Optimal Distribution Network Reconfiguration with Distributed Generation Using New Modified Camel Algorithm

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Abstract: One of the most significant lines of current distribution network planning research in the present systems with the sound of renewable energy scenario is to look at various ways to improve the stability and performance of these networks without having to extend the existing infrastructure. This paper proposes a new modified camel algorithm (NMCA) to find an optimal distribution network reconfiguration (DNR) and photovoltaic distributed generation (PVDG) unit's configuration (number, size, and location). The proposed NMCA with L∞ optimized Multi-objective functions. The multi-objective function considers the voltage profile, congestion of network lines, and power loss reduction with suitable weights without violating the system constraints. The proposed algorithm has successfully experimented on 33-bus, 69-bus, and 84-bus distribution networks. The obtained results confirmed the superiority effectiveness of NMCA for solving DNR and PVDGs configuration problems over other competitive algorithms. Furthermore, NMCA robustness and stability were proved through a detailed statistical analysis.

Keywords: Network Reconfiguration, New modified camel algorithm distributed generation congestion problem, power loss, voltage profile

1. Introduction

In a modern power system, the distribution networks integrated with PVDGs play an essential role in serving various loads in the grid; however, the power loss in the grid is high, and the network suffers from congestion also suffers from high deviation in voltage. To improve the voltage profile, relieve the congestion and reduce the power loss in grids, there are many ways such as balancing loads, compensating reactive power, increasing wire section, and increasing operating voltage. However, these solutions need a lot of investment cost. Therefore, the optimal PVDG units and DNR are known as effective methods to relieve the congestion, reduce the power loss and improve the voltage profile in distribution networks while not requiring much investment cost [1, 2].

In literature surveys, the researchers have used a variety of methodologies, ranging from heuristic methods to metaheuristic methods, to select the optimal configuration of the PVDGs and DNR problem in distribution networks. J. Shu and L. Zhang [3] introduced a new method of mixing the optimal power flow and optimization algorithm. As a result, the enhanced genetic algorithm can set up a feasible distribution system structure. As shown, the performance of the improved genetic algorithm method is better than those obtained by the simple genetic algorithm. Amanulla and Singh [4] present a new methodology for optimal DNR to enhance the power reliability in the grid. The optimal switches status in the distribution system is determined based on a binary particle swarm optimization-based method. As a result of this work, the power reliability was enhanced, and power loss was reduced. Sajad and Taher [5] present a methodology to deal with the multi-objective DNR in distribution systems with the sound of renewable energy sources. An effective probabilistic power flow strategy uses to handle the load demands. The proposed method was applied to two IEEE test systems to illustrate the superiority of the algorithm. The numerical results demonstrate that the bus's voltages are within the accepted limits considering the uncertainty in renewable energy sources and load. Xing and Zeng [6] presented an optimization method with Tree Structure Encoding technology to minimize the

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total active power loss. This work considers the intermittent renewable energy uncertainties and load uncertainties. Also tested the proposed method on two different systems. As a result of this work, the proposed method can efficiently deal with the uncertainty and reduce the total active power losses. Kritavorn and Lantharthong [7] proposed a new technique for optimally distributed generators and DNR to minimize power loss. This paper employed the simulated annealing algorithm to solve the problem. The simulation results of the test system were used to evaluate the effects of this technique. The results show that the optimal DNR and DG help minimize power loss and improve the voltage in the system. Ramadoni and Mochamad [8] introduced optimal DNR with the integration of distributed generation using an improved particle swarm optimization method. The result from the test of the proposed method in a 60-bus Bantul distribution network shows that optimal DNR with DG has successfully enhanced the efficiency of the distribution network. Caoyuan and Chunxiao [9] presented a new strategy based on DGs and DNR on a dual hybrid particle swarm algorithm. The results prove that this new strategy can find the optimal solution and minimize power loss with a fast convergence rate. Haijun and Shaoyun [10] proposed an ordinal optimization method for the DNR problem. The results from testing the algorithm in the TPC 84-bus system are compared with different methods and show that the proposed method can obtain a good enough solution with much less CPU time than other methods. CASSIO and LINDENBERG [11] presented an alternative method for the DNR problem to minimize the power loss, based on the firefly algorithm. The results of the test firefly algorithm in different test systems are compared with the selective bat algorithm. They show that the choice of the suggested method is an excellent choice for attaining decent results. Tung and Dieu [12] proposed the stochastic fractal search method to solve the integration of DGs and DNR problems. The loss sensitivity factor and stochastic fractal algorithm are used to determine the optimal allocation of DGs. The results of the test of the proposed method in different test systems (33-bus, 69-bus, 84-bus, 119-bus, and 136-bus) show that the proposed method has better solutions than other methods.

This paper proposed a new algorithm based on powerful tools (contingency analysis, L_∞ technique, and power flow analysis), promoting a synergy of these tools in the search for a solution to distribution networks problems integrated with PVDGs. The main contributions of this work are:

1. Proposed a novel method employing powerful tools to solve the congestion problem, power losses problem, and voltage droop problem.
2. Selected the optimal configuration of PVDGs and optimal DNR.
3. Tested the results in three distribution networks with different load conditions and compared different well-known optimization algorithms in the literature studies.

The paper structure is as next, in section two, the mathematical problem, in section 3, the proposed NMCA algorithm for distribution problems, in section 4, the simulation results, in section 5, the discussion about the convergence of NMCA. Finally, in Section 6, the conclusion and the future work.

2. Mathematical Problem

The DNR and PVDGs problem's multi-objective function enhances voltage profile, relieves congestion in distribution grid transmission lines, and minimizes power loss within system restrictions. Therefore, the expressed of the multi-objective function and constraints of the DNR and PVDGs problems are as follows:

A. Multi-objective function

The formulation of the problem of DNR and PVDGs in distribution systems is as follows.

A.1. Total active power loss

The mathematical expression of total active power loss (TPL) is given Equation (1):

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

N_{br}: the system's number of branches.
I_n: the n^{th} branch's current magnitude.
r_n: the n^{th} branch's resistance.

The parameters in the TPL equation are the line reactance and current. However, The TPL only depends on line current because the line reactance is constant regardless of the radial structure of the distribution network, and the calculation of line currents uses nodal voltages. Now, the nodal voltage equation and current Equation in vector form are as shown below [13]:

$$A^T.V = Z.I \tag{2}$$

$$I = A^T.V.Z^{-1} \tag{3}$$

A : the node branch incidence matrix for the radial distribution system
V : the nodal voltage vector.
Z : the branch reactance matrix.
I : the branch current vector.

The total power losses in vector form are as shown below:

$$TPL = I^T.R\,.I^* \tag{4}$$

Now, substituting (2) and (3) into (4), the total power losses can be computed as:

$$TPL = V^T.A.Z^{-T}.R\,.Z^{-*}.A^T.V^* \tag{5}$$

and

$$Z_n = r_n + j.x_n \tag{6}$$

$$V_n = e_n + j.f_n \tag{7}$$

In this study, the design of each branch is to have a controlled switch. Therefore, an explanation of the state of each switch is as follows::

$$S_m = \begin{cases} 1 & \text{the switch } m \text{ is closed.} \\ 0 & \text{the switch } m \text{ is open.} \end{cases} \tag{8}$$

and

$$A_{(n,m)} = A_{o(n,m)} \times S_m \tag{9}$$

$A_{o(n,m)}$: the node branch incidence matrix.
S_m : state of the switch.

and can be formed nodal incidence matrix from radial distribution network by defining the nodal incidence matrix as [14]:

$$a_{n,m} = \begin{cases} -1 & if\ branch\ n\ leave\ m\ node \\ 0 & branch\ n\ dose\ not\ toch\ \ m\ node \\ +1 & branch\ n\ enter\ m\ node \end{cases} \tag{10}$$

Now let the matrix $H_{n\times n}$ (with n total number of buses) is:

$$H = A.Z^{-T}.R\,.Z^{-*}.A^T \tag{11}$$

$$H = \begin{bmatrix} \sum_{i=1}^{m}\left(a_{1i}^2.r_i \big/ |z_i|^2\right) & \cdots & \cdots & \sum_{i=1}^{m}\left(a_{1i}.r_i.a_{ni} \big/ |z_i|^2\right) \\ \vdots & & \ddots & \vdots \\ \sum_{i=1}^{m}\left(a_{ni}.r_i.a_{1i} \big/ |z_i|^2\right) & \cdots & \cdots & \sum_{i=1}^{m}\left(a_{ni}^2.r_i \big/ |z_i|^2\right) \end{bmatrix} \tag{12}$$

substituting (9), (11) and (12) into (4), now TPL is:

$$TPL = \sum_{j=1}^{n}\left(V_j^*.\sum_{n=1}^{n}\left(V_i.\sum_{c=1}^{m}\left(a_{ic}^o a_{jc}^o S_c^2 r_c \big/ |z_c|^2\right)\right)\right) \tag{13}$$

A.2. Total power injected of PVDGs

To select the optimal PVDG with minimum total power injected in distribution level, Equation (14) is used in multi-objective function as [15,16]:

$$T_2 = \sum_{i=1}^{N_P} P_P, i \tag{14}$$

where,

N_P : The PVDG number in the distribution system.

P_P : The power of the i[th] PVDG.

A.3. The L_∞ approach

The installation of PVDGs unit in the distribution system has many benefits. But it can be an influential factor on the system because it affects the voltage rise in the system. The voltage rise is the bottleneck of PVDG in the radial distribution system. Therefore, many previous studies attempt to address how much PVDG can penetrate a distribution grid without risking overvoltage. In this study, the L_∞ is proposed to improve the voltage profile and solve the problem of PVDGs in the system, based on 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 defines the L_∞ norm as the supremum (least upper bound) of the absolute value as in equation (15) [17]:

$$\|x\|_\infty = sup_{\ t}\ |x(t)| \tag{15}$$

Now for the vector V and, $v(i)$ with i th number of buss in the distribution network, can find the supremum of the vector V as in Equation (15):

$$V = \{v(1), \quad \dots v(i), \quad v(N_{bus})\}^T \tag{16}$$

$$i = 1,2, \dots, N_{bus}.$$

$$\|V\|_\infty = sup_{\ i}\ |v(i)| \tag{17}$$

The desired value (target value) of voltage in the distribution system is the (1) pu. Therefore,

$$V_P = \{v_p(1), \quad \dots, \quad v_p(N_{bus})\}^T \tag{19}$$

Now, the L_∞ norm applied to V_p to find the supremum of the vector V_p, where the V_p vec represent the values of voltage change at each bus in the distribution system

$$T_3 = \|V_p\|_\infty = sup_{\ i}\ |v_p(i)| \tag{20}$$

One of the main targets of the proposed method is to make the difference (er) between the vector V and (1) pu (target) approach to zero as possible without violating the power system security limits.

As $\|V\|_\infty \to 1$, the $\|V_p\|_\infty \to 0$ and $er \to 0$.

Equation (18) represents the per-cent change of voltage in the distribution system:

$$v_p(i) = (v(i) - 1) * 100\% \tag{18}$$

A.4. The Congestion mitigation

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 (21):

$$J_C = \sum_j W_j \left(\frac{I_j}{I_{N,j}}\right)^{2n} \tag{21}$$

where,
W_j : weighting factor, $0 < W_j < 1$.
$I_{N,j}$: The line's current-based thermal limit.
I_j : the amount of the actual current flowing through the circuit j.
n : positive integer parameter defining the exponent.

The term of maximum congestion line in the objective function depends on the relation between I_j and $I_{N,j}$ of the line as in equation (22) [18]:

$$x = max\left(\frac{I_j}{I_{N,j}}\right) \tag{22}$$

$$u = \begin{cases} 0, & x < \propto \\ x/\propto, & x \geq \propto \end{cases} \tag{23}$$

$$T_4 = f(u) = 1 - \frac{1}{e^u} \tag{24}$$

where , $\propto < 1$

Now, the multi-objective function of the DNR and PVDGs in the network is:

$$T = (K_1T_1) + (K_2T_2) + (K_3T_3) + (K_4T_4) \tag{25}$$

K_1, K_2, K_3 and K_4 : the penalty factors in the fitness function.

Here, T is the Multi-objective function required to be minimized to relieve congestion, improve voltage profile and reduce power losses.

B. Constraints

B.1. System structure

In the power system, the protection schemes implementation of the radial structure constrains the Reconfiguration of radial distribution networks. Therefore, the distribution systems should maintain radial structure before and after Reconfiguration. To ensure the reconfiguration constraints are satisfied, the following requirement would be satisfied [19]:

$$N_{bus} - S_L = \sum_{n=1}^{N_{br}} |S_K|. \tag{26}$$

S_L : the total number of slack buses in the system.
N_{br}: The total number of branches in the system.

For each loop in the system, the absolute values of all the switch states need to satisfy the following Equation:

$$N_{busL} - 1 = \sum_{n=1}^{N_{brL}} |S_{KL}|. \tag{27}$$

N_{busL} : the number of branches in the Lth loop

In a radial distribution system with DNR, all loads should be served without disconnections, such that the rank of nodal branch incidence matrix is:

$$rank(A) \;= Q \tag{28}$$

Q : the node branch incidence matrix.

B.2. The PVDG units' capacity limits

The number of PVDG units and injected power of PVDG units are utilized within a specific range as shown [20]:

$$P_P^{min} \leq P_P \leq P_P^{max} \tag{29}$$

P_P : the power of the i^{th} PVDG.

P_P^{max} : the maximum power of the i^{th} PVDG

P_P^{max} : the minimum power of the i^{th} PVDG.

$$N_P^{min} \leq N_P \leq N_P^{max} \tag{30}$$

N_P : the number of the PVDG in the Distribution system.

N_P^{max} : the maximum number of the PVDG in the Distribution system.

N_P^{min} : the minimum number of the PVDG in the Distribution system.

B.3. The voltage and current limits

The lower and upper bounds of voltage in distribution networks are 0.95 pu. and 1.05 pu. Sequentially.

$$V_{min} \leq |V_i| \leq V_{max} \tag{31}$$

V_{min} : minimum voltage limit.

V_{max} : maximum voltage limit.

In the distribution grid, the line current limitation in the transmission line between buses (i and j) is imposed as in equation (27) [21]:

$$I_{ij} \leq I_{ij}^{max} \tag{32}$$

I_{ij} : the current of the line (*i,j*).

I_{ij}^{max} : maximum current-based thermal limit of the line (*i,j*).

3. NMCA algorithm for RND and PVDGs problem.

Nature-inspired metaheuristic methods have gained popularity, partly due to their capacity in solving non-linear global optimization problems. MCA is a metaheuristic algorithm inspired by camels and their behaviour in the desert [22]. All the camels are attracted towards the water and food sources in the desert, which have a higher temperature. This paper proposes a new version of the Modify Camel algorithm (NMCA). NMCA works in the same manner as MCA, with the following modification:

1-insert mutation step.
2-modify the position equation.
3-added the velocity equation.
4-added velocity limits.
5-added position limits.

The NMCA use the following equations:

$$T_d^{itr} = (T_{max} - T_{min})R + T_{min} \tag{33}$$

$$E_d^{itr} = \frac{\left(T_d^{itr} - T_{min}\right)}{\left(T_{max} - T_{min}\right)} \tag{34}$$

$$v_d^{itr} = \Theta\, v_d^{itr-1} + \left(x_d^{best} - x_d^{i,itr-1}\right)E_d^{i,itr} * c \tag{35}$$

$$x_d^{itr} = x_d^{itr-1} + v_d^{itr} \tag{36}$$

$$\gamma = (x_{max} - x_{min}) \tag{37}$$

$$x_d^{itr} = \gamma\, R + x_{min} \tag{38}$$

where

itr: Iteration

x_d^{itr} : Location

v_d^{itr}: Velocity
T_{max}: Maximum amount of temperature
T_d^{itr}: Temperature
E_d^{itr}: Endurance
x_{min}: the lower bound of all decision variables.
x_{max}: the upper bound of all decision variables.
T_{min}: Minimum amount of temperature
c : constant ∈ [1,3]
ϴ : constant ∈ [0,1]
R : random number ∈ [0,1].

The production of the initial population is a crucial stage in the optimization problem's implementation. Three elements are considered in the decision variables of this problem: tie switches, location, and size of all PVDG units. In addition, the entire population is generated at random within specific lower and higher bounds, as seen below:

$$x_m = [U_{m1}, .., U_{mk}, P_{m1}, .., P_{mi}, S_{m1}, .., S_{mj}] \quad (39)$$
$$x_m = [Tie\ switches, PVDGsize, PVDGlocation]$$
$$m = 1, \ldots ,\ N_{bus}$$

The NMCA algorithm is:

a) It has a few simple specific control parameters to be adjusted where it derives from the environment of Camel, and these make the NMCA a flexible algorithm for solving various and complex problems.
b) The strategy and mechanism of NMCA are powerful tools that may result in high exploration and fast convergence speed.

The whole process of a novel algorithm for optimal Reconfiguration and optimal PVDG units in a radial distribution system based on NMCA and $\boldsymbol{L_\infty}$ is described in detail as follows:

Step 1: Initialization:

a) **-Set the temperature range T_{min} and T_{max}**
-Set the location range
-Set the camel caravan size
-Set the dimensions
-Set the Visibility threshold
-Set Std. threshold
-Set c and ϴ values
-Initialize the location of each Camel.
b) **Upload system data (bus data and line data of system).**
c) **Define the constraints of the problem.**

Step 2:

-Applied the locations to a certain fitness function
-Determine the current best location
-Randomly assign visibility (v) for each Camel.
To calculate the multi-objective problem in Equation (25):

a) **Subject the solution (open switches and PV units (number, location and size) to the Distribution system.**
b) **Run power flow to obtain all variables.**
c) **Run contingency analysis.**
d) **Calculate L_∞ .**
e) **Calculate total power loss, then calculate fitness function by using Equation (25).**

For r=1: Run
Step 3:
While (iter < itermax) do
For i=1: Camel Caravan size
Compute the temperature T.
End If
- 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. (38)
Else
Update the camel location from Eq. (36)
End If
Apply Position 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.
Then
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
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

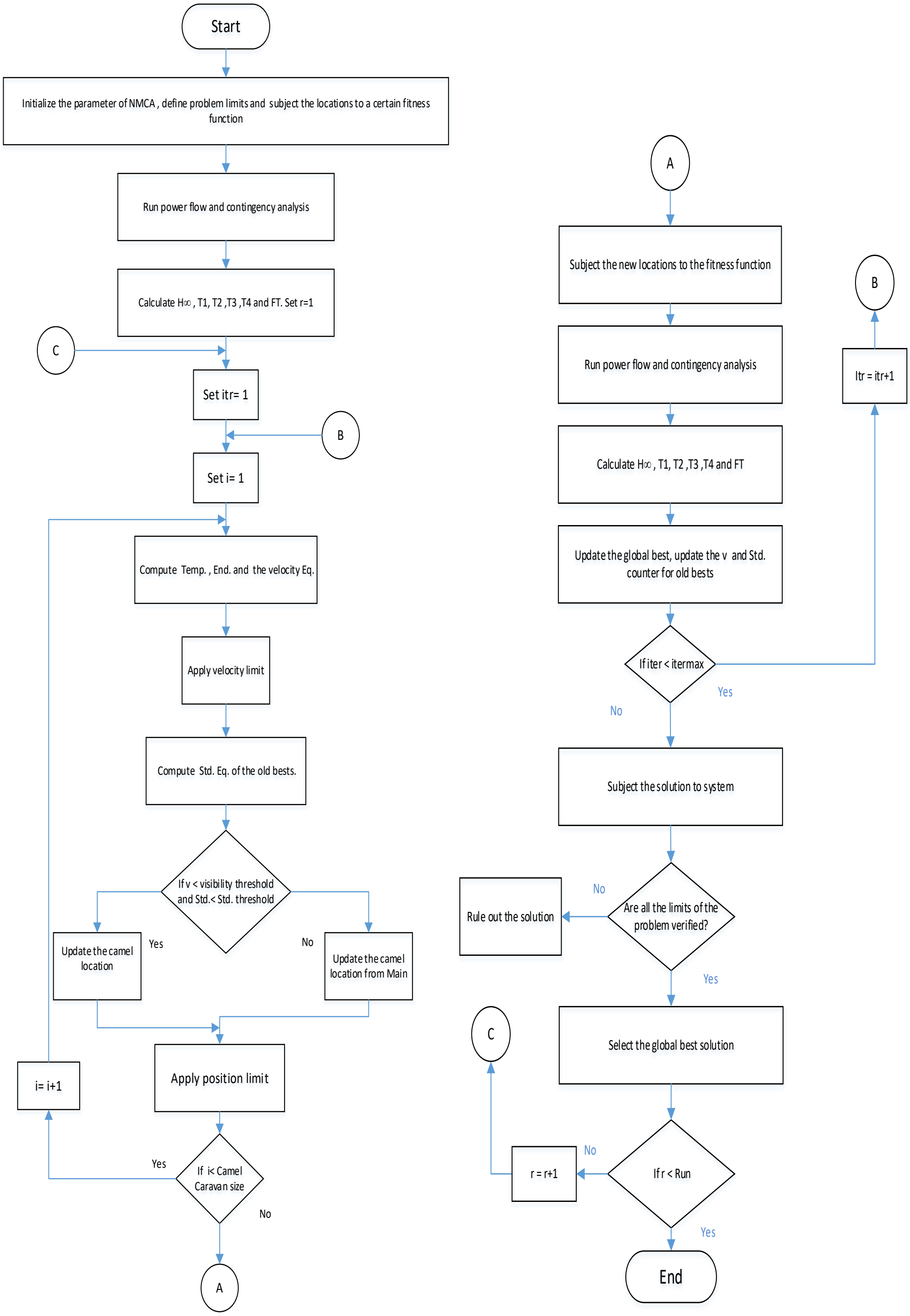

Figure 1. The flowchart of using the NMCA method for determining the allocation of PVDG units.

4. Results and Discussion.

In order to examine the proposed approach, consider the 33-bus system, 69-bus system, and 84-bus system. In this section, conducted different case studies were to evaluate the overall performance of the proposed strategy as follows:

Scenario 1: is a normal load-case of 33-bus with PVDG.
Scenario 2: is a normal load-case of 69-bus with PVDG.
Scenario 3: is a heavy load-case of 69-bus with PVDG.
Scenario 4: is a normal load-case of 84-bus with PVDG.

A. Scenario 1

The 33-bus system in the nominal case is 3.7 MW and 2.3 MVAR and has five ties and 32 sectionalizing switches, as shown in Figure 1 [23]. Performed power flow is Vbase =12.66 kV and Sbase = 100 MVA. The problem here is to find an optimal DNR and optimal configuration of PVDGs. To show the effectiveness of NMCA, performed three other methods (MCA, FA, and HS) and compared their results. In this case, by using Matlab's (2016) programming language, (10) trials of each method are run during each run with (400) iteration

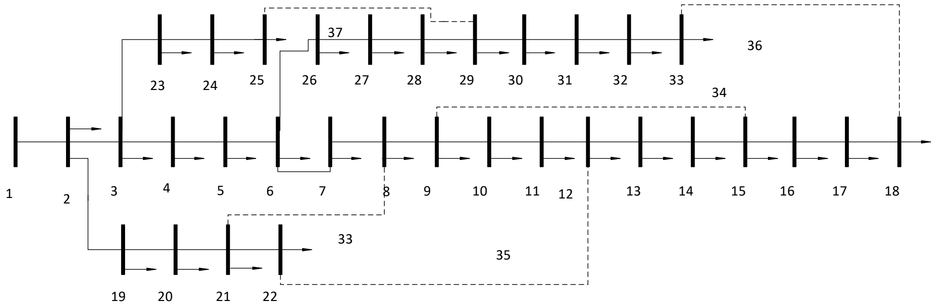

Figure 1. The 33-Bus test system with five tie lines.

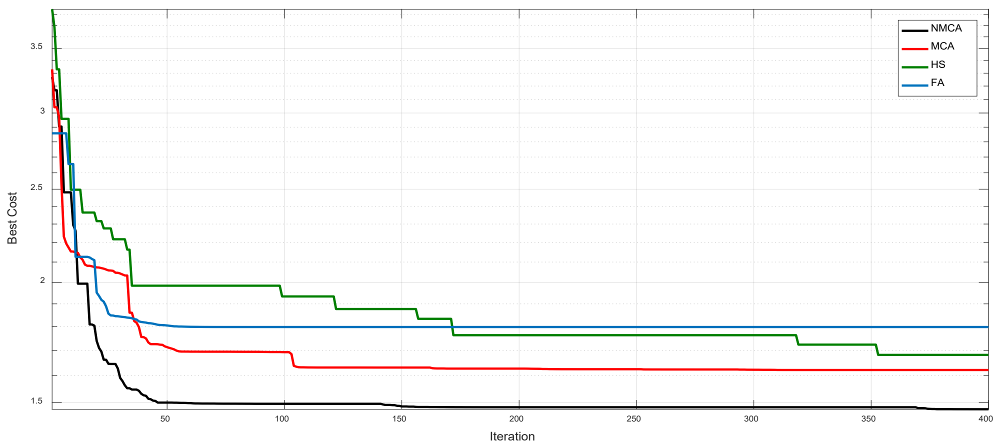

Figure 2. Several algorithms give convergence profiles of fitness function values for the 33-bus system.

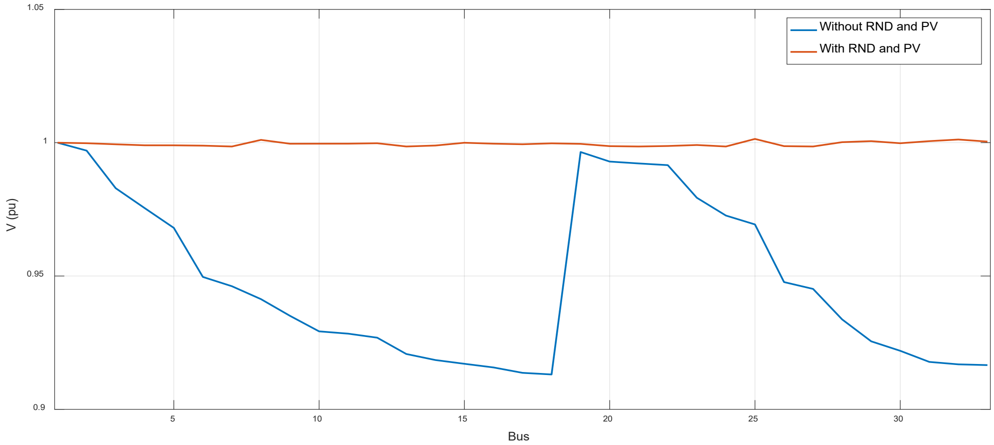

Figure 3. Volt profile without and with DNR and PVDG units. For a 33-bus system with normal load

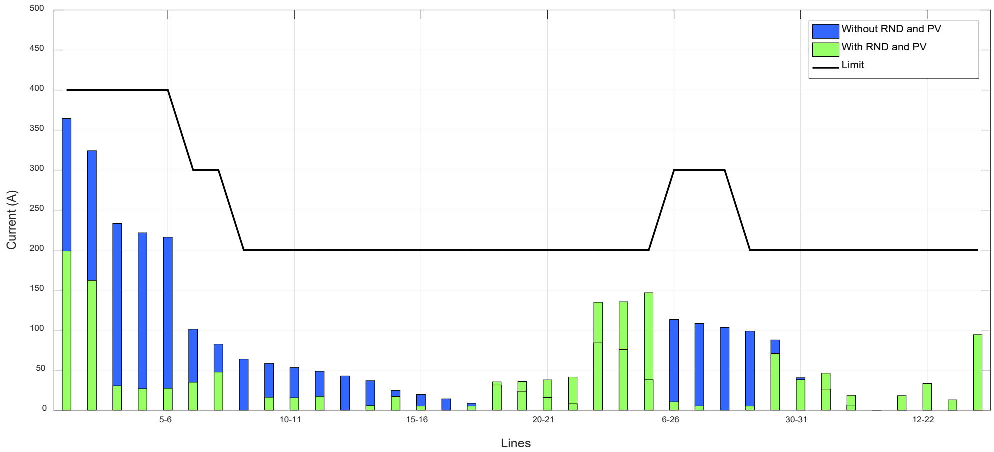

Figure 4. Lines current without and with DNR and PVDG units for IEEE 33-bus system.

Table 1. The comparisons of the different methods for IEEE 33-bus system (nominal load).

Methods	NMCA	MCA	FA	HS
P losses(kW)	80.175214	88.658783	80.275227	82.177492
min node voltage (pu)	0.998579297	0.9971279	0.994718386	0.9982054
$Max(I/I_{max})$	0.732946697	0.58214209	0.661285211	0.7335944
Open lines	[33,8,12,16,27]	[20,10,14,31,28]	[7,10,14,16,26]	[33,10,12,15,28]
Total PVDG power(MVA)	4.667328032	4.45653177	4.3400449	5.3578040
Injected busses	[7,11,14,21,24,28, 31]	[7,13,17,20,28,2 9]	[5,11,15,19,20,23, 28,30]	[1,7,12,17,21,24,2 9,30]
PVDG injected (kVA)	792.7664 386.9236 475.3767 187.5815 1166.526 688.9259 969.2279	789.9355 247.0553 763.71 629.661 1516.0263 510.13	372.6642 520.8022 388.8884 188.29 251.1134 14.03 1159.7445 1444.5125	681.072 1115.4773 228.95 582.3174 503.7828 1386.423 753.99 105.79
Cost	1.476412	1.62181	1.797546	1.707083
Mean cost	1.64208	1.7865	2.177852	1.741859

And (400) particles. The results in Figures 2-3 and Table 1 present the superiority of NMCA over the other algorithms. The minimum cost and minimum mean cost in this case reached by NMCA. Figures 2 - 4 show the convergence of fitness function from the best result obtained, influence for DNR and installing PVDGs on bus voltage deviation and the lines thermal limits, respectively. Table 1 and Figure 2 show that the NMCA has better results than other methods. Figure 3 illustrates the voltage profile of the system under consideration with and without DNR and PVDGs. The obtained results show that when there are no DNR and PVDGs, the voltage profile suffers from noticeable voltage droop unique in buses (16-17-18), where voltage droop to (0.91 p.u). Nevertheless, the system profile improved efficiently on applying DNR and PVDGs, and the voltage profile tolerated between (1 and 0.99) p.u. Figure 4 illustrates the current system lines with the presence and absence of DNR and PVDGs and line limits. From the Figure, one can deduce the following 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 relieves congestion in the system.

B. Scenario 2

In this case, applied the NMCA on the 69-bus system (Figure 5). The tested system under normal loading is 3.8 MW active power and 2.7 MVAR reactive power [24]. Also, The power calculation assumes Vbase =12.66 Kv Sbase = 100 MVA. Table(2) and Figures 6-8 illustrate the results for DNR and PVDGs in the 69 bus system. The optimal result by the NMCA algorithm provides the optimal cost (1.396991) and optimal mean cost (1.446), which is the lowest than other methods reported in Table 2. Table 2
Furthermore, Figure 6 illustrates that the convergence and stability of the proposed NMCA method are the best among all the compared methods. Figure 7 shows the following points:
1. When there are no DNR and PVDGs, the system suffers from a high deviation in the voltage profile (0.9092 p.u).
2. The voltage profile Improved when installed DNR and PVDGs, where the deviation in the voltage profile was reduced from (0.9092 p.u) to (0.9966 p.u).

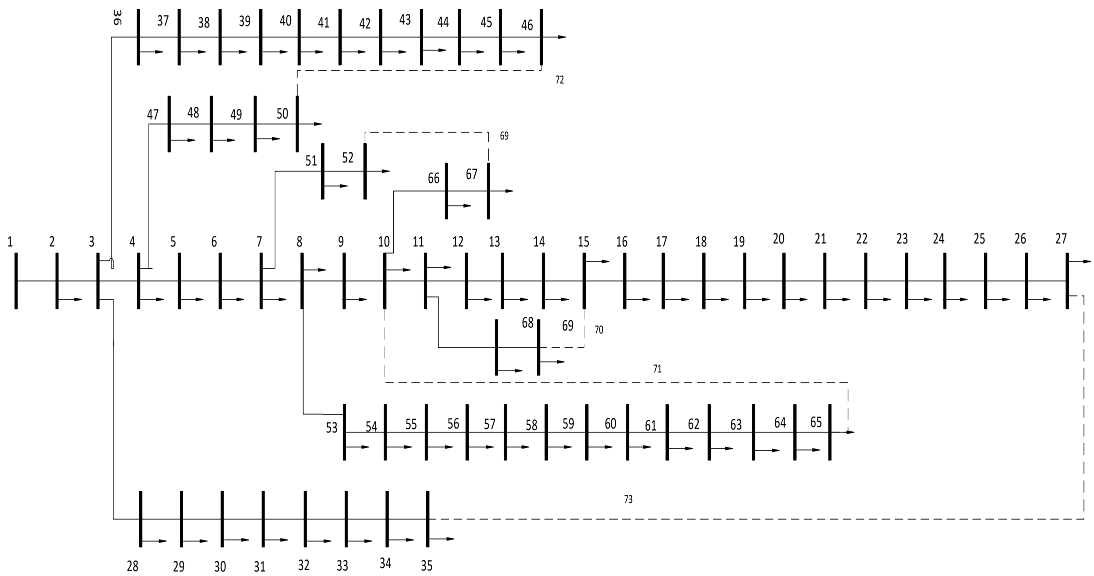

Figure 5. The 69-Bus test system with five tie lines.

Table 2.The comparisons of the different methods for IEEE 69-bus system (nominal load).

Methods	NMCA	MCA	FA	HS
P losses(kW)	60.890583	66.17471	67.394127	65.427686
min node voltage (pu)	0.996517628	0.9955	0.996825822	0.9949
Max(I/I_{max})	0.538287648	0.56396746	0.538155754	0.538892518
Open lines	[49,23,68,69, 63]	[44,24,13,6 9,63]	[49,73,12,51, 62]	[43,32,12,69, 63]
Total PVDG power(MVA)	3.721505861	4.720305	3.911005371	3.7139
Injected busses	[50,58,61,65, 69]	[15,31,45,5 0,51,54,56, 60,61]	[17,49,50,52, 61,64]	[12,14,15,43, 49,50,60,61, 62,63,65]
PVDG injected (kVA)	508.021 200.683 1581.734 981.839 449.227	791.052 376.198 256.945 370.948 676.430 335.619 286.566 1011.457 615.087	699.808 2.235 542.983 789.963 1872.927 3.072	40.369 128.756 952.571 13.489 301.356 192.416 190.457 635.437 429.258 485.101 344.715
Cost	1.396991	1.729559	1.43659	1.58073
Mean cost	1.446	1.852723	1.67917	1.698285

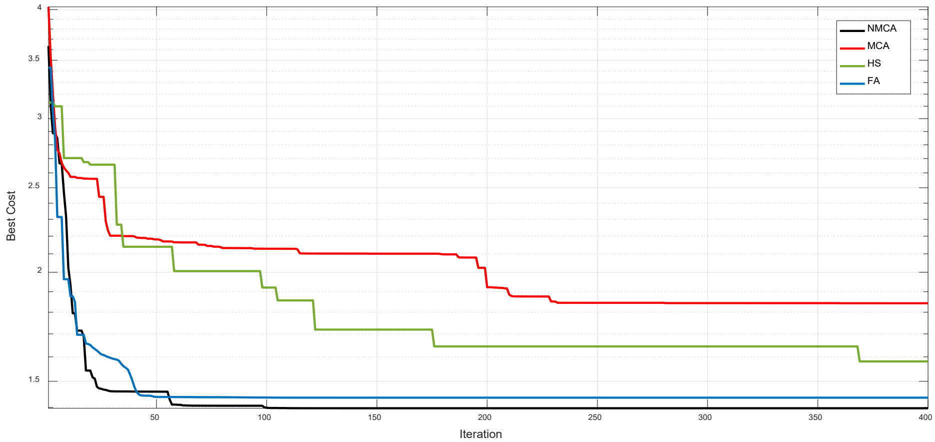

Figure 6. Several algorithms give convergence profiles of fitness function values for the 69-bus system.

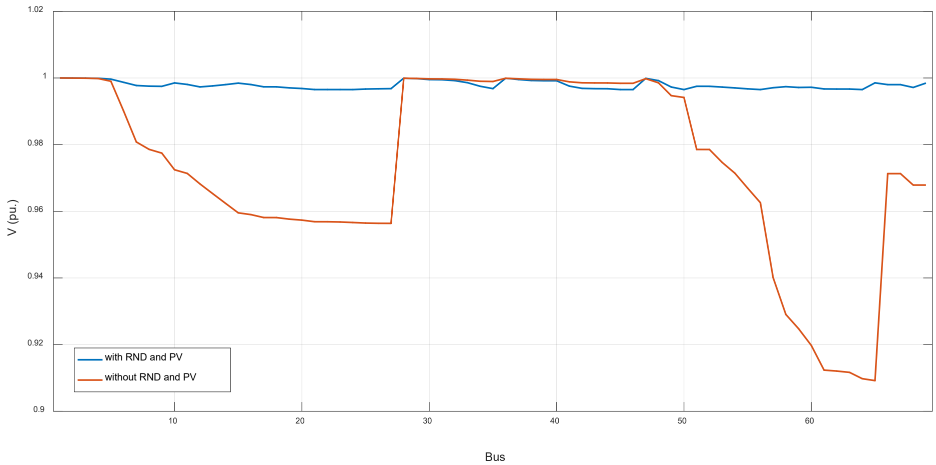

Figure 7. Volt profile without and with DNR and PVDG units. For a 69-bus system with a normal load.

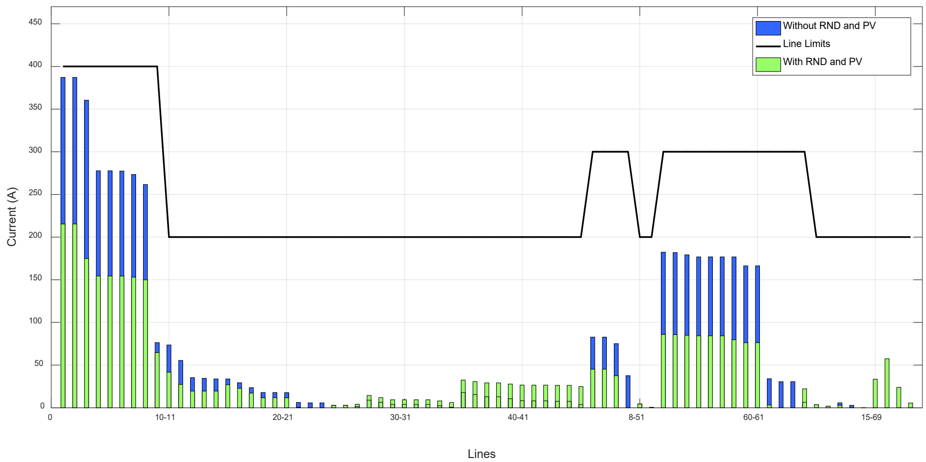

Figure 8. Lines current without and with DNR and PVDG units for IEEE 69-bus system.

Figure 8 illustrates the following points:

1. On the application of DNR and PVDGs, the lines current droop below their thermal limits, and there (inline (1-2) the current before DNR and installing PVDGs is (387.18 A) and after DNR and installed PVDGs is (215.31 A).
2. The results of the current reduction are power loss reduction and congestion relief in the distribution network.

C. Scenario 3

In this case, applied the NMCA on the 69-bus system (Figure 5). Under heavy loading conditions (1.6 from normal loads), the tested system is 6.082224MW and 4.30976 MVAR. Furthermore, the modified system has 652.216 kW power losses and 0.8445 p.u minimum node voltage. The power calculation assumes Vbase =12.66 kV and Sbase = 100 MVA. The convergence characteristics of the NMCA algorithm for the total active power loss, line congestion, and voltage profile objectives of the 69-bus system (heavy loads) are given in Tables (3-4) and Figures 9-11, respectively.

Table 3. The comparisons of the different methods for the IEEE 69-bus system (heavy load).

Methods	NMCA	MCA	FA	HS
P losses(kW)	157.280	168.217908	162.387	169.1228
min node voltage (pu)	0.9944173	0.9946	0.9906992	0.9949714
$Max(I/I_{max})$	0.866668	0.88995731	0.8939523	0.8710177
Open lines	[49,23,70,65,62]	[44,24,13,51,62]	[72,23,12,65,62]	[49,23,12,66,63]
Total PVDG power(MVA)	6.0373338	7.2709741	5.1541952	6.6785392
Injected busses	[10,11,17,50,54,61,62]	[10,12,24,31,45,50,57,61,62]	[17,54,55,61,62,68,69]	[4,5,10,14,15,17,25,44,45,55,62,63]
PVDG injected (kVA)	542.069 1088.340 567.423 813.514 252.331 1611.961 116.1693	281.920 1554.535 382.168 188.198 642.660 1006.238 1068.632 718.837 1427.782	1203.688 675.219 369.820 1141.673 1398.302 274.996 90.494	10.765 278.437 1130.768 108.293 239.254 838.059 47.609 137.493 939.183 69.942 1487.062 1391.668
Cost	2.552136	2.8392	2.772847	2.684173
Mean cost	2.69614	3.146595	2.87907	2.8114

Table 4. The results of the NMCA method for the IEEE 69-bus system.

No.	Line	I(A)without PVDG	I(A)with PVDG	$I_{max}(A)$
1	1-2	644.369	346.6674	400
2	2-3	644.369	346.6674	400
3	3-4	601.55	281.9243	400
4	4-5	468.78	249.4825	400
5	5-6	468.78	249.4825	400
6	6-7	468.34	249.3103	400
7	7-8	461.78	247.2684	400
8	8-9	442.6	241.3725	400
9	9-53	312.54	142.1150	300
10	53-54	311.81	141.9069	300
11	54-55	307.49	134.2145	300
12	55-56	303.53	133.0006	300
13	56-57	303.53	133.0006	300
14	57-58	303.53	133.0006	300
15	58-59	303.53	133.0006	300

After (10) runs and each run has 400 iterations with 400 partial for each iteration, the NMCA algorithm has converged to the optimal solution, proving that integrating the L_∞ technique has increased the effectiveness of the NMCA algorithm with a fast convergence process. As a result, the power loss decreased from 652.216 kW to 157.28 kW, and the voltage profile improved from

0.8445 p.u to 0.995 p.u. Besides, the current magnitude at all lines is significantly decreased, as indicated in Tables 3 and 11.

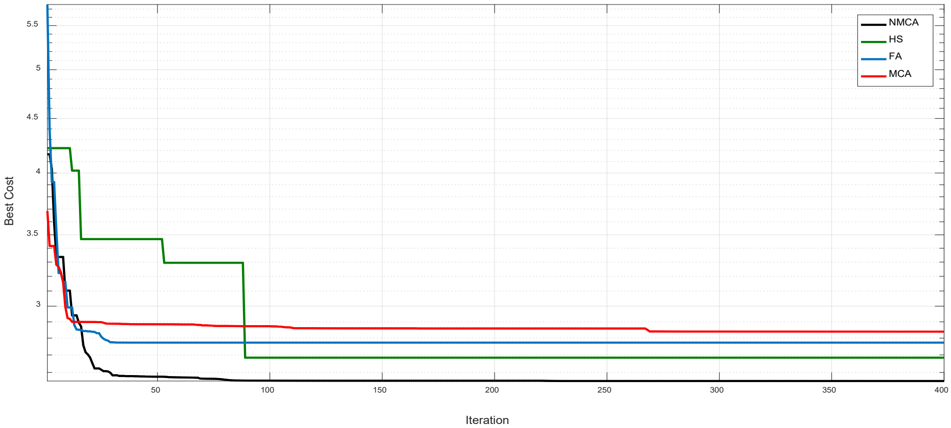

Figure 9. Comparative convergence profile of fitness function value offered by different algorithms about the 69-bus system (heavy loads)

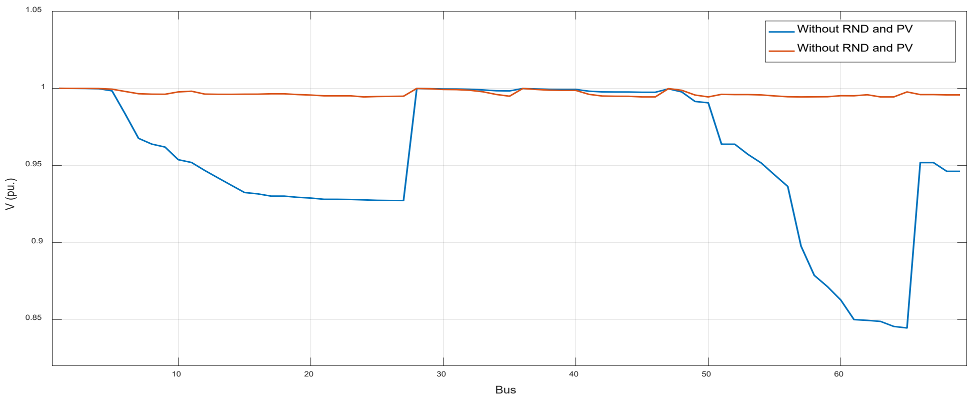

Figure 10. Volt profile without and with DNR and PVDG units. For 69-bus system (heavy loads)

D. Scenario 4

In this case, the NMCA for the practical distribution network of the Taiwan Power Company (TPC 84 bus system in Figure 12) [25] is applied. The tested system under normal loading is 28350 kW and 20700 kVar. The power calculation assumes Vbase =11.4 kV and Sbase = 100 MVA. The convergence characteristics of the NMCA algorithm for the total active power loss, line, congestion and voltage profile objectives of the 84-bus system are given in Tables (5) and Figures 13-15, respectively. After (6) runs and each run has 200 iterations with 400 partial for each iteration, the NMCA algorithm has converged to the optimal solution, proving that integrating the L_∞ technique has increased the effectiveness of the NMCA algorithm with a fast convergence process. The power loss decreased from531.994 kW to 268.722 kW, and the voltage profile improved from 0.9285 p.u to 0.9665 p.u. Besides, the current magnitude at all lines is significantly reduced, as indicated in Tables (5) and Figure 15. Table 5 shows four cases, the 84–bus system with RND and PVDGS, the 84-bus system with PVDGs only, the 84-bus system with RND only, and the original 84-bus system. One can see that the first case has a better solution than the other. The first case (DNR and PVDGs) has the minimum power losses and minimum voltage diversion.

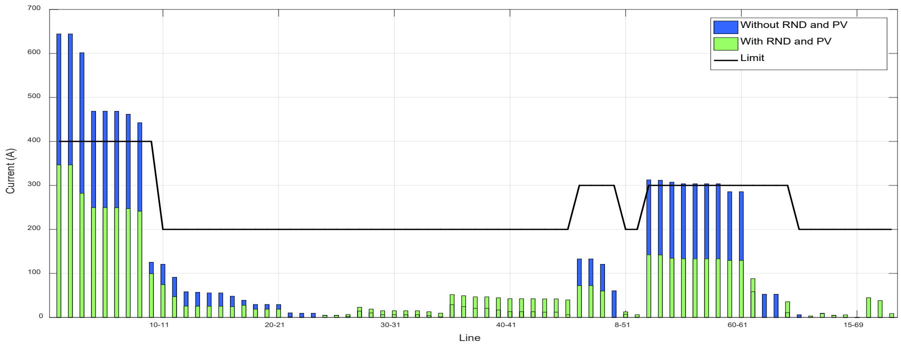

Figure 11. Lines current without and with DNR and PVDG units for IEEE 69-bus system (heavy loads).

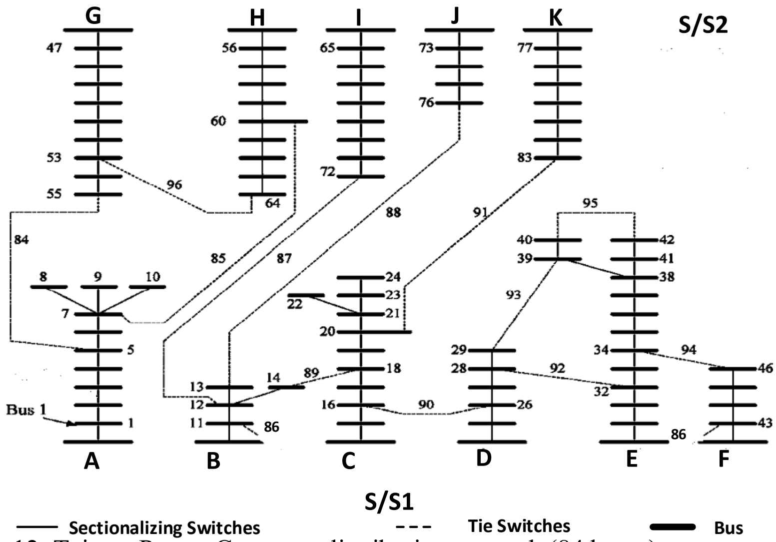

Figure 12. Taiwan Power Company distribution network (84 buses).

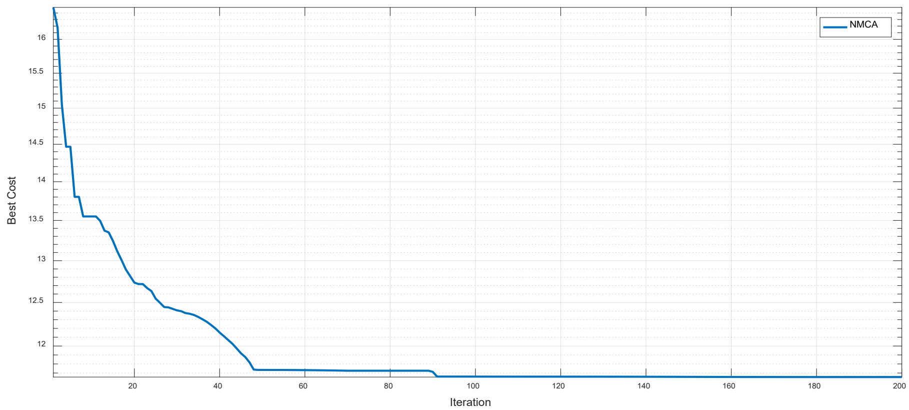

Figure 13. Convergence profile of fitness function value offered by NMCA of the 84-bus system.

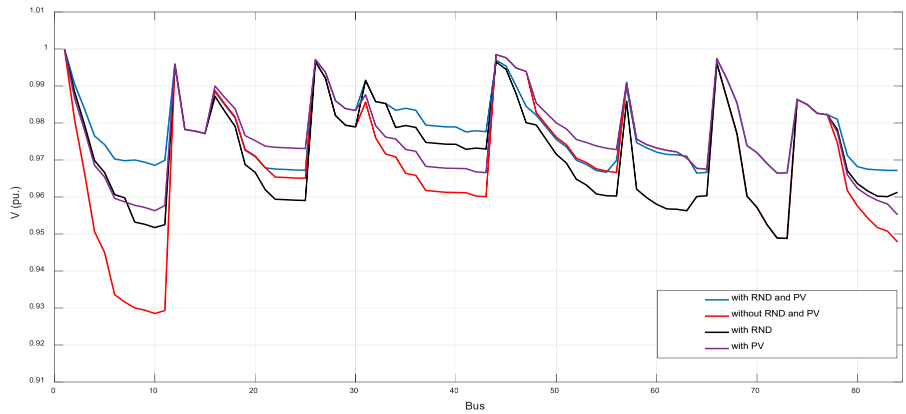

Figure 14. Volt profile without and with DNR and PVDG units. For 84-bus system.

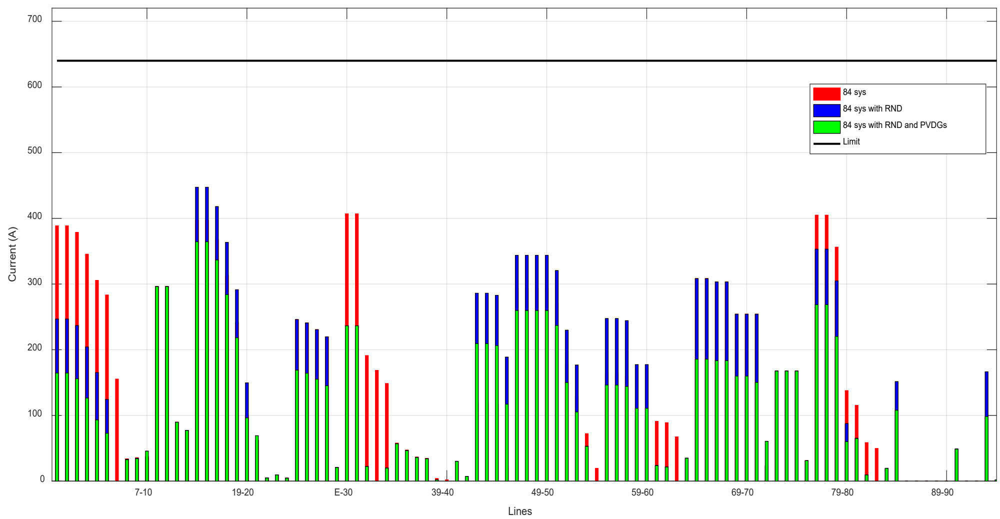

Figure 15. Lines current without and with DNR and PVDG units for the 84-bus system.

Table 5. The results of the NMCA method for the 84-bus system.

	The system with DNR and PVDGS	System with DNR	System with PVDGs	Original system
P loss(kW)	268.722	475.616	295.0172	531.994
min node voltage (pu)	0.9665	0.9488	0.9552	0.9285
$Max(I/I_{max})$	0.56946	0.69907	0.5113	0.63588
Open lines	[7, 86, 89, 90, 92, 93, 33, 40, 55, 63, 87, 88, 83]	[7, 86, 89, 90, 92, 93, 33, 40, 55, 63, 87, 88, 83]	[84,85,86,87,88,89,90,91,92,93,94,95,96]	[84,85,86,87,88,89,90,91,92,93,94,95,96]
PVDG injected (MVA)	[1.2, 1.2, 0.7352, 1.2, 1.2, 1.2, 1.2, 0.7728, 1.2, 0.851, 1.2]	/	[1.2, 1.2, 0.7352, 1.2, 1.2, 1.2, 1.2, 0.7728, 1.2, 0.851, 1.2]	/
Injected busses	[6,7,10,21,28,34,53,70,71,72,81]	/	[6,7,10,21,28,34,53,70,71,72,81]	/

	The system with DNR and PVDGS	System with DNR	System with PVDGs	Original system
Total PVDG power(MVA)	11.9591327	/	11.9591327	/
Cost	11.655	19.3870	13.567	23.1079
Mean cost	11.875	/	/	/

5. Discussion on NMCAconvergence

In order to prove the performance superiority and high effectiveness of the NMCA method in solving the main problems in the power system (power loss, congestion, and voltage profile), applied the convergence rate (CR) value to scenarios 1-3. To test the convergence speed Eq. (40) is used as shown below [26]:

$$CR = \left(1 - \frac{nFE^R}{nFE^{max}}\right) \times 100\ \% \tag{40}$$

where

CR ∈ [0, 1]

nFE: Number of function evaluations.

nFE^{max}: A maximum number of function evaluations.

Values of CR equal to zero and unity indicate the worst and best convergence profile, respectively. To calculate CR value for any optimization algorithm as flow:

1. The optimization methods run-up.
2. The selection minimum cost value is obtained as interest value.
3. Selection the nFE^EAll algorithms that have been tested reaches this value and set it as nFE^R
4. Find the CR as shown in Equation (40).

The obtained CR value is from the best optimal results of the noticed cases in three scenarios. From Table 6 and Figures 2-6-9, the NMCA algorithm is more stable and effective. Furthermore, the results of NMCA demonstrate that this algorithm has faster converges to the optimal solution than any other algorithms used.

Table 6. The nine methods comparison results of CR

Algorithms	CR%		
	IEEE 33 bus	IEEE 69 bus(nominal loads)	IEEE 69 bus (heavy loads)
NMCA	60.75	73.5	78.75
FA	58	62.75	52.5
HS	11.75	7.75	52.75
MCA	59.25	22.75	7.5

6. Conclusion

This study successfully used the NMCA algorithm to solve the PVDGs and DNR problem in distribution networks with multi-objective functions. NMCA has a straightforward structure and has a few parameters to tune, furthermore inspired by the Camel travelling behaviour for finding food and water in the desert. The L-∞ integration with the NMCA has enhanced process efficiency applied the NMCA on the 33-bus, 69 -bus (nominal load and heavy load), and 84-bus systems. Furthermore, the results of NMCA demonstrated the stability and robustness of the NMCA algorithm to solve the PVDGs and DNR problem in the power grid since it maximizes power loss reduction, lines congestion relief, and voltage deviation reduction. Furthermore, the results of the NMCA algorithm have been compared to the other well-known optimization algorithms in the literature. Therefore, the NMCA algorithm is suitable for effectively managing PVDGs and DNR problems in distribution systems.

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