Impact of Photovoltaic Systems Allocation on Congestion in Distribution Network: Iraq Case Study

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***Abstract*—As Photovoltaic Distributed Generation (PVDG) becomes increasingly popular in modern power systems, it has raised concerns for system operators, despite its remarkable and valuable opportunities, such as reduction in voltage deviation and active power loss. On another side, random distribution of PVDGs in the distribution network can lead to system security violations and congestion. Optimal allocation of PVDGs is one of the efficient methods to enhance the power systems' efficiency. This paper proposes a new version of the Modified Camel Algorithm (NMCA) based on the L∞ technique to optimize PVDGs. The proposed technique can retain a good solution group for each generation due to the expansion in the search space. In order to verify the validity of the NMCA, it has been tested with IEEE 69- bus network and the Baghdad distribution network built a simulation model for the Baghdad distribution network. The simulation model has been created depending on its obtained load profiles, feeders, voltage, and current settings in addition to available PVDG stations in this grid to determine optimum allocation PVDGs in the network.**

***Index Terms*—distributed power generation, optimization methods, photovoltaic systems, power demand, voltage control.**

I. INTRODUCTION

Nowadays, the installation of PVDGs is widespread in distribution systems. Adopting a suitable size and location when installing the PVDGs gives many benefits to the power system, like voltage profile improvement, congestion relief, and total power loss minimization. However, the incorrect allocation of PVDG units can increase power losses and causes unexpected issues [1-2]. The power system lines' ability to transmit the power is restricted by critical limits (voltage, stability, and thermal limits). The power system enters a congestion state if one or more of these parameters reaches its maximum limit. The congestion can cause the transmission lines trip, unexpected outages of generation, or unscheduled power flow [3-4]. In [5], presented a decentralized method based on optimal allocation for distribution generation (DG) installation to solve the congestion problems in power systems. The authors [6] proposed a Particle Swarm Optimization method (PSO) to select the optimal DGs allocation in the distribution system to improve loss reduction. In [7], the authors proposed a PSO algorithm to obtain the optimum allocation of DG units with a 13% reduction in power losses and minimize the deviation in the voltage profile. In [8], presented a new method for allocating PV units in local distribution networks based on Geographic Information System (GIS) to reduce power losses in the system. The authors [9] showed the effects of PVDGs location and size on the distribution network, as PVDG units positively affected the distribution network associated with these units. An enhanced Sine Cosine Algorithm was proposed to obtain the optimal allocation of DG units and optimal reconfiguration in the distribution system to reduce power losses and operation costs [10]. A new method to select an optimal allocation of PV units in the distribution network of Kosovo to minimize power losses and enhance power quality [11]. In [12], the authors discussed the impact of PV in power systems using the HOMER program. They concluded that the optimal allocation of PV units could reduce the pollutants and minimize the total cost. The authors [13] introduced Water Cycle Algorithm (WCA) to select the optimal location of PV units and find the optimal power flow with and without PV units in the system. With their method, claimed proposed method could reach less power with PV units than other methods. The authors [14] showed a new method to select an optimal allocation of PV units in Croatia power system based on GIS system to reduce power losses. A new method was introduced to determine the optimal location for constructing PV systems. That work assumed eleven elements as input parameters. It used the fuzzy method with Dempster-Shafer (DS) to homogenise the input parameters and obtain optimal PV systems to improve solar energy utilization. The Camel Travelling Algorithm (CA) is a metaheuristic algorithm introduced in 2016. The travelling behavior of Camels during foraging is the main inspiration factor of the CA algorithm [16]. However, the high nesting in the structure of the CA algorithm and the complex structure has negatively affected the execution speed and memory size. in addition, it has several parameters. In 2019 [17], the modified camel travelling algorithm (MCA) is presented, in which the algorithm structure was simplified, and the convergence was improved. The literature survey reveals that the conducted studies employed optimization methods to study different optimization problems [16-17], [26-27], as well as address the impact of the power losses and the congestion problem in a distribution system based on optimal DG units. The motivation of work is summarized as follows

i. Most conducted studies in this context adopted the IEEE standard bus system with virtual PV power specification. However, in the current work, the Iraqi power system network had been adopted in the real-

Digital Object Identifier 10.4316/AECE.2022.02010

time mode.

ii. Proposed NMCA algorithm with multi-objective function to obtain an optimum allocation of PVDG units, which reduced the power loss and congestion relief and improved the voltage profile in distribution networks.

This paper is organized as follows: Section II presents Baghdad's distribution network congestion. Then, section III offers the problem description. Next, the NMCA scheme for the congestion problem is considered in Section IV. Then, section V presents the demonstrative cases study. Finally, conclusions are explained in Section VI.

II. The Congestion in Baghdad's Distribution Network

The Iraq Electrical Unified Network (IEUN) is designed at levels of 400 kV, 132 kV, and 33 kV. This work concentrated on Iraq's Middle region / Baghdad / Mashtal's city, located in the middle of Baghdad, as shown in Fig. 1. The measurement and analysis implemented on Mashtal city distribution networks, 11 kV, suffers from congestion. Fig. 2 illustrates the 12-bus system measured and analysed from the Mashtal distribution network (feeder 14, from transformer 3). Fig. 3 describes the residential load through (24-h) in a day (18/August/2021, in this case) in Mashtal city/ Baghdad, which suffers from power losses and high deviations in voltage profile level. Fig. 4 describes the PVDG power through (24-h) in a day (18/August/2021, in this case) in Baghdad. The maximum loads at (13:00:00 - 17:00:00 h) are considered the worst case for all nodes. In this regard, the worst peak of loads is taken as a case study, deduced in two cases: the measured case before and after applying the NMCA algorithm and solving the voltage profile deviation, relieving congestion and reducing power losses in the network.

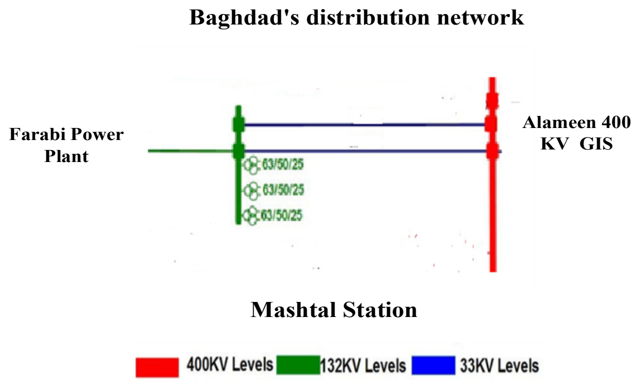


Figure 1. Mashtal city distribution networks, Iraq, Baghdad

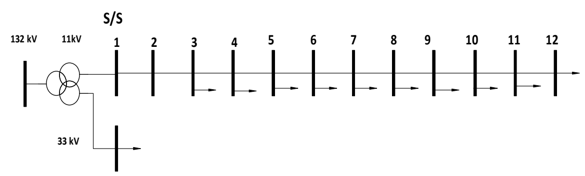


Figure 2. Mashtal city distribution network 12-Bus system, feeder14, transformer 3

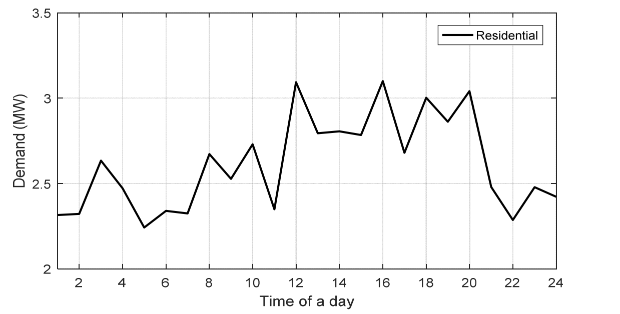


Figure 3. Residential load profiles in Mashtal city distribution networks, Iraq, Baghdad

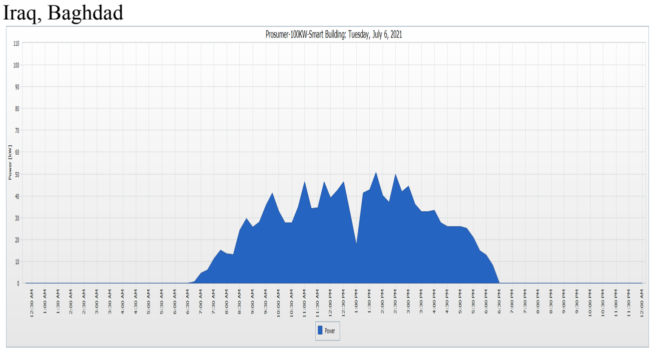


Figure 4. PVDG power from AL-Waziriah power plant, Training and Energy Researches Office, Ministry of Electricity, Iraq, Baghdad

III. Problem Description

Congestion problem in distribution network happens due to the gap between generation and load sudden demand increment, which causes system security to be violated [18]. The efficient studies solved this problem by one objective or more. In this study, the multi-objective function is proposed to solve the issues.

A. *Definition of Multi-Objective Function*

This work proposed a multi-objective function to solve the main problems in systems. The multi-objective functions include four main components. The first is total active power losses, the second is the L∞ technique (to handle the voltage profile), and finally, the congested lines.

1) *Total active power losses*

The mathematical expression of total active power losses (TPL) is given as follows [19]:

$$T_1 = TPL = \sum_{n=1}^{N_{br}} I_n^2 R_n \tag{1}$$

where, N_{br} is the number of branches in the system, I_n represents the current magnitude of the *nth* branch, and Rn represents the *nth* branch resistance.

2) *Congestion*

This section employed the contingency ranking to perform the selection of congestion lines. The circuit current-based index is used to measure the degree of line overloads, as given:

$$J_C = \sum_j W_j \left(\frac{I_j}{I_{(N,j)}} \right)^{2n} \tag{2}$$

where, $j=1, 2,....,m_j$. W_j is weighting factor, $0 < W_j < 1$. $I_{(N,j)}$ represent the current-based thermal limit, and I_j represents the magnitude of actual current through circuit *j*. The term of maximum congestion line in cost function depends on the relation that considered as [20]:

$$T_2 = \max(\frac{I_j}{I_{(N,j)}}) \quad (3)$$

3) The L∞ technique

The injection of PVDG in the radial distribution system has many benefits. Nevertheless, it represents an influencing factor on the voltage rise in the system. The voltage rise is the bottleneck of PVDG in the radial distribution system. Therefore, many previous studies attempted to address how much PVDG in the distribution grid can penetrate without risking overvoltage. In this study, the proposed $L\infty$ technique improves the voltage profile with algorithms to select the optimal size and placement of PVDG. The ∞-norm: As $p\rightarrow\infty$, the Lp norm tends to the so-called ∞-norm, or $L\infty$ norm, which define the $L\infty$ norm as the supremum (least upper bound) of the absolute value as expressed [21]:

$$\|x\|_\infty = \sup_t |x(\mathrm{t})| \quad (4)$$

To find the supremum of the measured voltage vector of the distribution (V):

$$\|V\|_\infty = \sup_i |\mathrm{v(i)}| \quad (5)$$

For the vector $V= \{(v(1),\ldots v(i),v(N_{bus}))\}^{\mathrm{T}}$, with, i =1,2,…, N_{bus}, where the N_{bus} represent a number of buses, V is the measured voltage of the distribution system and, v(i) is a measured voltage at the bus (i) in the distribution system. The desired voltage value in a distribution system is the (1 pu.). Equation (6) represents the per cent change of voltage in the distribution system:

$$v_p(i)=(v(i)-1)x100 \quad (6)$$

$$V_p=\{(v_p(1),\ldots,(v_p(N_{bus})\}^T \quad (7)$$

Now, the $L\infty$ norm will be applied to V_p to find the supremum of the vector V_p, where the V_p vector can represent the values of voltage change at each bus in the distribution system

$$T_4 = \|V_p\|_¥ = \sup_i |v_p(i)| \quad (8)$$

The main target of the proposed technique (L_∞ technique) is to make the difference (e) between the vector V and target of system (1 pu.) approach to zero as possible without violating the power system security limits.

As $\|V\|_\infty \rightarrow 1$, $\|V_p\|_\infty \rightarrow 0$, and $e\rightarrow 0$.

The multi-objective function of the PVDG in the grid is

$$T = (K_1T_1) + (K_2T_2) + (K_3T_3) + (K_4T_4) \quad (9)$$

Here, T represents the cost function, and it's required to be minimised in order to reduce congestion and get minimum losses with K_1, K_2, K_3 and K_4 as a penalty factor.

B. Definition of Distribution System Constraints

1) The current and voltage limits

In the distribution network, the lower and upper bounds for the voltage are 0.95 to 1.05 p.u [22].

$$V_{\min} \le V_i \le V_{\max} \quad (10)$$

where, the V_i is the variable voltage magnitude, V_{min} is the minimum voltage limits, and the V_{max} is the maximum voltage limit. The line current limitation in the transmission line between buses (ith and jth) is imposed as in equation (11) [19], [22]:

$$I_{ij} \le I_{ij}^{\max} \quad (11)$$

2) The PVDG units' capacity limits

The injected power of PVDGs and number of PVDGs are selected within a specific range as shown below [23]:

$$N_P^{\min} \le N_P \le N_P^{\max} \quad (12)$$

$$P_P^{\min} \le P_P \le P_P^{\max} \quad (13)$$

IV. NMCA Scheme for Congestion Problem

The MCA algorithm employs the simulation of camel visibility in the same manner as the mutation simulation in other algorithms like the GA algorithm. However, the visibility of the camel and the simple location equation in MCA are inefficient for solving congestion problems and other distribution problems due to the following reasons:

i. The mutation step in the food searching equation must not take place in a position close to the food source because this affects the solution convergence;
ii. The new camel positions may not provide a viable solution;
iii. The MCA algorithm does not have limits applied to the location equation where this affects the solution.

NMCA works in the same manner as MCA, but with the following modification:

i. Modification of the mutation step;
ii. Modification of the location equation;
iii. Addition of the velocity equation;
iv. Addition of the velocity limits and the location limits.

The modification in mutation steps has been presented in NMCA to feedback an essential level of heuristic knowledge, where this modification will lead to fast convergence of the optimization algorithm. In the NMCA algorithm, there are two scenarios for updating the location of each camel as in equations (14-19):

$$\gamma = (x_{\max} - x_{\min}) \quad (14)$$

$$x_d^{itr} = \gamma R + x_{\min} \quad (15)$$

where, R∈ [0, 1] and d =1, 2, D, also x^{itr} is the location of camel, x_{min} is the minimum location of camel, x_{max} is the maximum location of camel, and the γ is the range of camel location. The camel velocity and velocity limits terms can be mathematically expressed by:

$$v_{\max} = 0.25\gamma \quad (16)$$

$$v_{\min} = -v_{\max} \quad (17)$$

$$v_d^{itr} = \theta \times v_d^{itr-1} + (x_d^{best} - x_d^{i,itr-1})E_d^{(i,itr)} * c \quad (18)$$

The v_{min} is the minimum velocity of the camel, the v_{max} is the maximum velocity of camel, the v_d^{itr} is the velocity of the camel, and the E^{itr} is the endurance. Note: c ∈ [1, 3] and Θ ∈ [0, 1] are constants. Finally, the main location equation is:

$$x_d^{itr} = x_d^{itr-1} + v_d^{itr} \quad (19)$$

The description of the NMCA algorithm is shown below:

Step 1: Initialization: -Set the temperature range T_{min} and T_{max}, the location range, the camel caravan size and the dimensions, the Visibility threshold, the Stander deviation (Std) threshold, and set c and θ values - Initialize the location of each camel. Step 2: -Subject the locations to a specific fitness function -Determine the current best location

-Randomly assign visibility (v) for each camel.
For r=1: Run
Step 3:
While (iter < $iter_{max}$) do
For i=1: Camel Caravan size
Compute the temperature T, the endurance E, and the Std. of Best Costs.
Update the camel velocity.
Apply Velocity Limits
If v < visibility threshold and Std. < Std. threshold then
Update the camel location from Eq. (15)
Else
Update the camel location from Eq. (20)
End If
Apply location limits
End for
Subject the new locations to the fitness function
Calculate the fitness function
If the new best location is better than the older one
The new best is the global best
End If
Update the Std. counter for best costs
Assign new visibility for each camel
Step 4: End While
Step 5: If the new best solution is better than the older one.
Then the new best is the global best
End If
End for
End

Fig. 6 demonstrates the adopted variables vector. Where LPV is the location of PVDGs and SPV is the size of PVDGs.

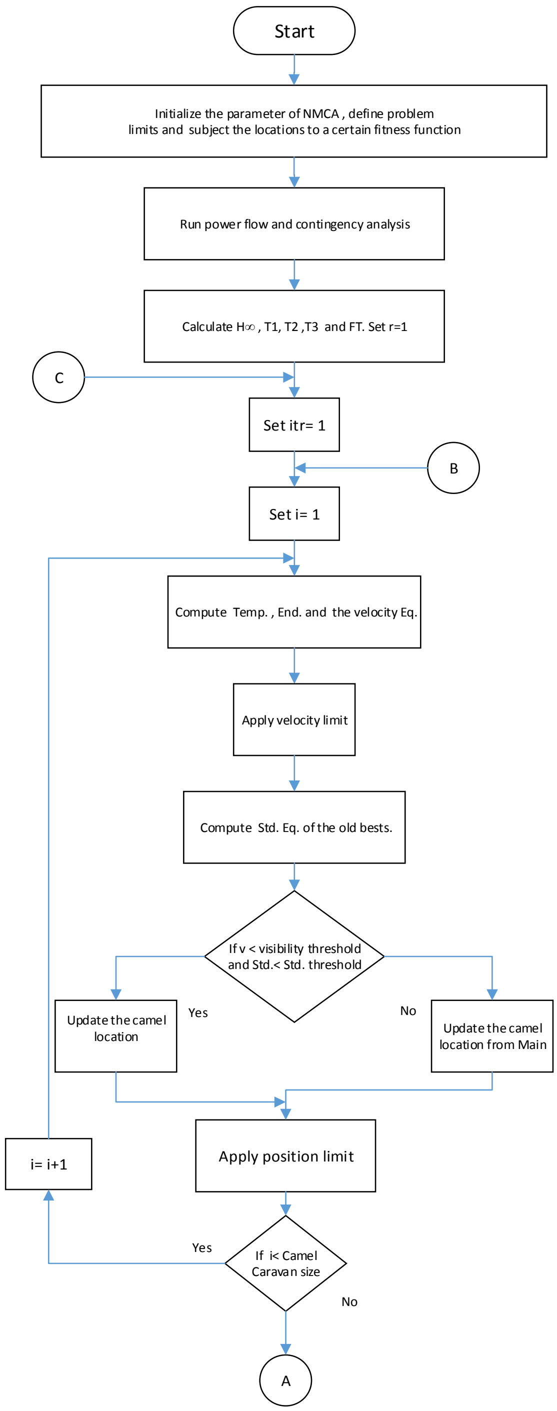
LPV_1	.....	LPV_N	SPV_1	.....	SPV_N

Figure 5. The Decision-making variables vector

The description of the whole process of the PVDG optimal allocation steps based on the NMCA algorithm is shown below:

Step 1: Initialization:
-Set the temperature range T_{min} and T_{max}, the location range, the camel caravan size and the dimensions, the Visibility threshold, the Stander deviation (Std) threshold, and set c and θ values
- Initialize the location of each camel.
-Upload system data (bus data and line data of distribution network).
-Define the constraints of the problem.
Step 2:
-Subject the locations to a specific fitness function
-Determine the current best location
-Randomly assign visibility (v) for each camel.
To calculate the fitness function:
-Applied the obtained solution (PV location and size) to the Distribution system.
-Run power flow to obtain all variables.
-Run contingency analysis.
-Calculate $L\infty$.
-Calculate total power loss, then calculate fitness function by using Equation (10).
For r=1: Run
Step 3:
While (iter < $iter_{max}$) do
For i=1: Camel Caravan size
Compute the temperature T, the endurance E, and the Std. of Best Costs.
Update the camel velocity.
Apply Velocity Limits
If v < visibility threshold and Std. < Std. threshold then
Update the camel location from Eq. (15)
Else
Update the camel location from Eq. (20)
End If
Apply location limits
End for
Subject the new locations to the fitness function
Calculate the fitness function
If the new best location is better than the older one
The new best is the global best
End If
Update the Std. counter for best costs
Assign new visibility for each camel
Step 4: End While
Step 5: If the problem limits are satisfied, then
Output the best solution
Else
Rule out the solution
End If
Step 6: If the new best solution is better than the older one.
Then the new best is the global best
End If
End for
End

The flow chart of the NMCA with $L\infty$ is shown in Fig. 6.



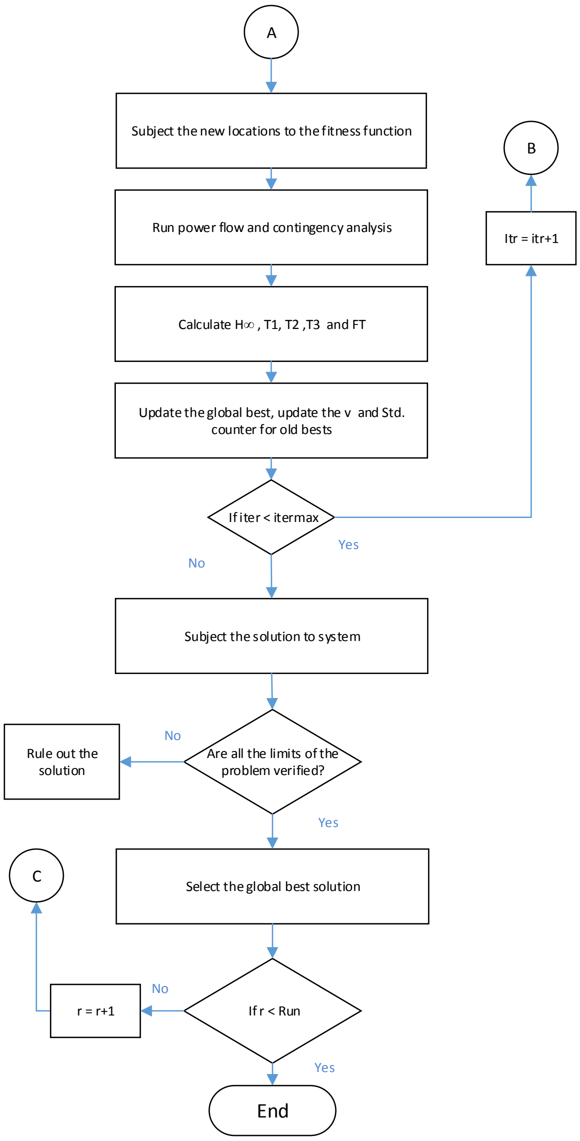


Figure 6. The NMCA method with L∞

V. A Demonstrative Cases Study

Now, in order to demonstrate the superiority and effectiveness of the proposed algorithm over other rest methods, two scenarios have been conducted:

i. Scenario I: 69-bus IEEE system with a heavy load;

ii. Scenario II: 12-bus system of Mashtal distribution network.

A. Scenario I

The proposed strategy has been applied to IEEE 69 bus structure system (Fig. 7) [24], with residential load demand. The load demand in this scenario follows the residential load pattern of Mashtal city (shown in Fig. 3). The variation in load demand is applied for 24 hours in a day, and the peak load is assumed to be 3.8 MW and 2.7 MVAR. Also, the power calculation has been done taking Sbase = 100 MVA and Vbase =12.66 kV. The NMCA has been compared with the eight optimization algorithms (PSO, GWO, IWO, ABC, FA, HS, MCA, and SSA), and computed the Convergence Rate (CR) values [25-26], the results are shown in Fig. 8-14. In this scenario, (30) trials of each algorithm, each run with (200) iteration and (200) particles.

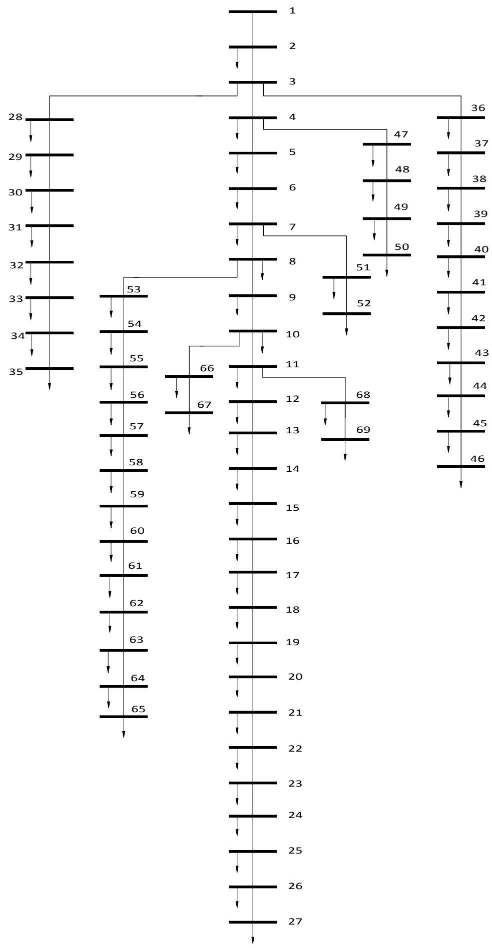


Figure 7. The IEEE 69-bus system

Fig. 8 and Fig. 9 demonstrates the applied PVDGs in the IEEE 69 system at peak load. From Fig. 8 and Fig. 9, the following points are clear:

i. On applying PVDGs, the line's current droop is below their thermal limits. For example, inline (1-2), the current before installing PVDGs was (387.18 A), and after installation, PVDGs became (216.1 A);

ii. The results of the reduction of current are power loss reduction and relief of the congestion in the system, as shown in Fig. 9.

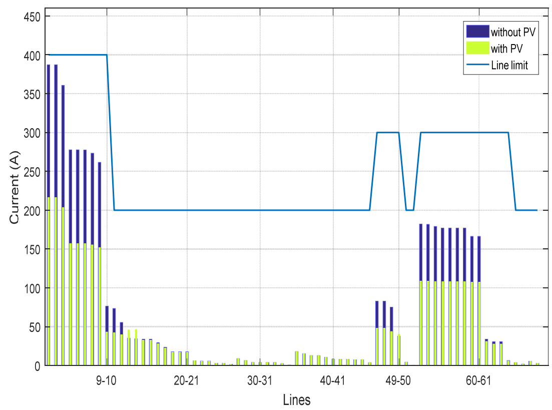


Figure 8. The lines currents without and with the PVDG units

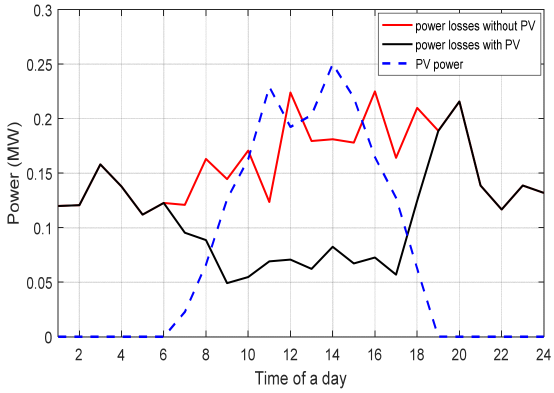


Figure 9. The power losses without and with PVDG units

From Fig. 10 and Fig. 11, the following points are clear:

i. When there is no PVDGs, the system suffers from high voltage profile deviation where it reaches (0.9092 p.u) at node 65;

ii. The voltage profile Improved when PVDGs has installed, where the deviation in the voltage profile reduces from (0.9092 p.u) to (0.9966 p.u).

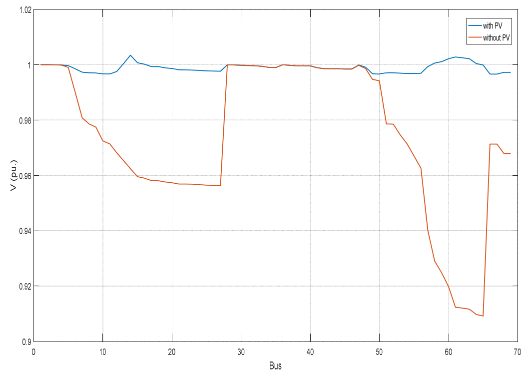


Figure 10. The voltage profile without and with PVDG in the system

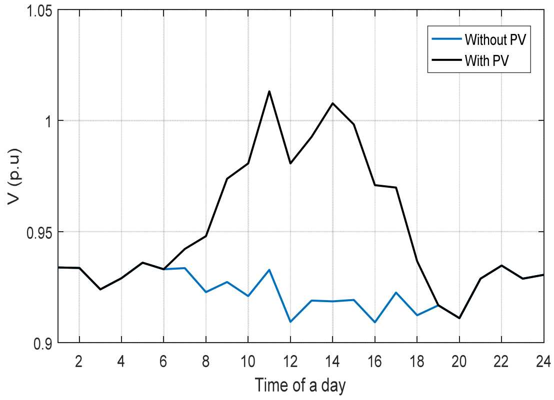


Figure 11. The voltage profile without and with PVDG units at bus 65

Fig. 12 - 14 verified the effectiveness of NMCA on the eight other methods, where the NMCA algorithm has the best CR values that point to this algorithm converging to the optimum solution with minimum cost and mean cost, as compared to other methods. NMCA algorithm is:

i. NMCA is a robust optimization algorithm for solving real problems for engineering applications;

ii. It has a few parameters and simple specific control parameters to be adjusted where this parameter derives from the natural environment of Camel, which makes the NMCA a flexible algorithm for solving complex and miscellaneous problems;

iii. The strategy and mechanism of NMCA are powerful tools that may lead to fast convergence speed and high exploration.

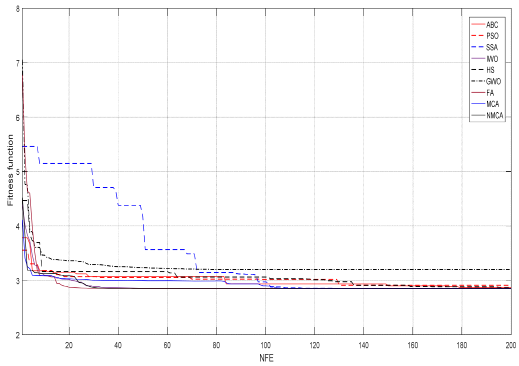


Figure 12. The fitness function of different algorithms of IEEE 69-bus system

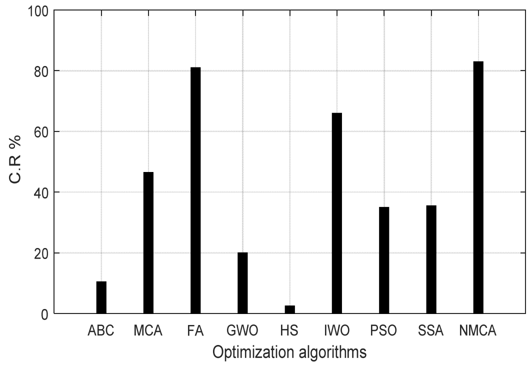


Figure 13. The Convergence rate of different algorithms of IEEE 69-bus

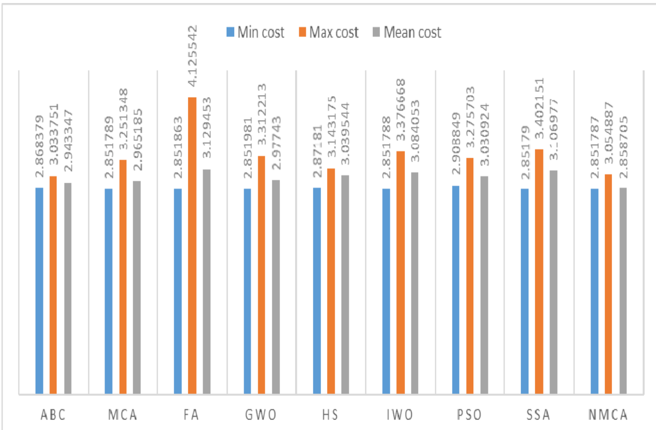


Figure 14. The comparison among nine methods for the 69-bus system

B. Scenario II

In this scenario, the distribution network of Baghdad/Mashtal 11.4 kV with 12 buses and 11 switches has been addressed. The Mashtal network has been employed an aluminum conductor, steel-reinforced (ACSR) 120/20 mm for overhead line, and copper conductor 150 mm for the underground line. The residential load demand in this scenario from Mashtal is shown in Fig. 3. The variation in load demand is applied for 24 hours a day, and the peak load is assumed to be 3.1 MW and 0.9 MVAR. Also, the power calculation has been done assuming Sbase = 100 MVA and Vbase =11.4 kV. The NMCA was used to obtain the optimal configuration of PVDGs in this network. The results are shown in Fig. 14-17. In this scenario, (10) trials of each algorithm, each run with (200) iteration and

(200) particles. Fig. 15–18 demonstrate the applied PVDGs in a 12-bus system at peak load. Fig. 15 points to the following:

i. On applying PVDGs, the line's current is below their thermal limits. For example, inline (1-2), the current before installing PVDGs was (284.825 A), and after installed PVDGs became (108.842 A);

ii. The power loss reduction from (15.83 kW) to (2.192 kW) and relief of the congestion in the system, as shown in Fig. 16.

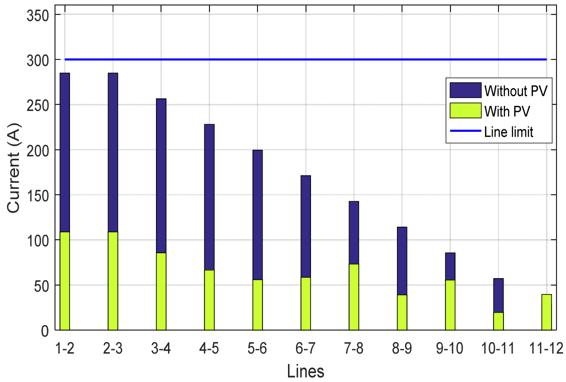


Figure 15. The lines current without and with the PVDG units in the system

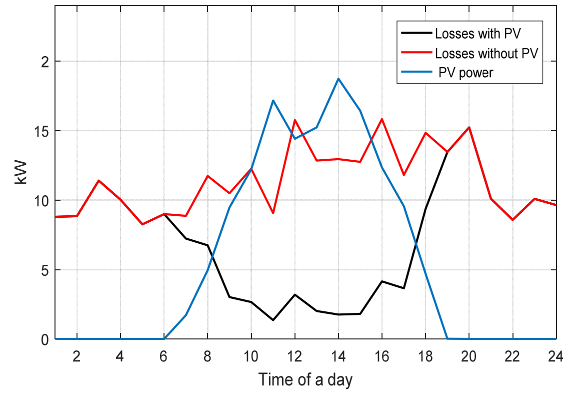


Figure 16. The power losses without and with PVDG units in the system

From Fig. 17 and 18, the following points are clear:

i. When there is no PVDGs, the system suffers from voltage deviation where it reaches (0.9925 p.u) at node 12;

ii. The voltage profile Improved when PVDGs has installed, where the deviation in the voltage profile reduces from (0.9925 p.u) to (0.9981 p.u), as shown in Fig. 18.

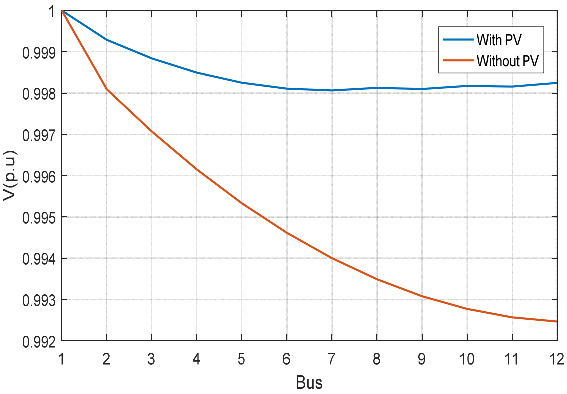


Figure 17. The voltage profile without and with PVDG system

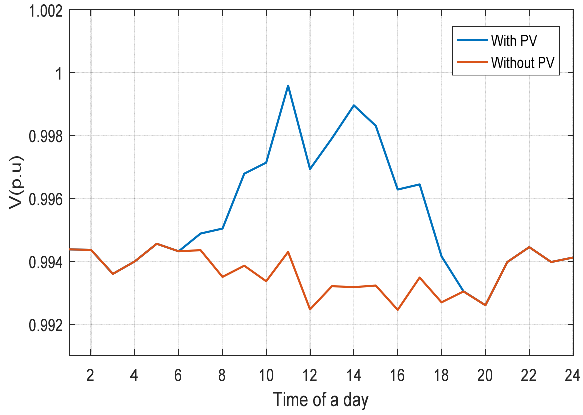


Figure 18. The voltage profile without and with PVDG system at bus12

VI. CONCLUSION

This paper presents a modified MCA algorithm based on L∞ to obtain optimal PVDG units configuration with a multi-objective function. The NMCA method with L∞ successfully achieved the optimal solutions at various test cases. Furthermore, results of the NMCA method have been compared to that of several well-known and recent algorithms (like ABC, MCA, FA, GWO, HS, IWO, PSO, and SSA). The main challenge is the insertion of PVDG units without losing system reliability and violating operation limits. Therefore, voltage deviation and current through feeders are of the most significant importance. The study's significant contribution was building a simulation model for the Baghdad distribution network, which contributes to relieving the network's congestion.

REFERENCES

[1] Z. A. Kamaruzzaman, A. Mohamed, and H. Shareef, "Effect of grid-connected photovoltaic systems on static and dynamic voltage stability with analysis techniques - A review," Przeglad Elektrotechniczny, pp. 134-138, 2015. doi:10.15199/48.2015.06.27

[2] M. Q. Duong, T. D. Pham, T. T. Nguyen, A. T. Doan, and H. V. Tran, "Determination of optimal location and sizing of solar photovoltaic distribution generation units in radial distribution systems," Energies, vol. 12, no. 1, 2019. doi:10.3390/en12010174

[3] T. Wang, Y. Xiang, C. Li, D. Mi, Z. Wang, "An improved analytical methodology for joint distribution in probabilistic load flow," Advances in Electrical and Computer Engineering, vol.20, no.1, pp.49-56, 2020. doi:10.4316/AECE.2020.01007

[4] X. Wu, X. Shen, J. Zhang, Y. Zhang, "A wind energy prediction scheme combining cauchy variation and reverse learning strategy," Advances in Electrical and Computer Engineering, vol. 21, no. 4, pp. 3-10, 2021. doi:10.4316/AECE.2021.04001

[5] S. Visalakshi and S. Baskar, "Covariance matrix adapted evolution strategy-based decentralised congestion management for multilateral transactions," IET Generation, Transmission & Distribution, vol. 4, no. 3, pp. 400-417

[6] W. Phuangpornpitak and K. Bhumkittipich, "Principle optimal placement and sizing of single distributed generation for power loss reduction using particle swarm optimization," Research Journal of Applied Sciences, Engineering and Technology, vol. 7, no. 6, pp. 1211-1216, 2014

[7] T. J. Sahib, M. R. Ab Ghani, Z. Jano, and I. H. Mohamed, "Optimum allocation of distributed generation using PSO: IEEE test case studies evaluation," International Journal of Applied Engineering Research, vol. 12, pp. 2900-2906, 2017

[8] H. Sadeghian, M. H. Athari, and Z. Wang, "Optimized solar photovoltaic generation in a real local distribution network,". 2017, doi:10.1109/ISGT.2017.8086067

[9] N. M. Saad et al., "Impacts of photovoltaic distributed generation location and size on distribution power system network," Int. J. Power Electron. Drive Syst. International Journal of Power Electronics and Drive Systems, vol. 9, no. 2, pp. 905-913, 2018. doi:10.11591/ijpeds.v9.i2.pp905-913

[10] U. Raut and S. Mishra, "Enhanced Sine–Cosine algorithm for optimal planning of distribution network by incorporating network reconfiguration and distributed generation," Arabian Journal for Science and Engineering, vol. 46, 08/12, 2020

[11] A. Ymeri and S. Mujovic, "Optimal location and sizing of photovoltaic systems in order to reduce power losses and voltage drops in the distribution grid," International Review of Electrical Engineering (IREE), vol. 12, p. 498, 12/31, 2017. doi:10.15866/iree.v12i6.12553

[12] S. O. Fadlallah and D. E. Benhadji Serradj, "Determination of the optimal solar photovoltaic system for Sudan," Solar Energy, vol. 208, pp. 800-813, 2020

[13] B. H. Dinh, T. T. Nguyen, T. T. Nguyen, and T. D. Pham, "Optimal location and size of photovoltaic systems in high voltage transmission power networks," Ain Shams Engineering Journal, vol. 12, no. 3, pp. 2839-2858

[14] I. Gašparović and M. Gašparović, "Determining optimal solar power plant locations based on remote sensing and GIS methods: A case study from Croatia," Remote Sensing, vol. 11, no. 12, 2019. doi:10.3390/rs11121481

[15] M. Mokarram, M. J. Mokarram, M. R. Khosravi, A. Saber, and A. Rahideh, "Determination of the optimal location for constructing solar photovoltaic farms based on multi-criteria decision system and Dempster–Shafer theory," Scientific Reports, vol. 10, no. 1, p. 8200, 2020. doi:10.1038/s41598-020-65165-z

[16] I. Mohammed Khalid and A. Ramzy Salim, "Novel optimization algorithm inspired by camel traveling behavior," Iraqi Journal for Electrical And Electronic Engineering, vol. 12, no. 2, pp. 167-177, 2016

[17] R. S. Ali, F. M. Alnahwi, and A. S. Abdullah, "A modified camel travelling behaviour algorithm for engineering applications," Australian Journal of Electrical and Electronics Engineering, vol. 16, no. 3, pp. 176-186, 2019. doi:10.1080/1448837X.2019.1640010

[18] N. Yusoff, A. Mohd Zin, and A. Khairuddin, Congestion management in power system: A review. pp. 22-27, 2017

[19] M. Q. Duong, T. D. Pham, T. T. Nguyen, A. T. Doan, and H. V. Tran, "Determination of optimal location and sizing of solar photovoltaic distribution generation units in radial distribution systems," Energies, vol. 12, no. 1, p. 174, 2019

[20] G. K. Stefopoulos, Fang Yang, G. J. Cokkinides and A. P. S. Meliopoulos, "Advanced contingency selection methodology," Proceedings of the 37th Annual North American Power Symposium, 2005, pp. 67-73, doi:10.1109/NAPS.2005.1560503

[21] J. C. Doyle. Feedback Control Theory. Macmillman, pp. 11-23, 2013

[22] A. Wazir and N. Arbab, "Analysis and optimisation of IEEE 33 Bus radial distributed system using optimisation algorithm," 2016

[23] T. D. Pham, T. T. Nguyen, and B. H. Dinh, "Find optimal capacity and location of distributed generation units in radial distribution networks by using enhanced coyote optimisation algorithm," Neural Computing and Applications, vol. 33, no. 9, pp. 4343-4371, 2021. doi:10.1007/s00521-020-05239-1

[24] M. M. Aman, G. B. Jasmon, A. H. A. Bakar, and H. Mokhlis, "A new approach for optimum simultaneous multi-DG distributed generation units placement and sizing based on maximization of system loadability using HPSO algorithm," Energy, vol. 66, pp. 202-215, 2014. doi:10.1016/j.energy.2013.12.037

[25] N. D. Vanli, M. Gürbüzbalaban, and A. Ozdaglar, "Global convergence rate of proximal incremental aggregated gradient methods," SIAM Journal on Optimization, vol. 28, no. 2, pp. 1282-1300, 2018

[26] A. H. Gandomi, "Interior search algorithm (ISA): A novel approach for global optimisation," ISA Transactions, vol. 53, no. 4, pp. 1168-1183, 2014/07/01/ 2014. doi:10.1016/j.isatra.2014.03.018

[27] R. Ibrahim, A. Ewees, D. Oliva, M. Elsayed Abd Elaziz, and S. Lu, “Improved salp swarm algorithm based on particle swarm optimization for feature selection,” Journal of Ambient Intelligence and Humanized Computing, vol. 10, 08/01, 2019. doi:10.1007/s12652-018-1031-9

[28] I. A. Zamfirache, R.-E. Precup, R.-C. Roman, and E. M. Petriu, “Policy iteration reinforcement learning-based control using a Grey Wolf optimizer algorithm,” Information Sciences, vol. 585, pp. 162-175, 2022. doi:10.1016/j.ins.2021.11.05