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A day-ahead hybrid optimization algorithm for finding the dispatch schedule of VPP in a distribution system

Seyed Iman Taheri*. Lucas Lima Rodrigues*.
Mauricio B. C. Salles*. Alfeu Joãozinho Sguarezi Filho**

** Polytechnic School of University of São Paulo (USP), CEP 05508-900, São Paulo, Brazil (e-mail: iman.taheri@usp.br, lucaslrodri@usp.br , and mausalles@usp.br).*
*** Universidade Federal do ABC,CEP 09210-580, São Paulo, Brazil (e-mail: alfeu.sguarezi@ufabc.edu.br).*

Abstract: Distributed renewable generations such as photovoltaic units are electricity generators for installing close to the loads on the distribution system. In this paper, the dispatch function of a non-centralized Virtual Power Plant (VPP) with having a photovoltaic unit in each bus is considered to optimize. This dispatch function is assigned based on the predicted load shape of the next day. A new day-ahead hybrid optimization algorithm is presented to optimize the dispatch function. The proposed algorithm implements a new hybrid combination of Particle Swarm Optimization (PSO) and Genetic Optimization (GA) algorithms simultaneously to benefit both algorithms' advantages. The objective function is the optimization of the voltage deviation of the VPP. The suggested algorithm is executed on a 13-bus-radial IEEE standard VPP system using MATLAB software coupled with open-source software called Open-DSS. The results show the importance of the proposed algorithm to optimize the voltage deviation of the VPP. The superiority of the proposed algorithm is related to the accuracy and calculation velocity in comparison with the other tested evolutionary algorithms. The Distribution System Operator could map and move towards its full benefits of the increasing integration of DGs with a strategic placement that could keen prosumers on integrating these actions.

Keywords: Distributed Generation; PSO; GA; single-objective; openDSS.

1. INTRODUCTION

Virtual power plant (VPP) is a technical, economic and practical structure that interconnects distributed generations (DGs) and energy storage systems (ESSs) within microgrids for the operator of the system to handle the integration of DGs (Yu et al. 2019). The common intelligent control center of VPP needs a linear programming cost minimization model of DGs and storage within microgrids (Yu et al. 2019; Kong et al. 2019).

Recently, the optimal dispatch of loads and DGs has classified as an advanced issue of the energy management system (EMS). The other important issues for EMS such as distribution power flow, integrated voltage control, and contingency analysis must be adapted to the characteristics of the distribution system (Kaur, Kumbhar, and Sharma 2014; Hosseinpour, Niknam, and Taheri 2011; Niknam, Azizipanah-Abarghooee, and Rasoul Narimani 2012). Increasing the DGs contribution percentage on the distribution system leads to benefits such as reducing power losses, harmonic distortion, and the cost of generating electricity. On the other hand, the non-optimal dispatch of DGs may increase the voltage deviation and losses of the distribution system. Hence, Optimal dispatch is essential to improve the power quality performance of the distribution system (Niknam et al. 2011; Zhang, Wang, and Ji 2015).

The computational time for simulation and accuracy to achieve the optimal point are the main differences of most optimization algorithms that have been used to solve the DGs dispatch problem (Zhang, Wang, and Ji 2015). Among optimization algorithms GA algorithm is accurate but the convergence is slow and the PSO algorithm has some advantages and disadvantages. On one hand, the PSO algorithm has simpler implementation and the parameters do not require tuning. On the other hand, the main disadvantage of the PSO algorithm is the convergence to a locally optimal solution (Bukar, Tan, and Lau 2019).

In this paper, a single-objective day–ahead hybrid optimization algorithm is presented to optimize the voltage deviation of a non-centralized VPP in a power distribution system. In the proposed algorithm, PSO and GA algorithm optimization solutions saved in a repository and non-dominated solutions of the repository are selected as optimization solutions. The suggested algorithm is worked based on the next day loads curve forecast but the time can be decreased to the next hour or the next minute if the prediction curves are available. The suggested algorithm has been applied in Matlab software that in a co-simulation environment with OpenDSS software can prepare the needed power flow data for finding optimal dispatch schedule on an IEEE (Institute of Electrical and Electronics Engineers) standard 13-bus test system. Additionally, the results of other evolutionary methods such as GA and PSO are compared with the results of the proposed algorithm.

The main contributions of the paper can be summarized as follows:

- A new single-objective algorithm is presented for finding optimal dispatch function in a VPP.
- Presenting a new optimization algorithm with combining PSO and GA to improve the robustness, accuracy and calculation speed of both algorithms.

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- A tool and algorithm are presented for load flow and dispatch analysis of a VPP.

	ACRONYMS
DG	Distributed Generation
EMS	Energy Management System
ESS	Energy Storage Systems
GA	Genetic Optimization Algorithm
IEEE	Institute of Electrical and Electronics Engineers
HBMO	Honey Bee Matting Optimization
PSO	Particle Swarm Optimization
	NOTATIONS
$f_1(\bar{X})$	Bus voltage deviation function
$f(\alpha)$	Normal distribution for achieved scores
$f_K(X)$	The K^{th} objective function
F	Matrix of all objective functions together
I	Actual current
I_{n_b}	Actual current n_b th branch of the distribution system
K	Number of objective functions
L	Number of objective functions in multi-objective Problems
M^k	Average knowledge of K^{th} learner
n	Summation of the total number of DGs and two times The total number of DGs (length of $\bar{X}$)
N_{bus}	Total number of bus
N_{DG}	Maximum number of DGs
N_b	Number of the distribution system branches
P	Active power [kW]
P_{DGi}	The power generated by i^{th} DG
$\bar{P}_{DG}$	Active power vector of all DGs
P_{DGi}^{max}	Maximum active power of the i^{th} DG
P_{DGi}^{min}	Minimum active power of the i^{th} DG
P_{sub}	Value of injected active power to the distribution system
$Price_{sub}$	Cost of substation
$Price_{DGi}$	The total cost of i^{th} DG
Q	Reactive power
R	Resistance
R_t	Teaching factor
R_{n_b}	Resistance n_b th branch of the distribution system
T^k	Average knowledge of the teacher
$V_{A,}V_B$	The magnitude of the voltage at point A and B
V_r	The magnitude of the voltage at r^{th} bus
V_r^{ref}	The magnitude of the suitable voltage
V_{max}	Upper voltage magnitude limits
V_{min}	Lower voltage magnitude limits
V_{nom}	Nominal voltage
V_{sub}	The magnitude of slack bus voltage
$\bar{X}$	Vector of location and size of DGs
$\bar{X}_{new}$	New learner (a new member of the population)
$\bar{X}_{old}$	Old learner(an old member of the population)
$X_K^{mut,v}$	Mutation vector (with K vector component for v^{th} Member of population)
X_K^v	Feasible solution vector (with K vector component for v^{th} member of population)
X_K^{new}	New generated member of the population
$Y_{sub,j}$	Value of admittance between slack bus and j^{th} bus
X_{K+1}^{new}	Equal to X_K^{new} or X_K^v based on mentioned conditions
$\theta_{sub,j}$	The angle of admittance between slack bus and j^{th} bus
Δt	New tap ration position
ΔV	Difference of voltages
δ_{sub}	The angle of the slack bus voltage
δ_j	The Angle of the voltage at the j^{th} bus

2. Placement of DGs formulation

2.1 Objective function

The bus voltage deviation in a power electrical distribution system objective function can be defined as follows:

$$f_1(X) = \sum_{m=1}^{N_{bus}} \frac{|V_{nom} - V_r|}{V_{nom}} \tag{1}$$

$$F_1(X) = \min(f_1(X)) \tag{2}$$

$f_1(X)$ is the second objective function that should be minimized by the optimization algorithm (Niknam, Azizipanah-Abarghooee, and Rasoul Narimani 2012).

2.2 Constraints

- Limitation of voltage

Permissible limits of voltage for the network should be kept as follows:

$$V_{min} \leq |V_m| \leq V_{max} \tag{3}$$

Where $|V_m|$ is the magnitude of the voltage at m^{th} bus and V_{max} and V_{min} are upper and lower voltage limits, respectively.

- DG's number

Actually, in the 'ideal case', losses of distribution system could be omitted if all loads would be supplied by their local DGs. This assumption is unrealistic as the cost of capital investment is too high but it can be considered in the VPP as a realistic assumption instead of a distribution system. Therefore, this paper has suggested a limit number of DGs in the distribution system, all loads of the VPP has a DG, to the implementation of the objective function and reduce the power losses with a given number of DGs.

$$n_{DG} \leq N_{DG} \tag{4}$$

Where N_{DG} and n_{DG} are the maximum number of DGs specified and the number of DG determined, respectively.

- Size of DGs

To limit the maximum allowable investment of DGs, the total size of DGs should be selected as:

$$\sum_{n=1}^{n_{DG}} KW_{DG}^n \leq \eta P_{load} \tag{5}$$

Where P_{load} is the total load power and KW_{DG}^n is the capacity of the nth DG. η is the mean demand of the load.

- PV System working time

In this paper, the working time for the PV system is 7:00 to 17:00 because in this range the PVs send power more than 10% of rated power.

2.3 Model for DG

DG can be modeled as PQ or PV models with considering simultaneous or independent three-phase control. It is noted that PV models should be considered reactive power for keeping the magnitude of bus voltage in their proper magnitudes (Hosseinpour, Niknam, and Taheri 2011). In the proposed approach of this paper, DGs are modeled as PQ buses, and each load has a DG with the same characteristic of the load in terms of connection.

The voltage profile and power flow of the distribution network can be changed when a DG unit has been connected to the network. The low value of $\frac{X}{R}$ in the distribution network may cause the effects of connecting DGs to the distribution network to become considerable (Niknam, Azizipanah-Abarghooee, and Rasoul Narimani 2012). For better clearance, two buses of the test system are shown in Fig. 1. This figure shows the DG and load models for bus 2 are considered as PQ models. In this paper, this model is used in the test system (i.e. 13-bus test system). The voltage sag from bus 1 to bus 2 is determined as follow:

$$\Delta V = (V_1 \prec \delta_1) - (V_2 \prec \delta_2) \tag{8}$$

$$\Delta V = (R + jX)I \tag{9}$$

$$I = \frac{(P + jQ)^*}{{V_2}^*} \tag{10}$$

$$P = P_{DG} + P_{Load} \tag{11}$$

$$Q = Q_{DG} + Q_{Load} \tag{12}$$

$$|\Delta V|^2 = \frac{(RP+XQ)^2 + (XP-RQ)^2}{{V_2}^2} \approx \frac{(RP+XQ)^2}{{V_2}^2} \tag{13}$$

Where reactive and active power components of Load and DG are shown by Q_{Load}, P_{Load}, Q_{DG}, and P_{DG} respectively, and angle and magnitude of the voltage at the i^{th} bus are shown by δ_i and V_i, respectively. Moreover, the line impedance is considered as $R + jX$ in the Eq. (13) neither XQ nor RP is negligible. Furthermore, the impacts of reactive power components on DGs are less than the active power components because the $\frac{X}{R}$ ratio is low.

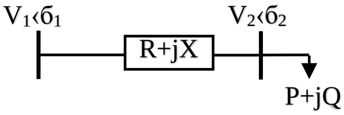


Fig. 1 Two buses of the test system show the PQ model of DG and load for Bus 2

2.4 *Virtual Power Plant Model*

VPP is defined as a combination of DGs and loads participating in the power market as an independent power plant for minimizing the voltage deviation (Yu et al. 2019). All kinds of DGs such as photovoltaic units, wind turbine or diesel generators can be implemented in the VPP structure. The core of VPP is EMS that it's duty is to coordinate the output power of generators, the load demand, and ESS capacity (Kong et al. 2019).

Fig. 2 illustrates a schematic overview of a VPP structure that is implemented in this paper. The passive management of distribution network which is generally found in a centralized system where power electricity flows from large power plants, through the transmission lines, and then through the distribution system to the load is changed here by VPP structure.

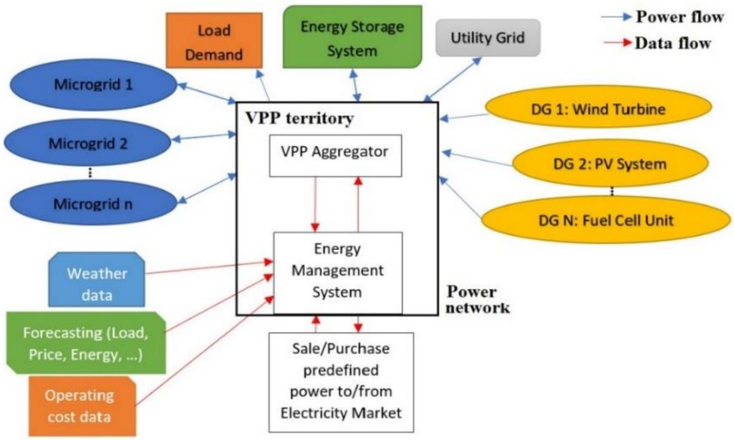


Fig. 2 The proposed VPP structure

3. PSO-GA algorithm

3.1 *PSO algorithm*

PSO is a stochastic search algorithm that was first introduced by (Zhang, Wang, and Ji 2015). It has been used extensively to solve optimization problems (Bukar, Tan, and Lau 2019). PSO algorithm consists of a population continuously updating the searching space knowledge. In the multidimensional space, each particle is moved toward the optimal point by changing its position according to velocity. The velocity of a particle is calculated by three components: inertia, cognitive and social.

The position and velocity of each particle are updated as follow:

$$S_i^{k+1} = \omega \times S_i^k + C_1 \times rand()_1 \times \left(p_i^k - X_i^k\right) + C_2 \times rand()_2 \times (g^k - X_i^k) \tag{14}$$

$$X_i^{k+1} = X_i^k + S_i^{k+1} \tag{15}$$

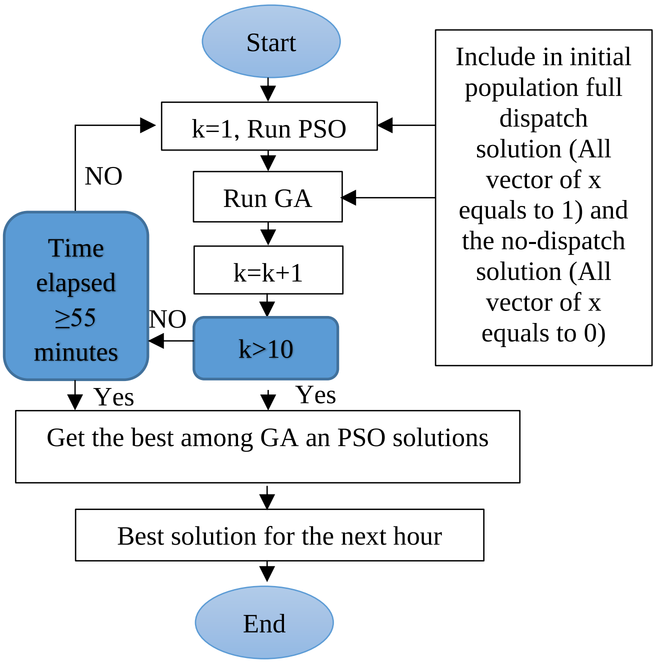
Where S_i^k is the velocity of i^{th} particle at k^{th} iteration, p_i^k is the best previous experience of the i^{th} particle that is recorded, g^k is the best particle among the entire population, $S_i^{k+1}$is the velocity of i^{th} particle at $(k+1)^{th}$ iteration, ω is an inertia weight, C_1, C_2 is positive coefficients between 0 and 2 that $C_1 + C_2 \leq 4$, and $rand()_1$, $rand()_2$ are random numbers selected between 0 and 1. The performance of the simple PSO greatly depends on C_1, C_2, and ω. The PSO details and Pseudocode of PSO are gathered in (Bukar, Tan, and Lau 2019).

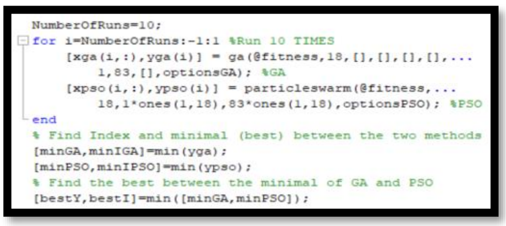
3.2 GA algorithm

The Genetic optimization algorithm is based on random search methods that are useful for global optimization problems (Jafar-Zanjani, Inampudi, and Mosallaei 2018). GA encodes the initial candidate solutions by using a population of strings. And then, it employs genetic operators (i.e. crossover, mutation, and selection) to generate new population-based on gradually evolves towards the best solution and initial population. The convergence velocity of GA is based on the values of genetic operators and the procedure of GA. The GA details and Pseudocode of GA are gathered in (Jafar-Zanjani, Inampudi, and Mosallaei 2018).

3.3 Hybrid GA-PSO algorithm for Dispatch problem

In this optimization algorithm, the population is simultaneously updated by PSO and GA algorithms (i.e. the results of both algorithms save in a repository and this repository is optimized by the proposed algorithm). If the new achieved solution of PSO or GA is better than the previous one, the best solution replaces the old solution. Otherwise, the existing solution is memorized. The flowchart and Pseudocode for implementation of the proposed algorithm for a sample of 10 times runs are shown in Fig. 3.





```
NumberOfRuns=10;
for i=NumberOfRuns:-1:1 %Run 10 TIMES
    [xga(i,:),yga(i)] = ga(@fitness,18,[],[],[],[],...
        1,83,[],optionsGA); %GA
    [xpso(i,:),ypso(i)] = particleswarm(@fitness,...
        18,1*ones(1,18),83*ones(1,18),optionsPSO); %PSO
end
% Find Index and minimal (best) between the two methods
[minGA,minIGA]=min(yga);
[minPSO,minIPSO]=min(ypso);
% Find the best between the minimal of GA and PSO
[bestY,bestI]=min([minGA,minPSO]);
```

Fig. 3 The flowchart and Pseudocode for combining PSO and GA

The impact of decision in GA leads to increase accuracy and the impact of decision in PSO algorithm leads to increase velocity. Thus, the proposed algorithm benefits the both impacts.

The proposed algorithm saves and updates the data in a repository for each iteration. Thus, it is possible to get the best solution even if all minimization process is not concluded or stopped. In this paper, the best solution of the worst scenario is the full dispatch solution or no dispatch solution (i.e. PV panels not working). Moreover, in this paper, we do not stop the minimization process but in the real system, the operator of the system stops and selects the best solution among optimized solutions. Therefore, we consider in each hour 5 minutes for the operator for performing the selection.

The fitness function for the implementation of the proposed algorithm is shown in Fig. 4. This function calculates a fitness value for each member of population (i.e. x) based on related forecast issues of next hour (I(h), c(h), and T(h)). In this figure, P_i is related power dispatched of the PV system. P_{nom} is the nominal power of the ith PV system and x_i is the dispatch of the ith PV system. $I(h), c(h) and\ T(h)$ are mean irradiation for the next hour (i.e. forecast), circuit topology (i.e. load demand for each hour, and mean temperature for the next hour (i.e. forecast), respectively. x is PVs dispatch (i.e. a vector that contains dispatch for each PV panel with considering the available power for each PV). The fitness function is defined as follow:

$$f(x, [I(h), c(h), T(h)]) \tag{16}$$

In this paper, each load contains a PV panel. The maximum absolute voltage deviation is calculated as follow:

$$M(x, h) = max\left(\left|v_{pu}(load_i) - 1\right| \cdot 100\right) \tag{17}$$

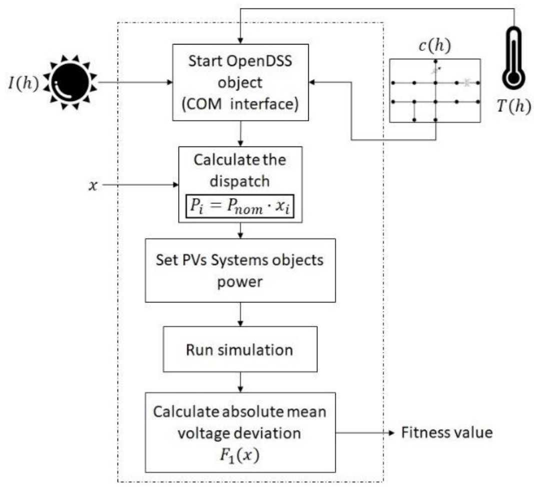


Fig. 4 the fitness function

4. Simulation Results

The proposed algorithm is employed to find the dispatch function on a test VPP IEEE 13-bus distribution system to optimize the objective function. This test feeder consists of the underground and overhead line segments, with various phasing and unbalanced loading with different types of loads. Data and details of the 13-bus test system are gathered in (Kersting 1991). The proposed method is implemented in a

MATLAB software coupled with OpenDSS software and simulations are performed on a personal computer having an i7 core processor, 3.70 GHz, and 32 GB RAM. The types of load demand prediction and interpolated curves that are used in this paper are shown in Fig. 5.

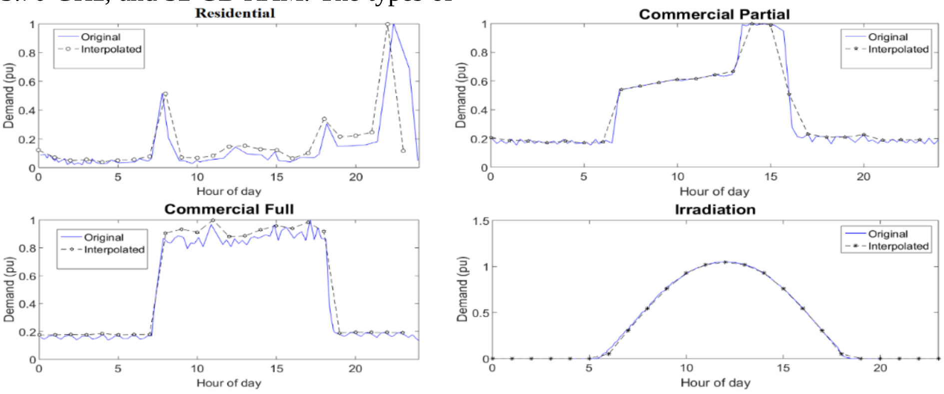


Fig. 5 Kinds of load demand prediction and interpolated curves

The prediction curve is obtained based on the next day load demand forecast. The next day, the load curve will not be the same but at least it is prepared some guesses for the operator of the VPP system. Also, the idea of decreasing the time of a day ahead to an hour ahead or a minute ahead can be performed with the same strategy. The VPP system is shown in Fig. 6. In this paper, the nominal power of each PV system is the average power of the load and we considered that all PVs have a power factor equal to one. Data and Power flow between VPP and other sections are considered in this simulation.

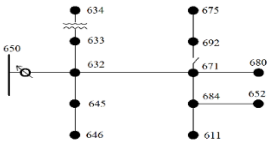


Fig. 6 Standard 13 bus VPP system as a test system (Kersting 1991)

Analysis of Fig. 7 shows the best places and capacities for working PVs. This figure is results of using fitness function in the proposed algorithm (i.e. fig.4 shows the details of implementation). It is noted that the results are based on the predicted load curve and it is considered that solar panels can work from 7 AM to 5 PM and weather prediction is not considered. In this paper, all buses (i.e. vertical axis of fig. 7) have the same PV panel but their electricity generation is optimized based on the objective function. Thus, in this figure, the best buses and size for electricity generation of solar panels are the buses that have the numbers near the 100.

PV System \ Hour	7	8	9	10	11	12	13	14	15	16	17
611c	4	0	4	70	82	99	53	95	5	1	9
692ca	11	0	100	100	99	94	100	98	100	98	100
675c	10	0	2	43	35	33	38	40	7	8	1
675b	97	99	3	1	1	2	3	1	3	1	6
675a	13	0	100	100	100	92	98	100	100	99	100
671	36	31	100	50	20	97	26	46	100	99	100
652a	8	0	100	100	98	93	98	100	100	99	100
646bc	9	0	100	34	69	95	67	25	100	99	100
645b	50	96	5	0	3	1	2	2	6	1	11
634c	9	4	5	1	2	2	4	0	4	0	17
634b	3	96	0	1	1	4	2	4	5	7	13
634a	7	1	100	100	99	100	97	100	100	99	100

Fig. 7 Best fitness for the next day to show the best buses and size for electricity generation of solar panels

Fig. 8 shows the cumulative distribution function for the standard deviation of the dispatch. Analysis of this figure shows GA optimum solutions are more dispersion than the PSO algorithm. It means that in some cases the PSO algorithm may achieve local optimum instead of global optimum but as shown in Fig. 9, in this case, the result of both optimization algorithms was the same.

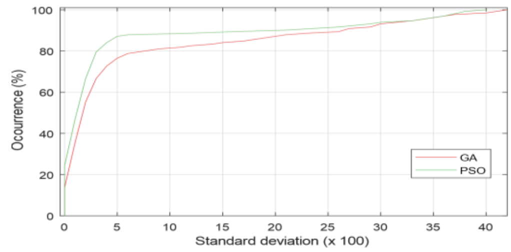


Fig. 8 Cumulative distribution function for the voltage standard deviation of dispatch to compare optimization algorithms

The performance between PSO and GA optimization algorithm is shown in Fig. 9. Analysis of the figure shows the PSO and GA algorithms have the same outputs in minimization. However, GA has a higher standard deviation than the PSO algorithm.

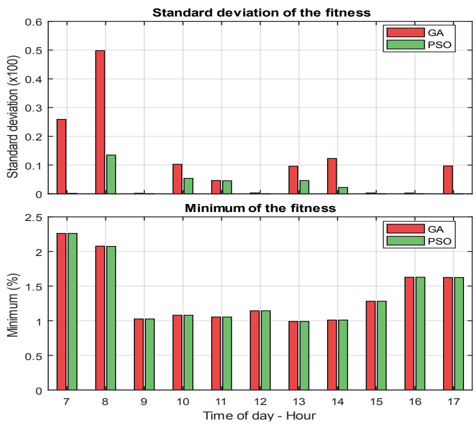


Fig. 9 Performance between PSO and GA algorithms

Fig. 9 and Fig. 10 show the best solutions (i.e. the best dispatch). Analysis of Fig.10 shows the average voltage deviation for controlled, full and no-load dispatch is 1.38%, 1.62%, and 2.01%, respectively. Fig. 11 shows three phases voltage deviation in loads and the best voltage profile at 11:00 for controlled, full and no dispatches. This figure shows the voltage profile via increasing distance from the feeder.

Analysis of this figure shows the no-dispatch voltage deviation is more than the others and the voltage deviation of the controlled dispatch is less than the full dispatch.

5. Conclusion

A new hybrid GA-PSO algorithm has been presented for optimizing the dispatch function of a VPP. The proposed algorithm has been employed in the purpose of optimizing voltage profile. Simulation results prove the capability of the proposed algorithm to minimize the voltage deviation of the distribution system. The results obtained by other evolutionary algorithms such as GA and PSO in compare of proposed algorithm results demonstrate the prevalence of proposed hybrid optimization algorithms from the perspective of calculation accuracy. The 13-bus system was used as a small sample of distribution system to approve the capability of the proposed algorithm in optimization issues and the use of a more complex system should be reserved for future work.

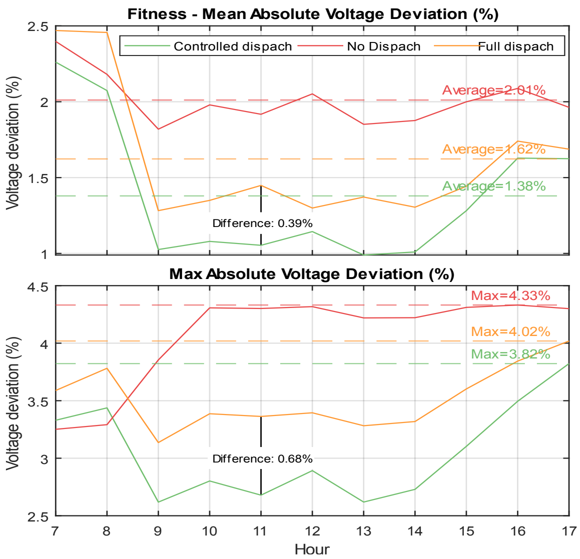


Fig. 10 Mean and maximum absolute voltage deviation for different dispatches

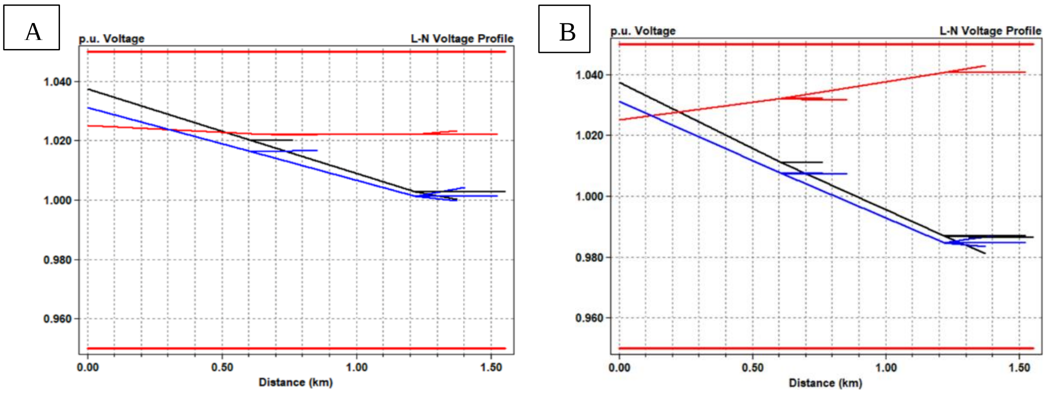


Fig. 9 Voltage profile via increasing distance from the feeder (i.e. bus 650) to show the voltage deviation at 11:00 for the different dispatches that are A. controlled, B. no-dispatch

References

Bukar, Abba Lawan, Chee Wei Tan, and Kwan Yiew Lau. 2019. "Optimal Sizing of an Autonomous Photovoltaic/Wind/Battery/Diesel Generator Microgrid Using Grasshopper Optimization Algorithm." *Solar Energy*. https://doi.org/10.1016/j.solener.2019.06.050.

Hosseinpour, Hossein, Taher Niknam, and Seyed Iman Taheri. 2011. "A Modified TLBO Algorithm for Placement of AVRs Considering DGs." *26th International Power System Conference* 1 (1): 1–8.

Jafar-Zanjani, Samad, Sandeep Inampudi, and Hossein Mosallaei. 2018. "Adaptive Genetic Algorithm for Optical Metasurfaces Design." *Scientific Reports*. https://doi.org/10.1038/s41598-018-29275-z.

Kaur, Sandeep, G. B. Kumbhar, and Jaydev Sharma. 2014. "Performance of Mixed Integer Non-Linear Programming and Improved Harmony Search for Optimal Placement of DG Units." In *IEEE Power and Energy Society General Meeting*. https://doi.org/10.1109/PESGM.2014.6939165.

Kersting, W.H. 1991. "Radial Distribution Test Feeders." *IEEE Transactions on Power Systems*. https://doi.org/10.1109/59.119237.

Kong, Xiangyu, Jie Xiao, Chengshan Wang, Kai Cui, Qiang Jin, and Deqian Kong. 2019. "Bi-Level Multi-Time Scale Scheduling Method Based on Bidding for Multi-Operator Virtual Power Plant." *Applied Energy*. https://doi.org/10.1016/j.apenergy.2019.04.130.

Niknam, Taher, Rasoul Azizipanah-Abarghooee, and Mohammad Rasoul Narimani. 2012. "A New Multi Objective Optimization Approach Based on TLBO for Location of Automatic Voltage Regulators in Distribution Systems." *Engineering Applications of Artificial Intelligence*. https://doi.org/10.1016/j.engappai.2012.07.004.

Niknam, Taher, Seyed Iman Taheri, Jamshid Aghaei, Sajad Tabatabaei, and Majid Nayeripour. 2011. "A Modified Honey Bee Mating Optimization Algorithm for Multiobjective Placement of Renewable Energy Resources." *Applied Energy* 88 (12): 4817–30.

Yu, Songyuan, Fang Fang, Yajuan Liu, and Jizhen Liu. 2019. "Uncertainties of Virtual Power Plant: Problems and Countermeasures." *Applied Energy*. https://doi.org/10.1016/j.apenergy.2019.01.224.

Zhang, Yudong, Shuihua Wang, and Genlin Ji. 2015. "A Comprehensive Survey on Particle Swarm Optimization Algorithm and Its Applications." *Mathematical Problems in Engineering*. https://doi.org/10.1155/2015/931256.