

Power Loss Minimization in a Radial Distribution Network by Optimal Sizing and Placement of Energy Storage Units

Suresh Babu. Maddina¹, Dr. R. Thirunavukkarasu², Dr. N. Karthik³

¹Research Scholar,

Department of Electrical Engineering,

Annamalai University, Annamalai Nagar, Chidambaram -608002, Tamil Nadu, India

e-mail : suri.253@gmail.com.

²Assistant Professor

Department of Electrical Engineering,

Annamalai University, Annamalai Nagar, Chidambaram -608002, Tamil Nadu, India

e-mail : thirunavukkarasurajanandam@gmail.com.

³Associate Professor

Department of Electrical & Electronics Engineering,

Bapatla Engineering College, Bapatla

Andhrapradesh, India.

e-mail : wizitkarthik@gmail.com.

Abstract— It is possible to reduce distribution losses by strategically placing and sizing DG and BESS sources. Assuring low loss requires strategically placing the aforementioned devices; otherwise, the system may experience either under- or overvoltage. It is preferable to choose bus stations with less risk for loss. The proposed approach tries to pinpoint the optimal BESS size and placement to cut down on investment and operating expenses while still achieving the desired level of energy reduction. The development of optimisation algorithms for finding and scaling BESS units is the fundamental focus of this study. Two such strategies are being explored here: the Genetic Algorithm (GA) and the Ant Colony Optimization Algorithm (ACO). The goal function, like the original issue, seeks to minimise system-wide power losses while adhering to specified levels of equality and inequality. This article explores the appropriate capacity and placement of the DGs in a 33-bus radial distribution grid to reduce power dissipations. Matlab code is used to perform a simulation, and the results are put to use gauging the method's sturdiness..

Keywords- Battery Energy Storage Systems (BESS), Distributed Generation (DG), Genetic Algorithm (GA), Ant Colony Optimization Algorithms (ACO).

I. INTRODUCTION

Power from distributed generation (DG) systems is manufactured in close proximity to the site of consumption. This reduces transmission losses and utility costs. Moreover, it's crucial to the design of power system networks since it boosts the delivery of electricity to such systems. Whilst it plays a crucial role in the generation of electricity, it may have unintended consequences if it is not placed and scaled properly [1].

The present transmission system cannot keep up with the ever-increasing demand for electrical electricity. Thus, either investments must be made to increase the capacity of the transmission system or distributed generation must be deployed to locally fulfil consumer demand. Many professionals are worried about the effects on the electrical grid caused by the widespread adoption and integration of

different distributed power generation technologies. Network losses may be reduced and the voltage profile enhanced with strategic placement. The goal is to choose bus stops that have a manageable loss profile and some promising upside. As the number of distributed generators (DGs) in use grows, engineers in charge of system planning are finding that a particular technique is highly helpful for analysing the effect that the distribution of DGs has had on several aspects of the system [2]-[3].

Distributors should strategically place DG so that it can operate the distribution network under ideal conditions. When deciding where to put DG units, it's crucial to minimise the active power lost by the network. Installing an excessive quantity of DG raises grid connection costs, boosts power loss in the distribution network, and possibly causes system instability. Intermittent energy sources like solar, wind, and

others make for the overwhelming bulk of the DG presently connected to the grid. It is more challenging to develop and plan a distribution system that contains DG because of the uncertainty of DG's production, which in turn makes load forecasting, planning, and management of the transmission system more challenging. While trying to find a solution to the optimum issue of the location and capacity of distributed generation supply access to distribution network, there are a few different factors that need to be thought about at the same time. It is required to do an analysis of a number of distinct technical indicators in order to locate a solution that is appropriate for the target location.

Several planning models in DG planning research need extremely complex algorithms for solution, hence research into and selection of solving algorithms has a direct bearing on the planning schemes chosen. Several studies in the present literature provide a variety of optimisation strategies and objective functions for positioning and sizing DG units to maximise the advantages to distribution companies. There are a number of approaches [3, 4, 5]-[6] that have been developed to address the question of where and how to set up massive DG systems. The fundamental motivation for deploying DGs is the desire to lower power system losses. Many studies have focused on the voltage profile and dependability, cost, and distributed generation (DG) capacity and penetration.

In order to determine where precisely DG units and capacitors should be located in an RDS, a more refined evolutionary algorithm was created in [7]. One of the goals of this optimisation task was to lessen the system-wide voltage fluctuations while also cutting down on the overall active power loss. Fuzzy logic controllers, the Ant-lion optimisation technique, and particle swarm optimisation are combined in [8] to provide a revolutionary approach to DG unit placement. Voltage fluctuations and power losses are to be kept to a minimum, as planned. In [9], we see a novel method for identifying the best number of DG penetrations, one that is inspired by the search algorithm for quasi-opposing chaotic symbiotic organisms. The authors of present an approach for DG unit placement via a fuzzy expert system in [10]. Distribution loss reduction index (DLRI) and voltage deviation reduction index (VRDI) were used to find the best place to put the infrastructure (VDRI).

Installing an excessive quantity of DG raises grid connection costs, boosts power outage in the distribution network, and possibly causes system instability. Intermittent energy sources like solar, wind, and others make for the overwhelming bulk of the DG presently connected to the grid. It is more challenging to develop and plan a distribution system that contains DG because of the uncertainty of DG's production, which in turn makes load forecasting, planning, and management of the transmission system more challenging.

Several elements must be considered concurrently when seeking an answer to the optimisation problem of the placement and capacity of distributed generation supply access to distribution network. In order to find a solution that fits the target region, it is necessary to analyse several different technical indications.

As indicated in the aforementioned literature, numerous studies have addressed various distributed system issues and have suggested storage systems as a potential remedy. The practice of load levelling may be the most prevalent and advantageous application of storage systems. As power loss is related to the square of the current, changing the load to the off-peak period may significantly minimise power loss. This is easily and cheaply achieved by the careful placement of storage devices in the most advantageous areas [21]. This study creates an optimal BESS allocation strategy for a radial distribution network (RDN) with significant PV penetration, which reduces system losses overall.

In order to find the best placements and sizes for DG units on selected buses while minimising power loss, this study develops two optimisation techniques, GA and ACO, both of which are based on random search. For the purpose of demonstrating the efficacy of the presented strategy, a comprehensive analysis of an IEEE 33 bus Radial Distribution System is performed. In order to prove the algorithms' worth, they are applied to a number of different scenarios and their results are shown. The simulation results, which use power loss as performance metrics, are used to compare the two techniques. The findings show that both algorithms produce superior results and outperform one another on a number of parameters. This investigation reveals the benefits and drawbacks of using GA and ACO algorithms for optimally designing and allocating DG units in power system networks.

II. PROBLEM STATEMENT AND OBJECTIVE FUNCTION OF DG PLACEMENT

(A) System Description

The distribution network's active power losses may be estimated via DG planning by using the proper network losses calculation approach in light of the distribution network's anticipated load characteristics. The addition of DG will cause a shift in the distribution network's power losses; how much of a shift will depend on the DG's isolation from the grid and its power output. Within this part, we offer a mathematical model for optimal DG unit placement making use of a combination of the hybrid meta-heuristic approach and the distribution load flow algorithm. Figure 1 displays the IEEE-standard line diagram for the 33-bus radial network.

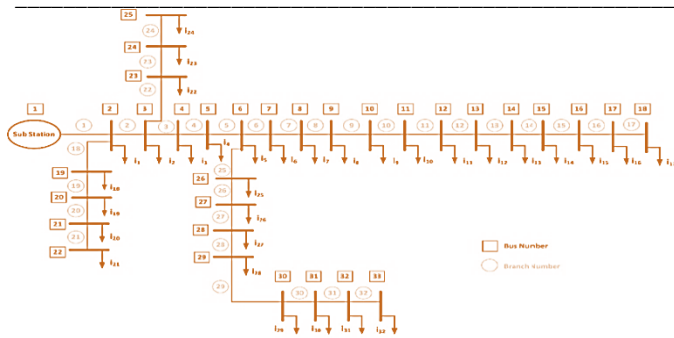


Fig. 1 33-bus Radial Network

Figure 2 depicts a simpler model of the distributing system that incorporates PV and BESS. This research looks at the potential for connecting solar power, battery storage, and loads to an existing power grid. The unpredictability of solar photovoltaic (PV) systems has a considerable effect on the system balance between the amount of electricity that is used and the amount that is produced. The usage of BESS in these circumstances is generally acknowledged as a workable option to supply or store electrical power as needed. The current flow in DN is decreased by installing solar PV systems and BESSs near demand centers, which reduces energy losses. However, the distributed system power losses might be greatly reduced further with the proper BESS allocation into DN.

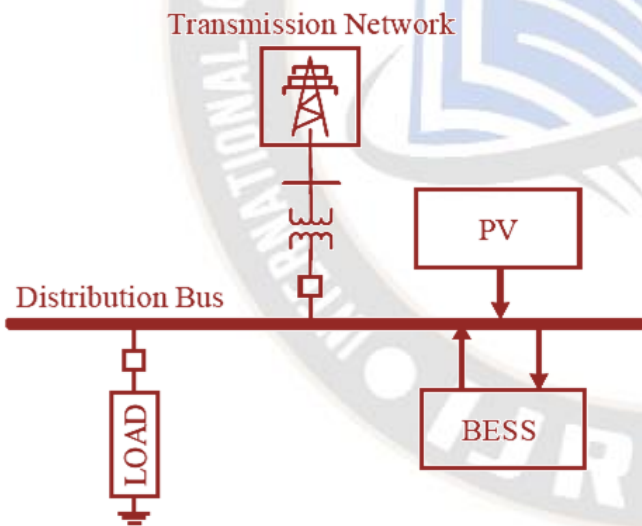


Fig. 2 Basic Structure of Distribution System with DG (PV) and BESS

(B) Objective Function Formulation

As shown in Eq. 1, minimising active power losses in the distribution network is the goal function in mathematically modelling the DG location optimisation issue. Inequalities for the topic under study include voltage and line thermal limitations.

$$P_l = \text{Re} \left\{ \sum_{t=1}^N \left(\frac{|V_t^s - V_t^r|}{Z_t} \right)^2 R_t \right\} \quad (1)$$

The decision factors are the location and the DG unit's generation capacity. Eq. 2 presents the boundary values for these two decision parameters.

$$P_i^{\min} \leq |P_i| \leq P_i^{\max} \quad (2)$$

Eq. 3 presents the inequality restrictions that apply to this optimization issue. Voltage constraints state that a node's voltage magnitude must fall within a certain range, as illustrated in Eq. 3, from the minimum voltage (V_{\min}) to the highest voltage (V_{\max}).

$$V_k^{\min} \leq |V_k| \leq V_k^{\max} \quad (3)$$

The maximum current capacity of this branch, i_{\max} , as established in Eq. 4, must be smaller than the current i_k through any line "k" is.

$$|i_k| \leq i_k^{\max} \quad (4)$$

Here,

P_l – Active power losses in the network.

N – Total number of lines in the network.

V_t^s – sending end node voltage of line t.

V_t^r – receiving end node voltage of line t.

Z_t – impedance of line t.

R_t – resistance of line t.

P_i^{\min} – Minimum value of active power generated in DG i.

P_i – Active power generated in the DG i.

P_i^{\max} – Maximum value of active power generated in DG i.

V_k^{\min} – minimum value of bus potential of bus k

V_k – bus potential of bus k

V_k^{\max} – maximum value of bus potential of bus k

i_k – current flowing through the line k.

i_k^{\max} – maximum value of current flowing through the line k.

III. PROPOSED METHODOLOGIES FOR OPTIMIZATION

(A) Genetic Algorithm (GA)

Generation (G), population size, objective function, selection, crossover parameter and probability, and mutation parameter and probability are just a few of the GA's essential optimisation techniques and parameters that must be modified dependent on the particular optimisation scenario [20]. Several parameters affect the processing speed and precision of the GA. This requires careful consideration on their part. Crossover and mutation are the principal GA processes that generate a new population (Pnew) of optimal solution candidates (Xi). These routes are governed by the odds of crossing and mutation. Following the selection step, two candidates (Ym, Yn) are chosen at random from the current generation for the crossover (Gk). There are higher (Ymax) and lower (Ymin) bounds on the range of Y values (Ymin).

By solving equations (5) and (6), we can see that the aim of the crossover operation is to provide two upgraded solutions for the next generation (Gk+1) (6). These two terms are Ymd and Ynd. Yet, the GA may get entrapped in local minima or maxima, necessitating a specific strategy to release it. To

accomplish this, the mutation procedure may be used (see equations (7) and (8)), where r_1 and r_2 are two random values between 0 and 1. The basic steps of a GA procedure are shown in a flowchart format in Figure 3.

$$y_{md} = y_m + \tau(y_m - y_n) \quad (5)$$

$$y_{nd} = y_n + \tau(y_n - y_m) \quad (6)$$

$$y_{md} = y_{md} + \delta(y_{\max} - y_{\min}) \quad (7)$$

$$y_{nd} = y_{nd} + \delta(y_{\max} - y_{\min}) \quad (8)$$

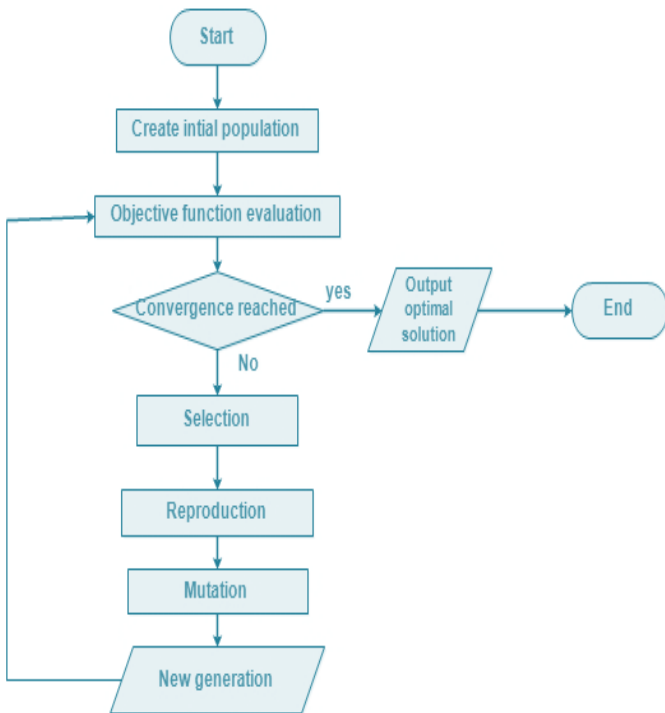


Fig. 3 Flowchart of GA Algorithm

(B) Ant Colony Optimization Algorithm (ACO)

ACO was inspired by the foraging strategies of many kinds of ants. These ants use pheromone to designate a path on the ground that the rest of the colony may follow. The first step in putting the ant colony algorithm into practice is to create a matrix containing all the currents and voltages. The appropriate number of ants are then chosen after that. Two ants were ultimately selected for this scenario. Every ant starts their journey by selecting a first-stage condition at random. Every ant chooses a stage at random, then moves through every state. The foraging activities of ants increased the ACO. Since ants build pheromone traces that enable them to connect with one another and share information about food paths, researchers claim that ants typically choose the shortest distance between the food and the ant's shelter. A swarm of ants often begins its search for food by following haphazard trails. Ants left behind ongoing concentration traces linked to their journeys across time during the early expeditions. They can more easily calculate the shortest path to food as a result of the increase in track density on shorter pathways [23].

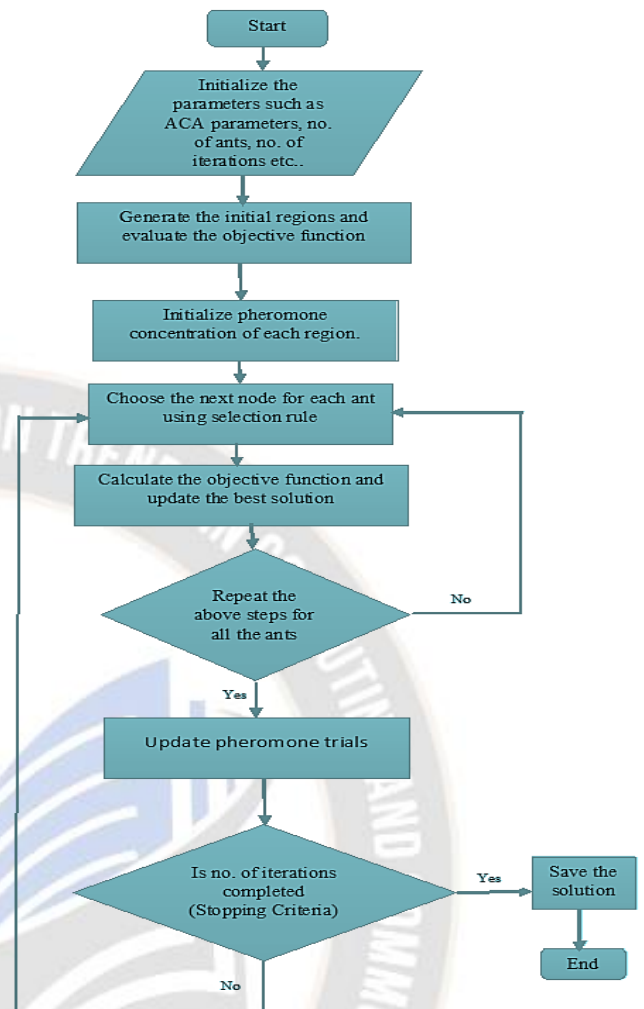


Figure 4 ACO Algorithm Flowchart

Figure 4 depicts the major workflow for the proposed ACO algorithm. The ACO metaheuristic utilises a colony of synthetic ants to work together and solve complex problems in discrete optimisation. One option is to use a network of hypothetical microorganisms, like imaginary ants, all working together to solve a problem; this is an aspect of ACO algorithms.

IV. RESULTS AND DISCUSSION

For the purpose of positioning DG units in the MATLAB environment, the recommended methodologies were used to the IEEE 33 bus distribution test system shown in figure 1. Randomly placed to the distribution network at bus locations 3, 9, 16, 25, 27, and 32 are six solar PVs, each with a capacity of 2 kW. The results are mapped out and verified. The GA and ACO algorithms calculate the optimal DG size and position.

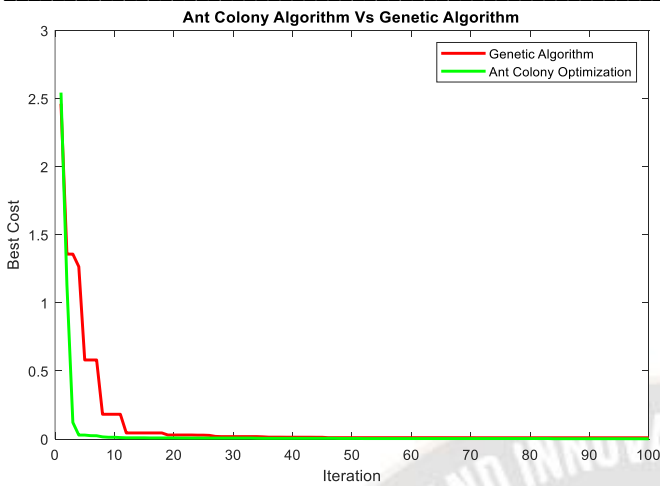


Fig. 5 Cost Function for GA and ACOA techniques

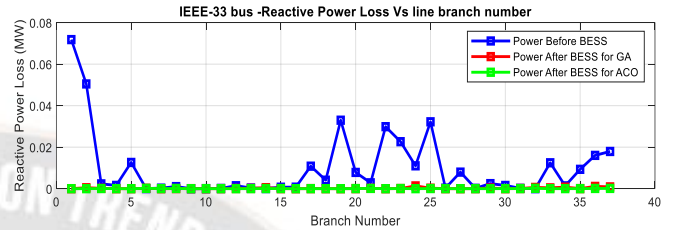
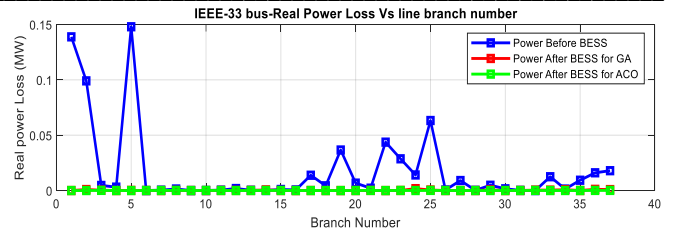


Figure 7 Power losses with & without BESS for GA and ACOA techniques

Figures 5 through 11 illustrate the IEEE-33 bridge system utilising the specified methods. Figure 5 shows how DG and BESS go through several iterations to get the optimal pricing. The ACOA approach is shown to be more cost-effective than the GA technique. Figure 6 shows that both approaches are used to measure the voltage both before and after the BESS is installed. Figures 7 through 9 illustrate the actual power losses as well as the reactive power losses for the 33-bus system. The power losses for both the GA and ACOA systems are shown in Figure 7 both before and after the installation of the BESS.

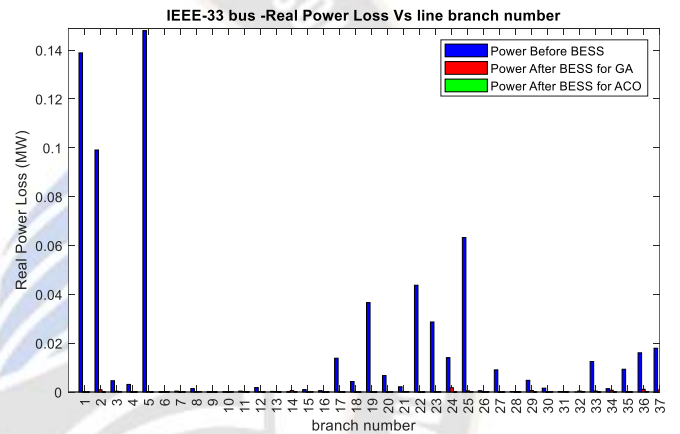


Figure 8 Real Power losses with & without BESS for GA and ACOA techniques

Active power losses before to and after installing the BESS are shown in Figure 8 for the two algorithms investigated in this work. Figure 9 depicts the reactive power losses both before to and after to the installation of the BESS for the two algorithms that were explored for this body of work. The suggested ACOA algorithm unquestionably suffers from less loss than the other approach.

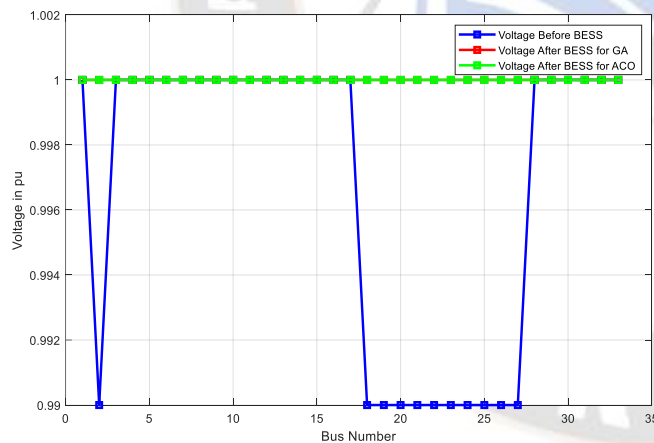


Fig. 6 Comparison of p.u. Voltage with and without BESS for GA and ACOA techniques

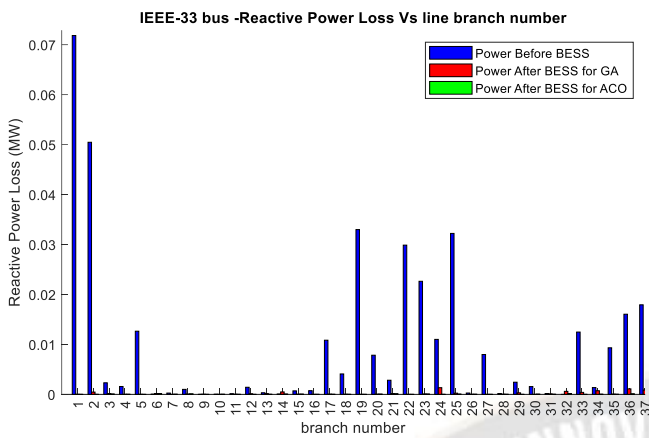


Figure 9 Reactive Power losses with & without BESS for GA and ACOA techniques

Figure 10 shows the size and location of the BESS in their ideal states for the suggested ACOA methodology. Similarly, figure 11 shows the size and location of the BESS in their ideal states for the suggested GA methodology.

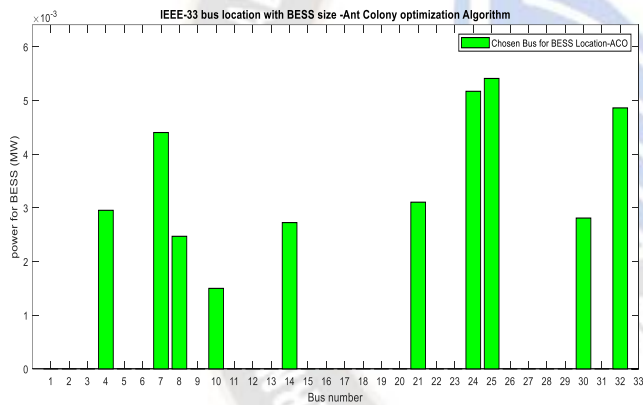


Figure 10 Location and Power of BESS for ACOA technique

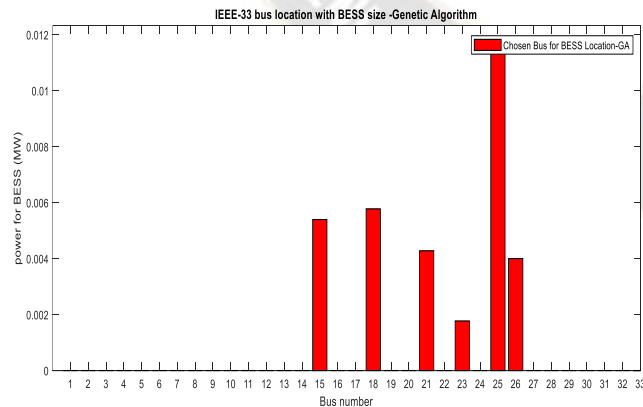


Figure 11 Location and Power of BESS for GA technique

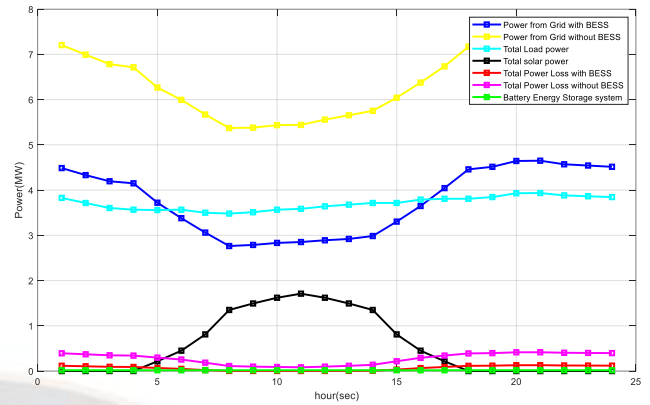


Figure 12 Comparison of Various Powers flowing in the System

The several authorities that are a part of the system under study are shown in Figure 12. As compared to the system that did not include the BESS, it is possible to see that the overall amount of electricity consumed from the grid has decreased noticeably as a result of the installation of the BESS. Since the BESS was installed in the network in the most advantageous location, overall network losses have been cut down, as can be seen above.

Table 1 Power Losses for different cases

Cases	Average Power Losses (kWh)	Total Power Losses Reduction (%)
Reference Case (Without PVs and BESS) - Case-I	0.68888	-
With inclusion of PVs - Case-2	0.68624	0.37
With inclusion of PVs and Distributed BESSs - Case-3	0.0022599	99.67

Table 2 Comparison of Results for the proposed methods

Parameters	Without Optimization	Using GA	Using ACOA
Power Losses including PV & BESS (MW)	0.68624	0.009308	0.001699
Average voltages of buses in p.u.	0.99667	1	1
Reduction in real power loss (%)	89.1914	98.6436	99.75

In Tables 1 and 2, the relevant parameters for the proposed GA and ACOA approaches are presented and compared. It amply demonstrates how superior the suggested ACOA strategy is to GA methodology. Table 1 provides the losses data with three different cases considered namely, without the inclusion of PV's and BESS, next case where only PV's are included and the lost case where both the PV and BESS are included. It is easy to see that the power losses are significantly decreased in the scenario when both PVs and BESS are included, which accomplishes the primary goal of this study. The comparison of the different output parameters that were produced for the various optimisation approaches

that were taken into consideration in this work can be found in table 2.

V. CONCLUSION

This research provides a solution for sizing and installing BESS in radial electrical distribution networks. These modifications use GA and ACOA optimisation strategies to lessen the yearly operational expenses brought on by energy waste from the DG and BESS setup. For the purpose of resolving nonlinear and discrete optimal problems, the ACOA approach that has been suggested is a random searching optimum algorithm that is globally applicable, simple, quick, and trackable. In order to effectively develop the necessary algorithms in Matlab by using m-file coding, as well as in order to correctly identify the right BESS size and location, and in order to minimise loss. Validation of the IEEE-33 bus test system is accomplished via the use of both of these methods. The output is examined, looked over, and compared to previous iterations. All of the data and the inferences made from it are presented. As can be shown in Table 2, the suggested ACOA approach has a loss reduction percentage of 99.75%, whereas the GA only achieves a reduction of 98.64%. As a result, it can be deduced that the output of the proposed technique excelled over the GA methods with regards to power losses.

Acknowledgement

The authors are gratefully acknowledge the authorities of Annamalai University for the facilities offered to carry out this research work.

REFERENCES

- [1] Zhang, C., Xu, Y., Dong, Z.Y., et al.: 'Robust operation of microgrids via two-stage coordinated energy storage and direct load control', *IEEE Trans. On Power Syst.*, 2017, 32, (4), pp. 2858–2868
- [2] El-Khattam, W., Hegazy, Y., Salama, M.: "An integrated distributed generation optimization model for distribution system planning", *IEEE Trans. on Power Syst.* 20, 1158–1165 (2005).
- [3] Pilo, F., Jupe, S., Silvestro, F., et al.: "Planning and optimization methods for active distribution systems", WG C6.19: TB 591, CIGRE, Paris, France, 2014
- [4] Ganguly, S., Samajpati, D.: Distributed generation allocation on radial distribution networks under uncertainties of load and generation using genetic algorithm. *IEEE Trans. Sustain. Energy* 6, 688–697, 2015.
- [5] Jamian, J., Mustafa, M., Mokhlis, H.: Optimal multiple distributed generation output through rank evolutionary particle swarm optimization. *Neuro-computing* 152, 190–198, 2015.
- [6] Montoya-Bueno, S., Muñoz, J., Contreras, J.: A stochastic investment model for renewable generation in distribution systems. *IEEE Trans. Sustain. Energy*. 6, 1466–1474, 2015.
- [7] Tanwar, S.S., Khatod, D.K.: Techno-economic and environmental approach for optimal placement and sizing of renewable DGs in distribution system. *Energy*. 127, 52–67, 2017.
- [8] Awad, A.S.A., El-Fouly, T.H.M., Salama, M.M.A.: 'Optimal ESS allocation for load management application', *IEEE Trans. Power Syst.*, 2015, 30, (1), pp. 327–336
- [9] Bahramirad, S., Reeder, W., Khodaei, A.: 'Reliability-constrained optimal sizing of energy storage system in a microgrid', *IEEE Trans. Smart Grid*, 2012, 3, (4), pp. 2056–2062
- [10] Nick, M., Hohmann, M., Cherkaoui, R., et al.: 'Optimal location and sizing of distributed storage systems in active distribution networks. *Power Tech (POWERTECH)*, 2013, Grenoble, 2013, pp. 1–6
- [11] Chen, S., Gooi, H.B., Wang, M.: 'Sizing of energy storage for microgrids', *IEEE Trans. Smart Grid*, 2012, 3, (1), pp. 142–151
- [12] Surender Reddy Salkuti, "Optimal location and sizing of DG and D-STATCOM in distribution networks", *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 16, No. 3, pp. 1107–1114, December 2019.
- [13] Giannitrapani, A.; Paoletti, S.; Vicino, A.; Zarrilli, D. Optimal allocation of energy storage systems for voltage control in LV distribution networks. *IEEE Trans. Smart Grid* 2016, 8, 2859–2870.
- [14] Quan, H.; Li, B.; Xiu, X.; Hui, D. Impact analysis for high-penetration distributed photovoltaic generation integrated into grid based on DiGSILENT. In *Proceedings of the 2017 IEEE Conference on Energy Internet and Energy System Integration (EI2)*, Beijing, China, 26–28 November 2017; pp. 1–6.
- [15] Zhang, L.; Zhou, Y.; Flynn, D.; Mutale, J.; Mancarella, P. System-Level Operational and Adequacy Impact Assessment of Photovoltaic and Distributed Energy Storage, with Consideration of Inertial Constraints, Dynamic Reserve and Interconnection Flexibility. *Energies* 2017, 10, 989.
- [16] Venkatesh, B.; Ranjan, R. Optimal radial distribution system reconfiguration using fuzzy adaptation of evolutionary programming. *Int. J. Electr. Power Energy Syst.* 2003, 25, 775–780.
- [17] Faessler, B.; Schuler, M.; Preißinger, M.; Kepplinger, P. Battery Storage Systems as Grid-Balancing Measure in Low-Voltage Distribution Grids with Distributed Generation. *Energies* 2017, 10, 2161.
- [18] M. Moazzami, G.B. Gharehpetian, H. Shahinzadeh, S.H. Hosseini, "Optimal locating and sizing of DG and D-STATCOM using Modified Shuffled Frog Leaping Algorithm", 2nd Conference on Swarm Intelligence and Evolutionary Computation, Kerman, 2017, pp. 54-59.
- [19] Abou El-Ela, A., El-Sehiemy, R., Kinawy, A., Mouwafi, M.: Optimal capacitor placement in distribution systems for power loss reduction and voltage profile improvement. *IET Gener. Transm. Distrib.* 10, 1209–1221 (2016)
- [20] Gampa, S.R., Das, D.: Optimum placement of shunt capacitors in a radial distribution system for substation

- power factor improvement using fuzzy GA method. *Int. J. Elect. Power Energy Syst.* 77, 314–326 (2016)
- [21] Karimi, H., Dashti, R.: Comprehensive framework for capacitor placement in distribution networks from the perspective of distribution system management in a restructured environment. *Int. J. Elect. Power Energy Syst.* 82, 11–18 (2016)
- [22] Ramadan, H.S., Bendary, A.F., Nagy, S.: Particle swarm optimization algorithm for capacitor allocation problem in distribution systems with wind turbine generators. *Int. J. Elect. Power Energy Syst.* 84, 143–152 (2017)
- [23] M. Dorigo, G. DiCaro and L. M. Gambardella, “Ant algorithms for discrete optimization”, *Artificial Life Journal*, vol. 5, pages 137-172, 1999.
- [24] Janga Reddy M, Nagesh Kumar.D, “Evolutionary algorithms, swarm intelligence methods, and their applications in water resources engineering: a state-of-the-art review”. *H2OpenJ* 3 135-188, 2020.
- [25] T. Yuvaraj, K. Ravi, K.R. Devabalaji, "Optimal allocation of DG and DSTATCOM in Radial Distribution System using Cuckoo search optimization algorithm", *Modelling and Simulation in Engineering*, pp. 1-11, vol. 2017, 2017.
- [26] M.M. Aman, G.B. Jasmon, A.H.A. Bakar, H. Mokhlis, A new approach for optimum simultaneous multi-DG distributed generation Units placement and sizing based on maximization of system load ability using HPSO (hybrid particle swarm optimization) algorithm, *Energy*, vol. 66, pp. 202-215, Mar. 2014.

