A New Version of Modified Camel Algorithm for Engineering Applications

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Abstract. The paper presents the new modified camel algorithm (NMCA) as a new optimization method for solving optimization tasks. NMCA is different from the modified camel algorithm (MCA) and other metaheuristic algorithms. Where it provides a new insight for global optimization. The proposed method is verified using power distribution system problems (engineering problems) commonly used in the area of optimization. Simulations were conducted on the IEEE 69- and 33-bus systems. The NMCA algorithm successfully achieved the optimal solutions at various test cases. NMCA results are further compared with MCA and well-known optimization algorithms. The results show that the NMCA is efficiently capable of solving optimization problems.

Keywords: New modified camel algorithm; distributed generation; solar photovoltaic; congestion problem; power loss; voltage profile..

1 Introduction

As the spatial and temporal complexity of the power resources management problems increases, the application of metaheuristic algorithms extends dramatically. Different algorithms are proposed and applied to solve various problems in power resources and engineering problems in general. The photovoltaic (PV) power generated by solar is one of the important power source. Where the photovoltaic distribution generator (PVDG) is one of the most promising renewable power technologies in distribution grids. Due to the flexibility in scale application and pollution-free, PVDG generation capacity has increased exponentially in the past years [1-2].

The literature survey reveals that optimization algorithms are widely used for solving complex power system problems (optimization problems). Metaheuristic algorithms are generally more powerful in compared to conventional methods based on mathematical programming [3]. In [4] the researcher study the problem of the network reconfiguration in the presence of distributed generation (DG) using a Harmony Search Algorithm (HS) to simultaneously reconfigure and identify the optimal locations for installation of DG units in a distribution grid. Amin [5] presented a hybrid configuration of particle swarm optimization (PSO) with ant colony optimization (ACO) algorithm called hybrid PSO–ACO algorithm to solve the distribution network minimizing power losses problem and improving the voltage profile problem. The major points in the modified camel traveling algorithm are the diversification and intensification [6-7]. The diversification phase guarantees that the MCA explores the search space more efficiently and the intensification phase searches through the current best solutions and selects the best candidates. MCA is developed to solve engineering problems faster and to obtain more robust results [6]. In this paper, a new modified camel algorithm (NMCA) is introduced for global optimization. The performance and efficiency of the NMCA are verified using congestion problems and losses in distribution networks. The results confirm the applicability of NMCA for solving optimization tasks of distribution networks. The NMCA can also outperform the existing optimization algorithms.

This paper is organized as follows: Section 2 presents the MCA and NMCA and the characteristics of the proposed NMCA, including the formulation of the algorithm. The problem formulation and constraint in section 3. Section 4 deals with the applicability of NMCA algorithm for congestion, voltage profile power losses problems. In section 5, the performance of the proposed algorithm is tested using congestion problems, voltage profiles, and power losses in distribution networks. Section 6 deals with a discussion on convergence mobility of the proposed NMCA algorithm. Finally, in Section 7 the concluding remarks and suggestions for future research are provided.

2 The Camel Travelling Algorithm

The Camel Travelling Algorithm (CA) is a swarm intelligence-based technique proposed by Ramzy and Mohammed in 2016 [8]. CA is inspired by the traveling behaviour of camels during foraging. The CA algorithm has a complex structure that negatively affects the execution speed and memory size, where the CA consist of multi-loop nesting and several parameters selection. In 2019 Ramzy introduce the modified Camel traveling algorithm (MCA) with a simple structure, which significantly improve its convergence and computation speed [6]. The MCA is presented to solve engineering optimization problems. In this section, a new version of MCA algorithm (New-MCA) is presented. The NMCA uses to find the optimum configuration (size, position, and number) of the PV units in the distribution grid to solve the congestion problem, improve voltage profile and reduce power losses. NMCA works in the same manner of MCA, with the following modification:

1-Modification of the mutation step.
2-Modification of the location equation.
3-Addition of the velocity equation.
4-Addition of the velocity limits.
5-Addition of the location limits.

Simulation of camel visibility in the MCA algorithm is employed in the same manner as the mutation simulation in other algorithms like the GA algorithm. In MCA algorithm there are two scenarios for updating the location of each camel. When, the camel visibility v is larger than a specific visibility threshold, the update function is change from main location equation to the second location equation. The purpose of modified mutation in NMCAs is to introduce diversity into the camel locations. Mutation operators are used in an attempt to avoid local minima by preventing the locations of camels from becoming too similar to each other, thus slowing or even stopping convergence to the global optimum.

The visibility of the camel and the simple location equation in MCA, inefficient for solving congestion problem and other distribution problems due to the following reasons:

1. Mutation step in the food searching equation must not take place in a position taken close to the food source because this affects the solution convergence.
2. The updated locations of camels might not generate a feasible solution, and rounding off the new food source becomes essential.
3. MCA algorithm does not have limits applied on location equation where this affects the solution.

The modified mutation process has been introduced in NMCA to retain a certain level of heuristic knowledge. In the original MCA, the camels will search for the new food source at the neighborhood location that exists in their memory. In NMCA, the camels will search for the new food source at the neighborhood location that exists in their memory, and certain knowledge is retained from the stored good results. This strategy will result in fast convergence of the optimization algorithm. A camel probabilistically produces a modification on the camel location in her memory for finding a new food source, in order to produce a candidate food position. For the implementation of new modified camel algorithm, it is assumed that there are N camels (Camel Caravan) traveling through a (D) dimensional environment of camels. Where $x^{i,itr}$ is the location of camel (i) at time iteration (itr) can be denoted by:

$$x^{i,itr} = \{x_1^{i,itr}, \quad x_2^{i,itr}, \quad \ldots., \quad x_D^{i,itr}\} \tag{1}$$

and

$i = 1,2, \ldots., N.$

itr: Iteration, $\quad itr = 1,2, \ldots., itr_{max}.$

At the beginning (itr = 0), where the camels are spread in the desert and looking randomly for the water supply and food as demonstrated in the formula below:

$$\gamma = (x_{max} - x_{min}) \tag{2}$$

$$x_d^{itr} = \gamma\, R + x_{min} \tag{3}$$

where

$R \in [0,1]$

$d = 1,2, \ldots., D.$

x_d^{itr} : Location of camel.

x_{min}: Minimum location of camel.

x_{max} : Maximum location of camel.

γ: Rang of camel location

The temperature (T) and effect of the temperature on the camel endurance (E) of camel i at the time iteration as shown below:

$$T_d^{itr} = (T_{max} - T_{min})Rand + T_{min} \tag{4}$$

$$E_d^{itr} = \frac{\left(T_d^{itr} - T_{min}\right)}{(T_{max} - T_{min})} \tag{5}$$

where

T_{min}: Minimum amount of temperature

T_{max}: Maximum amount of temperature

T_d^{itr}: Temperature

E_d^{itr}: Endurance

The camel velocity and velocity limits terms can be mathematically expressed by:

$$v_{max} = 0.25\,\gamma \tag{6}$$

$$v_{min} = -v_{max} \tag{7}$$

$$v_d^{itr} = \Theta\, v_d^{itr-1} + \left(x_d^{best} - x_d^{i,itr-1}\right)E_d^{i,itr} * c \tag{8}$$

where

v_{min}: Minimum velocity of camel.
v_{max} : Maximum velocity of camel.
v_d^{itr}: Velocity of camel.
Note: $c\ \in[1,3]$ and $\theta\ \in[0,1]$ are constants.
Finally the main location equation is:

$$x_d^{itr} = x_d^{itr-1} + v_d^{itr} \tag{9}$$

Algorithm: New Modified CA

Begin

Step 1: Initialization: Set the temperature range and the location range Tmin and Tmax; set the camel caravan size and the dimensions; set the visibility threshold; set std. threshold; set c and θ values; initialize the location of each camel from Eq. (3).

Step 2: Subject the locations to a certain fitness function; determine the current best location; randomly assign a visibility (v) for each camel.

Step 3: While ($\boldsymbol{itr} < \boldsymbol{itr_{max}}$) do
    for i=1: Camel Caravan size
        Compute the temperature T from Eq. (4)
        Compute the endurance E from Eq. (5)
        Compute the Std. of Best Costs.
        Update the camel velocity from Eq. (8)
        Apply velocity limits
    If v <visibility threshold and Std. <Std. threshold
      then
        Update the camel location from Eq. (3)
      else
        Update the camel location from Eq. (9)
          end If
        Apply location limits
          end for
    Subject the new locations to 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: Output the best solution
End

3 Problem Formulation

In today's modern power systems with large loads and renewable sources, including solar power, network security limits, such as thermal, angular stability, or voltage stability are violated. Where penetration of renewable sources, could adversely affect the power flow in the system and may cause congestion in parts of transmission or distribution systems. A congestion problem in power systems is a situation where the demand for transmission capacity exceeds the transmission grid capabilities. While the reduction of congestion for that reason will become very important in the near future [9]. This paper focuses on the congestion problem of the network at the distribution level.

3.1 Objective Function

The multi-objective function includes four main components, including total active power losses, the L∞ to handle the voltage profile, congestion lines in distribution network and PVDG which are installed at the distribution level.

3.1.1 Total Active Power Loss

In the optimal operation of a working power system, total active power loss (TPL) can be considered, the major factor of economic performance, where this issue is the main objective in the optimal power system. The mathematical expression of total active power loss is given equation (10) [2, 9]:

$$T_1 = TPL = \sum_{n=1}^{N_{br}} I_n^2 \ R_n. \tag{10}$$

N_{br}: number of branches in system.

I_n: the current magnitude of the n^{th} branch.

R_n: The resistance of the n^{th} branch.

The TPL will be from zero MW up to tens of MW.

3.1.2 The Congestion lines in distribution system

One of the factors that preventing the integration of PVDG power in a distribution system is the congestion of a distribution grid due to the limited availability of distribution grid capacity. Therefore, the selection of the maximum congestion line in the distribution grid is the major factor in the objective function to solve the congestion problem in this study. The selection of the maximum congestion line is performed by employing the contingency ranking. The performance index is the main factor used for ranking the system. The circuit current-based index is used to measure the degree of line overloads as in equation (11):

$$J_C = \sum_j W_j \left(\frac{I_j}{I_{N,j}}\right)^{2n} \tag{11}$$

$j = 1,2, \dots, mj$.

Where,

j : number of line.

W_j : weighting factor, $0 < W_j < 1$.

$I_{N,j}$: current-based thermal limit of the line.

I_j : magnitude of actual current through circuit j.
n : positive integer parameter defining the exponent.

The term of maximum congestion line in objective function depends the relation between the magnitude of actual current through circuit and current-based thermal limit of the line as in equation (12) [10]:

$$T_2 = max\left(\frac{I_j}{I_{N,j}}\right) * 100 \tag{12}$$

3.1.3 PVDG Injected Power

The PVDG is available in sizes from several kilowatts to tens of megawatts and is connected to the power system at the substation or distribution levels. To find optimal PVDG with minimum total power injected in distribution level, equation (13) is used in multi-objective function as[11]:

$$T_3 = \sum_{i=1}^{N_P} P_P, i \tag{13}$$

Where,

N_P : The number of the PVDG in Distribution system.

P_P : The power of the gth PVDG.

3.1.4 The L_∞ technique

The injection of PVDG in the radial distribution system has many benefits to the system. But it represents an influencing factors 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 the question of how much PVDG can be penetrated in a distribution grid without risking overvoltage. In this study, the L_∞ technique is proposed to improve the voltage profile, with an optimal algorithm to select the optimal size and placement of PVDG.
The ∞-norm: As $p \to \infty$, the L_p norm tends to the so-called ∞-norm, or L_∞ norm, which define the L_∞ norm as the supremum (least upper bound) of the absolute value as in equation (14) [12]:

$$\|x\|_\infty = sup_{\ t}\ |x(t)| \tag{14}$$

For the vector $V = \{v(1), \ \ldots, \ v(N_{bus})\}^T$, with, $i = 1,2, \ldots, N_{bus}.$, where the N_{bus} is the number of buses in distribution system. V is the measured voltage of the distribution system and, $v(i)$, is measured voltage at bus (i) in distribution system. To find the supremum of the vector V:

$$\|V\|_\infty = sup_{\ i}\ |v(i)| \tag{15}$$

$$v_p(i) = (v(i) - 1) * 100 \tag{16}$$

$$V_P = \{v_p(1), \ \ldots, \ v_p(N_{bus})\}^T \tag{17}$$

Now, the L_∞ 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 distribution system

$$T_4 = \left\|V_p\right\|_\infty = sup_{\ i}\ \left|v_p(i)\right| \tag{18}$$

The multi-objective function of the PVDG in the grid is considered as follows:

$$T = (K_1T_1) + (K_2T_2) + (K_3T_3) + (K_4T_4) \tag{19}$$

Here, T is the fitness function which is required to be minimized in order to reduce congestion and get minimum loses with K_1, K_2, K_3 and K_4 are represent the penalty factors.

3.2 Constraints

The objective function in equation (19) is subjected to a set of constraints, as shown below:

3.2.1 The power Balance Constraints

Power losses are due to the flow of the current through impedances of energized conductors and calculated by using equation (10). The power balance constraint has the following form [2]:

$$\sum_{i=1}^{N_l} P_l, i \ - \ P_{Grid} \ - \ \sum_{i=1}^{N_P} P_P, i \ + \ \sum_{n=1}^{N_{br}} P_{loss}, n \ = 0 \tag{20}$$

3.2.2 The Voltage and current Limits

The distribution grid is modelled as buses connected by a set of transmission lines with PVDGs connect to the grid. Bus 1 is the slack bus and has a constant voltage magnitude and phase, and the buses (i = 2,…, $Nbus$) have variable voltages within allowable limits to ensure the required quality of service of the system. The lower and upper bounds for the voltage are 0.95 to 1.05 pu in distribution systems [13].

$$V_{min} \le |V_i| \le V_{max} \tag{21}$$

V_i : the variable voltage magnitude .
V_{min}: the minimum voltage limits.
V_{max}: the maximum voltage limits.

The line current limitation in the transmission line between buses (i and j) imposed as in equation (22) [2, 13]:

$$I_{ij} \le \ I_{i\,j}^{max} \tag{22}$$

3.2.3 The PVDG Units' Capacity Limits

The acceptable voltage limits in the distribution network will be violated due to further addition of PVDGs, which cause an increase in network losses due to the reverse power flow. Thus, the hosting capacity of PVDG of the distribution network is limited by overvoltage.The power of each PVDG units are select within a specific range:

$$P_P^{min} \le P_P \le P_P^{max} \tag{23}$$

Also, the sum of the capacity of all PVDG units should not be exceeded the load demand in the distribution grid as represented in equation (24):

$\sum_{i=1}^{N_P} P_P, i \leq \sum_{i=1}^{N_l} P_l, i$ (24)

4 NMCA Optimization Algorithm for PVDG Units

One of the major important issues with significant impacts on economic and technical is the planning of PVDG. With the strong growth in the connection of PVDG units in the power grid, several methods have been employed to solve optimization problems considering the different objective functions and constraints. By selection an optimal location and sizing of PVDGs, an extra power source can be added to enhance the grid and reduce itis congestion. In this section, NMCA has been applied for determining the best location and size of PVDG units so that congestion problems are released and all total power loss is minimized.

The whole process of using NMCA algorithm for optimal allocation of PVDG units in radial distribution power system is described in detail as follows:

Step 1: Initialization:

Set the temperature range T_{min} and $T_{min}$and the location range, set the camel caravan size and the dimensions, set the Visibility threshold, set Std. threshold, set c and θ values, initialize the location of each camel.

Upload system data, which includes bus data and line data of the radial distribution system.

Define the constraints of the problem.

Step 2: Subject the locations to a certain fitness function, determine the current best location, and randomly assign a visibility (v) for each camel.

To calculate the fitness function:

Subject the solution (PV location and size) to Distribution system.

Run power flow to obtain all variables.

Run contingency analysis.

Calculate L_∞ .

Calculate total power loss, then calculate fitness function (multi-objective function) by using Equation (19).

For r=1: Run

Step 3:

While (iter < itermax) do

For i=1: Camel Caravan size

Compute the temperature T.

Compute the endurance E.

Compute 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. (3)

Else

Update the camel location from Eq. (9)

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

2 Application of proposed algorithm on radial distribution system.

The In this section, different case studies are conducted to evaluate the overall performance of the proposed strategy. Two IEEE test systems are used in this study as follows:

Scenario 1: normal load-case of 33-bus with PVDG.
Scenario 2: heavy load case of 33-bus with PVDG.
Scenario 3: normal load-case of 69-bus with PVDG.
Scenario 4: heavy load case of 69-bus with PVDG.

5.1 Case Study (1)

The proposed strategy has been applied on IEEE 33 bus structure system. Here, the problem is to find an optimal configuration (the number, locations, and sizes) of PVDGs. This system has been modefied such that the current load is 3.7 MW active power and 3.53 MVAR reactive power, where as the origenal system with 3.7 MW active power and 2.3 MVAR reactive power [14]. the modification purpuse is to a create a suitable enviermante for congestion problem and voltage droop problem. The power calculation has been done asumming Sbase = 100 MVA and Vbase =12.66 kV. Figures (1) and (2) reflects the system behaiver with and without PVDGs for normal loading condition. Figures (1) show the system busses current with resence and absens of PVDGs in addition with line limits. From the figure one can canculude the flowing points:

1- Reduction of lines current. Such that all the current droop below limits values.
2- Reduction of current has a significant effect on a power loss reduction and relief the congestion in the system..

Figures (2) show the voltage profile of the system under consdriation with and with out PVDGs installition. From the obtained result's one can see when there are no PVDGs the voltage profile suffer from noticeable voltage droop special in buses (16-17-18), where voltage droop to (0.8658 pu). but on the application of PVDGs the system profile improved efficiently and the voltage profile tolerated between (1 and 0.9901) pu.

5.2 Case Study (2)

In this case the system has been tested for heavy loading represented by 5.1401MW active power and 4.942MVAR reactive power. also The power calculation have been done assuming Sbase = 100 MVA and Vbase =12.66 Kv. From the figures (3) the following points are clear:

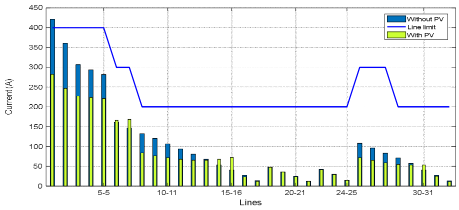


Fig. 1. Lines current without and with PVDG for 33-bus system with normal load.

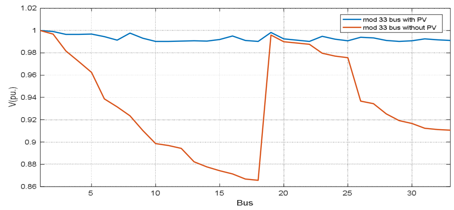


Fig. 2. Volt profile without and with PVDG units for 33-bus system with normal load units

1- When there is no PVDGs power the system loading for lines (1-2 ,2-3, 3-4, 4-5 and 5-6) exceding there thermal limits and the system can not deal the such loading specalic in these buses.
2- On the aplication of PVDGs the buses current droop below there themal limits and there (in line (1-2) the current befor installing PVDGs is (611A) and after installed PVDGs is (399A)

From the figures (4) the following points are clear:

1- When there is no PVDGs the system sufler from high deviation in voltage profile where it reach to (0.8003 pu) and the accebted limit in destribution grid is (1.05 to 0.95) pu.
3- The PVDGs Improve the voltage profile when installed, where the deviation in the voltage profile reduces from (0.8003 pu) to (0.9861 pu).

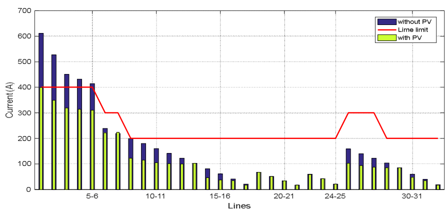


Fig. 3. Lines current without and with PVDG units for 33-bus system with heavy load.

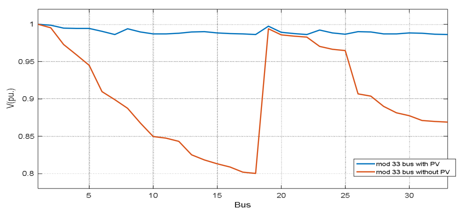


Fig. 4. Volt profile without and with PVDG units. For 33-bus system with heavy load.

5.3 Case Study (3)

The proposed strategy has been applied on IEEE 69 bus structure system. In this case the system has been tested for normal loading represented by 3.8 MW active power and 2.7 MVAR reactive power [15]. also The power calculation have been done assuming Sbase = 100 MVA and Vbase =12.66 Kv Figure(5) and figure (6) demonstrate the results for applied PVDGs in IEEE 69 system. From figure (5), the following points are clear:

1. On the aplication of PVDGs the buses current droop below there themal limits and there (in line (1-2) the current befor installing PVDGs is (387.18 A) and after installed PVDGs is (216.1A)
2. The result of the reduction of current are power loss reduction and relief of the congestion in the system.

From the figures (6) the following points are clear:

1. When there is no PVDGs the system sufler from high deviation in voltage profile where it reach to (0.9092 pu).
2. The voltage profile Improved when PVDGs has installed, where the deviation in the voltage profile reduces from (0.9092 pu) to (0.9966 pu).

5.4 Case Study (4)

In this case the system has been tested for heavy loading (1.6 from normal) represented by 6.082224MW active power and 4.30976 MVAR reactive power. also The power calculation have been done assuming Sbase = 100 MVA and Vbase =12.66 Kv Figure(7) and figure (8) demonstrate the results for applied PVDGs in IEEE 69 system. From figure (7), the following points are clear:

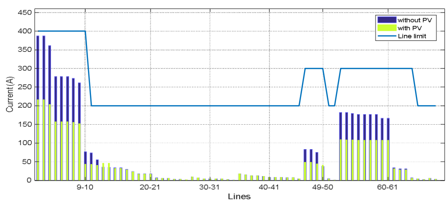


Fig. 5. Lines current without and with PVDG units for 69-bus system with normal load.

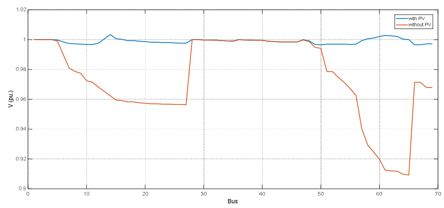


Fig. 6. Volt profile without and with PVDG units , for 69-bus system with normal load.

1- When there is no PVDGs power the system loading for lines (1-2 , 2-3, 3-4, 4-5, 5-6, 6-7, 7-8, 8-9, 51-52, 9-53, 53-54, 54-55, 55-56, 56-57, 57-58 and 58-59) exceding there thermal limits.

2- On the aplication of PVDGs the buses current droop below there themal limits and there (in line (1-2) the current befor installing PVDGs is (644.3694 A) and after installed PVDGs is (348.5021 A)

From the figures (8) the following points are clear:

3. When there is no PVDGs the system sufler from high deviation in voltage profile where it reach to (0.8445 pu).
4. The PVDGs Improve the voltage profile when installed, where the deviation in the voltage profile reduces from (0.8445 pu) to (0.9947 pu).

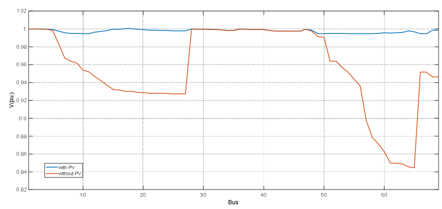


Fig. 7. Lines current without and with PVDG units for 69-bus system with heavy load.

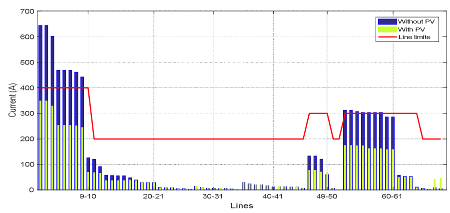


Fig. 8. Volt profile without and with PVDG units for 69-bus system with heavy load.

For verifying the performance of NMCA, eight other methods (Firefly algorithm (FA), particle swarm optimization (PSO), Grey Wolf Optimizer (GWO), Improved invasive weed optimization algorithm (IWO), Artificial Bee Colony (ABC) Optimization, Harmony Search (HS), modified Camel Algorithm MCA and Salp Swarm Algorithm (SSA)) are applied on the IEEE 33 and IEEE 69 systems (in case of normal and heavy load). For each algorithm in case (1) has been 20 trials, and the other cases have been 30 trials (in Matlab program), and for each run, 400 iterations with 400 particles. The results of these cases are shown in tables (1) to table (4). From Tables (1-4). The following points can be concluded:

1. Minimum cost and minimum mean cost (in all cases) find by The NMCA algorithm.
2. There is a significant improvement in the performance of NMCA than MCA in all cases, wherein case (4) for mean cost improved (14.72%).
3. The numerical results have verified the effectiveness of NMCA on the eight other methods.

Table 1. The comparison among eight methods for IEEE 33-bus system (normal load).

optimization Algorithms	Min cost	Max cost	Mean cost
ABC	3.297414	3.337504	3.317941
MCA	3.292848	3.394979	3.324087
FA	3.282356	3.406839	3.323749
GWO	3.282579	3.634918	3.323069
HS	3.297804	3.347978	3.321397
IWO	3.293783	3.382496	3.31921
PSO	3.290107	3.345048	3.31598
SSA	3.287941	3.634899	3.362063
NMCA	3.282302	3.316998	3.300953

Table 2. The comparison among eight methods for IEEE 33-bus system (heavy load).

optimization Algorithms	Min cost	Max cost	Mean cost
ABC	19.75975	21.8354	20.40861
MCA	19.70274	23.54049	21.05797
FA	19.52142	19.77067	19.58841
GWO	19.51542	19.72042	19.56593
HS	19.51121	19.64605	19.58954
IWO	19.52976	22.9247	20.25597
PSO	19.51977	19.80548	19.62532
SSA	19.51679	20.11197	19.71944
NMCA	19.5	19.683	19.56436

Table 3. The comparison among eight methods for IEEE 69-bus system (normal load).

optimization Algorithms	Min cost	Max cost	Mean cost
ABC	2.868379	3.033751	2.943347
MCA	2.851789	3.251348	2.965185
FA	2.851863	4.125542	3.129453
GWO	2.851981	3.312213	2.97743
HS	2.87181	3.143175	3.039544
IWO	2.851788	3.376668	3.084053
PSO	2.908849	3.275703	3.030924
SSA	2.85179	3.402151	3.106977
NMCA	2.851787	3.054887	2.858705

Table 4. The comparison among eight methods for IEEE 69-bus system (heavy load).

optimization Algorithms	Min cost	Max cost	Mean cost
ABC	11.93381	12.26654	12.14651
MCA	12.09206	16.05889	13.79611
FA	11.74758	13.41285	12.25348
GWO	11.74021	12.12139	11.9055
HS	11.88661	12.12976	11.99741
IWO	11.73223	15.15766	12.56227
PSO	11.73144	12.59769	11.80033
SSA	11.74168	12.86283	12.22365
NMCA	11.70647	12.09886	11.76586

The minimum cost and minimum mean cost in two cases normal and heavy load for 69-bus system reached by NMCA algorithms. The implement NMCA algorithm for finding optimal allocation of PVDG units to reduce the congestion, reduce power loss and keeping voltage of all buses within an accepted range. Two study systems including an IEEE 33-bus and an IEEE 69-bus system are chosen for running the NMCA algorithm.

6 Discussion on NMCA convergence

For further examining the performance of the proposed NMCA to solve the major problems in distribution grid (power losses, congestion and voltage profile), the convergence rate (CR) value is determined for all the considered cases in order to test the convergence speed as follows[15]:

$$CR = \left(1 - \frac{NFE^R}{NFE^{max}}\right) \times 100\ \% \quad (25)$$

NFE : number of function evaluations.

NFE^{max} : maximum number of function evaluations.

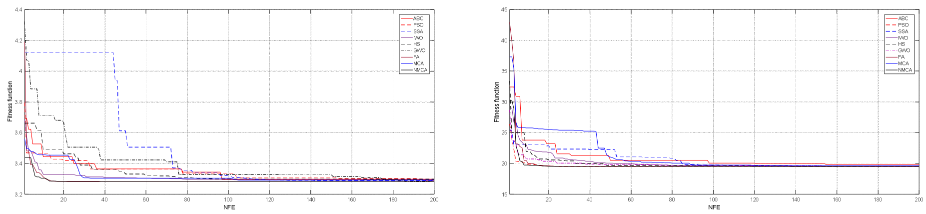
where CR ∈ [0, 1] and the values of CR equal to zero and unity, respectively, indicate the worst and best convergence profile of the considered algorithm. The adopted scheme to find the value of CR for any number of optimization methods stated as [15]:

(a) Run all the optimization methods up to NFE^{max}.
(b) Set minimum objective value found (in case of minimization problem) as value-of interest.
(c) Find in which NFE, each algorithm has reached to this value and set it as NFE^R
(d) Compute the CR for each algorithm as shown in equation (25).

The CR value is determined from the best obtained convergence profiles of the observed test cases. From Table 5, can be noticed that the proposed NMCA algorithm has the highest average CR value that clearly indicates that this algorithm converges to the optimum solution in lesser number of NFFEs as compared to any other compared methods used. In Figure (9) and figure (10) depicted the comparative plots of the fitness function for all the studied optimization methods. NMCA is finds the lowest fitness value with a faster convergence profile for most of the cases. Where, it is clearly outperforming the other compared algorithms in this study.

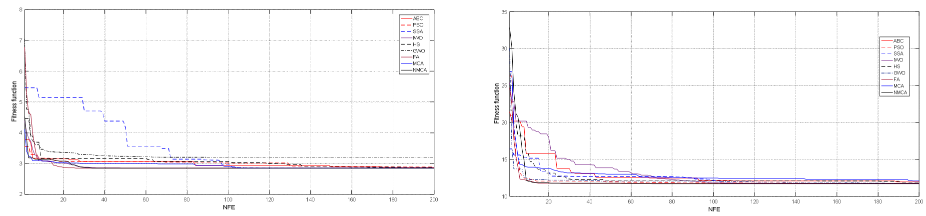
Table 5. The CR value of various algorithms used for optimisation

Algorithms	CR%			
	IEEE 33 bus		IEEE 69 bus	
	Case1	Case2	Case3	Case4
ABC	51.5	22.5	10.5	6
MCA	46.5	54	46.5	1
FA	84	84	81	67.5
GWO	7	11	20	0.5
HS	17	31.5	2.5	4.5
IWO	45	23	66	17.5
PSO	2.5	12.5	35	19.5
SSA	29.5	34	35.5	23.5
NMCA	86	89	83	69.5



Case 1 Case 2

Fig. 9. Comparative convergence profile of fitness function value offered by different algorithms pertaining to IEEE 33-bus: Case 1 and Case2



Case 3 Case 4

Fig. 10. Comparative convergence profile of fitness function value offered by different algorithms pertaining to IEEE 69-bus: Case 3 and Case 4

7 Conclusion

An optimal configuration of PVDGs to relieve congestion problems in the power system has been selected in this paper. A novel NMCA algorithm has been utilized for this purpose. The NMCA is inspired by the camel travelling behaviour for finding food and water in the desert. The proposed algorithm is very simple and it has a few parameters to tune, which makes it adaptable to a wider class of optimization problems not only for engineering application problems. NMCA validity is verified using power system problems. Congestion in the overloaded lines, voltage profile, and power losses in the distribution system are considered here. The proposed NMCA method is, successfully, implemented on IEEE 33-bus and IEEE 69-bus test power systems. According to the results, the proposed algorithm can outperform the well-known algorithms (like ABC, MCA, FA, GWO, HS, IWO, PSO, and

SSA) and the convergence of the algorithm is evaluated here using convergence rate and convergence plots. Based on the results, the proposed algorithm is also very effective for constrained engineering problems. NMCA is so effective, and improvements in designing are possible such as improvements for multi-objective and high-dimensional optimization problems. NMCA is very encouraging for future researchers as an effective optimization tool to deal with multi-objective large-scale power systems problems.

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