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IFAC PapersOnLine 55-9 (2022) 413–418

Optimal Power Flow Considering Global Voltage Stability Based on a Hybrid Modern Heuristic Technique

Wenlei Bai*, Kwang Y. Lee and Ibrahim Eke*****
** Oracle Energy and Water, Austin, TX 77042, USA*
(e-mail: baiwenlei123@ gmail.com)
*** Baylor University, Waco, TX 76706, USA*
(e-mail: Kwang_Y_Lee@baylor.edu)
**** Kirikkale University, Kirikkale 71000, Turkey*
(e-mail: eke@kku.edu.tr)

Abstract: Integrating large renewable energy to grid complicates power systems' steady-state operation which leads to the high risk of voltage instability due to its intermittent and stochastic properties. The steady-state voltage stability margin (VSM) can be measured by the smallest singular value (SSV) of the load flow Jacobian matrix. Unlike other voltage stability indices such as L-index which shows the probability of voltage collapse for a particular bus, namely, local stability index, SSV represents the global voltage stability and the smaller the value is, the riskier the whole system's stability is. Voltage stability constrained-optimal power flow (VSC-OPF) is an effective tool to stabilize system voltage. Yet VSC-OPF is a highly non-linear and non-convex problem because of AC power flow and implicit SSV constraints. Such challenge is tackled, in this work, by a novel hybrid heuristic method, differential evolutionary particle swarm optimization (DEEPSO) which can easily formulate explicit constraints and objective functions to obtain near-optimal solutions efficiently. Several case studies are conducted on the IEEE 30-bus system, and they demonstrate the effectiveness of the hybrid technique and presents some insights on voltage profiles under various system operating condition.

Keywords: Global voltage stability, Optimal power flow (OPF), Hybrid heuristic technique, Differential evolution (DE), Evolutionary particle swarm optimization (EPSO).

1. INTRODUCTION

Renewable energy has been given an increasing attention by policy makers all over the world due to its environmental-friendly merit and new technologies to reduce the capital cost. For instance, the projected total installed wind power capacity in 2050 is up to 6044GW (IRENA, 2019) globally. Such large penetration of renewable energy would complicate power system operation considerably due to its intermittency (Bai, Lee and Lee, 2017). Furthermore, it increases the risk of under voltage instability because, power electronics-based renewable energy penetration decreases the system inertia and increases more variability in operating points as they fluctuate. Therefore, power systems with high renewable energy penetration operate closer to stability boundaries. Various research has been conducted to address the issue. In essence, they aim to improve the voltage stability margin (VSM). Abri, Saadany and Atwa (2013) proposed a method to redispatch generation and find the optimal size and location of the distributed energy resources (DERs). Yao, Molzahn and Mathieu (2019) proposed a novel demand response technique to improve voltage stability.

In all, most of those methods, in a high level, can be seen as an optimal power flow (OPF) problem with different variations. The OPF operates power system under optimal states to satisfy certain objectives, such as minimizing total operational cost, active power loss, voltage deviation, etc., and meets certain constraints, such as power balance, generation, conductor flow, transformer and capacitor limits etc. (Bai, Eke and Lee, 2017). OPF normally can be categorized as ACOPF or DCOPF, where ACOPF considers the full AC trigonometric power balance node equations, which will be described in Section 2. DCOPF simplifies such equations into linear functions. Therefore, ACOPF is a highly non-linear and non-convex optimization problem due to the power balance node equations and possible discrete variables. Even though feasible solutions can be obtained via OPF, there is still chances that system operating point is near the voltage stability margin. Therefore, VSC-OPF has been widely discussed (Yao, Molzahn and Mathieu, 2019). To quantify system's voltage stability, Glavitch and Kessel (1986) introduced L-index for each bus which depends on the viability of load flow equations for every node. The L-index varies from 0 to 1, and the closer it is to 1, the less stable the node bus voltage is, because it denotes the possibility of voltage collapse for that bus, where 0 means no load and 1 means voltage collapse. Trivedi, Parmar and Jangir (2018) have developed the OPF to enhance voltage stability with the aid of L-index. A voltage collapse proximity indicator (VCPI) is proposed in (Zabaiou, Dessaint and Kamwa, 2017) to indicate the level of voltage instability in the system. Yet, those indices are local instead of global VSM indicators.

As mentioned above, OPF is a highly non-linear and non-convex problem. The VSC-OPF considering SSV is also a very challenging problem because SSV is non-linear and has very complicated relationship with state variables (voltage

10.1016/j.ifacol.2022.07.072

magnitude and angle). Traditional methodologies such as mixed integer programming, non-linear programming (interior point method, quadratic programming etc.) have been proposed to solve the OPF problem (Wang and Chiang, 2021). The drawbacks of those methods include 1) original ACOPF is simplified as DCOPF which sacrifices the accuracy and even the solutions may not be feasible when plugging back to real OPF, 2) no integer control variables are considered, 3) without simplification, problems with large number of buses may take very long time to solve. Modern heuristic optimization techniques which include evolutionary computation, has been widely discussed, developed, and improved with variants to solve power system problems (Lee and Vale, 2020). It is demonstrated that, if with the good balance of exploration and exploitation, the OPF can be efficiently solved by modern heuristic methods. (Lee and El-Sharkawi., 2008; Bai, Eke and Lee, 2017). Therefore, a successful hybrid method, differential evolutionary particle swarm optimization (DEEPSO) is adopted and modified in this work to tackle the problem.

In all, the contributions of this paper are:

(1) A global stability index, SSV is adopted to formulate VSC-OPF. The SSV is modelled explicitly with the aid of load flow results.
(2) A novel hybrid technique, DEEPSO is adopted and modified to tackle the VSC-OPF problem. Results on the IEEE-30 bus system have demonstrated its effectiveness.
(3) The effects of all bus voltage conditions for SSV are conducted to analyze operational conditions, which can help operators gain more insights into voltage stability margins and thus better understand system's stability.

The paper is organized as follows: Section II presents classic power flow problem and SSV, and then formulates the VSC-OPF problem. Section III describes the DEEPSO methodology and its implementation in the optimization problem. In Section IV the proposed algorithm is evaluated in two case studies. Finally, the conclusion is provided in Section V with recommendation for future works.

2. PROBLEM FORMULATION

In this section the classical power flow (PF) is derived first by using bus injection model (BIM) and introduces SSV of the load flow Jacobian matrix as a voltage stability index. Lastly, we formulate the VSC-OPF to consider different objectives.

2.1 Power Flow and System Stability

When analyzing power systems, neither the complex bus voltages nor the complex current injections are known. Rather, we know the complex power being consumed by the load (negative injection), and the power being injected by the generators plus their voltage magnitudes. If we consider BIM, the injection current can be calculated as:

$$I_i = I_{Gi} - I_{Di} = \sum_{k=1}^{n} Y_{ik} V_k \quad (1)$$

where I_i is the complex current injection at bus i, I_{Gi} is the total generation current, I_{Di} is the total load current at bus i, Y_{ik} is the ik-element in Y admittance matrix and V_k is the complex voltage at bus k. As mentioned above, complex power injection Si is known:

$$\mathrm{S_i} = V_i I_i^* = V_i \left(\sum_{k=1}^{n} Y_{ik} V_k\right)^* = V_i \sum_{k=1}^{n} Y_{ik}^* V_k^* \quad (2)$$

$$\mathrm{S_i} = S_{Gi} + S_{Di} = P_i + jQ_i \quad (3)$$

Therefore, the net real and reactive power injection to bus i, also known as the power balance equations can be formulated as (Bai, Eke and Lee, 2017):

$$\mathrm{P_i} = \sum_{k=1}^{n} |V_i||V_k| \left(G_{ik}\cos\theta_{ik} + B_{ik}\sin\theta_{ik}\right) = P_{Gi} - P_{Di} \quad (4)$$

$$\mathrm{Q_i} = \sum_{k=1}^{n} |V_i||V_k| \left(G_{ik}\sin\theta_{ik} - B_{ik}\cos\theta_{ik}\right) = Q_{Gi} - Q_{Di} \quad (5)$$

where P_i, Q_i are the real and reactive power injection, P_{Gi}, P_{Di}, Q_{Gi}, Q_{Di} are the real and reactive power generation and demand at bus i, respectively, G_{ik}, B_{ik} and θ_{ik} are the conductance, susceptance, and the angle difference between bus i and k, respectively.

As shown in Fig.1, the 4-bus system demonstrates the concept of complex power injection. S_inj1 is the injection power due to generator at Bus 1, S_inj3 and S_inj4 are the injection power due to load 1 and load 2. Note that S_inj2 is zero because there are no injection components.

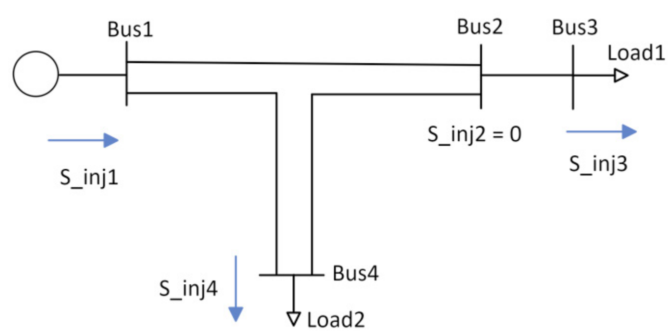

Fig.1. 4-bus system load flow illustration.

In essence, PF problem is to determine the voltage magnitude/angle of each node, where we assume bus 1 as slack bus whose voltage magnitude and angle are known. The load flow is to solve $\boldsymbol{f}(\mathbf{X}) = 0$ to obtain state variables for other buses:

$$\boldsymbol{x} = \begin{bmatrix} \theta_2 \\ \vdots \\ \theta_n \\ |V_2| \\ \vdots \\ |V_n| \end{bmatrix} \qquad \boldsymbol{f}(\boldsymbol{x}) = \begin{bmatrix} P_2(\boldsymbol{x}) - P_{G2} + P_{D2} \\ \vdots \\ P_n(\boldsymbol{x}) - P_{Gn} + P_{Dn} \\ Q_2(\boldsymbol{x}) - Q_{G2} + Q_{D2} \\ \vdots \\ Q_n(\boldsymbol{x}) - Q_{Gn} + Q_{Dn} \end{bmatrix} = 0 \quad (6)$$

where $f(\mathbf{X})$ is the power balance equation rewritten from (4) and (5). The most common way to solve $\mathbf{X}$ is by Newton-Raphson iterative method, in which Jacobian matrix $\mathbf{J}$ is calculated in each iteration:

$$\boldsymbol{x}^{(v+1)} = \boldsymbol{x}^{(v)} - \boldsymbol{J}(\boldsymbol{x}^{(v)})^{-1}\boldsymbol{f}(\boldsymbol{x}^{(v)}) \tag{7}$$

$$\boldsymbol{J}(\boldsymbol{x}) = \begin{bmatrix} \frac{\partial f_1(x)}{\partial x_1} & \frac{\partial f_1(x)}{\partial x_2} & \cdots & \frac{\partial f_1(x)}{\partial x_n} \\ \frac{\partial f_2(x)}{\partial x_1} & \frac{\partial f_2(x)}{\partial x_2} & \cdots & \frac{\partial f_2(x)}{\partial x_n} \\ \vdots & \ddots & \ddots & \vdots \\ \frac{\partial f_n(x)}{\partial x_1} & \frac{\partial f_n(x)}{\partial x_2} & \cdots & \frac{\partial f_n(x)}{\partial x_n} \end{bmatrix} \tag{8}$$

where v is the iteration index.

Inverting $\mathbf{J}$ takes a lot of computing time, and sometimes if $\mathbf{J}$ is ill-formed, the matrix inversion will fail. Thus, there is a high positive correlation between system stability and the success of $\mathbf{J}$ inversion. Therefore, we denote $\sigma_s(\mathbf{J})$ as the smallest singular value of $\mathbf{J}$ matrix to represent the current distance between the operating point and voltage stability limit (Tiranuchit and Thomas, 1988).

2.2 VSC-OPF Formulation

The goal of OPF is to optimize objective functions by determining a setting of control variables while satisfying network constraints and operational requirements. Its mathematical formulation is:

$$\text{Min} f(x,u) \tag{9}$$

$$\text{s.t. } g(x,u) = 0 \tag{10}$$

$$h(x,u) \le 0 \tag{11}$$

where vector u represents decision/control/independent variables and it includes generator real power P_G except at the slack bus, generator bus voltage V_G, transformer tap T, and shunt compensator Q_C at selected buses. The vector x is state/dependent variables which include real power P_{G1} at the slack bus, voltages V_L at load bus, reactive power Q_G at generator bus, and loadings S_L of transmission lines. As mentioned above, VSM can be measured by SSV of $\mathbf{J}$, $\sigma_s(\mathbf{J})$, and to be included in the OPF. The following lists three objective functions, minimizing total operational cost, line losses, and maximize the SSV of Jacobian matrix:

$$f_1 = min \sum_{i=1}^{Ng} a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{12}$$

$$f_2 = min \sum_{k=1}^{N_l} \frac{r_k}{r_k^2 + x_k^2} \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j) \right] \tag{13}$$

$$f_3 = \max\ \sigma_s(\boldsymbol{J}) \tag{14}$$

where a_i, b_i, c_i, and P_{Gi} denote for the fuel cost coefficients and real power of the i-th unit, N_l is the total number of transmission lines, N_g is the total generation bus, r_k and x_k represent the resistance and reactance of the transmission line k that links bus i and j, and V_i, V_j, δ_i and δ_j are the voltages and angles at bus i and j, respectively. The equality constraints g in (10) are the AC power flow balance equations at each bus, defined in (4) and (5). Inequality constraints h in (11) are listed as generator limits, tap position of transformers, shunt capacitor constraints, security constraints, load bus voltage and transmission line flows. To handle the inequality constraints, penalty function is introduced as:

$$p(x_i) = \left\{ \begin{array}{lll} (x_i - x_{i,max})^2 & if & x_i > x_{i,max} \\ (x_i - x_{i,min})^2 & if & x_i < x_{i,min} \\ 0 & if & x_{i,min} < x_i < x_{i,max} \end{array} \right\} \tag{15}$$

where p is the penalty function of dependent variable x_i at bus i. Thus, the augmented objective function by adding the penalty function of the slack bus, reactive power generation, and PQ bus voltage and transmission line capacity is described as:

$$\begin{aligned} F = f + C_p p(P_{G1}) + C_q \textstyle\sum_{i=1}^{N_G} p(Q_{Gi}) \\ + C_v \textstyle\sum_{i=1}^{N_{pq}} p(V_{Li}) + C_s \textstyle\sum_{i=1}^{N_l} p(S_{Li}) \end{aligned} \tag{16}$$

where f is the original fuel cost function, C_p, C_q, C_v and C_s respectively denote for penalty factors for real power generation of slack bus, reactive power output of the generator buses, PQ bus voltage, and transmission line capacity. In this paper, VSC-OPF is to optimize (14), the SSV.

3. METHODOLOGY

In this section, EPSO is briefly discussed and then followed by the idea of DEEPSO and its application to OPF.

3.1 EPSO concept

Particle Swarm Optimization (PSO) was first introduced by Kennedy and Eberhart in 1995. In essence, this algorithm is to explore the search space by particles. From one iteration to the following, each particle Xi (a vector of optimization variables) obeys to a movement rule which depends on a velocity V_i^{new}, which in turn depends on three main factors known as inertia, memory, and cooperation:

$$X_i^{new} = X_i + V_i^{new} \tag{17}$$

$$V_i^{new} = D(t)w_{i0}V_i + R_1 w_{i1}(b_i - X_i) + R_2 w_{i2}(b_g - X_i) \tag{18}$$

The first term represents the inertia of the particle, making it to move in the previous direction, which is affected by a function $D(t)$ responsible to decrease the importance of the inertia term during the algorithm. The second term represents the memory of the particle, making its movement being attracted to the *personal best bi*. The last term denotes cooperation, with the particles exchanging information to define the *global best*, b_g, found by the whole swarm. The parameters w_{i1}, w_{i2} are the weights of each term and R_1 and R_2

are random numbers generated from a uniform distribution in [0,1].

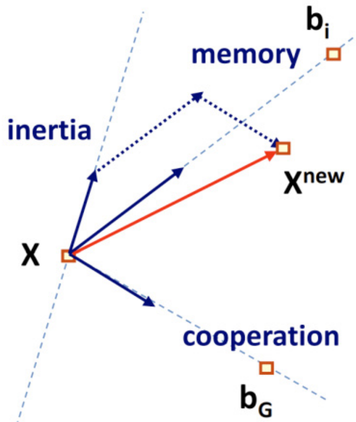

Fig. 2. PSO illustration.

Fig. 2 illustrates how new particle is governed by inertia, memory, and cooperation. Apparently, one downside is that original PSO requires too many parameters to tune, which can be another complex optimization problem. Thus, adopting the concept of evolutionary computing algorithm, evolutionary PSO (EPSO) was first introduced by (Miranda and Fonseca, 2002). The main structure of the velocity function remains the same, but those parameters will evolve by themselves to adapt the search process.

$$V_i^{new} = w_{i0}^* V_i + w_{i1}^* (b_i - X_i) + w_{i2}^* (b_g^* - X_i) \quad (19)$$

$$b_g^* = b_g + w_{i3}^* N(0,1) \quad (20)$$

$$w_{ik}^* = w_{ik} [LogN(0,1)]^{\tau} \quad (21)$$

where w_{ik}^* (w_{i0}^*, w_{i1}^* ...) are weights, as opposed to the constant weights in PSO, they undergo certain mutation. They are defined by a random variable based on a log distribution with mean 0 and variance 1; b_g^* is the global best with normal distribution (mean 0 and variance 1) random variable added to the original b_g. Details can be found in (Miranda and Fonseca, 2002).

3.2 DEEPSO and its application to OPF

Given a population (swarm) of individuals (particles), the basic idea of differential evolution (DE) is to generate a new individual by adding the information of the difference of two randomly selected individuals (X_{r1}, X_{r2}) to the current solution X_i (Storn and Price, 1997). Such process ensures more diversity, and thus increase the exploration ability. The DEEPSO was proposed by (Miranda and Alves, 2013). It combines the concepts of DE and EPSO to increase the efficiency. Its movement rule is now defined as:

$$V_i^{new} = w_{i0}^* V_i + w_{i1}^* (X_{r1} - X_i) + w_{i2}^* (b_g^* - X_i) \quad (22)$$

Compare (22) with (19), we notice that DEEPSO leans more to EPSO, and the only difference is to replace the personal best, b_i with X_{r1} in current generation as shown in Fig. 3.

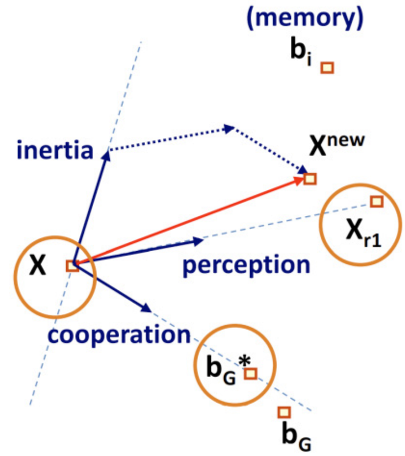

Fig. 3. DEEPSO illustration.

Fig. 3 illustrates a flavour of differential evolution in EPSO, which is the X_{r1} information. DEEPSO consists of inertia, perception, and cooperation terms. In this work, to gain better performance of DEEPSO, the movement rule (22) is modified as:

$$\begin{cases} V_i^{new} = w_{i0}^* V_i + w_{i1}^* (X_{r1} - X_i) + w_{i2}^* (b_g^* - X_i) \\ V_i^{new} = w_{i0}^* V_i + w_{i1}^* (X_i - X_{r1}) + w_{i2}^* (b_g^* - X_i) \end{cases} \quad (23)$$

If the fitness value of X_{r1} is less than that of X_i ($F(X_{r1}) < F(X_i)$), then use the second equation in (23), otherwise use the first equation in (23). Eventually, how DEEPSO is applied to OPF is summarized in the flow chart in Fig. 4:

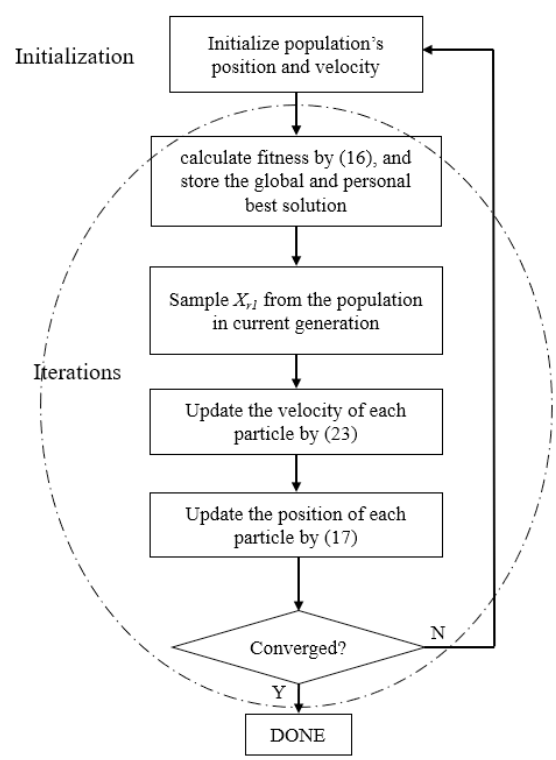

Fig. 4. Flow chart of OPF based on DEEPSO.

4. CASE STUDIES

IEEE 30-bus system is used to test the proposed algorithm. There is total 24 control variables which consist of 5 real power output control at PV bus and voltage magnitudes control of all 6 generator buses, 9 shunt compensators control for injecting reactive power and four transformer tap controls. In addition, lines 4-12, 6-9, 6-10, and 28-27 are equipped with tap-changing transformers. The system is at 100 MVA base with active power demand of 2.834 p.u. and reactive power demand of 1.262 p.u.

In Case 1, we conduct OPF with two traditional objectives to test the proposed algorithm's effectiveness, and then VSC-OPF is conducted in Case 2 where some insights are given regarding system stability. The computer used for simulation has 3.4 GHz Intel core i7 Processor and 32 GB RAM. The AC power flow was calculated by MATPOWER package (Zimmerman, Murillo-Sanchez, and Thomas, 2011).

Case 1: Traditional OPF on two objective functions

Case 1 includes 2 scenarios: minimizing quadratic cost function (12) and minimizing line loss (13). The data of IEEE 30-bus test system, and control variable limits and fuel cost coefficients can be found in (Lee, Park, and Ortiz, 1985). Table I gives the generator data. Table II and III presents the cost and computing time in seconds by different methods.

Table I. Generator Data

Buses	Pmax (MW)	Pmin (MW)	Qmax (Mvar)	Qmin (Mvar)
1	250	50	10	0
2	80	20	50	-40
5	50	15	40	-40
8	35	10	40	-10
11	30	10	24	-6
13	40	12	24	-6

Table II. Cost

Scenario	ABC		PSO		DEEPSO	
	mean	std	mean	std	mean	std
1	\$831.31	21.16	\$830.29	63.35	\$801.94	0
2	1.67MW	0.17	1.37MW	0.07	1.32MW	0.01

Table III. Computing time (s)

Scenario	ABC		PSO		DEEPSO	
	mean	std	mean	std	mean	std
1	40.46	0.58	27.94	1.85	42.46	1.51
2	42.56	0.71	34.18	1.26	46.17	1.80

As shown from above tables, DEEPSO was compared with artificial colony bee (ABC) and the basic PSO. It was able to find best solutions in two cost functions which demonstrates its search ability. The DEEPSO has nearly 0 standard deviations in both scenarios, which proves the stability. Note that (13) in Scenario 2 contains more non-linearity than (12) and yet DEEPSO shows better improvement, which demonstrates its search ability in complex problem.

Also, since DEEPSO contains extra sampling and adaptive process, in both scenarios, it spent more time than other two methods given the same iterations.

Case 2: VSC-OPF and analysis

The objective of Case 2 is to maximize SSV of Jacobian matrix (in reality, minimizing negative SSV) to increase the voltage stability.

Table IV. SSV by DEEPSO

	Normal condition	Ill condition 1	Ill condition 2
Average voltage	1.03p.u	0.73p.u	0.53p.u
SSV	0.2351	0.1289	0.0307
SSV by DEEPSO	0.2414	0.1378	0.0828

As shown in Table IV, we adjusted bus voltages and experimented the effects of VSC-OPF. The SSV of normal condition of IEEE-30 bus is 0.2351, and PF solves successfully. The average bus voltage is 1.03 pu; then we modified each bus voltage to an ill condition, where average bus voltage is 0.73p.u and PF still solves; then we changed the bus voltage to a very low point, where average bus voltage is 0.53, PF fails to converge, and SSV is 0.03.

It is noticed that SSV found by DEEPSO got improved on all cases: in normal condition, it had least improvement because system operating condition has enough distance to stability margin, while in ill condition 2, it improves the most because system has already collapsed, in other words, it has lots of room to improve. It is also noticed that by controlling capacitors, VSC-OPF can improve SSV more efficiently than the case without capacitors. One additional thing to point out is that VSC-OPF doesn't consider constraints such as bus voltage limits because if the initial condition is already very ill (e.g., average bus voltage is 0.5), even after VSC-OPF controls, it will be almost impossible for all bus voltages to increase into the normal ranges.

6. CONCLUSIONS

In this paper, DEEPSO, a successful hybrid modern heuristic method, is adopted and modified to tackle the VSC-OPF problem to increase system's voltage stability. The DEEPSO outperformed the basic PSO and ABC in OPF under two objectives due to its self-adaptive process of weights and differential evolution concept of including more diverse solution. The method stands out significantly on very low standard deviation, which proves its stability. Then we adopted SSV as the global index of system voltage stability and proves its positive correlation with system voltage stability. By DEEPSO, SSV were successfully increased, in all scenarios and thus make OPF from unsolvable to solvable. Also, VSC-OPF can be an effective tool to increase the system stability, and study tool for operators to understand deeper on what may affect system stability. Future work can focus on combining maximize SSV with other objective functions for OPF to tackle practical problems.

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