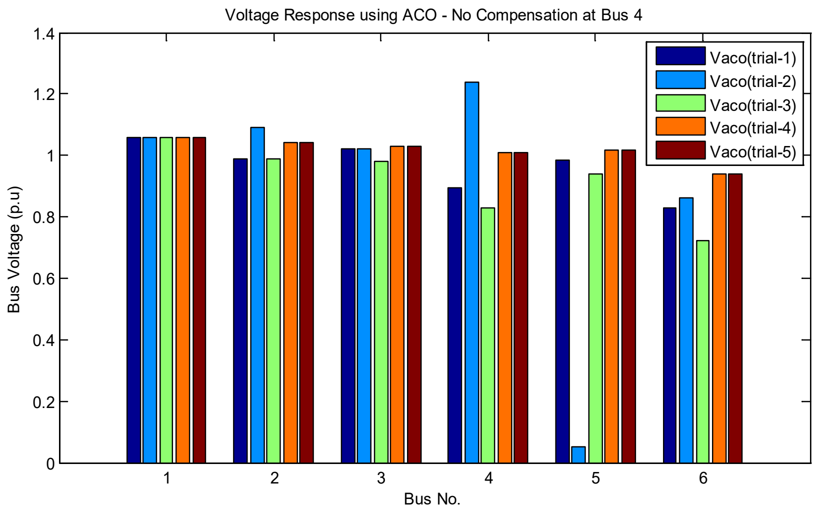

Fig. 5. Solved voltages of the ACO optimizer without compensation (5 simulation trials).

4.1.2. Bus loading with shunt compensation at Bus site 4

In the compensation experiments, the load range setting for Bus 4 is defined in accordance to the shunt MVAR levels as specified in Table 1. The results for loading at Bus site 4 are as shown in Figure 6 to Figure 8 for the PSO, BCO and ACO SWAMI optimizers respectively. The solved permissible loading and shunt MVAR injections for the various considered techniques are provided in Tables 2 and 3 respectively.

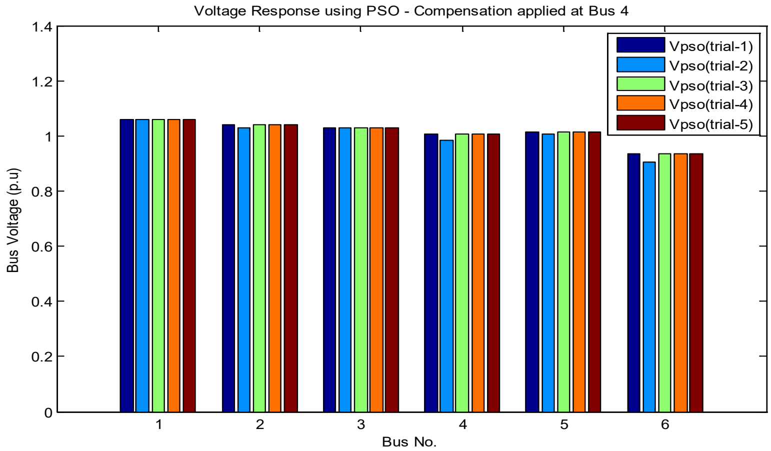

Fig. 6. Solved voltages of the PSO optimizer with shunt compensation at Bus 4 (5 simulation trials).

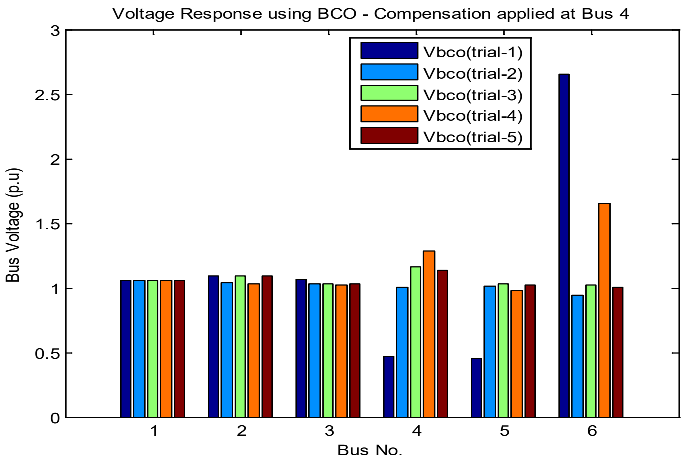

Fig. 7. Solved voltages of the BCO optimizer with shunt compensation (5 simulation trials).

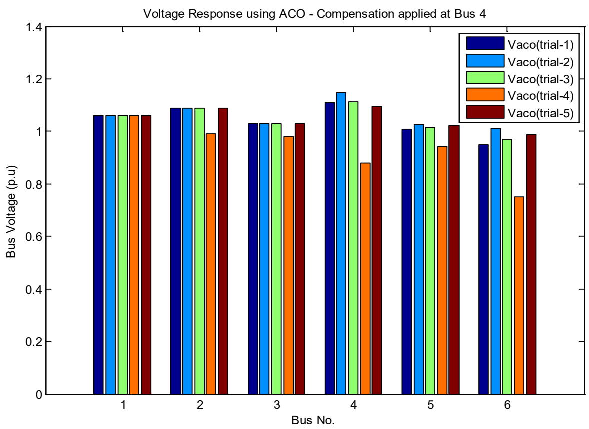

Fig. 8. Solved voltages of the ACO optimizer with shunt compensation (5 simulation trials).

Table 2. Solved permissible loading of the SWAMI techniques at Bus 4 (5 simulation trials).

SWAMI Optimizer	*loading1* (MW)	*loading2* (MW)	*loading3* (MW)	*loading4* (MW)	*loading5* (MW)
PSO	180.9565	180.6873	180.6575	180.9512	180.9668
BCO	129.0000	377.6401	76.5435	175.3767	169.7477
ACO	501.5441	483.5152	277.4875	357.5780	357.4326

Table 3. Solved Shunt injections of the SWAMI techniques at Bus 4 (5 simulation trials).

SWAMI Optimizer	*Shunt_injection1* (MW)	*Shunt_injection2* (MW)	*Shunt_injection3* (MW)	*Shunt_injection4* (MW)	*Shunt_injection5* (MW)
PSO	50.3015	50.057	50.0947	50.3015	50.3732
BCO	0.0000	161.7765	0.0000	0.0000	0.0000
ACO	235.9870	264.6301	135.9401	205.6994	174.2764

4.1.3. Bus loading without compensation at Bus site 5

In the compensation experiments, the load range setting for Bus 5 is defined in accordance with the shunt MVAR levels as specified in Table 1. The results for loading at Bus site 5 are as shown in Figure 9 to Figure 11 for the PSO, BCO and ACO SWAMI optimizers respectively.

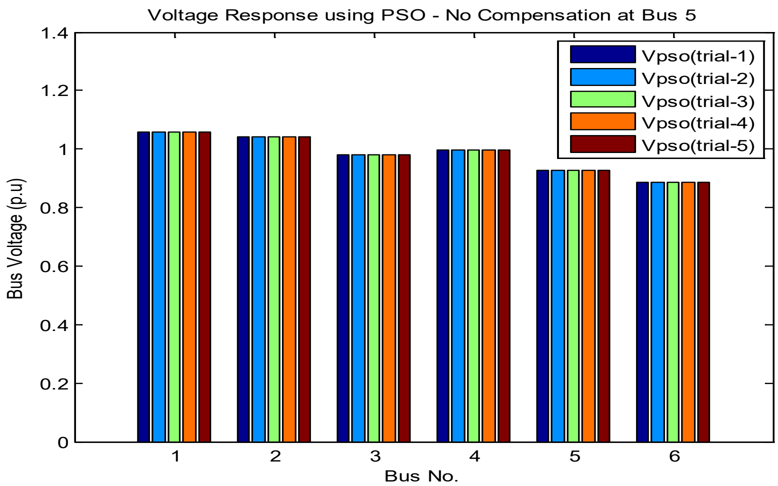

Fig. 9. Solved voltages of the PSO optimizer without compensation (5 simulation trials).

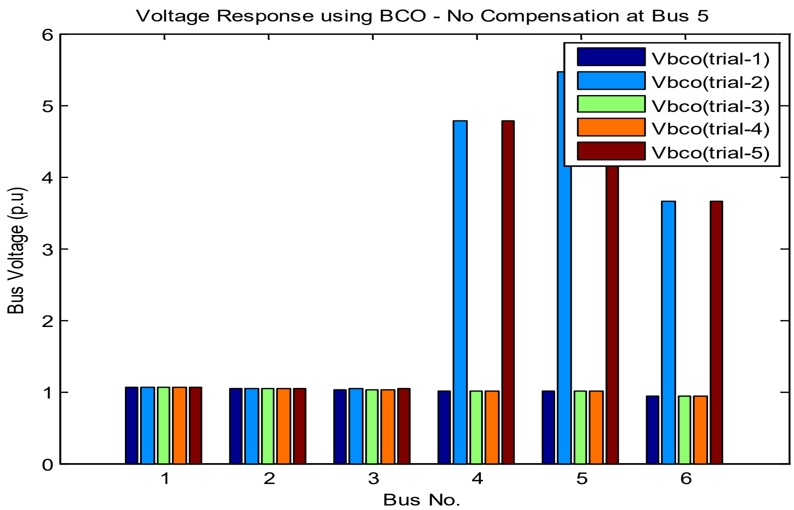

Fig. 10. Solved voltages of the BCO optimizer without compensation (5 simulation trials).

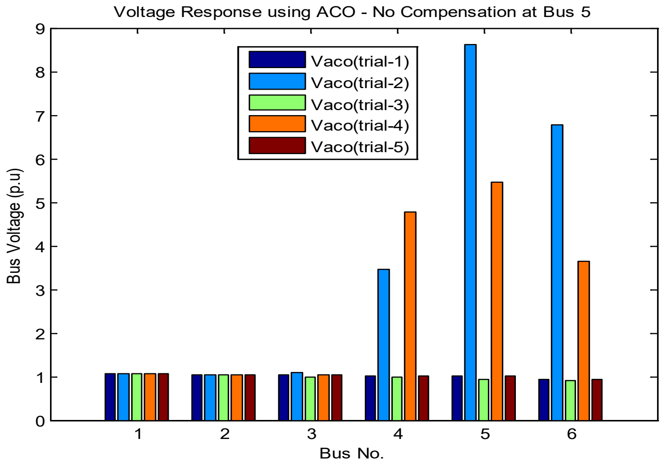

Fig. 11. Solved voltages of the ACO optimizer without compensation (5 simulation trials).

4.1.4. Bus loading with shunt compensation at Bus site 5

In the compensation experiments, the load range setting for Bus 5 is defined in accordance with the shunt MVAR levels as specified in Table 1. The results for loading at Bus site 5 are as shown in Figure 12 to Figure 14 for the PSO, BCO and ACO SWAMI optimizers respectively. The solved permissible loading and shunt MVAR injections for the various considered techniques are as provided in Tables 4 and 5 respectively.

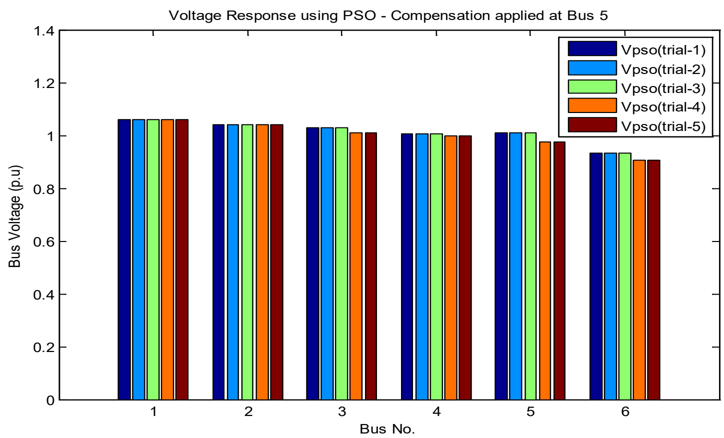

Fig. 12. Solved voltages of the PSO optimizer with shunt compensation (5 simulation trials).

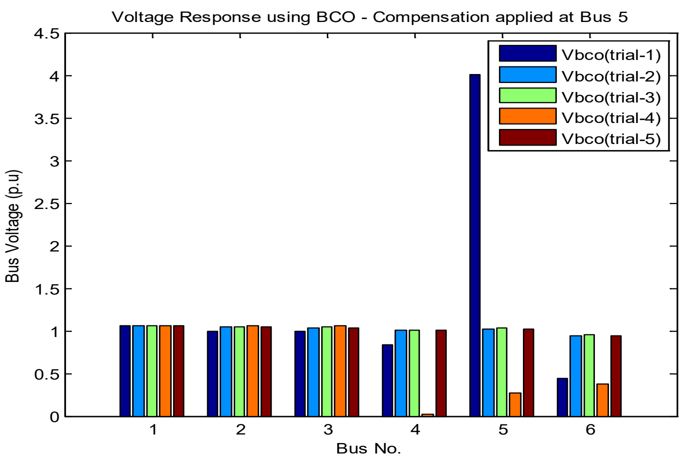

Fig.13. Solved voltages of the BCO optimizer with shunt compensation (5 simulation trials).

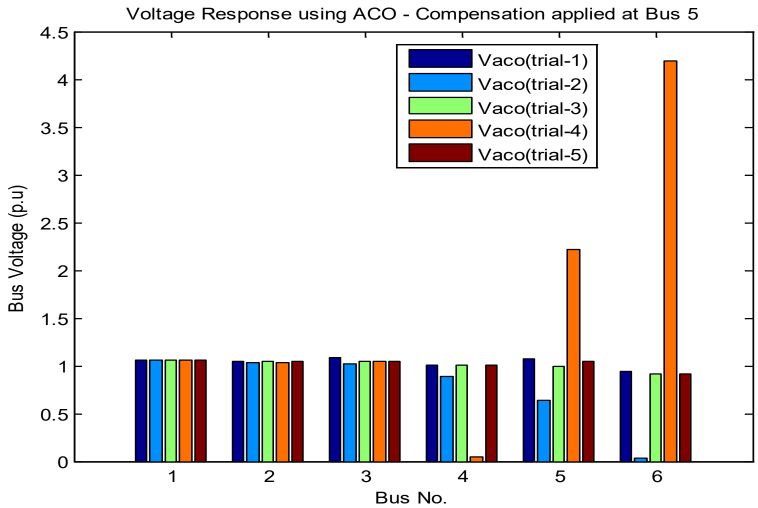

Fig.14. Solved voltages of the ACO optimizer with shunt compensation (5 simulation trials).

Table 4. Solved permissible loading of the SWAMI techniques at Bus 5 (5 simulation trials).

SWAMI Optimizer	*loading1* (MW)	*loading2* (MW)	*loading3* (MW)	*loading4* (MW)	*loading5* (MW)
PSO	250.4322	250.7035	250.9547	250.7176	250.8856
BCO	58.6426	268.3129	200.8738	459.4129	224.1240
ACO	825.9031	390.9839	1119.5944	461.7103	615.1005

Table 5. Solved shunt injections of the SWAMI techniques at Bus 5 (5 simulation trials).

SWAMI Optimizer	*Shunt_injection1* (MW)	*Shunt_injection2* (MW)	*Shunt_injection3* (MW)	*Shunt_injection4* (MW)	*Shunt_injection5* (MW)
PSO	50.0844	50.3278	50.0769	50.2178	50.0632
BCO	0.0000	0.0000	0.0000	205.5550	0.0000
ACO	427.2700	99.6191	241.1555	103.5374	255.8316

4.1.5. Correlation tests

In this section, we evaluated through correlation t-tests in the MATLAB program whether there is any significant difference in the voltage responses as computed by the different algorithms for each trial run after compensation in terms of their linguistic significance level. The essence of the tests was to identify the SWAMI optimization technique that should be considered for further experiments based on the data obtained from the experiments (see Figure 6-8 sub-section 4.1.2 and in Figures 12-14, sub-section 4.1.4.). In Tables 6 and 7, the correlation tests are presented for bus sites 4 and 5 respectively.

Table 6. Significance level of each SWAMI technique for bus site 4.

SWAMI Optimizer	*Significance*
PSO	no significant statistical difference among the observations
BCO	significant statistical difference among the observations
ACO	significant statistical difference among the observations

Table 7. Significance level of each SWAMI technique for bus site 5.

SWAMI Optimizer	*Significance*
PSO	no significant statistical difference among the observations
BCO	significant statistical difference among the observations
ACO	significant statistical difference among the observations

5. DISCUSSIONS

The simulations performed in the prior section have shown that the PSO exhibit the most stable performance when compared to the BCO and ACO techniques. In particular, during bus loading experiments (bus sites 4 and 5), the BCO and ACO techniques were characterized by wide variations in solution voltages prior to compensations at the considered bus sites (see Figures 4-5 and Figures10-11); this is clearly noticeable in buses 4, 5 and 6. This situation is somewhat replicated after compensation is applied to bus site 4 with reasonable improvements in the voltage profile across all buses for the PSO and ACO (see Figures 6 and 8) and slight improvements in that of the BCO (see Figures7). As per the bus site 5, the PSO exhibited a better voltage response after compensation when compared to the BCO and ACO techniques which performed poorly (see Figures 12 - 14).

The solution permissible loading and the required shunt injections considering the study bus loading sites (bus sites 4 and 5) also show stable performance of the PSO over the BCO and ACO techniques. For the case of the PSO and at study bus site 4, the solved permissible loading across all buses is about 180MW while the required shunt injections is about 50MVARs (see Tables 2 and 3). For the case of the PSO at study bus site 5, the solved permissible loading across all buses is about 250MW while the required shunt injections is about 50MVARs (see Tables 4 and 5).

In general, correlation tests performed on the voltage response data generated by the different techniques after compensation showed that only the PSO technique gave no significant statistical difference among the observations (see Tables 6 and 7).

CONCLUSIONS

The problem of voltage collapse from the perspective of optimal permissible loading and shunt compensation have been studied in this research study. The primary discoveries in this research study are as follows:

- SWAMI optimizers exhibit stochastic behavior on their voltage response during compensation.
- The PSO exhibits the most stable response.
- The ACO showed promising results to maintain stable voltage response.

From these observations, it may be inferred that the PSO gives the most stable voltage response after stability analysis and this is followed by the ACO. It becomes obvious that the PSO should be recommended as a primary SWAMI technique for voltage collapse mitigation and compensation. The implications for power system researchers are twofold.

First, the optimization technique for a voltage collapse mitigation scheme should be carefully studied and chosen. Secondly, the PSO technique should be a key swarming intelligence choice when considering alternatives or hybrid solutions for such schemes.

APPENDIX

Table A.1. Key PSO Parameters.

PSO Parameter	Default Value
Population size	10
Maximum number of iterations (Generations)	5
Constriction coefficient (Personal and Global)	1.05

Inertia weight damping ratio	1

Table A.2. Key BCO Parameters.

BCO Parameter	Default Value
Population size	10
Maximum number of iterations (Generations)	5
Acceleration coefficient	2.05

Table A.3. Key ACO Parameters.

ACO Parameter	Default Value
Population size	10
Maximum number of iterations (Generations)	5
Sample size	1
Intensification Factor (Selection Pressure)	0.5
Deviation-distance ratio	1

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