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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 12, Issue 2 | Pages 575-580 | e-ISSN: 2347-470X

An Enhanced Multi-Objective Evolutionary Optimization Algorithm based on Decomposition for Optimal Placement of Distributed Generation and EV Fast Charging Stations in Distribution System

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ABSTRACT- An Enhanced multi-objective evolutionary optimization algorithm based on decomposition (E-MOEA-D) proposed for optimal placement of Distributed Generation (DG) and Electric Vehicle (EV) Fast Charging Station (FCS) in distribution system. The diversity of the evolutionary algorithm improves the convergence and diverse solution in the process of evolutionary optimization. The proposed algorithm is improved using enhanced diversity algorithm, which yield diverse candidate solutions in population. The optimal placement of DGs and FCS are formulated using three objective functions as i) Active power loss ii) Voltage deviation iii) DG cost. The proposed algorithm is simulated on IEEE-33 bus distribution system. The proposed algorithm is compared with other competitive multi-objective evolutionary algorithms such as decomposition based multi-objective evolutionary algorithm (MOEA-D) and Non-dominated sorting multi-objective evolutionary algorithm (NSGA-II).

Keywords: Enhanced multi-objective evolutionary optimization algorithm based on decomposition (E-MOEA-D), Fast Charging Station (FCS).

ARTICLE INFORMATION
Author(s): Varun Krishna Paravasthu, Balasubbareddy Mallala and B. Mangu;
Received: 03-03-2024; **Accepted**: 30-05-2024; **Published**: 20-06-2024;
E- ISSN: 2347-470X;
Paper Id: IJEER24040D;
Citation: 10.37391/ijeer-120232
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-12/ijeer-120232.html

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THE CITATION LINKING BACKBONE

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1. INTRODUCTION

The power demand is increasing day by day and posing the challenge to the power system generation, transmission and distribution to deliver quality and reliable power. The renewable power generation is gained the popularity due to environmental reasons and posing different technical and operating challenges in distribution system [1]. The depletion of fossil fuels, increased load requirements, competitive power markets, and environmental concerns are the challenges on transmission and distribution networks. Addition to the operating issues, the use of electrical vehicles (EVs) increased in recent years, which adding the dynamic load on the distribution system [2].

A comprehensive review of electric vehicles and the demand on load profile is discussed in [3],[4]. The distribution system is negatively impacted by improper FCS placement and sizing, which results in increasing distribution system power losses and reducing voltage profile. Numerous researchers [5–11] focused on the most optimal locations and size of EV fast charging stations (FCSs), with varying degrees of difficulty.

The authors [7] used the HPSO-GWO algorithm to determine the optimal location for fast charging stations (FCS) in the distribution system. In, [8] the fuzzy-based multi-objective grasshopper optimization method is used for DG and FCS optimal planning with the objective of improving the distribution system's technical metrics.

In addition to concurrently designing FCS, this study takes into account of DG placement and sizing. The authors in [9] addressed the DG placement using differential evolutionary algorithms to enhance the performance of the distribution system. In [10], the authors attempted to improve the distribution system performance by placing and sizing the DGs in distribution system using PSO algorithm. In addition, most research works tackle the DG deployment problem using single-objective optimization methods. On the other hand, these one-objective optimizers are unable to manage several objectives at once. Thus, in order to reduce the multiple - objectives problem to a one objective problem, authors often

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turn to using a weighted-sum approach. Although weighted sum method is easy to execute, it has the disadvantage that optimal solutions are optimal with respect to one objective and determining the appropriate weight values is tedious process [11-15]. Therefore, this study utilizes an improved dominance based multi-objective (E-MOEA/D) algorithm, which maximize many objectives at once in order to mitigate these challenges. The present study makes the following contributions:

The fast charging and DG placement problem is formulated as multi-objective evolutionary algorithm with decomposition method using enhanced diversity selection method to improve the diversity of the population. The facilitation problem is formulated using the three objectives with i) Active power loss ii) Voltage deviation iii) DG cost. The contribution of this paper is as follows:

(1) EV fast charging station facilitation problem is formulated as a decomposition based multi-objective evolutionary optimization algorithm with three objectives as *(i)* Active power loss *(ii)* Voltage deviation *(iii)* DG cost.
(2) Proposed a new decomposition based multi-objective evolutionary algorithm (E-MOEA-D) using enhanced diversity selection method to improve the diversity of the algorithm population.
(3) The problem considered the impact of active distribution network on the EV charging station facilitation problem and DG placement effect on the distribution system are considered.

This paper is structured as accordingly: *section 2* discusses problem formulation of EV charging stations facilitation. The proposed method (E-MOEA-D) is discussed in *section 3*. *Section 4* describes test conditions of simulations. Results are discussed in *section 5* and *section-6* presents conclusions.

2. PROBLEM FORMULATION

This section presents the modelling of DGs, FCSs, objective functions and operating constraints associated with the efficient deployment of DGs and FCSs in radial distribution system.

Objective functions:

Active power loss (f_{APL}):

$$\min f_{APL} = \sum_{k=1}^{NL} (G_k (V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij})) \quad (1)$$

Where G_k conductance and V and θ are voltage and phase angle. Where NL is lines.

Voltage deviation (f_{VMD}):

$$\min f_{VMD} = \sum_{i=1}^{NPQ} |(V_i - V_{ref})| \quad (2)$$

Where V_i and V_{ref} are voltage at node and reference voltage, N_{PQ} are the subset of node on the distribution network.

DG Power Cost (C_{DG}): The DG power cost C_{DG}

$$C_{DG} = C_{inv} + C_{opr} + C_{mnt} \quad (3)$$

$$C_{inv} = \sum_{g=1}^{N_{DG}} (P_{DG,g} C_{inv,g}) \quad (4)$$

$$C_{opr} = \sum_{y=1}^{N_y} \sum_{g=1}^{N_{DG}} (P_{DG,g} T_h C'_{opr} (\frac{1+R_{inf}}{1+R_{int}})^{N_y}) \quad (5)$$

$$C_{mnt} = \sum_{y=1}^{N_y} \sum_{g=1}^{N_{DG}} (P_{DG,g} T_h C'_M (\frac{1+R_{inf}}{1+R_{int}})^{N_y}) \quad (6)$$

Where C_{inv} represents investment cost, C_{opr} represents operation cost, C_{mnt} represents maintenance cost, $P_{DG,g}$ and $C_{inv,g}$ are rated actual power and inverter cost of gth DG unit; R_{inf} and R_{int} are the inflation rate and interest rate of each DG unit; Th and Ny are total number of hours in a year and life span expected in years; and N_{DG} is the number of DGs. The aforementioned factors that are needed to determine the cost of DG power are extracted from [16].

3. PROPOSED ALGORITHMS

This paper proposed a new (E-MOEA-D) using enhanced diversity selection method to improve the diversity of the algorithm population. The diversity of the evolutionary algorithm improves the convergence and diverse solution in the process of evolutionary optimization. The proposed algorithm is improved using enhanced diversity algorithm, which yield diverse candidate solutions in population.

The algorithm which is proposed produces initially 'N,' size population randomly with integer strings indicating DG size, DG locations and FCS locations. The *figure 1* shows the pattern of the location string, which includes the location of FCS, DG and their size.

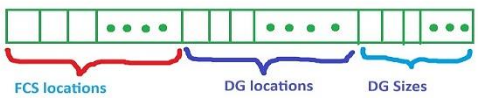

Figure 1. Population String and its representation

By utilizing a systematic sampling technique, the weight vectors with uniform distribution are produced. Every member of the population is associated with a neighbourhood and given a weight vector. Utilizing criteria of minimum angle criteria. 'δ' being selection probability use to choose mating parents from surrounding region. Selection probability 'δ' is usually assigned a value of 0.8. Utilizing Angle criterion to ascertain the closest neighbour of weighted vectors. The minimum valued angle between weighted vectors is used to select the nearest neighbours. Based on the angle, a neighbourhood is assigned to each weight vector. In the mating operation, mating parent pair is chosen from the neighbourhood based on corresponding weight of vector for each weighted vector. If an individual is not chosen from neighbouring region, then the mating parent is selected from entire population. The selection of the surrounding subregion for each weight vector is based on the

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angle criteria. The following is an expression of the angle criteria:

$$\tan\varphi = \frac{d_2}{d_1} \qquad (7)$$

$$where\ d_1 = \frac{\|w_i^T . w_j\|}{\|w_j\|}$$

$$and\ d_2 = \left\|w_i - d_1 \frac{w_j}{\|w\|}\right\|$$

$$where\ i, j = 1, 2, \dots\dots, N\ and\ i \neq j$$

In this case, *N* represents population size which is equivalent to number of weight vectors, w indicates weight vector, and φ represents angle deviation intervening *d1* and *d2*.

Genetic operators like two-point crossover and mutation are used to generate the new offspring population.

The enhanced diversity selection procedure increases population diversity [17]. The normalized objective values for each solution should be summed up. The distance between origin and the total of all normalized objective values is to be calculated as Euclidian distance. The solution which yields total normalized objective values near the origin determines the stopping point. Objective space to be divided equally in to "Bn" bins, scanning of bins should be repeated until scanning process reaches stopping point. For each scanned bin, solution with shortest sum of normalized objective value is entered in preferred set. Both unselected solutions and solutions dominated by the stopping point are included in the back up.

Utilizing PBI method and NSGA-2 method for comparing every solution for local solutions of neighbourhoods defined by a weight vector, the old and new populations are merged and separated into a subpopulation known as "*N*. "The elitist selection process is executed to "*N*" subpopulations to select competent individuals. This process repeats until termination requirement is met. A maximum number of generations was employed as the termination criterion in this method. From the final Pareto optimal front, the optimal solution is found using a fuzzy min-max approach [18].

Pseudo-Code: The pseudo-code of the algorithm

Step 1*. Initialization:** Produced arbitrarily **"N*" size population. Every candidate in the population shows where FCS and DGs are located on the distribution system. Create the weight vectors with a uniform distribution by employing the systematic sampling technique.

***Step 2*.** Run power flow to determine the objective values for each population candidate.

***Step 3*.** Using angle criterion (7), find neighbors with the least angles for each weight vector.

***Step 4*.** Determine the minimal values for every objective in order to compute current optimal point. Perform While ("The Stopping Criteria is not met").

***Step 5*. Reproduction:** select *N* pairs of mating parents by utilizing angle criterion. For every weight vector a pair of mating parent is choose with probability *δ*.

***Step 6*.** Create a new population (*Qt*) by applying the crossover and mutation.

Step 7. The normalized objective values for each solution should be summed up. The distance between origin and the total of all normalized objective values is to be calculated as Euclidian distance. The solution which yields total normalized objective values near the origin determines the stopping point. Objective space to be divided equally in to "*Bn*" bins, scanning of bins should be repeated until scanning process reaches stopping point. For each scanned bin, solution with shortest sum of normalized objective value is entered in preferred set. Both unselected solutions and solutions dominated by the stopping point are included in the back up.

***Step 8*. Partition of the combined population:** *N* subpopulations are created from the old (*Pt*) and new (*Qt*) populations. *Step 9* is being used to compare the contenders and divide the partition.

***Step 9*.** To create *N* subpopulations, compare two individuals, *x* and *y*, and choose the one that is closest to them based on the related weight vectors.

If *x* dominates *y*, associate the weight vector with *x*. If neither *x* dominates and nor *y* dominates then compare both with PBI method as follows:

PBI (x|w, z***) < PBI (**y|w, z***)**

***Step 10*. Elitist Selection:** '*N*' divisions of the population are used to choose the elitist candidates for the next generation population, *Pt+1*.

Select one individual at a time from each population division until the population size "*N*" is obtained.

Make a random selection from the divided population if the size of the population is less than "*N*".

END While

***Step 11*.** For the final Pareto front, use the fuzzy min-max method [18] and print the results.

Parameter Selection:
The different parameters of the algorithm are selected by executing the algorithm multiple times and the values with better results are chosen. The algorithm is executed with different population sizes as 50, 100, 200. The algorithm converged fast and gave best results with population size (N) 100. The stopping criteria for the algorithm is the number of iterations. The algorithm is compared with 500, 1000 and 2000

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iterations, and in this work 1000 iterations yielding the better results compared to other number of iterations. The mating parents are selected based on probability of δ with a value of 0.8. The 20% parents are carry forwarded to next generation and this improves the diversity of the population. The parameter values are tabulated in *table 1*.

Table 1. Parameters

Parameter	Value
'N' Population Size	100
Number of Iterations (Stopping Criteria)	1000
Mating Probability (δ)	0.8

4. RESULTS AND DISCUSSION

In this section, the impact on the improvement of three distribution system metrics (network power loss minimization, minimization of total voltage deviation, minimization of DG cost) due to optimal deployment of various DG technologies is presented at first. Then the enhancement of the above-cited metrics by simultaneous optimal deployment of DGs and PFCSs is discussed in the second stage.

4.1 IEEE-33 Bus System

Figure 2 shows the 33-bus radial distribution system's single-line diagram. A detailed description of the 33-bus system can be found in [19]. 3715 kW and 2300 kVar are the system's total real and reactive power requirement. The base MVA is 100 and base KV is 12.66 KV.

The ideal placement for fast charging stations as well as the DGs including sizing of FCS and DGs is implemented on IEEE 33 bus system using proposed method. The objective functions considered are minimization of active power loss, voltage deviation and DG cost.

The distribution system has been separated into zones in order to ascertain the fast-charging station locations, which provide the charging facility to the geographical location of electrical vehicles in that area. Each zone is considered to be an equal area of 4km^2 (2km x 2km radius). The zones on the distribution network are shown in the *figure 2* which is divided into four zones. Each DG maximum size is considered as 1000 KW.

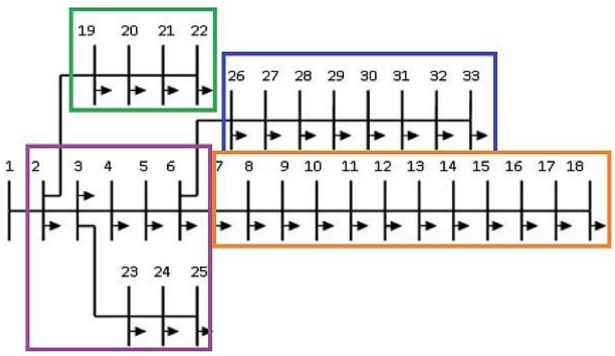

Figure 2: IEEE-33 bus system with zones.

The results are tabulated in *table-1*. The proposed method shows the best results compared to the other methods MOEA-D and NSGA-II. The proposed algorithm provides 48.12 kW power losses, whereas the MOE-D produces 52.04 kW losses and NSGA-II provides 51.77 kW losses on the distribution system. The losses are reduced in case of the proposed algorithm, which influenced by the optimal location of DGs and FCS. Whenever DGs are positioned closer to the load demand, then power losses decrease. The DG size is constrained with minimum and maximum value of DGs. The maximum of 1000KW and minimum as zero is considered.

Also, the proposed algorithm shows better results in other objective DG cost and voltage deviation. In all the aspects the proposed algorithm shows best results compared to the other muti-objective optimization algorithms like MOEA-D and NSGA-II. The *figure. 3,4,5* shows the Pareto fronts for Power loss Vs DG cost objective, DG cost objective Vs voltage deviation objective and Voltage Deviation objective Vs Power loss objective respectively.

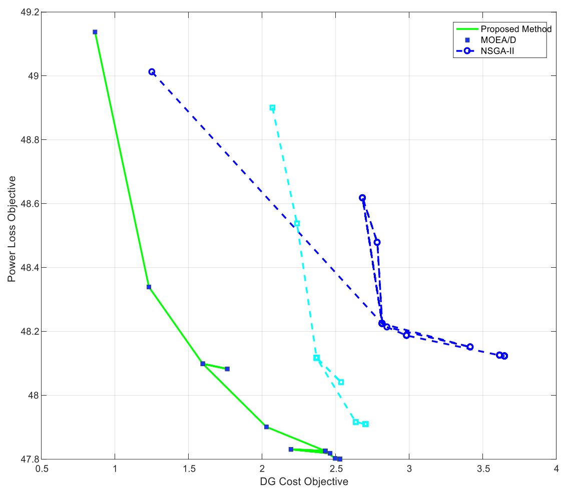

Figure 3. Pareto front: DG cost Objective Vs Power loss objective

Table 2. IEEE-33 bus radial distribution system results

Optimization Technique	FCS location	DG location/ DG size (kW)	Active power Loss (kW)	Voltage Deviation (%)	DG cost (M$)
Proposed algorithm(E-MOEA-D)	5, 14, 21, 30	6/850, 17/450, 32/360	48.12	15.832	1.16 5
MOEA-D	3, 16, 23, 32	8/780, 18/550, 31/450	48.56	17.355	2.31 5
NSGA-II	6, 17, 20, 32	23/480, 17/740, 28/650	48.97	18.567	2.87 5

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Research Article | Volume 12, Issue 2 | Pages 575-580 | e-ISSN: 2347-470X

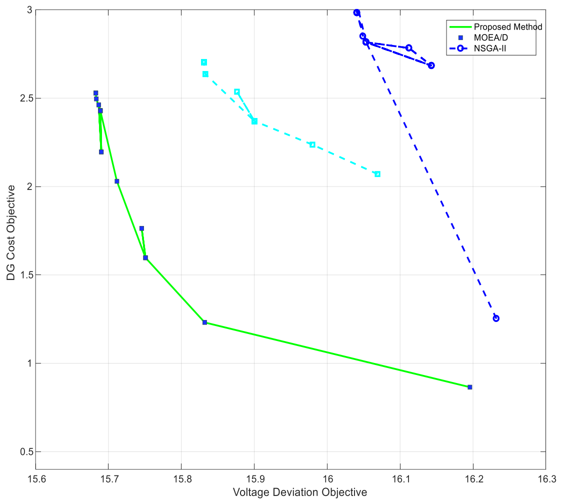

Figure 4. Pareto front: DG cost Objective Vs Voltage Deviation objective

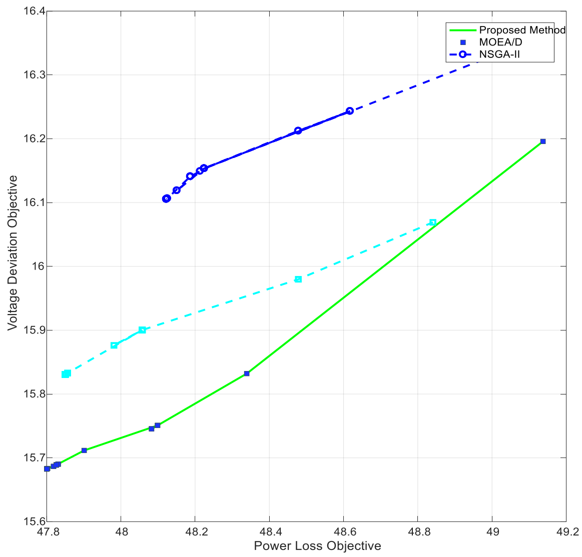

Figure 5. Pareto front: Voltage Deviation objective Vs Power loss objective

5. CONCLUSION

This paper proposed an (E-MOEA-D) for optimal placement of Distributed Generation (DG) and Electric Vehicle (EV) Fast Charging Station (FCS) in distribution system. The diversity of the evolutionary algorithm improves the convergence and diverse solution in the process of evolutionary optimization. The optimal placement of DGs and FCS are formulated using three objective functions as *(i)* Active power loss *(ii)* Voltage deviation *(iii)* DG cost. The proposed algorithm is simulated on IEEE-33 bus distribution system and shows better results in terms of objective such as active power loss is reduced by 1.73 %, voltage deviation is reduced by 17.27% and DG cost reduced by 59.47% when compared to MOEA-D and NSGA-II. The better results are due to the improved diverse candidate solutions in population of each evolution iteration process. The problem can be extended for future work by considering the renewable penetration and uncertainty of the renewable generation and uncertainty in EV load on the distribution system can be effectively studied. Therefore, the proposed algorithm can be utilized in planning studies of fast charging and distributed generation placement.

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