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Multi-Objective Optimal Allocation and Sizing of Hybrid Photovoltaic Distributed Generators and Distribution Static Var Compensators in Radial Distribution Systems Using Various Optimization Algorithms

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Abstract

In the recent years, a considerable growth was about the integration of renewable sources in the Radial Distribution Systems (RDS), as Photovoltaic Distributed Generators (PVDG) due to their importance in achieving plenty desired technical and economic benefits. Implementation of the Distribution Static Var Compensator (DSVC) in addition to the PVDG would be one of the best choices that may provide the maximum of those benefits. Hence, it is crucial to determine the optimal allocation of the devices (PVDG and DSVC) into RDS to get satisfactory results and solutions. This paper is devoted to solving the allocation problem (location and sizing) of hybrid PVDG and DSVC units into the standards test systems IEEE 33-bus and 69-bus RDSs. Solving the formulated problem of the optimal integration of hybrid PVDG and DSVC units are based on minimizing the proposed Multi-Objective Functions (MOF) which is represented as the sum of the technical-economic parameters of Total Active Power Loss (TAPL), Total Reactive Power Loss (TRPL), Total Voltage Deviation (TVD), Total Operation Time (TOT) of the overcurrent relays (OCRs) installed in the RDS, the Investment Cost of PVDGs (ICPVDG) and the Investment Cost of DSVC (ICDSVC)), by applying various recent metaheuristic optimization algorithms. The simulation results reveal the superiority and the effectiveness of the Slime Mould Algorithm (SMA) in providing the minimum of MOF, including minimization of the powers losses until 16.209 kW and 12.110 kVar for the first RDS, 4.756 kW and 7.003 kVar for the second RDS, enhancing the voltage profiles and the overcurrent protection system. Based on the paper's results it is recommended to optimally integrate both PVDG and DSVC units into practical distribution networks.

Introduction

The capacities of the distribution lines are usually limited; therefore, it is important to consider the future load additions, and how they will be served [1]. The renewable energy sources-based Distributed Generation (DG) can help to solve the challenges mentioned above for future MV Radial Distribution System (RDS).

Aside from traditional producing units, modern power systems incorporate a variety of Renewable Energy Sources (RESs) [2]. There are several FACTS (Flexible Alternating Current Transmission System) devices available.

For now, FACTS devices are the most sophisticated tools of reactive energy compensation used in RDS [3]. In RDS, the reactive power flow produces issues such as power losses, poor power factor, voltage drop, and so on. As a result, reactive power compensation is critical in the operation of the RDS in order to tackle the concerns outlined [4]. In passive RDSs, some of the achieved benefits when the Photovoltaic Distributed Generation (PVDG) sources are present, assigned to other devices among which Distributed Static Var Compensator (DSVC) stand out. The allocation of DSVC to enhance the reliably and performance of the RDS, is known as one of the most affordable solutions.

For the past few years, many methods and optimization algorithms applied for finding the optimum allocation of PVDG and DSVC simultaneously, to compensate both of active and reactive powers in RDSs: applied Mixed integer linear programming (MILP) to the maximum hosting capacity of DG and SVC in RDS in [5], an analytical method based the bus impedance matrix for minimizing active power loss in [6], Chu-Beasley Genetic Algorithm (CBGA) to reduce the investment and operation costs in [7], Enhanced Genetic Algorithm (EGA) to minimize both of total active power losses and the voltage deviation in [8]. Applied fuzzy and GA technique for reducing the power supply and the active power loss in [9], Implemented Mutation Differential Evolution (IMDE) algorithm to mitigate the total cost of losses in the year in [10], Adaptive Differential Search (ADS) algorithm to reduce the total power loss and total combined cost in [11].

Applied Particle Swarm Optimization (PSO) algorithm-based loss sensitivity factor for power loss and voltage deviation reductions in [12], External PSO (EPSO) algorithm to maximum value for the economic savings in [13], Constriction Factor PSO (CFPSO) algorithm for minimizing power losses and voltage deviation with improving the voltage stability index in [14], Cuckoo Search Algorithm (CSA) to minimize loss power, voltage deviation and the SVC's investment cost of in [15], Improved Grey Wolf algorithm (IGWA) to minimize the investment costs, the active power losses, and the system voltage deviations in [16], Enhanced Grey Wolf Algorithm (EGWA) for minimizing the investment equipment, and maximizing the benefits from power losses reduction in [17], Applied Biogeography-Based Optimization (BBO) algorithm for minimization of total harmonic distortion, also to reduce powers loss in [18], Moth–Flame Optimization (MFO) algorithm applied for minimizing the power loss, voltage deviation, and annual operating cost in [19], used Back-tracking Search Algorithm (BSA) for minimization the power losses in [20], Water Cycle Algorithm (WCA) for minimizing the voltage deviation, power losses, energy cost, and emissions in [21], Implanted the Salp Swarm Algorithm (SSA) to attain technical, economic, and environmental benefits in [22], Mutated Salp Swarm Algorithm (MSSA) for the power losses minimization in [23], the new Gbest-guided Artificial Bee Colony (GABC) algorithm for the minimization of power losses and various cost [24], recently applied an Opposition-based Competitive Swarm Optimizer (OCSO) algorithm to minimize the annual operating cost [25].

In this paper, an allocation (location and sizing) problem of PVDG and DSVC units have been formulated in order to minimize a Multi Objective Functions (MOF) which is considered as the sum of the technical and economical parameters of Total Active Power Loss (TAPL), Total Reactive Power Loss (TRPL), Total Voltage Deviation (TVD), Total Operation Time (TOT) of the overcurrent relays installed in the RDN, the Investment Cost of PVDGs (IC_{PVDG}) and the Investment Cost of DSVC (IC_{DSVC}). Solving the mentioned allocation problem of PVDGs and DSVC was based on the applying and comparing of various new optimization algorithms that been developed in the last years, which are Particle Swarm Optimization (PSO) [26], Whale Optimizer Algorithm (WOA) [27], Ant Lion Optimization (ALO) [28], Grasshopper Optimization Algorithm (GOA) [29], Salp Swarm Algorithm (SSA) [30] and Slime Mould Algorithm (SMA) [31]. The selected algorithms were tested on the two standards IEEE 33-bus and 69-bus radial distribution systems.

The study is composed of 4 main sections followed by a list of references, where it is organized as:

Section I: presenting the models of PVDG and DSVC units.

Section II: demonstrates the evaluation of the proposed Multi-Objective Functions.

Section III: reveal the obtained Optimal Results and Analysis. Final Section: Contains the Conclusions and the achievements including the future perspectives.

The PVDG and DSVC Modeling

Model of PVDG

The beta Probability Density Function (PDF) represent the model of solar irradiance at each of the day's hours, which is based on historical data [32]. For every period (in the actual study: 1 h), the PDF for solar irradiance may be formulated in [33]:

$$f_b(s) = \begin{cases} \dfrac{\Gamma(A+B)}{\Gamma(A)\Gamma(B)} s^{(\alpha-1)}(1-s)^{(\beta-1)} & 0 \le s \le 1 \; A, B \ge 0 \\ 0 & Otherwise \end{cases} \tag{1}$$

where: A – and B – the parameters of $f_b\ (s)$, and are defined as:

$$B = (1-\mu)\left(\frac{\mu(1-\mu)}{\sigma^2} - 1\right) \tag{2}$$

$$A = \frac{\mu \times B}{1-\mu} \tag{3}$$

where: σ - and μ - the standard deviation and mean, respectively [34]. The solar irradiance state's probability s through any certain hour could be formulated as:

$$P_s\{G\} = \int_{s_1}^{s_2} f_b(s)\, ds \tag{4}$$

The PV module's output power can be formulated as in [31-35]:

$$P_{PV_0}(s) = N \times FF \times V_y \times I_y \tag{5}$$

$$FF = \frac{V_{MMP} \times I_{MPP}}{V_{oc} \times I_{sc}} \tag{6}$$

$$V_y = V_{oc} \times K_v \times T_{cy} \tag{7}$$

$$I_y = s[I_{sc} + K_i \times (T_{cy} - 25)] \tag{8}$$

$$T_{cy} = T_A + s\left(\frac{N_{OT} - 20}{0.8}\right) \tag{9}$$

The total output power of the DG unit depends on the PV panel specification and its irradiance characteristics.

$$P_{PV}(t) = \int_{s_1}^{s_2} P_{PV_0}(s)\, P_s\{G\} ds \tag{10}$$

Model of DSVC

The DSVC's general circuit structure is demonstrated in Figure 1 [36, 37]. It may be seen that a DSVC is composed of a thyristor-controlled reactor and fixed capacitor.

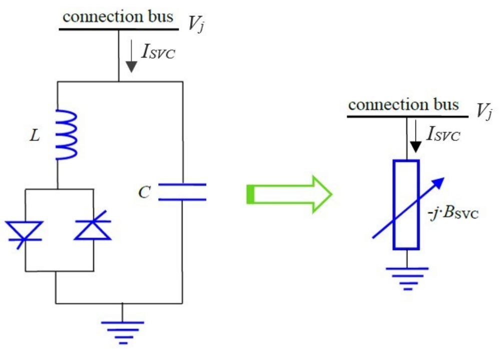

Figure 1: A model of DSVC device. Left - Circuit structure, right - Equivalent model

The equivalent susceptance of the DSVC device (BDSVC) is determined by the firing angle (α) of the thyristors [36-38], can be expressed as follows:

$$B_{DSVC} = B_L(\alpha) + B_c \tag{11}$$

$$B_L(\alpha) = -\frac{1}{L\omega}\left(1 - \frac{2\alpha}{\pi}\right), B_C = C\omega \tag{12}$$

where: B_C – the parallel capacitor reactance, B_L – the series inductance reactance. C – and L – the capacitance of the capacitor and the inductance of the reactor, respectively. V_j - the value of voltage in node j. The reactive power and current controlled by the DSVC device represented by the following equations:

$$Q_{DSVC} = -B_{DSVC} V_j^2 \tag{13}$$

$$I_{DSVC} = -B_{DSVC} V_j^2 \tag{14}$$

When the load of system is capacitive, the DSVC utilize thyristor-controlled coils to consume Q_{DSVC}, otherwise, when the load of system is inductive which is predominantly, the DSVC utilize the parallel-coupled capacitors and delivers Q_{DSVC}, thus ameliorating voltage conditions [38]. The acceptable limits of DSVCs are also included in the problem formulation as a reactive power (inductive or capacitive) function [39, 40]:

$$-Q_{DSVC}^{\max} \le Q_{DSVC} \le +Q_{DSVC}^{\max} \tag{15}$$

where: $-Q_{DSVC}^{\max}$ and $+Q_{DSVC}^{\max}$ are the maximum injected inductive and capacitive reactive power boundaries of the DSVCs, respectively.

Multi-Objective Functions Evaluation

Multi-Objective Functions

The Multi-Objective Functions (MOF) is proposed and developed in this paper to optimally locate and size both of PVDG and DSVC units in the RDS by minimizing simultaneously the technical and economical parameters of Total Active Power Loss (TAPL), Total Reactive Power Loss (TRPL), Total Voltage Deviation (TVD), Total Operation Time (TOT) of the overcurrent relays installed in the RDS, the Investment Cost of PVDGs (ICPVDG) and the Investment Cost of DSVC (ICDSVC)), where it would be formulated as follows:

$$MOF = Minimize \sum_{i=1}^{N_{BLG}} \sum_{j=2}^{N_{BLG}} \sum_{i=1}^{N_{R}} \sum_{i=1}^{N_{PVDG}} \sum_{i=1}^{N_{DSYC}} \begin{bmatrix} TAPL_{i,j} + T_{RPL_{i,j}} \\ +TVD_j + TOT_i + \\ IC_{PVDG,i} + IC_{DSVC,i} \end{bmatrix} \quad (16)$$

The first technical parameter is the TAPL [41], which is formulated as follows:

$$TAPL_{i,j} = \sum_{i=1}^{N_{\text{bus}}} \sum_{j=2}^{N_{\text{bus}}} APL_{i,j} \quad (17)$$

$$APL_{i,j} = \alpha_{ij}\left(P_i P_j + Q_i Q_j\right) + \beta_{ij}\left(Q_i P_j + P_i Q_j\right) \quad (18)$$

$$\alpha_{ij} = \frac{R_{ij}}{V_i V_j} \cos\left(\delta_i - \delta_j\right) \quad (19)$$

$$\beta_{ij} = \frac{R_{ij}}{V_i V_j} \sin\left(\delta_i + \delta_j\right) \quad (20)$$

where: R_{ij} – resistance of the line. N_{bus} – the bus number, (δ_i, δ_j) – and (V_i, V_j) – the angles and the voltages, respectively. (P_i, P_j) – and (Q_i, Q_j) – active and reactive powers, respectively.

The second technical parameter is the TRPL [42], which is formulated as follows:

$$TRPL_{i,j} = \sum_{i=1}^{N_{\text{bus}}} \sum_{j=2}^{N_{\text{bus}}} RPL_{i,j} \quad (21)$$

$$RPL_{i,j} = \alpha_{ij}\left(P_i P_j + Q_i Q_j\right) + \beta_{ij}\left(Q_i P_j + P_i Q_j\right) \quad (22)$$

$$\alpha_{ij} = \frac{X_{ij}}{V_i V_j} \cos\left(\delta_i - \delta_j\right) \quad (23)$$

$$\beta_{ij} = \frac{X_{ij}}{V_i V_j} \sin\left(\delta_i + \delta_j\right) \quad (24)$$

where: X_{ij} - the resistance of the line.

The third technical parameter is the TVD [43, 44], and it is formulated as:

$$TVD_j = \sum_{j=2}^{N_{\text{bus}}} \left|1 - V_j\right| \quad (25)$$

The fourth technical parameter is the TOT of the overcurrent relay (OCR) [45, 46]:

$$TOT_i = \sum_{i=1}^{N_R} T_i \quad (26)$$

$$T_i = TDS_i\left(\frac{A}{M_i^B - 1}\right) \text{ and } M_i = \frac{I_F}{I_P} \quad (27)$$

where: I_t the relay operation time, TDS is the time dial setting. A and B are the relay's constants which set to 0.14, 0.02, respectively. M – the multiple of pickup current, I_F and I_P are the fault and the pickup current, N_R is the OCRs' number.

The fifth economical parameter is the IC_{PVDG} [47, 48]. The Investment cost (IC_{PVDG}) as the sum of installed PVDG capital cost, operation, and maintenance cost, can be formulated as follows:

$$IC_{PVDG} = \sum_{i=1}^{N_{PVDG}} C_{PVDG,i} \cdot P_{PVDG,i} \quad (28)$$

where: N_{PVDG}, C_{PVDG} and P_{PVDG} are the number of PVDG units installed, the cost of one PVDG in $/kW, and the active power injected in distribution system by PVDG in kW, respectively. The IC_{PVDG} consists of capital cost ($C_{Capital}$), operation, and maintenance ($C_{O\&M}$):

$$C_{PVDG} = C_{Capital} + C_{O\&M} \quad (\$/kW) \tag{29}$$

Capital cost is 4000 \$/kW, including PV module, inverter, transportation, and installation engineering.

The final economical parameter is the Investment cost of DSVCs (IC_{DSVC}) which are placed in the system is represented by the following equation [49, 50]:

$$IC_{DSVC} = \sum_{i=1}^{N_{DSVC}} C_{DSVC,i} \cdot P_{DSVC,i} \tag{30}$$

where: N_{DSVC}, C_{DSVC} and Q_{DSVC} the number of DSVCs installed, the cost of one DSVC in \$/kVar, and the reactive power injected in distribution system, respectively. The cost function of one DSVC is given by [49, 50]:

$$C_{DSVC,i} = 0.0003Q_{DSVC,i}^2 - 0.3051Q_{DSVC,i} + 127.38 \quad (\$/kVar) \tag{31}$$

Equality Constraints

Equality constraints may be expressed by the balanced powers equations as follows:

$$P_G + P_{PVDG} = P_D + APL \tag{32}$$

$$Q_G + Q_{DSVC} = Q_D + RPL \tag{33}$$

where: (Q_G, P_G) are the total reactive and active power from the generator. (Q_D, P_D) are the total reactive and active power of the load. (RPL, APL) are reactive and active power loss, respectively. P_{PVDG} and Q_{DSVC} are the output powers coming from PVDG and DSVC, respectively.

Distribution Line Constraints

Distribution line constraints would be given as inequality constraints and formulated as:

$$V_{min} \le |V_i| \le V_{max} \tag{34}$$

$$|1 - V_j| \le \Delta V_{max} \tag{35}$$

$$|S_{ij}| \le S_{max} \tag{36}$$

where: V_{min} and V_{max} are the minimum and maximum limits of bus voltage, ΔV_{max} is the maximum limits of voltage drop. S_{ij} and S_{max} are the apparent power in the distribution line and the maximum of apparent power, respectively.

PVDG and DSVC Units Constraints

PVDG and DSVC units constraints could be formulated as follows:

$$P_{PVDG}^{min} \le P_{PVDG} \le P_{PVDG}^{max} \tag{37}$$

$$Q_{DSVC}^{min} \le Q_{DSVC} \le Q_{DSVC}^{max} \tag{38}$$

$$\sum_{i=1}^{N_{PVDG}} P_{PVDG}(i) \le \sum_{i=1}^{N_{bus}} P_D(i) \tag{39}$$

$$\sum_{i=1}^{N_{DSVC}} Q_{DSVC}(i) \le \sum_{i=1}^{N_{bus}} Q_D(i) \tag{40}$$

$$2 \le PVDG_{Position} \le N_{bus} \tag{41}$$

$$2 \le DSVC_{Position} \le N_{bus} \tag{42}$$

$$N_{PVDG} \le N_{PVDG \cdot max} \tag{43}$$

$$N_{DSVC} \le N_{DSVC \cdot max} \tag{44}$$

$$n_{PVDG,i} / \ Location \le 1 \tag{45}$$

$$n_{DSVC,i} / \ Location \le 1 \tag{46}$$

where: P_{PVDG}^{min}, Q_{DSVC}^{min} are the minimum of the output power injected by PVDG and DSVC, respectively. P_{PVDG}^{max}, Q_{DSVC}^{max} are the maximum of output power injected by PVDG, and DSVC, respectively. N_{PVDG} and N_{DSVC} are the PVDG and DSVC units' number, respectively. n_{PVDG} and n_{DSVC} are the locations of PVDG and DSVC units at bus i.

Optimal Results and Analysis

Test Systems

The performance of the selected algorithms was tested on different standards test systems IEEE 33-bus and 69-bus RDSs which are represented in Figure 2. The first standard comprises total loads of 3715.00 kW and 2300.00 kVar, also with 33 bus and 32 branches. The second standard comprises total loads of 3790.00 kW and 2690.00 kVar, also with 69 bus and 68 branches. Both of standards test systems operate with a nominal voltage of 12.66 kV. Each of both test systems' buses is actually protected by an OCR, where it would be calculated for the first system 32 OCRs, and 68 OCRs for the second system.

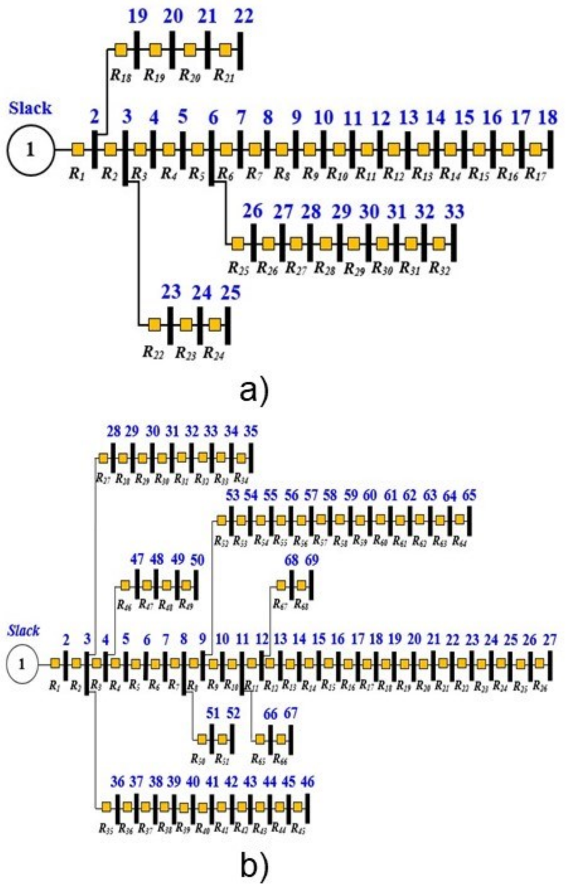

Figure 2: Single diagram of test systems: a) IEEE 33-bus, b) IEEE 69-bus

Comparison of Applied Algorithms

The following results were obtained after applying the various recent algorithms on the two standards test systems RDSs to minimize the MOF, for a maximum iterations' number of 150, and a population size equal to 10. In this paper is studied four cases (before and after the optimal allocation):

Case 1: RDS without PVDG or DSVC.

Case 2: RDS with PVDG only.

Case 3: RDS with DSVC only.

Case 4: RDS with hybrid PVDG and DSVC.

Figure 3 represents the convergence curves when applying the different algorithms for the optimal hybrid PVDG and DSVC presence in both test systems RDSs.

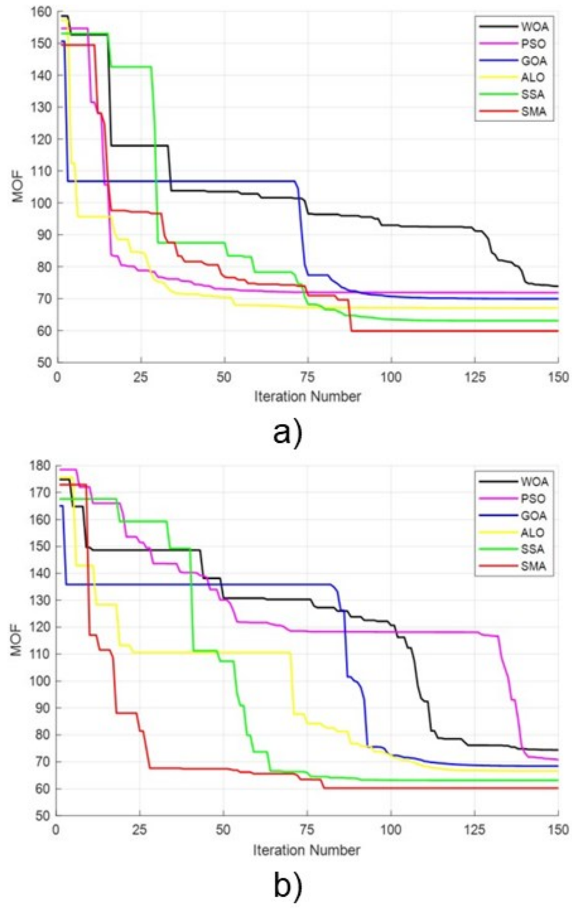

Figure 3: Convergence curves of algorithms for the PVDGDSVC integration in both RDSs: a) IEEE 33-bus, b) IEEE 69-bus

To clarifying the effectiveness and robustness of the selected recent algorithms when reaching the optimal solution for the previous formulated problem, their convergence characteristics were implemented and shown in Figure 3 for both standards test systems RDSs. It may be noted after analysing and comparing the obtained results, that all the algorithms showed a good efficiency in delivering suitable results of MOF minimization.

Hence, the SMA was the best approach that provided the minimum value of the MOF for the optimal allocation of hybrid PVDG and DSVC units in both standards test systems RDSs. For the IEEE 33-bus RDS, the SMA minimized the MOF until a value of 59.828

and converges in less than 90 iterations when searching the optimal solution. For the IEEE 69-bus RDS, the

SMA minimized the MOF until a value of 60.248 and converges in less than 80 iterations when reaching the optimal solution.

Table 1 and 2, contain the optimized technical and economical parameters, also the the optimal allocation of hybrid PVDG and DSVC units in both standars test systems RDSs respectively, when applying the different algorithms.

From Tables 1 and 2, it is revealed the effectiveness of all the applied algorithms in delivering good results for both test systems RDSs. Meanwhile, when basing on the comparison, it is obvious that the SMA was the best approach that provided the minimum of MOF when optimally allocated the hybrid PVDG and DSVC units into both RDSs. Besides, the SMA showed good efficiency in delivering even the minimum of most parameters (each by its own) for both systems.

For the IEEE 33-bus RDS, the SMA minimized the TAPL until 16.209 kW and the TRPL until 12.110 kVar, with a PVDG and DSVC units' cost of 10.894 M$ and 137.027 k$, respectively.

For the IEEE 69-bus RDS, the SMA also reduced the TAPL until 4.756 kW, the TRPL until 7.003 kVar and the TVD until 0.134 p.u. including a medium cost of PVDG and DSVC units of 9.586 M$ and 261.854 k$, respectively.

The rest of algorithms could not overcome the SMA in delivering the minimum of MOF, nevertheless, delivered some minimum values of each parameter by its own. The ALO algorithm reduced the TVD until 0.150 p.u. and the GOA delivered the minimum PVDG units' cost of 8.074 M$ for the first standard RDS. Besides, the SSA gave the minimum PVDG units' cost of 9.387 M$ and the WOA provided the PVDG units' cost of 112.602 k$, for the second standard RDS.

Tables 3 and 4 illustrate a statistical analysis for the utilized algorithms which applied to optimally integrate the hybrid PVDG and DSVC units into both test systems RDSs.

Table 3: Statistical analysis of applied algorithms for the IEEE 33-bus

	$Worst$	$Mean$	$Best$	SD	CPU $Time$
WOA	96.255	86.286	73.849	6.561	7.839
PSO	89.333	80.093	71.856	5.035	8.722
GOA	92.538	79.430	69.926	7.744	12.823
ALO	88.078	76.765	67.093	6.016	11.521
SSA	87.155	75.945	63.080	6.962	9.595
SMA	76.239	68.389	59.828	4.789	7.531

Table 4: Statistical analysis of the applied algorithms for the IEEE 69-bus.

	$Worst$	$Mean$	$Best$	SD	CPU $Time$
WOA	96.875	86.745	74.401	6.700	14.152
PSO	89.595	80.378	70.765	6.140	18.051
GOA	91.252	77.183	68.430	5.795	16.945
ALO	88.535	75.463	66.563	6.798	17.668
SSA	85.645	75.005	63.133	6.280	14.260
SMA	72.932	65.817	60.248	4.223	13.387

The statistical analysis-based Worst, Mean, Best, Standard Deviation (SD) and CPU Time, was carried out after 20 runs for each of the applied algorithms to prove their effectiveness and efficiency. Based on the analysis summary, which is mentioned in Tables 3 and 4, it is clear that SMA showed a good efficiency in all sides of the statistical analysis for both test systems RDSs, by providing the Best and the smallest Worst MOF value, also the minimum MOF's

Mean and SD values, including the quickest CPU Time for its convergence characteristics when reaching the optimal solution.

Performance of RDS Parameters

Figure 4 demonstrates the comparison of the voltage profiles in the basic case, and the rest of the studied case optimal integration into both test systems RDSs based on the optimal results obtained by the SMA approach.

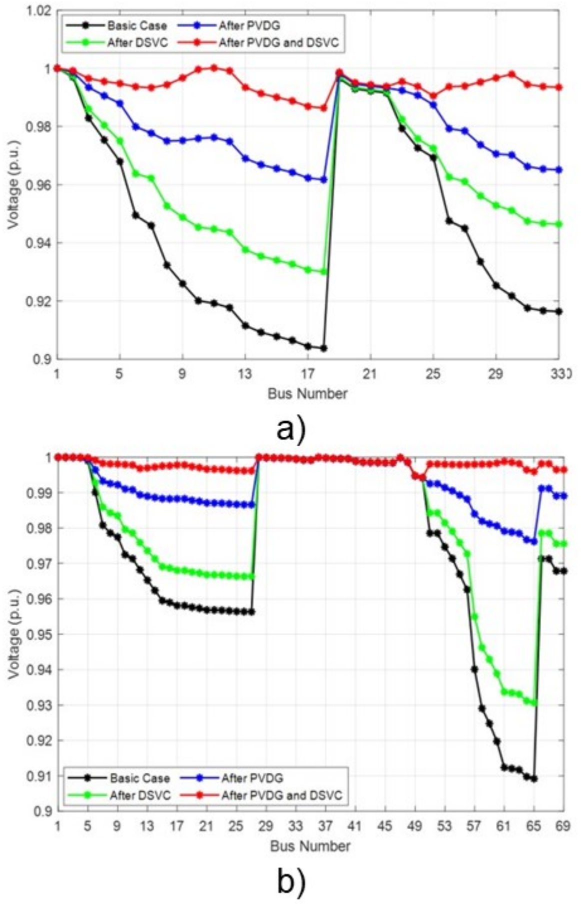

Figure 4: Voltage profiles of buses for RDSs: a) IEEE 33-bus, b) IEEE 69-bus

The influence of all cases studies integration on the voltage profiles of both test systems RDSs is mentioned in Figure 4. The voltage was improved almost in every bus of both RDSs after all cases studies integration. Beside is noticed that superior results and a significant enhancement was achieved when integrating the case of hybrid PVDG and DSVC units into both RDSs. This impact and enhancement were related to the minimization of voltage deviation, as long as it indicates the value of RDS's voltage and how much it is far from the nominal voltage value of 1 p.u.

Figure 5 illustrates the effect of all cases studies' optimal integration on the active power loss in each branch of both test systems RDSs.

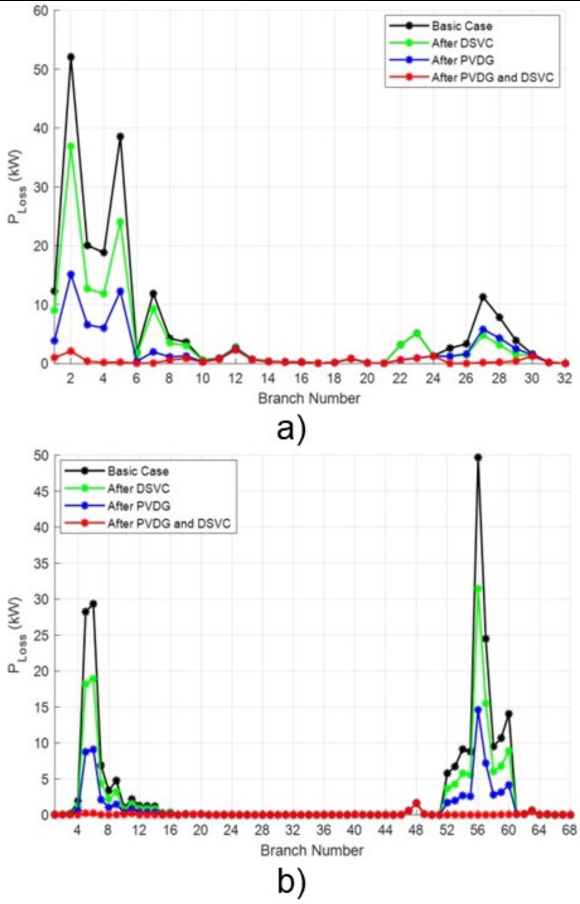

Figure 5: Active power losses in branches for RDSs: a) IEEE 33-bus, b) IEEE 69-bus.

Due to the structure of both the distribution systems which is radial, the active power losses are high in most of their branches, and that is why it is important to reduce them to attain many technical and economic advantages. As seen in Figure 5, the integration of all cases studies in both test systems RDSs, contributed excellently to reducing of the active power losses almost in each branch of both RDSs. The case of hybrid PVDG and DSVC units provided the best results of that minimization in each branch of both RDSs, if it delivers both of active and reactive powers. The integration of hybrid PVDG and DSVC units also reduced the TAPL from 210.987 kW until 16.209 kW for the IEEE 33-bus, and from 224.945 kW until 4.756 kW for the IEEE 69-bus.

Figure 6 demonstrates the difference between the primary overcurrent relays' operation time at the basic case, and after the rest of studied cases' optimal integration for both RDSs.

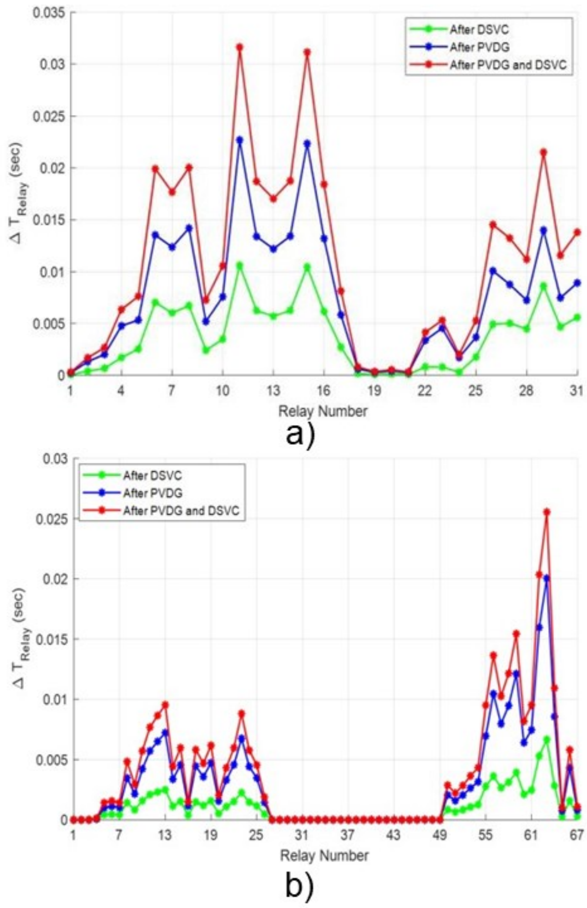

Figure 6: Overcurrent relay operation time for RDSs: a) IEEE 33-bus, b) IEEE 69-bus.

The main task of the overcurrent relays is to detect the fault current that occurs in the lines and do the quick isolation and protecting of the system. Minimizing the operation time of those OCRs is so beneficial technically (protect the system parts) and economically (extend the equipment's lifetime).

The optimal integration of all cases studies by the SMA, led to the minimization of the operation time in all OCRs installed in both standards RDSs, if it was one of the MOF parameters that should be minimized. Also, it is clear from Figure 6, that the hybrid PVDG and DSVC units' integration was best case that occurs this minimization, also providing the reducing of the TOT from 20.574 seconds to 20.232 seconds for the first standard RDS, and from 38.772 seconds to 38.507 seconds for second standard RDS.

This impact was directly related to the increasing of the fault current which was affected by the improvement of voltage profile as mentioned in the Equation 27, where the more I_F increases, the OCR will quick operate.

Figure 7 represents the graphical comparison of active and reactive power losses including the minimum value of the voltage after each of the optimal studied cases integration for both standards RDSs.

When analysing Figure 7, it may note that the minimum value of RDSs' voltage kept raising proportionally while the reducing of the active and reactive powers after all cases studies' optimal integration for both test systems RDSs. The best result for both terms of V_{min} increasing and P_{loss} and Q_{loss} decreasing were provided by the case of hybrid PVDG and DSVC units' optimal integration for both standards RDSs.

The injection of active and reactive powers by the hybrid PVDG and DSVC units into both standards RDSs reduced the active and reactive power losses until 16.209 kW and 12.110 kVar respectively, including a value of V_{min} equal to 0.986 p.u. for the first test system, meanwhile, it reduced the active and reactive power losses until 4.756 kW and 7.003 kVar respectively, including a value of V_{min} equal to 0.994 p.u. for the second test system.

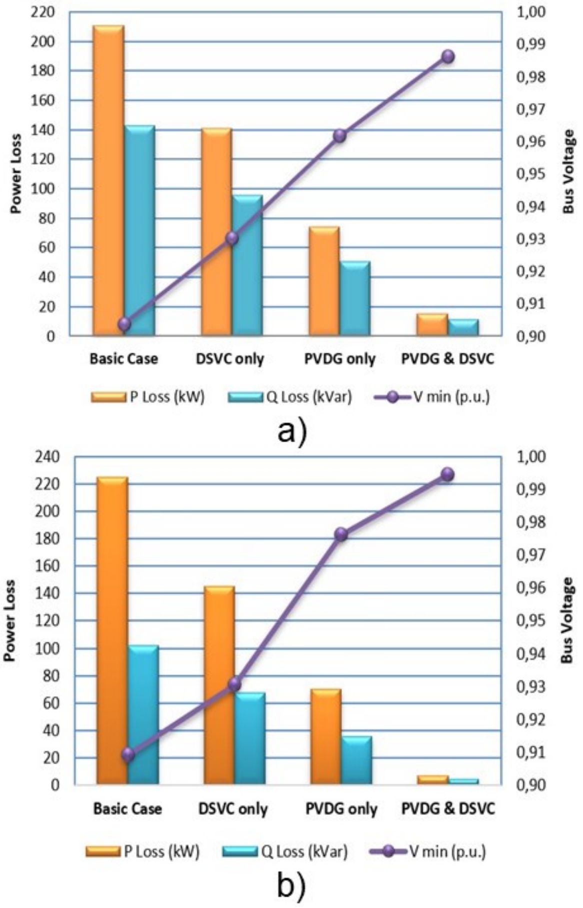

Figure 7: Comparison the power losses and minimum voltage: a) IEEE 33-bus, b) IEEE 69-bus.

Conclusions

This paper compared the effectiveness and performance of a recent metaheuristic optimization algorithms, which consecrated to solve the optimal allocation's problem of various studied cases into standards IEEE test systems when minimizing the multi-objective functions.

The results reveal that the SMA approach was successfully applied and implemented to solve the mentioned formulated problem, besides, it was the best approach among the rest of the algorithms that reached the optimal solutions. The SMA showed a good robustness and efficiency in delivering the best location and sizing of all cases studies with a quick convergence characteristic for both standards RDSs.

The best choice that provided the best results of MOF's minimization was the case of hybrid PVDG and DSVC units which led toward the best reducing of power losses, ameliorating voltage profiles by minimizing the voltage deviation until 0.194 p.u. for the first RDS and 0.134 p.u. for the second RDS, enhancing the overcurrent protection system of both studied RDSs, also providing a reasonable operation and investment costs of both integrated units (PVDG and DSVC) all in simultaneously.

Basing the previous discussions, it is recommended to widely integrate the hybrid PVDG and DSVC units into practical RDSs. Hence, the future work will be oriented and focus on optimally allocate and implement other units as the Battery Energy Storage Systems (BESS) in addition to the DSVC by applying newly optimization algorithms considering uncertainties of load demand and DGs output variation, to solve a complex MOF that includes various technical-economic indices to more improve the studied distribution systems.

Table 1: Optimization results of hybrid PVDG and DSVC for the IEEE 33-bus

	P_{PVDG} in MW, (Bus)	Q_{DSVC} in MVar, (Bus)	$TAPL$ (kW)	$TRPL$ (kVar)	TVD (p.u)	TOT (sec)	TIC_{PVDG} (M$)	TIC_{DSVC} (k$)
Basic Case			210.987	143.128	1.812	20.574	–	–
WOA	1.0343(10)	0.0871(3)						
	0.8385(25)	0.0951(5)	24.431	18.230	0.418	20.271	10.324	228.601
	0.6954(31)	1.1669(30)						
PSO	0.8149(6)	0.8018(7)						
	0.6736(14)	0.0748(22)	23.704	18.169	0.233	20.235	9.295	147.053
	0.8237(30)	0.8732(30)						
GOA	0.5060(11)	0.3748(13)						
	0.4344(16)	0.4119(23)	24.158	17.053	0.185	20.230	8.074	178.372
	1.0680(29)	1.0312(30)						
ALO	1.2065(6)	0.4407(12)						
	0.6355(14)	0.9312(30)	20.941	15.804	0.150	20.225	9.775	129.811
	0.5897(31)	0.1118(33)						
SSA	1.0018(11)	0.4793(12)						
	0.4926(25)	0.8119(23)	19.590	13.912	0.282	20.245	8.906	140.720
	0.7211(31)	0.7677(30)						
SMA	0.9363(11)	0.4706(12)						
	0.8616(24)	0.9618(30)	16.209	12.110	0.194	20.232	10.894	137.027
	0.9121(30)	0.0544(32)						

Table 2: Optimization results of hybrid PVDG and DSVC for the IEEE 69-bus

	P_{PVDDG} in MW, (Bus)	Q_{DSVC} in MVar, (Bus)	$TAPL$ (kW)	$TRPL$ (kVar)	TVD (p.u)	TOT (sec)	TIC_{PVDG} (MS)	TIC_{DSVC} (k$)
Basic Case			224.945	102.139	1.870	38.772	–	–
WOA	0.3012(3)	0.5930(36)						
	0.3444(14)	0.7499(61)	14.721	11.064	0.456	38.543	9.511	112.602
	1.7202(61)	0.5977(62)						

	0.7441(12)	1.4956(9)						
PSO	0.4565(49)	0.2853(24)	12.031	7.610	0.259	38.500	11.733	635.001
	1.7181(61)	0.9544(61)						
	0.5336(9)	0.3103(12)						
GOA	0.5630(12)	0.2686(23)	9.782	8.990	0.237	38.517	10.658	237.800
	1.5546(63)	1.1521(61)						
	0.5682(14)	0.5434(11)						
ALO	0.3000(56)	0.0224(45)	9.110	8.591	0.208	38.501	9.867	272.503
	1.5864(62)	1.2149(61)						
	0.3000(25)	0.2875(24)						
SSA	1.7022(61)	0.0410(53)	6.893	7.903	0.171	38.511	9.387	254.802
	0.3329(68)	1.1993(61)						
	0.3721(18)	0.3291(10)						
SMA	1.6706(61)	0.2723(18)	4.756	7.003	0.134	38.507	9.586	261.854
	0.3418(66)	1.1884(61)						

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