

An Enhanced Evolutionary Algorithm for Providing Energy Management Schedule in the Smart Distribution Network

Hossein Lotfi^{1*}, Amir Safaei Nikooei¹, Ali Asghar Shojaei¹, Reza Ghazi², Mohammad Bagher Naghbi Sistani²

1- Department of Electrical Engineering, Neyshabur Branch, Islamic Azad University, Neyshabur, Iran.
Email: Hossein_lotfi95@yahoo.com (Corresponding author)

2- Department of Electrical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran.

Received: August 2019

Revised: November 2019

Accepted: December 2019

ABSTRACT:

Penetration of distributed generation resources including wind power and solar photovoltaic units in distribution system has been increased, and it is important to examine their impact on the distribution systems' operation in term of reliability. In this paper, the multi-objective dynamic feeder reconfiguration is introduced as an efficient approach for providing an energy management schedule in the distribution grid considering energy loss and energy not supplied as the objective functions in the presence of renewable energy sources and capacitor units. In addition, the effect of uncertainty related to power demand is considered in the evaluations. To this end, an enhanced particle swarm optimization algorithm is provided in this paper, the proposed approach is applied to the 33-node testing system.

KEYWORDS: Dynamic Distribution Feeder Reconfiguration (DDFR), Distributed Generators (DGs), Enhanced Particle Swarm Optimization Algorithm (EPSO), Multi-Objective Optimization.

1. INTRODUCTION

Emerging of Distributed Generators (DGs) including solar photovoltaic (PV) units and wind turbine in the distribution grids has completely changed the networks' performance [1]. The merge of distributed generators and Battery Energy Storage (BES) units into distribution grid provides various benefits such as improved voltage characteristics, reduced line losses and enhanced branch current profile. Accordingly, frequent transfer of power from DGs and BES units can significantly reduce their lifetime and capability [2]. So an optimal energy management scheme can improve the distribution system performance and protect these units from destruction.

Many recent researches have been done to obtain an optimal energy management schedule in the distribution grid considering DGs, BES units and electrical vehicles with various purposes including reducing the power loss [3] and minimizing the network operational cost [4]. A multi-objective energy management was presented in the distribution grid at the presence of energy storage units [5]. A new bi-objective approach was provided for energy management in the distribution grid considering energy storage units [6]. In [7], a new energy management approach was provided in the distribution grid considering effects of DGs and BES units to modify the peak load shaving and voltage regulation. A new

energy management pattern was presented in the distribution system in the presence of large scale DGs to minimize the operational cost [8]. In [9], an adaptive energy management approach was provided in the distribution system integrated with micro-grid. A new energy management pattern based on driving pattern recognition was presented in the hybrid distribution system integrated with electrical vehicles [10].

One of the most common energy schedule approach in the automation distribution grids, feeder reconfiguration is performed on the distribution grids considering DGs. The reconfiguration process concept is altering the distribution feeders structure for optimizing the certain objectives such as power loss and operational cost while satisfying an operational and physical limitations [11]. Distribution Feeder Reconfiguration (DFR) is implemented by changing the status of switches in a distribution grid to search a radial operating configuration without isolating any part of network [11]. In term of reliability importance, a gravitational search algorithm was provided for solving DFR problem with DGs to minimize the energy not supplied [12]. A hybrid evolutionary algorithm including Particle Swarm Optimization (PSO) and modified shuffled frog leaping was provided for DFR problem considering effect of DGs to enhance the network security [13]. According to grid's cost importance, a hybrid evolutionary algorithm consisting

particle swarm optimization and Shuffled Frog Leaping Algorithm (SFLA) was presented [14] to solve the Dynamic Distribution Feeder Reconfiguration (DDFR) problem with DGs for operational cost minimization. In [15], a genetic algorithm was provided to solve the DDFR problem in the unbalanced distribution grid considering DGs to minimize the network loss. In [16], an ant colony optimization algorithm was introduced for DDFR problem and capacitor switching considering DGs to minimize the network loss.

The main challenge in this study is providing energy management schedule based on using the DDFR approach in the distribution grid considering renewable energy sources and capacitor units. Different objective functions including energy not supplied and energy loss are considered in this study. Optimization decision variables in the dynamic approach include capacitors' reactive power output, active power generation of DGs and optimal status of network switches. Solving the DDFR problem in the distribution network is very complicated for providing an optimal energy management schedule and it becomes more sophisticated by considering the impact of power demand's uncertainty. Therefore, it is necessary to provide a robust method that can deal with the DDFR problem. Toward this end, an Enhanced Particle Swarm Optimization (EPSO) algorithm is presented to handle the complexities of the DDFR problem. The PSO algorithm has some weaknesses including trapping in local optima due to its random nature. To this end, a novel mutation strategy is presented in EPSO algorithm to increase the search ability and population diversity of the algorithm. Since the two different objective functions (energy loss and energy not supplied) conflict with each other in the DDFR optimization problem, it is necessary to find an approach for optimizing all objectives. In this regard, the Pareto-method is presented for obtaining set of non-dominated solutions.

The outstanding features of this study are as follows:

- presenting the energy management schedule by solving the DDFR problem in the distribution network.
- Presenting energy not supplied (ENS) function in order to enhance distribution system reliability.
- Considering the power demand's uncertainty to evaluate the objective functions.
- Considering the effects of DGs and capacitors on different objective functions.
- Presenting a novel evolutionary algorithm, EPSO for solving the multi-objective problem.

The rest of paper is provided as follows: Section II describes problem formulation including objectives and constraints. Section III presents EPSO algorithm and multi-objective optimization strategy. Sections IV and

V present the EPSO algorithm's steps for solving the DDFR problem and simulation result, respectively. Sections VI and VII present conclusions and references, respectively.

2. PROBLEM DEFINITION

A literature survey on the energy management schedule in the distribution grid demonstrated that most studies have considered various objective including power loss [2-3], operation cost [1-2], [4-6], [8], peak shaving [7], reliability index [6] and grid's security index [1], [5]. As well as some constraints of the optimization problem were load flow equations, bus voltage, current feeder, DGs power generation and energy storage units' limitations [1-8]. Considering the mentioned objective functions for providing energy management schedule leads to distribution grid operation at an acceptable level of reliability and security. Moreover, the subscribers' blackout time is reduced and they pay less for electricity demand.

In order to provide energy management schedule, the Dynamic Distribution Feeder Reconfiguration (DDFR) problem at the presence of renewable energy sources and capacitor units is formulated in this section. Energy Not Supplied (ENS) and energy loss are defined as objective functions of the DDFR problem. Another important point is to consider the effect of power demand's uncertainty on the evaluation of objective functions. In most studies [1-10], this issue has not been addressed for energy management in the distribution network. Considering the power demand's uncertainty in solving the considered optimization problem leads to provide near-realistic solutions. In the following, this section is divided to three sub-sections; objective functions, constraints and uncertainty modeling.

A. Objective functions

Two objective functions and decision variables in the proposed optimization problem are as follows:

• Energy loss

The minimization of the energy loss can be calculated as follows [14]:

$$f_1(X) = \sum_{h=1}^{24} \sum_{j=1}^{N_{brch}} R_j |I_j^h|^2 \quad (1)$$

$$X = [Q_{cap}, P_{Dg}, Tie, SW] \quad (2)$$

$$Q_{cap} = [Q_{cap1}^h, Q_{cap2}^h, \dots, Q_{capN_{cap}}^h] \quad (3)$$

$$P_{Dg} = [P_{Dg1}^h, P_{Dg2}^h, \dots, P_{DgN_{Dg}}^h] \quad (4)$$

$$Tie = [Tie_1^h, Tie_2^h, \dots, Tie_{N_{tie}}^h] \quad (5)$$

$$SW = [SW_1^h, SW_2^h, \dots, SW_{N_{SW}}^h] \quad (6)$$

Where, R_j and I_j^h are the resistance and current of the j^{th} line at h^{th} hour, respectively. N_{brch} is the

number of lines (branches of distribution grid), \mathbf{X} is the vector of control variables, Tie_i^h is the state of i^{th} tie switch at the h^{th} hour and SW_i^h is the sectionalizing switch number that forms a loop with Tie_i^h . N_{tie} and N_{SW} are the number of tie switches and number of switches, respectively. $Q_{cap,r}^h$ and $P_{dg,u}^h$ are the reactive power of r^{th} capacitor and active power of u^{th} DG at the h^{th} hour, respectively.

- **Energy Not Supplied**

Energy Not Supplied (ENS) is an important reliability indicator that indicates the total energy load not distributed during outage [17]. ENS formulation at each node is as follows:

$$ENS_x = P_x \sum_{x,y \in Z, x \neq y} (U_{x,y} + U'_{x,y}) \quad (7)$$

$$U_{x,y} = K_{x,y} \times t_{x,y} \quad (8)$$

$$U'_{x,y} = K'_{x,y} \times t'_{x,y} \quad (9)$$

Where, Z includes branches of network which are connected to x^{th} node. $U_{x,y}$ and $U'_{x,y}$ are the service unavailability related to the repair time of all line associated with x^{th} node and service unavailability related to the restoration time of all line associated with x^{th} node, respectively. Moreover, $K_{x,y}$ is the failure rate of the line between x^{th} and y^{th} nodes (*fail/year*), $t_{i,j}$ and $t'_{i,j}$ are the average repair time and restoration time of the line between x^{th} and y^{th} nodes (*h/fail*). The ENS index can be mathematically modeled as follows:

$$f_2(x) = \sum_{i=2}^{N_{Bus}} ENS_i \quad (10)$$

B. Constraints

In this section, all equality and inequality constraints of the proposed problem are described. Equations (11) -(12) are related to radial structure of network and load flow equation, respectively. Equations (13) -(14) are related to bus voltage and current feeder, respectively. Finally, (15)- (16) are related to DGs power generation and capacitor limitation, respectively.

$$N_{branch} = N_{bus} - N_{sub} \quad (11)$$

$$S_j = \sum_{k=1}^{N_{bus}} V_j V_k Y_{jk} \cos(\delta_j - \delta_k - \theta_{jk}) \quad (12)$$

$$V_{min} \leq V_j \leq V_{max} \quad i = 1, 2, \dots, N_{Bus} \quad (13)$$

$$|I_{fdr,j}| \leq I_{fdr,j}^{Max} \quad i = 1, 2, \dots, N_{feeder} \quad (14)$$

$$P_{dg}^{min} \leq P_{dg,j} \leq P_{dg}^{max} \quad (15)$$

$$Q_{cap}^{min} \leq Q_{cap,j} \leq Q_{cap}^{max} \quad (16)$$

Where, N_{bus} and N_{sub} are the number of buses and number of sub-stations. V_{min} and V_{max} are the lower and upper bounds of voltage at the j^{th} node, V_j is the voltage magnitude at the i^{th} bus. $I_{fdr,j}$ is the current amplitude and $I_{fdr,j}^{Max}$ is the maximum acceptable current of the j^{th} feeder. N_{feeder} indicates the number of feeders. S_j is the net injected power at the j^{th} bus. V_j and δ_j are the magnitude and angle of voltage at j^{th} bus, Y_{jk} and θ_{jk} are the magnitude and angle of admittance between j^{th} and k^{th} buses, respectively. Q_{cap}^{min} , Q_{cap}^{max} are the lower and upper bounds of the reactive power at the j^{th} capacitor. P_{dg}^{min} , P_{dg}^{max} are the lower and upper limitations of the active power at the j^{th} DG, respectively.

C. Uncertainty Modeling

In this study, power demand is considered as the uncertainty parameter in the optimization problem assessment which is developed as following:

- *Power demand modeling*

Normal distribution is commonly used to express the random loads of a distribution networks. The Probability Density Function (PDF) of the normal probability distribution can be expressed as:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (17)$$

Where, σ and μ are the mean value and standard deviation value of random variable, respectively. In this approach the scenario generation strategy [18] is utilized to model the uncertainty of power demand. Toward this end, many different scenarios are generated from the aforementioned PDFs. Then the backward reduction approach [19] is implemented in order to extract different scenarios with high probability.

3. OPTIMIZATION APPROACH

In this section, multi-objective strategy and Enhanced Particle Swarm Optimization (EPSO) are introduced:

A. Multi-objective optimization strategy

In solving the multi-objective problem, there are non-dominated solutions instead of optimal solution [13]. The solution X_2 dominated solution X_1 if the conditions are satisfied:

$$\forall k \in \{1, 2, \dots, N_{obj}\}, f_k(X_1) \leq f_k(X_2) \quad (18)$$

$$\exists h \in \{1, 2, \dots, N_{obj}\}, f_h(X_1) < f_h(X_2) \quad (19)$$

According to the objectives, values are different, so fuzzy sets are implemented for substituting each objective value between 0 and 1. In this regard, the fuzzy membership function for j^{th} objective function [14] can be modeled as follows:

$$\mu_j(X) = \begin{cases} 1 & f_j \leq f_j^{\min} \\ 0 & f_j \geq f_j^{\max} \\ \frac{f_j^{\max} - f_j}{f_j^{\max} - f_j^{\min}} & f_j^{\min} \leq f_j \leq f_j^{\max} \end{cases} \quad (20)$$

Where, f_j^{\min} and f_j^{\max} are maximum and minimum bounds of the j^{th} objective function. The non-dominated solutions are stored in a repository at each iteration, these solutions are sorted based on decision maker by using (21) to select the best compromise solution among the top solutions in the repository.

$$N_{\mu r} = \frac{\sum_{k=1}^n \beta_k \times \mu_{rk}}{\sum_{r=1}^m \sum_{k=1}^n \beta_k \times \mu_{rk}} \quad (21)$$

Where m and n are the number of non-dominant solutions and objectives and β_k is weight of k^{th} objective function.

B. Enhanced particle swarm optimization algorithm

The PSO algorithm is one of the evolutionary methods first used by Eberhart and Kennedy to solve various optimization problems [20]. In this algorithm, which was inspired by groups of birds and fishes, each particle is a potential solution for the optimization problem in which particles find the best location using previous experiences and the best particle in the whole population. More details on the matting process in PSO algorithm can be found in [20-21]. Mutation strategy is the process to improve the performance of algorithm so that the probability of reaching the optimal global solution is increased. In the EPSO algorithm unlike PSO, mutation strategy can improve the position of each particle to avoid trapping in the local optimal. A new position of i^{th} particle is calculated as follows:

$$X_{i,new1}^{t+1} = X_i^t + r_1(gb^t - \sigma\rho^t), \quad X_{i,new2}^{t+1} = X_i^t + r_2\Delta X_i \quad (22)$$

$$\Delta X_i = \begin{cases} r_3 \cdot (X_i^t - X_k^t) & \text{if } f(X_i^t) \geq f(X_k^t) \\ r_4 \cdot (X_k^t - X_i^t) & \text{if } f(X_k^t) \leq f(X_i^t) \end{cases} \quad i \neq k \quad (23)$$

$$X_{i,new}^{t+1} = \begin{cases} X_{i,new1}^{t+1} & \text{if } f(X_{i,new2}^{t+1}) \geq f(X_{i,new1}^{t+1}) \\ X_{i,new2}^{t+1} & \text{if } f(X_{i,new2}^{t+1}) \leq f(X_{i,new1}^{t+1}) \end{cases} \quad (24)$$

Where, r_3 and r_4 are random numbers between zero

and one, σ is a constant value that can assume 1 or 2. ρ^t is the average value of the position over the total population in the previous iteration. If the new i^{th} individual has a better position than i^{th} individual in the current population, the new vector will replace it in the next population, the following steps are required to implement the EPSO algorithm in order to solve the multi-objective problem.

1. Generate initial particle with randomly position.
2. Equations (1), (10) are used to evaluate the objective function.
3. Calculate membership function using (20) for two objectives including energy loss and ENS.
4. Calculate normalized membership using (21) for all members of population.
5. Use Pareto optimality approach to obtain the non-dominant solutions and store in the repository.
6. Update the population of particles by using (22)-(24).
7. Equations (1), (10) are used to evaluate the objective function.
8. Calculate membership function using (20) for two objectives including energy loss and ENS.
9. Calculate normalized membership using (21) for all members of population.
10. Use Pareto optimality approach to obtain the non-dominant solutions and store in the repository.
11. Check the convergence criterion, which in this algorithm, is the predetermined maximum iteration number.

4. SIMULATION RESULT

In this section, for assessing the EPSO algorithm's ability to solve the DDFR problem, a 33-nonde test system is introduced. Parameters of the EPSO algorithm are as follows: number of initial population is 1500, maximum number of iterations is 200. All simulations are done in MATLAB software with core i5, 4GB RAM computer.

A. 33-Bus Test System

The test system consists of two-feeders, 33 buses, 37 branches including sectionalizing- switches and tie-switches [22]. In normal condition, all the sectionalizing-switches and tie switches are closed and opened, respectively. The 33-node test network is depicted in Fig.1. Two 500 kW DGs (diesel generator) are located at nodes # 7 and # 24, as well as three capacitors 100 kVAR are installed at nodes # 24, # 25 and # 30. Fig. 2 shows the load profile during 24-hour for the test network, 50 scenarios are implemented in order to simulate the uncertainty parameter.

B. Single-Objective Optimization

Tables 1 and 2 show the optimization results for energy loss and ENS objective functions considering

DGs and capacitors, employing PSO, SFLA and EPSO algorithms. The best solution, mean solution, worst solution and standard deviation value for EPSO and other algorithms in 30 iterations are shown in Tables 1 and 2.

According to the results of Tables 1 and 2, obviously, the EPSO algorithm has achieved better results than other algorithms such as PSO and SFLA. The optimal values obtained by EPSO for ENS and energy losses using EPSO are 29245.85 kWh/year and \$ 1950.22, respectively. These values obtained by EPSO for case before installing DGs and capacitors are equal to 53798.65 kWh/year and \$ 3523.45, respectively. Obviously, DGs and capacitors can play a significant role in the reduction of energy losses and ENS objective functions.

The convergence curve of energy loss optimization by ESGA, ICA and EPSO algorithms is depicted in Fig 3. In accordance with Fig .3, obviously the EPSO algorithm converges to optimal answer earlier than PSO and SFLA algorithms.

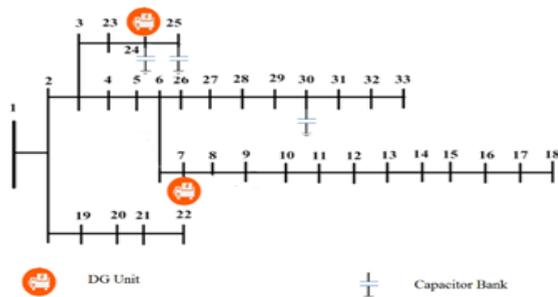


Fig. 1. Single-line diagram of 33 bus test system.

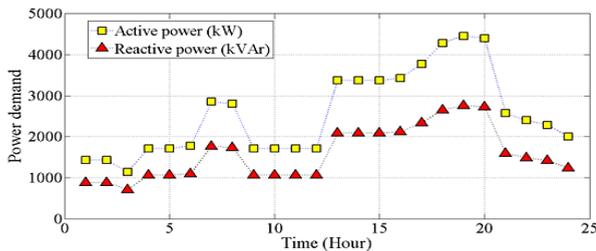


Fig. 2. The load profile of test system during 24-hour.

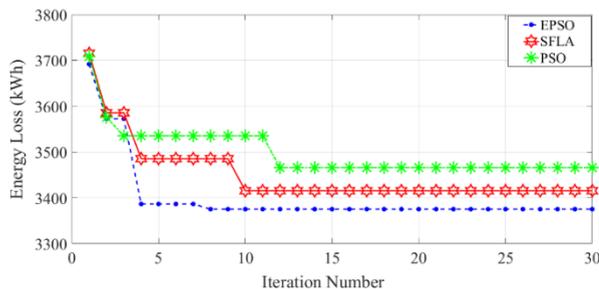


Fig. 3. Convergence curve of different algorithms for energy loss optimization.

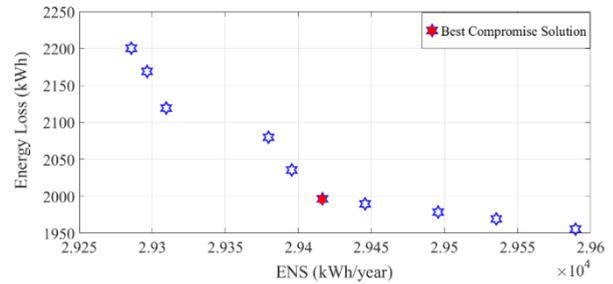


Fig. 4. Pareto-front objective functions using EPSO algorithm.

Table 1. Results obtained by optimizing the energy loss considering DGs and capacitors.

Method	Best	Mean	Worst	STD
PSO	2097.199	2145.42	2185.231	37.51
SFLA	2019.676	2060.05	2095.159	28.45
EPSO	1950.256	1965.819	1995.347	20.85

Table 2. Results obtained by optimizing the ENS considering DGs and capacitors.

Method	Best	Mean	Worst	STD
PSO	29732.09	29818.87	29915.33	56.13
SFLA	29456.96	29539.34	29635.95	49.71
EPSO	29245.85	29314.93	29392.96	44.33

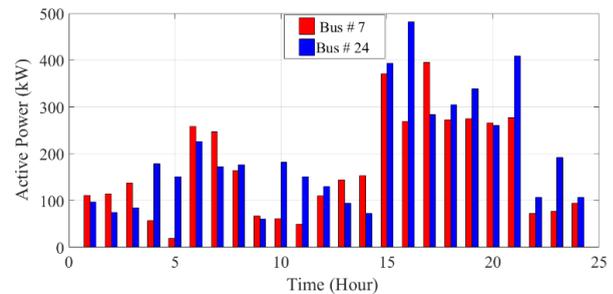


Fig. 5. Active power output of DGs obtained from the EPSO algorithm for solving the multi-objective optimization problem.

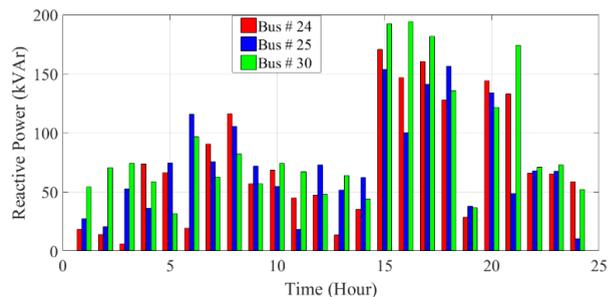


Fig. 6. Reactive power output of capacitors obtained from the EPSO algorithm for solving the multi-objective optimization problem.

C. Multi-Objective optimization

Since the main purpose of this study is solving the two-objective DDFR problem, in this section, the Pareto-approach is utilized to satisfy different objective functions. Fig. 4 depicts the non-dominated solutions for two-objective DDFR problem employing the EPSO algorithm. Moreover, the optimal scheduling of DGs' active power output, capacitors' reactive power output and optimal switching scheme obtained by EPSO algorithm for solving multi-objective DDFR problem during 24-hour are shown in Figs. 5, 6 and Table 3. According to Fig. 4, the optimal values of ENS and energy loss in the Pareto-front are 1955.45 kWh and 29286.45 kWh/year, respectively. These values for the best-compromise solution (i.e., indicated with the red color) are equal to 1991.45 kWh and 29425.15 kWh/year, respectively. According to Fig. 4, obviously, the difference between these values for each objective function in the best-compromise solution is less than 2% in comparison with optimal values of each objective, which shows the effectiveness of the EPSO algorithm for solving the two-objective DDFR problem.

5. CONCLUSION

In this study, a novel approach is provided for presenting an optimal energy management schedule based on using the distribution feeder reconfiguration in the dynamic framework at the presence of DGs and capacitors. Furthermore, effect of uncertainty related to power demand is considered in the evaluations. The proposed DDFR problem consists of minimizing energy loss and ENS objective functions. As well as radial topology, voltage of the buses, current of lines are defined as proposed problem's constraints. A EPSO algorithm is provided to solve the DDFR in the single and multi-objective problems. Considering the simulation results, the EPSO algorithm obtained an optimum answer compared to other algorithms. Therefore, the effectiveness of the proposed method is confirmed in comparison with other algorithms for presenting an optimal energy management schedule. Finally, the conclusions can be as follows:

- Based on the simulation results of the DDFR problem in the single and multi-objective frameworks, the capability of the proposed method is proved regardless of the dimension and complexity of the problem.
- Investigating effects of DGs and capacitors simultaneously reduced the energy loss and ENS.

Table 3. The optimum switching scheme obtained from the EPSO algorithm for solving the multi-objective optimization problem.

L.L.	Open Switches				
	Sw1	Sw2	Sw3	Sw4	Sw5
1	33	34	11	17	28
2	6	14	8	36	28
3	6	14	9	36	28
4	7	14	11	36	37
5	6	14	35	36	28
6	33	34	10	17	37
7	33	14	10	17	37
8	6	12	9	15	28
9	7	12	9	15	5
10	33	12	35	32	28
11	6	12	35	32	37
12	20	14	11	17	5
13	6	34	8	36	28
14	6	14	8	32	28
15	33	34	10	32	28
16	7	34	11	15	5
17	7	14	35	32	5
18	33	34	9	36	4
19	7	34	8	36	28
20	33	14	11	17	5
21	33	14	9	36	37
22	7	14	35	17	22
23	6	34	9	32	28
24	20	34	10	17	28

L.L.: Load Level

REFERENCES

- [1] Azizivahed, A., et al., "Energy Storage Management Strategy in Distribution Networks Utilized by Photovoltaic Resources," *IET Generation, Transmission & Distribution*, Vol. 12(21), pp. 5627-5638, 2018.
- [2] Azizivahed, A., et al. "New Energy Management Approach in Distribution Systems Considering Energy Storages," *20th International Conference on Electrical Machines and Systems (ICEMS)*, 2017, IEEE.
- [3] Tabari, M. and A. Yazdani, "An Energy Management Strategy for a DC Distribution System for Power System Integration of Plug-In Electric Vehicles," *IEEE Transactions on Smart Grid*, Vol. 7(2). pp. 659-668, 2015.
- [4] B. Lin and W. Wu, "Economic Viability of Battery Energy Storage and Grid Strategy: A Special Case of China Electricity Market," *Energy*, Vol. 124, pp. 423-434, 2017
- [5] Azizivahed, A., et al., "Multi-Objective Energy Management Approach Considering Energy Storages in Distribution Networks with Respect to Voltage Security". 2018.

- [6] Azizivahed, A., et al., "A New Bi-objective Approach to Energy Management in Distribution Networks with Energy Storage Systems". *IEEE Transactions on Sustainable Energy*, Vol. 9(1), pp. 56-64, 2017.
- [7] Reihani, E., et al., "Energy Management at the Distribution Grid using a Battery Energy Storage System (BESS)," *International Journal of Electrical Power & Energy Systems*, Vol. 77, pp. 337-344, 2016.
- [8] Korada, N. and M.K. Mishra, "Grid Adaptive Power Management Strategy for an Integrated Microgrid with Hybrid Energy Storage," *IEEE Transactions on Industrial Electronics*, Vol. 64(4), pp. 2884-2892, 2016.
- [9] Lv, T. and Q. Ai, "Interactive Energy Management of Networked Microgrids-based Active Distribution System Considering Large-Scale Integration of Renewable Energy resources," *Applied Energy*, Vol. 163, pp. 408-422, 2016.
- [10] Lei, Z., et al., "Dynamic Energy Management for a Novel Hybrid Electric System based on Driving Pattern Recognition," *Applied Mathematical Modelling*, Vol. 45, pp. 940-954, 2017.
- [11] Mahboubi-Moghaddam, E., et al., "Multi-objective Distribution Feeder Reconfiguration to Improve Transient Stability, And Minimize Power Loss and Operation Cost Using an Enhanced Evolutionary Algorithm at The Presence of Distributed Generations," *International Journal of Electrical Power & Energy Systems*, Vol. 76, pp. 35-43, 2016.
- [12] Narimani, M.R., et al., "Enhanced Gravitational Search Algorithm for Multi-Objective Distribution Feeder Reconfiguration Considering Reliability, Loss and Operational Cost," *IET Generation, Transmission & Distribution*, Vol. 8(1), pp. 55-69, 2014.
- [13] Azizivahed, A., et al., "A Hybrid Evolutionary Algorithm for Secure Multi-Objective Distribution Feeder Reconfiguration," *Energy*, Vol. 138, pp. 355-373, 2017.
- [14] Azizivahed, A., et al. "Dynamic Feeder Reconfiguration in Automated Distribution Network Integrated with Renewable Energy Sources with Respect to the Economic Aspect". in *2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)*. 2019. IEEE
- [15] Ding, F. and K.A. Loparo, "Feeder Reconfiguration for Unbalanced Distribution Systems with Distributed Generation: A Hierarchical Decentralized Approach," *IEEE Transactions on Power Systems*, Vol. 31(2), pp. 1633-1642, 2015.
- [16] Larimi, S.M.M., M.R. Haghifam, and A. Moradkhani, "Risk-based Reconfiguration of Active Electric Distribution Networks," *IET Generation, Transmission & Distribution*, Vol. 10(4), pp. 1006-1015, 2016.
- [17] Lotfi, H., R. Ghazi, and M. bagher Naghibi-Sistani, "Multi-objective Dynamic Distribution Feeder Reconfiguration Along with Capacitor Allocation Using A New Hybrid Evolutionary Algorithm". *Energy Systems*, pp. 1-31, 2019.
- [18] Barani, M., et al., "Optimal Partitioning of Smart Distribution Systems into Supply-Sufficient Microgrids," *IEEE Transactions on Smart Grid*, 2018.
- [19] Niknam, T., M. Zare, and J. Aghaei, "Scenario-based Multiobjective Volt/Var Control in Distribution Networks Including Renewable Energy Sources," *IEEE Transactions on Power Delivery*, Vol. 27(4), pp. 2004-2019, 2012.
- [20] Kennedy, J., Eberhart, R, "Particle Swarm Optimization," In: IEEE international conference on neural networks Piscataway, 1995, NJ, 4: p.1942-48.
- [21] Lotfi, H., M. Samadi, and A. Dadpour. "Optimal Capacitor Placement and Sizing in Radial Distribution System Using An Improved Particle Swarm Optimization Algorithm". in *2016 21st Conference on Electrical Power Distribution Networks Conference (EPDC)*. 2016. IEEE
- [22] Lotfi, H. and R. Ghazi. "An Optimal Co-operation of Distributed Generators and Capacitor Banks in Dynamic Distribution Feeder Reconfiguration". in *2019 24th Electrical Power Distribution Conference (EPDC)*. 2019. IEEE.
- [23] Eusuff, M., K. Lansey, and F. Pasha. "Shuffled Frog-Leaping Algorithm: A Memetic Meta-Heuristic for Discrete Optimization". *Engineering optimization*, Vol. 38(2), pp. 129-154, 2006.