International Journal of Recent Engineering Science
ISSN: 2349-7157/ https://doi.org/10.14445/23497157/IJRES-V13I3P102
Volume 13 Issue 3, 6-23, May-Jun 2026

Original Article

Enhanced Power Loss Reduction Through Optimal RDG Location and Size Using Bi-GRU Integrated Golden Eagle Optimization

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Received: 20 April 2026 Revised: 29 May 2026 Accepted: 17 June 2026 Published: 29 June 2026

Abstract - *The Renewable Distributed Generator (RDG) mainly including solar PV arrays and wind turbines are found to be an effective auxiliary power system to provide optimal power supply for increasing load demands. The sizing and location of these power generators face many challenges, such as power loss, voltage deviation, instability in voltage and shortage of power. In this paper, an Optimal Sizing and location of RDG (OSL-RDG) is carried out to overcome the conventional limitations. The methods involved in this approach are as follows: (i) the forecasting of load and weather conditions based on time is carried out by implementing the Bi-Gated Recurrent Unit (Bi-GRU) model, in which the uncertainties in the load demand are forecasted based on the historical load data. (ii) The optimal sizing and location of RDG is executed to minimize the voltage deviation, power loss and maximize the voltage stability. This is performed by implementing Multi-Objective Golden Eagle Optimization (MOGEO), in which the forecasted load demand and location characteristics are utilized to optimally place the RDG. (iii) The stable power flow is achieved by monitoring the load demand, in which the categorization of load takes place by Advantage Actor Critic with Generalized Advantage Estimation (A2C-GAE), which further minimizes the power loss. The presented model is simulated in MATLAB R2020a simulation tool and validated using the IEEE-33 bus. The evaluation of the proposed model is carried out in terms of performance metrics such as power loss, voltage stability and deviation, forecasting error and iteration time.*

Keywords *- Renewable Distributed Grid With Solar/Wind Turbine System, Load Forecasting, Optimal Sizing And Location, Stable Power Flow, Load Monitoring.*

1. Introduction

The development of Renewable distributed generation (RDG) facilitates the increasing demand of the electricity due to the emergence of electric vehicles, which has enabled the usage of renewable resources to generate electricity and pass it through the distribution network. The size and location of the distributed generation should be determined in an optimal manner in order to enhance the cost efficiency and to lower the power loss during transmission, along with the development of reliability, voltage level and stability. Several existing works provided optimal sites and sizes for the placement of the distributed generation, but these works did not consider the location characteristics for the placement of the RDG, resulting in inefficient performance. The historical data from the smart meters is used for the purpose of optimizing the power flow and also to lower the power loss in the network. However, these approaches only considered the exogenous parameters such as weather and time and the lack of consideration of voltage stability restricted the deployment of these approaches in real time scenario[1]-[5]. The objectives of minimization of total power loss and total cost in the distributed network were considered by various existing works, and the optimization algorithms were implemented to accomplish the objective; nevertheless, these approaches had slow convergence and were inefficient to solve the multi-objective problem [6]. The interrelationship between the photovoltaic power and load was analyzed to perform the uncertain power flow calculation of the power flow calculation while ensuring constraint satisfaction. Several methods addressed the optimal location and size of the RDG using power flow matrices and solving the optimization problem using different algorithms. However, these methods were inefficient as they had slow convergence [7]-[9]. Few existing works adopted unique approaches based on generator coherency to identify the optimal location and size of the RDG; however, residing only on the center of inertia was considered to be inefficient, which affected the performance of these works. The placement of heterogeneous energy storage was designed, and the data-driven models were carried out to satisfy the constraints [10]-[12].

Multi-objective optimization algorithms were implemented to satisfy the power loss constraints and to reduce the factors affecting the optimal power flow in the distribution networks; however, the absence of consideration of location and weather characteristics made these approaches inefficient [13]-[14]. The optimal power flow was achieved, and the communication between the nodes was implemented while ensuring data security manner but the stability of the voltage was left out by these methods, which affects the performance. The optimal power dispatch was implemented for various cases, and the best case was chosen in a distributed manner [15]-[18]. The benefits of renewable distributed generation include reducing transmission power loss, improving stability, enhancing voltage, reducing distribution congestion and increasing the overall system efficiency. The economic benefits of renewable distributed generation is reduce fuel consumption, reducing electricity price and reducing distribution costs because the DG units are assigned near the load centers, and the maintenance and operational costs also decrease. These benefits cannot be achieved without the optimal location and sizing of a renewable distributed generation system. Improper location may increase the power losses, which leads to low performance [19]-[20].

Existing methods for RDG placement do not jointly consider load forecasting, location characteristics, and voltage stability, and they often exhibit slow convergence in multi-objective optimization.

1.1. Research Aim and Objectives

The primary aim of this research is to optimize the power flow in the distribution network by optimally selecting the size and location of the Renewable Distributed Generations (RDGs). This is carried out by knowing the demand through forecasting the upcoming load in the network. The common issues faced in power flow are,

- Uncertainties in demand – the demand in the consumption of power has many uncertainties which vary due to time and weather conditions. To optimize power flow, it is necessary to consider demand uncertainties.
- Lack of stability – the variable nature of the load in the distribution network causes unstable flow of power, which thereby increases the power loss during transmission. The stability of the power flow should be monitored for optimal power flow in the network.

The primary objective of this research work is to minimize the power loss in the distribution network by optimally determining the location and size of the distributed generations based on the forecasted demand of the electricity. This main objective is achieved by accomplishing the following sub objectives given below,

- To find the demand of the load in the distribution network by forecasting the load demand from the historical load and weather conditions, and to minimize the power loss in the distribution network by placing the distributed generation in an optimal location based on the location characteristics.
- To maximize the cost efficiency of DG by optimally determining the size based on the capacity of the RDG, and to maximize the reliability of the distribution network by monitoring the power flow based on the criticality of the load in the network.

1.2. Research Contribution

1.2.1. Novelty and Comparison with Existing Work

Existing research on RDG optimization primarily focuses on either conventional optimization techniques or standalone machine learning models for load forecasting. However, these approaches lack integration between accurate demand prediction and efficient optimization, leading to suboptimal placement and sizing of RDGs. In contrast, the proposed work combines Bi-GRU-based load forecasting with a GEO-based multi-objective optimization approach, enabling better handling of demand uncertainty, improved convergence, and enhanced voltage stability. Unlike prior methods that neglect location characteristics or system constraints, the proposed approach incorporates both spatial and temporal factors, resulting in more reliable and efficient power flow optimization.

The proposed work concentrates mainly on optimal power supply to fulfill the increasing load demand. The stability of voltage is achieved by proper monitoring of the load in the grid. The major contributions of our proposed OSL-RDG model are as follows,

- The forecasting of load and weather conditions is implemented in order to obtain prior knowledge about the load requirement for optimal placing of RDG. The Bi-GRU model is used for this purpose, which is an unsupervised learning model that does not require labelling of training data.
- The efficient location and sizing of RDG is performed to reduce the power loss and voltage deviations and to maximize the voltage stability in the grid. The MOGEO algorithm is employed, taking into account the forecasted load and location characteristics for this purpose.
- The optimal power flow is achieved by performing stability-concerned load monitoring in which the categorization of load based on criticality and demand is carried out by implementing A2C-GAE, further minimizing the power loss.

1.3. Paper Organization

The remaining part of this paper is structured as follows: Section II provides the literature survey on optimal sizing and location of RDG and optimal power flow in the grid. Section III presents the specific problem in the sizing and location of RDG and power flow, from which the research gap in formulating an effective placement method is examined. Section IV explains the methodology involved in the proposed OSL-RDG model to achieve a stable power supply. Section V presents the experimentation and validation of the proposed OSL-RDG model. Section VI provides the conclusion and future work of the presented model.

2. Literature Survey

An approach for simultaneous placement of tie-lines and distributed generations to optimize distribution system post-outage operation and minimize energy losses was proposed in [21]. The operational constraints during both normal conditions and post-outage conditions were considered. The BIBC and BCBV matrices were formulated to evaluate operational constraints and to calculate energy loss by using the direct power flow method in normal operational mode. In post-outage mode, the tree generation was implemented to determine the radial topology. The optimal location and size were determined by using Teaching Learning Based Optimization (TLBO). This approach was tested and validated using IEEE 33 and 69 buses. However, the distributed power flow factor is not considered for the formulation of the power flow model to calculate the energy losses, and the implementation of TLBO for the purpose of optimal size and location is not efficient, as it has slow convergence.

An efficient approach for selecting locations and sizes of the battery storage systems based on the frequency of the center of inertia and principle component analysis was proposed in [22]. Initially, the need for finding the generator coherency was addressed, and the frequency deviation vector of the center of inertia was formulated, with that the index of coherence was computed. The principle component analysis was implemented to obtain the coherence pattern and to eliminate the unwanted information. The location and sizing of the distributed generation were based on the coherence index, in which the busses having a low constant value were chosen to deploy the DG. However, the deployment of PCA was carried out to find the optimal location and size of DG based on the coherence index, but considering only the center of inertia is not sufficient to compute the optimal result.

The optimal stochastic development of heterogeneous energy storage in a residential multi-energy micro grid with demand side management was proposed in [23]. The size and site of the HES were computed based on the residential energy requirements. The price-based electricity demand was modeled, and based on that, the multistage HES were carried out. This framework consisted of two phases' investment phase and the operation phase. The constraints for the optimal location and size of the HES were formulated, and the solutions were presented based on stochastic modeling by satisfying the constraints. This approach was tested on the IEEE 33 bus in order to prove its efficiency. However, the size and location of the HES depend on both exogenous and endogenous characteristics, and the lack of consideration of these factors affects the performance of the approach.

The optimal placement of a DG system using an improved Harris hawk optimizer based on single and multiple objectives was proposed in [24]. The aim of this paper was to reduce the real power loss, voltage deviation and to maximize the voltage stability index. The Harris hawk optimization was implemented, in which the random location was replaced by the rabbit location for better results. The integration of multi objective Harris Hawk optimizer with grey decision analysis was executed in order to optimally find the location and size of the distributed generation. The demand for power is rising day by day, and the factors affecting the demand for power were not considered for the determination of the location and size of the DG in an optimal manner, which affects the performance of this approach. The optimal allocation of fast charging stations and wind-based DGs using stochastic planning was introduced in [25]. The demands of electricity due to the introduction of electric vehicles were considered, and the probabilistic distribution function was developed based on the energy demand. The important parameters affecting the demand were considered, and a new scoring scheme was formulated in order to rank the location of the fast charging stations. The genetic Algorithm was implemented to optimally determine the location and size of the DG in a cost-effective manner. Authors in [26] proposed a distributed consensus-based algorithm for optimal power flow in direct current distribution grids. The Semi-Definite Relaxation (SDR) method was found to have high efficiency, which was proved by the mathematical proof. For the DC distribution system, a fully distributed consensus-based method was presented in which the privacy of the components was also preserved, as only limited information was shared with neighbor nodes. As there was no provision for a centralized controller, there was no single point of failure, and the optimal power flow was achieved using this approach. The proposed approach was validated using IEEE 30, 57, 14, 118 buses.

An increment exchange-based decentralized multi-objective optimal power flow for active distribution grids was proposed in [27]. The customer model and the network model were formulated separately to address the exchange of information between the two entities. The decentralized solutions of the multi-objective optimal power flow model were presented by computing the normalized normal constraint-based scalarization in order to convert the multi-objective function to single objective problems, and the constraints were classified into normal constraints and global constraints. The increment exchange-based algorithm based on KKT optimal conditions was proposed to optimize the power flow in the distributed network. Authors in [28] proposed a distributed optimal power flow algorithm for system-level control of active multi-terminal directed current distributed grids. The multi-objective function of optimal power flow for active network management in the multi-terminal direct current distributed network consisting of distributed energy resources was proposed. The local power dispatch for RES-1, global power dispatch for RES-2, and local power dispatch for CL were proposed, and with the help of these equations, the optimal power flow was computed for the multi-terminal DC distribution grids.

Author [29] proposed Modified Moth Flame Optimization (MMFO) for performing optimal sizing and location of distributed generators developed on renewable sources. The objective of the research is to minimize the distribute system operating cost by considering the parameters of total active power loss, DG cost units cost, voltage deviation and emission. In this research, the bus location index is deployed to sort the locations of candidate buses. From the location index, the proposed MMFO algorithm selects the optimal sizing and location of the distributed generator.

The proposed method is evaluated using the IEEE-68 bus system. The result shows that the proposed method achieved high efficiency compared to other methods. However, the MMFO algorithm has low convergence and latency during optimal sizing and localization of distributed generators. Author [30] proposed a Social Spider Optimizer (SSO) algorithm for optimal sizing of renewable energy resources RES that includes a wind turbine, photovoltaic, diesel generator, and inverter. Here, the cost of energy is known as an objective function. The main objective of this research is to minimize the cost of energy. The energy management strategy is used to minimize battery scarcity and the cost of fuel consumption. The simulation result shows that the proposed method achieved better performance in terms of reliable and low cost compared to existing methods. However, the SSO algorithm achieves a low fitness value because of considering insufficient objective functions, thus reduce the performance of optimal sizing of RES.

Author [31] proposed optimal location and sizing of DGs using vortex search and Chu Beasley genetic algorithms for distributed networks. Here, master slave optimization approach is proposed for sizing and location of DGs. At the master stage, the Chu-Beasley genetic algorithm is proposed for detecting optimal location. In the slave stage, the vortex search algorithm is proposed for detecting the optimal dimension of the distributed generator. The simulation result shows that the proposed model achieved high efficiency in power loss reduction compared to the existing model. Author [32] proposed a method of optimal deployment of several DGS using a plant propagation algorithm in a distributed network. The main objective of this research is to maximize the power loss reduction. This Algorithm has four rounds. In the first round, one DG is deployed optimally and in the second round, two DGs are deployed. In the third round, three DGs are deployed, and in the final round, four DGs are deployed optimally. The simulation result shows that the proposed model achieved higher performance in terms of cost reduction compared to the existing models. Moreover, the performances are evaluated using the IEEE 33-bus network.

3. Problem Statement

The objective function can be defined as the minimization of power loss for a year, which is formulated as,

$$Obj = \min N_d * \left[\sum_{\tau=1}^{M_t} L_P(S) + \sum_{\tau=1}^{M_t} L_P(W) + \sum_{\tau=1}^{M_t} L_P(SP) \right] \tag{1}$$

Where, N_d denotes the number of days in each season and M_t denotes the maximum number of times in a day. S, W, and SP denote the summer, winter and spring seasons, respectively.

The power balance is a crucial constraint for achieving a stable power supply with maximum voltage stability, which can be formulated as follows,

$$G1_{AP} - \sum_{k=1}^{n} k_L - \sum_{bh=1}^{nbh} L_{P(bh)} = 0 \tag{2}$$

Where the active power of the grid is denoted as $G1_{AP}$, k_L and $L_{P(b)}$ denote the load in the kth node and power loss in bh branch, respectively. The reference voltage at every bus in order to maintain the voltage stability is represented as,

$$min_V \leq V_r \leq max_V \tag{3}$$

Where min_V and max_V denote the lower and upper bounds of the voltage. The slack voltage (V) of the bus is considered as 1 with zero phase angle (μ), which can be represented as,

$$\mu_1 = 0, V_1 = 1 \tag{4}$$

DG has evolved as a significant approach to meet the increasing demand for power consumption. Several existing works have addressed optimal power flow in distributed networks; however, the reliability of the distribution network has not been efficiently addressed. The specific problems encountered in optimal placement and power flow are mentioned below. Recent studies have used advanced deep learning models for load forecasting in smart grids. Asiri et al. [33] used a hybrid deep learning model to improve forecasting accuracy. Ullah et al. [34] proposed a BiGRU-CNN model to better capture load variations, especially with renewable energy. Lv [35] introduced a BiGRU-based hybrid model that further improves prediction performance. However, these works mainly focus on forecasting and do not combine it with optimization for RDG placement and power flow improvement.

The integration of crow search optimization and particle swarm optimization was used for this purpose. The major problems faced in these approaches are,

- The active and reactive power of the load on the customer side was assumed to be constant, but this is not applicable in practical situations where the active and reactive power of the load is varying in nature.
- The optimal location of the DG was computed using an improved decomposition-based evolutionary algorithm, but the lack of consideration of location

characteristics affects the performance of this approach.

- The optimal allocation of renewable DG was carried out by CSA, and the optimal power flow was calculated using PSO, but PSO has major limitations of slow convergence and convergence into local minima.
- The optimal power flow and optimal allocation of RDG were performed by implementing the CSA-PSO, but the lack of consideration of voltage stability in the optimal power flow process affects the performance of this approach.

The optimal power flow was facilitated by implementing machine learning approaches [34], [36]. The historical data of generators and load were considered in [34] to minimize the power loss by adjusting the power injections. Only exogenous variables were considered for facilitating the power flow.

In [36], the dynamic correlation between the PV power and the HVAC load was determined for different weather conditions, and the weather condition factor was modeled by considering both the state transition probabilities and the cross-correlation function. The major problems faced by these approaches are,

- The probabilistic power flow was calculated by considering the weather conditions, but the varying power load and unstable voltage factors make this approach inefficient, which limits this approach to be adopted in real-life scenarios.
- The exogenous variables that have an impact on the power flow are only considered, such as time and weather conditions, and the lack of consideration of voltage stability will affect the efficiency of this approach.
- The functions were determined by implementing the supervised learning method, but the labeling of the huge historical data is nearly impossible and affects the accuracy of the function determination process.

3.1. Research Solutions

The proposed OSL-RDG approach is designed in such a way as to overcome the problems of the existing approaches. The research solutions of our approach are mentioned below,

- The load forecasting is performed to know the customer side demand, in which the active and reactive loads were calculated in order to optimally place the distributed generation.
- The factors such as time and weather conditions are used to forecast the load demand, and the factors such as load demand, active power loss, voltage stability and voltage deviation were also considered in order to optimally determine the location and size of the distributed generations.
- In our proposed research work, the optimal placement of distributed generations is carried out by using multi-objective golden eagle optimization, which has fast convergence and attains the global maxima in a smaller number of iterations.
- The unsupervised learning model is implemented for the purpose of load forecasting, which does not need labelling of a huge training dataset.

4. OSL-RGD MODEL

In this research work, we concentrate on minimizing the power loss and cost involved in optimal power flow by determining the location and size of the distributed generation and monitoring the power flow to the critical and non-critical loads to improve the reliability and stability of the distribution network. Figure 1 depicts the overall architecture of our proposed OSL-RDG model. There are three processes involved in the proposed research work, which are described below.

4.1. Multi-Objective Based Load Forecasting

As power consumption continues to rise, it is necessary to understand the load requirements to efficiently manage power flow in the distribution network. To achieve this, load forecasting is done using past data collected from the control center. The load demand is influenced by several uncertainties; hence, these factors are considered to provide a precise forecasting of the load. The forecasting is performed by using a Bi-GRU model in which one is used to process *the load based on the time,* as the consumption of power is based on a time factor, and the other model is used to process the *weather conditions,* which affect the load, as depicted in Figure 2. Various Probability Distribution Functions (PDFs) are dynamically adapted to estimation the power changes of solar radiation, wind, along with the temporal and spatial relationship (weather) over the geographical area. For instance, the PDF for the solar PV array is described as follows,

$$PDF\ (g) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}\left(\frac{g}{g_{max}}\right)^{a-1}\left(1-\frac{g}{g_{max}}\right)^{b-1} \tag{5}$$

Where Γ is the gamma function, a and b are the adaptive parameters to change the input values, g and g_{max} are the maximum and current solar radiation values, respectively.

Similarly, temperature based PDF for the normal distribution is described as follows,

$$PDF(t) = \frac{1}{\sigma_{sh\sqrt{2\pi}}} exp\left[-\frac{(t-\mu_{sh})^2}{2\sigma_{sh}^2}\right] \tag{6}$$

Where t represents the outdoor temperature and μ_{sh} and σ_{sh} are the mean and standard deviations, respectively. Further, a copula function is used as an independent variable, which uses marginal cumulative probability distributions for the temperature and radiation.

$$Y = copulacdf(CDF(g), CDF\ (t), rho) \tag{7}$$

Where CDF (.) represents the Cumulative Distribution Function, rho is the linear correlation matrix, and $copulacdf$ is the copula of CDF. A CDF-based copula is used to control the model for dynamic correlation among the time series weather samples. Our proposed Bi-GRU model is constructed using time series weather historical information, and also stochastic generation was used to simulate the copula CDF by setting up various CDF regimes. Bi-GRU consists of the following layers: embedding layer, Bi-GRU layer, attention layer, and capsule layer. In the embedding layer, a sequence of input readings of the past historical information is taken as input, and the first step is to map the discrete language symbols for embedding vector distribution.

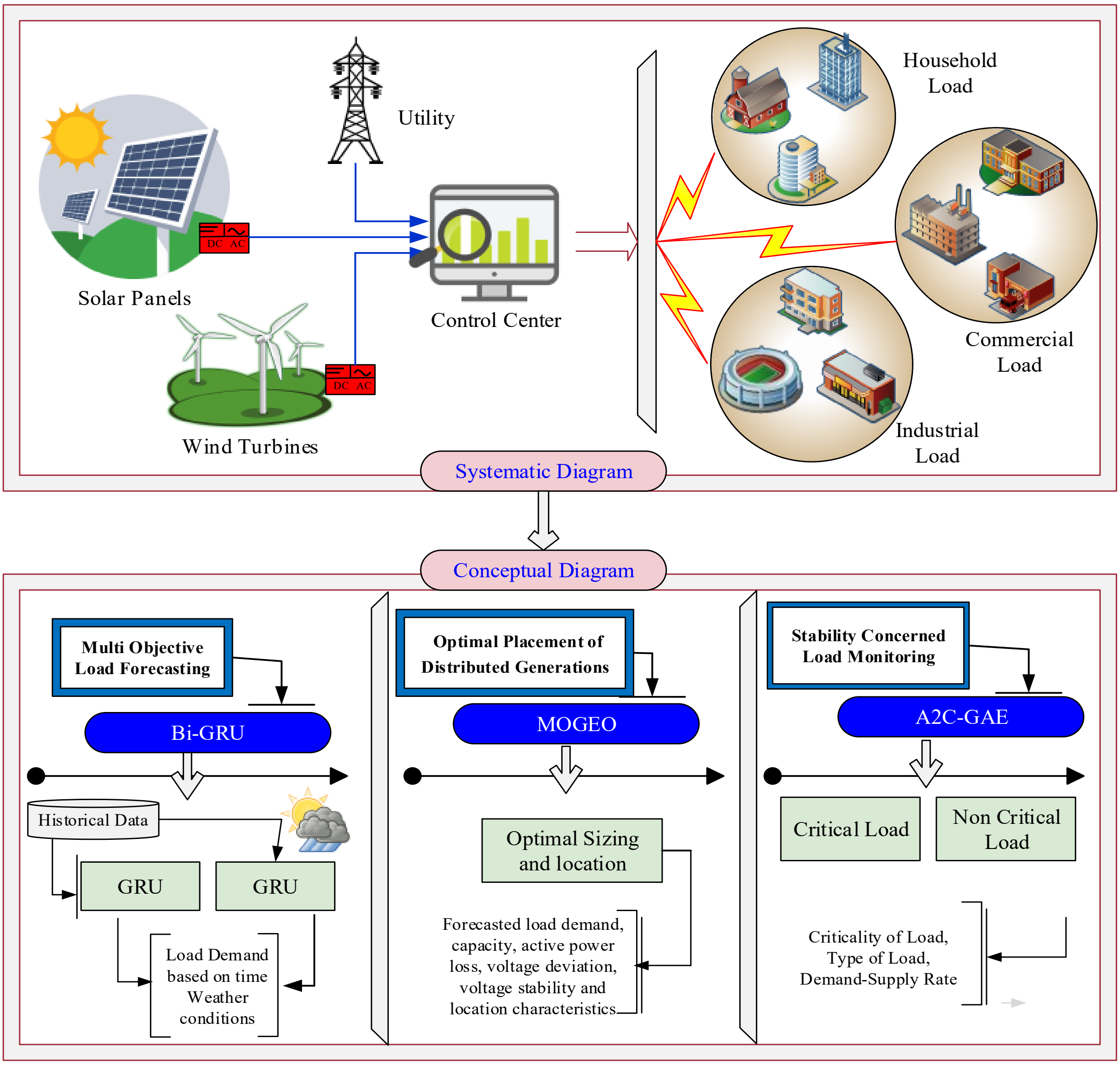

Fig. 1 Overall architecture of the OSL-RDG model

In the Bi-GRU layer, the current state is computed based on the previous state h_{t-1} for the current input measurements X_t. In the following, we compute the states of Bi-GRU,

$$r_t = \sigma(w_r x_t + u_r h_{t-1}) \quad (8)$$

$$u_t = \sigma(w_u x_u + u_u h_{t-1}) \quad (9)$$

$$\breve{h}_t = \tanh\ (w_c x_t + U(r_t . h_t - 1) \quad (10)$$

$$h_t \ = (1 - u_t). h_{t-1} + u_t \ . \ \breve{h}_t \quad (11)$$

Where r_t, u_t and h_t are the d dimensional hidden state, reset state, and update state, respectively, σ is the sigmoid function, and (.) represents the product operation and $w_{u,r,c}$ Moreover, U are the input parameters for Bi-GRU.

The attention layer is used to compute the feature values and their importance by computing the mean and standard deviation of those. For that set of feature vectors from the past historical data is collected, and the capsule layer predicts the expected load demand over the consumers.

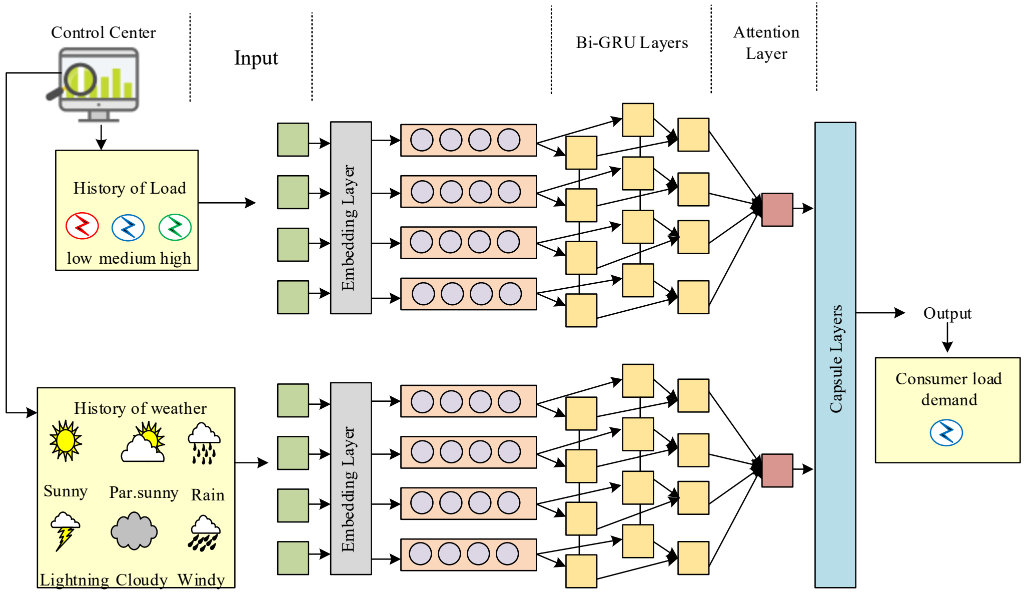

Fig. 2 Bi-GRU-based forecasting of data

The RDG generation is obtained using the PDFs by means of past historical data. Every year, the season is split into multiple classes as summer, Monsoon and winter. Consider the average values of each season. When computing the mean and standard deviation of the input weather data, we can obtain the expected amount of load demand using generated power, power losses and weather information. A day in the season represents the whole season, and each day is further split into 24 time segments. Considers these information for each month m, then we have d days, and each time t, which is computed, $y * m * d$ for solar and wind-based RDGs for the speed data points.

4.2. Optimal Placement Of Distributed Generations

The distributed generation should be placed in an optimal manner in order to reduce the power losses and the cost involved in it, as shown in Figure 3. The placement of distributed generation refers to optimal sizing and location of the distributed generation, which are influenced by several factors, they are load demands, capacity of DG, real power loss, voltage deviation, voltage stability and location characteristics.

The load demand is provided by the precise forecasting of the load, which will support the determination of the size and location of the DG. The location characteristics are defined as the placement of DG; for instance, the placement of the wind turbines is based on the *wind speed* of the location, and the placement of the solar power plants is based on the *irradiance and temperature*.

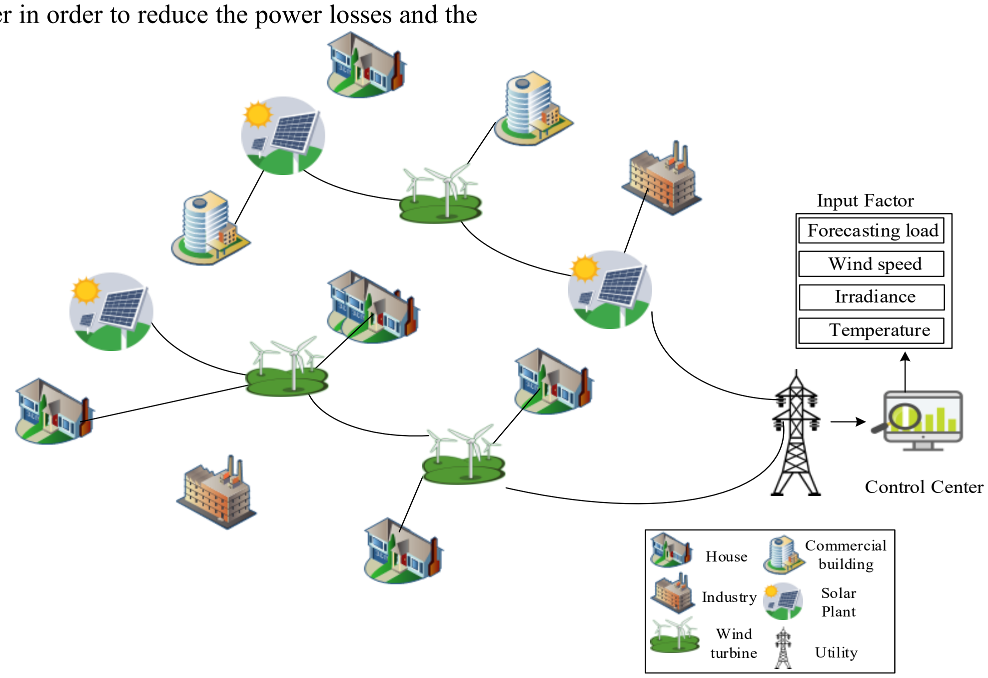

Fig. 3 Optimum Sizing and Placement of RDGs

In this paper, optimum sizing and location of RDGs are obtained using a heuristic approach and the objective function to optimize is the location and size of the RDGs.

A mathematical formulation for optimum sizing can be as follows,

- Solar RDG: Based on the expected generation of power P_S and the location of SDG is given below,

$$P_{SDGE,i} = n_{s,i} \times P_{SG} \qquad \forall i \in d \qquad (12)$$

Where $n_{s,i}$ represents the number of SDGs for the ith bus, P_{SG} represents the expected power generation, and d is the candidate bus. If the optimum is determined for the size and location, the expected generation rate is obtained for the solar RDG as follows,

$$P_{SDG,i} = n_{s,i} \times P_{SDG,R} \qquad (13)$$

Where $P_{SDG,R}$ is the discrete size rate of solar RDG.

- Wind Turbine RDG: Based on the expected generation rate of power P_{WT} We can find the optimum size and location of the wind turbines of RDG, which is given as follows,

$$P_{WDGE,i} = n_{w,i} \times P_{WG} \qquad \forall i \in d \qquad (14)$$

Where $n_{w,i}$ and P_{WG} represents the number of wind turbines and the expected amount of power generated at the wind turbine, respectively. Then, the rated size and location of WDG are obtained as follows,

$$P_{wDG,i} = n_{w,i} \times P_{wDG,R} \qquad (15)$$

Where $P_{SDG,R}$ is the discrete size rate of wind RDG.

The computational complexity of the proposed Multiobjective Golden Eagle Optimization (MOGEO) algorithm includes two phases, which are discussed as follows:

- Initialization: The Algorithm takes $O(N_p \times N_d$ time for initializing the step vector, position vector and memory for every golden eagle.
- Main loop of this Algorithm takes $O(N_p \times N_d \times N_i \times N_o \times N_a)$
- Finally, we calculate the total complexity of the proposed MOGEO algorithm as $O(N_p \times N_d \times N_i \times N_o \times N_a)$

The optimal placement of distributed generations is performed by the GEO, which has fast convergence and has proven to be more efficient than other meta-heuristic optimization algorithms.

The above-mentioned complex optimization problem is addressed using the GEO algorithm, which performs accurately for obtaining the optimum solutions. This Algorithm is inspired by the golden eagle, which consists of different species of birds, such as Hawks and Eagles. The major key features and their working can be described as follows,

- It follows the Spiral (circular) trajectory that returns the straight and search path for the attack.
- It shows the more propensity at the initial stage to normalize the transition for the final stage.
- It retains the tendency for both attack and cruise over every moment of flight.

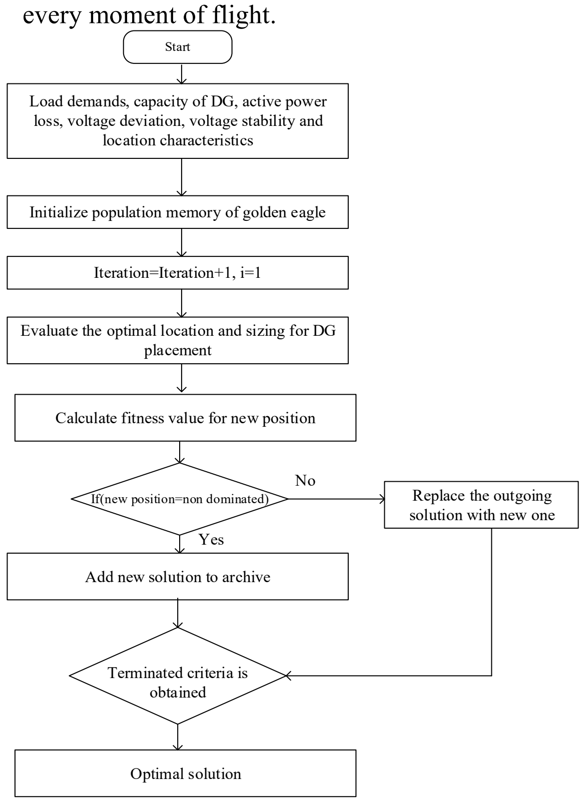

Fig. 4 Flowchart for MO-GEO

It looks for the eagle's information about the prey.

In MO-GEO, fitness is evaluated using the Crowding Score. CS_i which is computed using the crowding distance idea and it is formulated by follows, This distance is the value of Pareto Front and computed between the two nearest values over the time and computed by follows,

$$CS_i = \frac{1}{n}\sum_{j\in J} \frac{(f_{i+,j}-f_{i,j})-(f_{i,j}-f_{i-1,j})}{f_j^{max}-f_j^{min}} \qquad (16)$$

Where $f_{i-1,j}$, $f_{i,j}$ and $f_{i+1,,j}$ are the 3 consecutive members which archive is sorted by the objective functions and the objective values for optimization. A new score is computed based on the roulette wheel procedure, which is computed by using the sparsity score as follows. S_i, which is computed by following,

$$S_i = 1 - CS_i \qquad (17)$$

The procedure of the proposed MO-GEO is explained in the following. In the proposed MO-GEO, initialization is implemented by the load predicted data, IEEE 33 bus data, expected solar and wind power generation, peak and off-peak time and the power losses. At the end of this Algorithm, the total number of solar and wind RDGs and the location of RDGs are computed. In the Algorithm, the number of searches, initial states, distance score computation and termination criteria. Here, the fitness of the agent is computed using the distance-based objective function between two neighbor data points and also minimizes the losses. Afterwards, the position of initialized parameters is updated. If the termination criteria are reached, then the optimal values of the fitness values are stored, and otherwise the process is repeated until the best fitness value is reached.

Algorithm 1: MO-GEO Algorithm

1. Begin
2. Initialize input parameters
3. Initialize MO-GEO parameters // golden eagles parameters
4. Compute the fitness for each parameter
5. For each iteration i
6. Compute Crowding Distance CS_i for existing members
7. For each golden eagle i
8. Randomly choose the prey using Roulette Wheel using CS_i
9. Update Position
10. Compute the fitness for the new position
11. End for
12. Update for all golden eagles
13. End For
14. Return

4.3. Stability Concerned Load Monitoring

Control centers, responsible for ensuring a steady power supply to consumers, continuously monitor the load in the distribution network to enhance its stability. The actor critic algorithm consist two neural networks, such as the actor and critic networks. The load demand is categorized into two types, namely (i) Critical Load and (ii) Non-Critical Load, based on the *criticality of the load* (L_C), *type of the load* (L_T) *and demand Supply Rate* (S_R) and the Power Flow (P_F) is monitored dynamically by the A2C-GAE. Reinforcement learning algorithm monitors the environment and provides an action based on the current state. Here, *criticality of the load, the type of the load, the demand supply rate* and the power flow, which are considered as the state of the environment, based on which the load is classified into critical and non-critical. The home load is known as a non-critical load, and the industry and hospital loads are considered critical loads. By doing so, the stability of the power flow is improved, which further minimizes the power loss during transmission in the distributed network. The IEEE 33 bus is used for the purpose of validation. In reinforcement learning algorithm policy is used to calculate the advantage, which is defined as follows,

$$\nabla_\theta J(\theta) = D_{\pi(\theta)} \nabla_\theta log\pi_\theta(Ac|St) A^\pi(st, Ac) \quad (18)$$

The value of the Q function is defined as follows,

$$Q^\pi(St, Ac) \approx R + \alpha U^\pi(St') \approx R + \alpha U^\pi_\emptyset(St') \quad (19)$$

Where, $\pi_\theta(Ac|St)$ represent the policy that is also called the actor and $U^\pi_\emptyset(St)$ that of estimating the performance of an actor, which is called a critic. The difference between the state-action value function and the state value function is known as the advantage function, which is defined as follows,

$$A^\pi(St, Ac) = Q^\pi(St, Ac) - U^\pi(s) \approx R + \alpha U^\pi_\emptyset(St') - \alpha U^\pi_\emptyset(St) \quad (20)$$

This function is used to estimate how much better an action is than the average action selected by the policy. π_θ. The training of the critic network is given as follows,

$$U^\pi(St) = D_{Ac\sim\pi(AC|Sc)} D_{St'\sim(S'|St,Ac)}[R + \alpha U^\pi(St') \quad (21)$$

The reinforcement learning algorithm is used to select the optimum policy variable θ, which leads to high expected reward.

$$\theta = Arg \max R(\theta') \quad (22)$$

The training procedure of actor critic network takes the values from the current policy. Generally, the actor critic algorithm is an on-policy algorithm; we used n step estimates instead of using one step, which increases the advantage of the advantage actor critic algorithm.

$$Q^\pi(St, Ac) \approx \sum_{n=0}^{N-1} \alpha^n R^{(n+1)} + \alpha^N U^\pi(t^N) \quad (23)$$

The N-step advantage estimator function is calculated as follows,

$$A^\pi_{(N)}(St, Ac) := \sum_{n=0}^{N-1} \alpha^N R^{(n+1)} + \alpha^N U^\pi_\emptyset(t^N) - U^\pi_\emptyset(St) \quad (24)$$

Where N=1 represents the one-step estimation of the current actor-critic network. The N-step advantage estimator includes exponential smoothing with several hyperparameters μ

$$A^\pi_{GAE}(St, Ac) := (1-\mu)(A^\pi_1(St, AC) + \mu A^\pi_2(St, AC) + \cdots) \quad (25)$$

Where the hyper parameter $\mu \in [0,1]$ helps to smooth control, and the value of $\mu = 0$ represent the actor critic with lower variance and higher bias. $\mu = 1$ represents high variance and low bias. GAE represent the high advantage of using n step advantage estimators, which is defined as follows,

$$A^\pi_{Trunc.} GAE(St, AC) := \frac{A^\pi_1(St,AC) + \mu A^\pi_2(St,AC) + .. + \mu^{N-1} A^\pi_n(St,AC)}{1 + \mu + \mu^2 + \cdots + \mu^{N-1}} \quad (26)$$

Where the number of n advantage estimators may be different for difference transition. Finally, the load is classified into critical and non-critical.

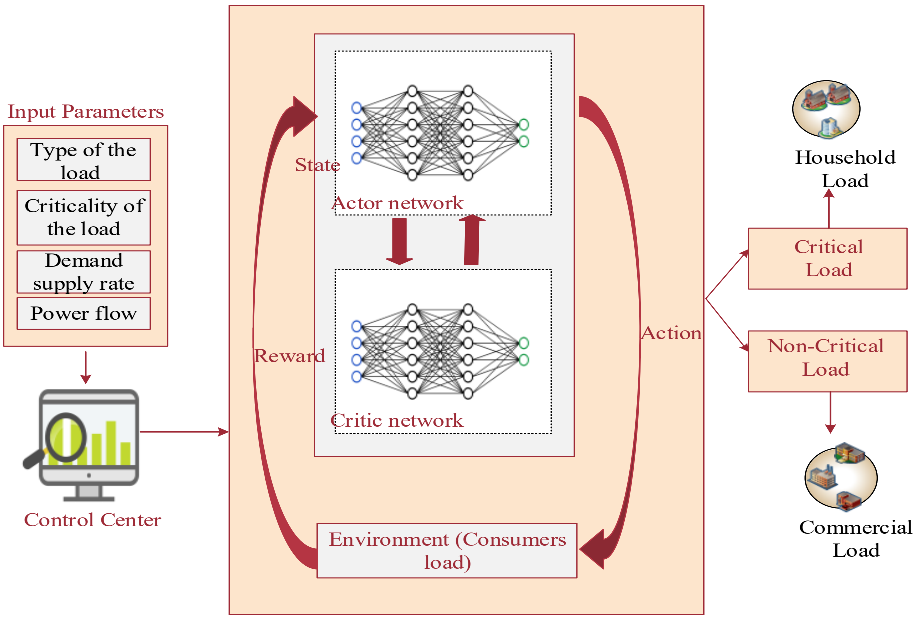

Fig. 5 Stability concerned load monitoring

Algorithm 2: A2C-GAE Algorithm

INPUT: L_C, L_T, S_R, P_F and policy θ
OUTPUT: Critical load and non-critical load
Begin
{
Initialize L_C, L_T, S_R, P_F
for $i = 0,1, \dots n$ do
Calculate L_C, L_T, S_R
Calculate P_F
Calculate policy value using equation(18)
Estimate $A^{\pi}(St, Ac)$ using equation (20)
Update policy using equation(22)
If $(\sigma > L)$
{
Defined as the critical load
}
else
defined as a non-critical load
end for
for $i = 0,1, \dots . n$ do
Calculate one-step advantage estimation using equation(25)
Calculate n-step advantage estimation using equation(24)
end for
}
end

4. Experimental Study

In this section, the experimentation of the proposed OSL-RDG model is carried out in an extensive manner. This section is divided into three sub-sections, namely simulation study, comparative analysis and research summary.

4.1. Simulation Study

The simulation of the proposed OSL-RDG model is executed in MATLAB R2020a simulation tool and validated using a Simulink model. Table.1 presents the system configurations required for the simulation of our model. The RDG parameters involved for the simulation of our model are presented in Table.2. The overall Simulink model of our proposed OSL-RDG containing wind turbines, solar PV arrays and utility grid is depicted in fig.6. The individual models of solar PV arrays and wind turbines are illustrated in Figure 7 (a), (b). The IEEE-33 bus architecture is utilized to validate the effectiveness of our proposed OSL-RDG model, which is illustrated in Figure 8.

Table. 1 System configuration

Hardware specifications	Processor	Pentium Dual Core and Above
	RAM	8GB
	Hard Disk	60GB
Software Specifications	Simulation tool	MATLAB R2017b
	OS	Windows 10

Table. 2 RDG Parameters

Parameters	Values
Total load demand	3715
Number of Wind	3
Number of Solar Arrays	4
PV Solar Array Module Type	Sun Power SPR-305
Voltage stability	0.6686pu
Filter Inductance	8 mH
Maximum PV Power	800 kW
State of Charge	95%
Total active power loss	0.503 kW
Depth of Discharge	30%
Maximum Wind Power	4 – 6 kW
Filter Capacitance	250μF
Voltage deviation	0.9036pu
Filter Resistance	0.1Ω

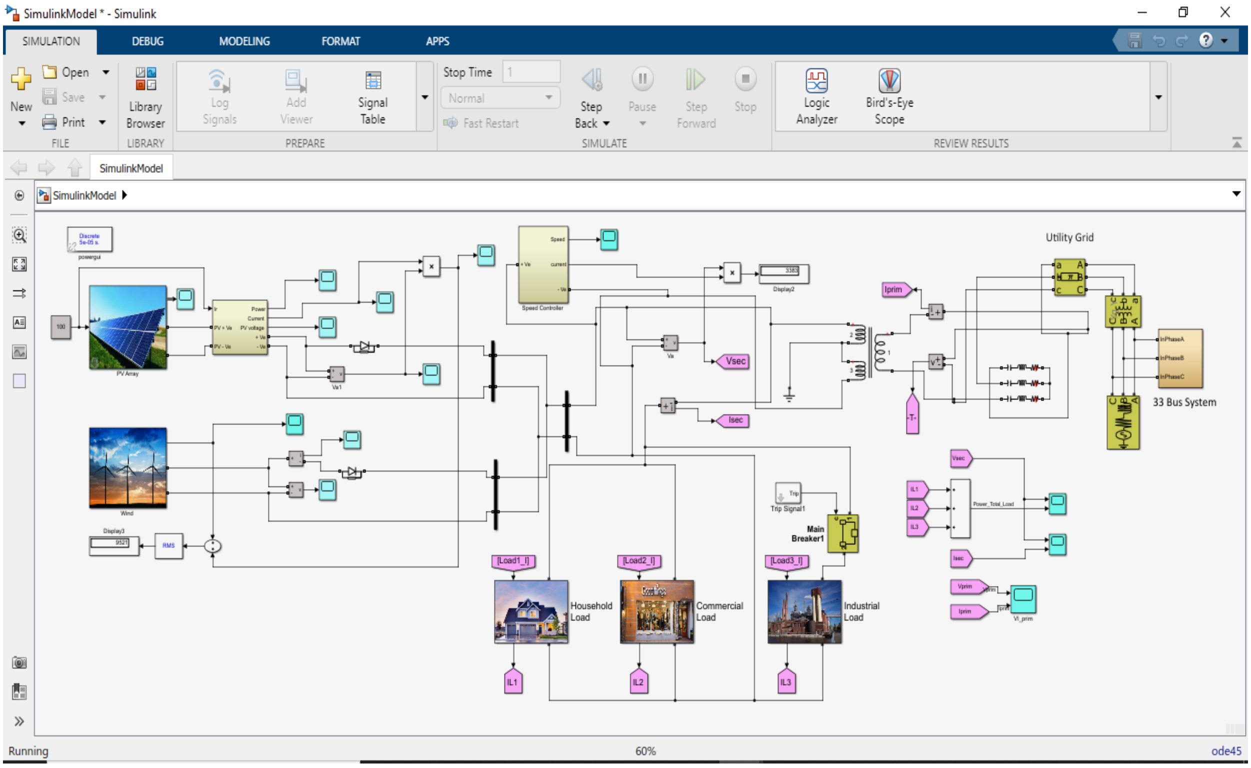

Fig. 6 Overall Simulink model

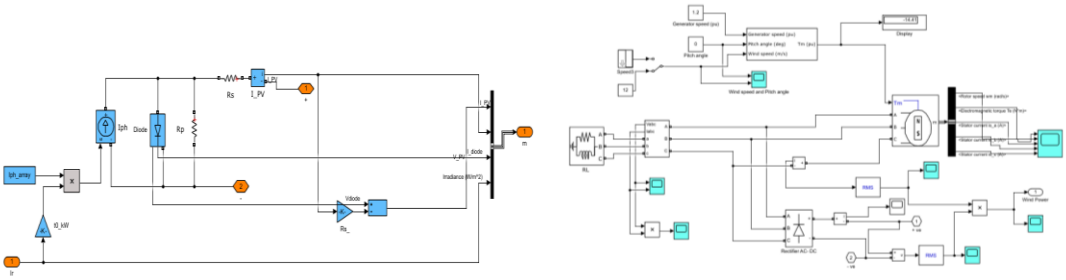

Fig. 7 (a) **(b)**

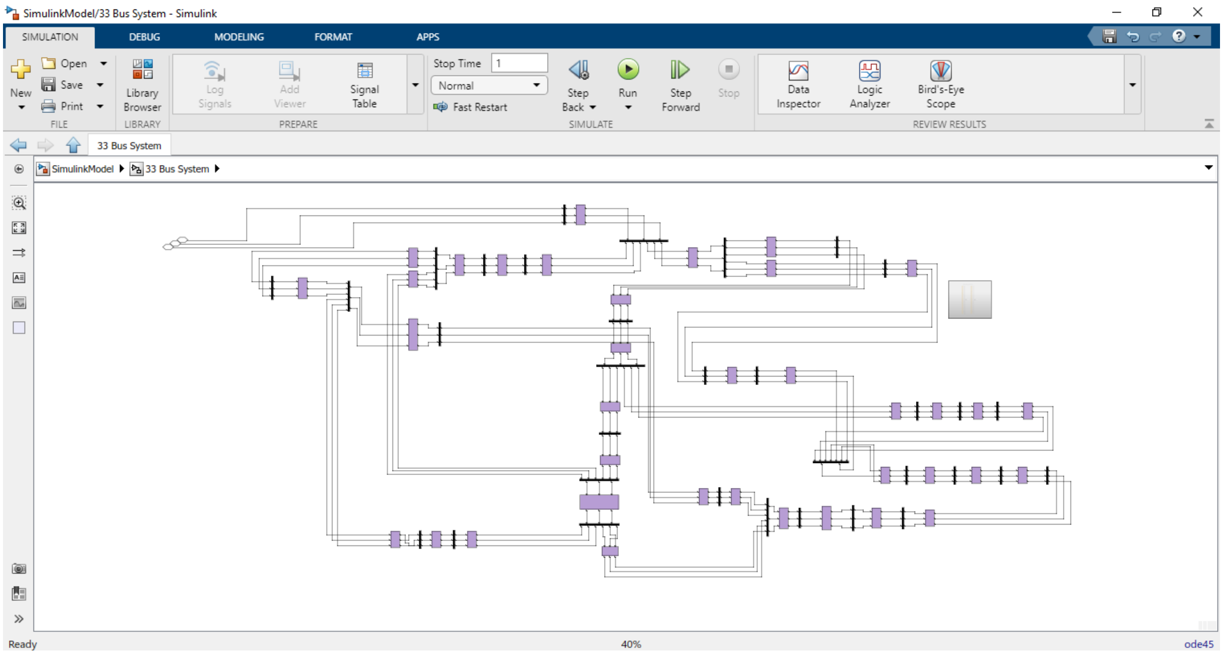

Fig. 8 IEEE 33 architecture

4.2. Comparative Analysis

In this sub-section, the proposed OSL-RDG model is correlated with the existing approaches like OSS-DG (Optimal Site and Size of Distributed Generation Allocation in RDN Using Multi-objective Optimization) and TDES (Towards Distributed Energy Services: Decentralizing Optimal Power Flow with Machine Learning). The validation of our model is performed in terms of performance metrics such as power loss, voltage stability, voltage deviation, forecasting error, and iteration time.

4.2.1. Scenario 1: Critical load

Impact of Power Loss

The power loss is termed as the measure of the quantity of power wasted during transmission. This is caused by the inefficient placement of distributed generators in the grid, resulting in reverse power flow. Figure 9 depicts the comparison of the power loss of our proposed OSL-RDG model with the existing models with respect to the number of RDGs. The power loss decreases with an increase in the number of RDGs. The power loss of our proposed model is low due to the optimal placing of RDG by considering the load demand, capacity of RDG, location characteristics and other significant factors. The MOGEO algorithm is implemented to make a decision on the number of RDG, its location and size. The existing approaches assumed constant active and reactive power of the load on the customer side, proving it inefficient in optimally placing the RDG. Further, the consideration of only exogenous factors lacks in providing stability of the power flow.

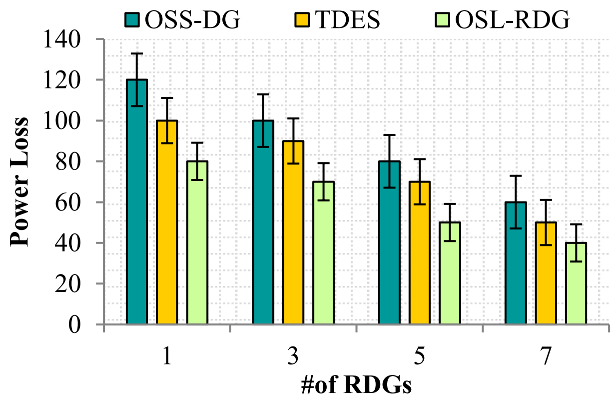

Fig. 9 Power loss (critical load)

The numerical analysis of power loss of our proposed OSL-RDG model and existing models with respect to the number of RDGs is presented in table.3. The proposed model is found to possess 60.1 kW of average power loss, whereas the existing approaches possess power loss up to 90.5 kW, which affects the stable power flow to the critical load.

Table 3. Analysis of Power Loss

Techniques	# of RDGs
OSS-DG	90.5±5
TDES	77.5±4
OSL-RDG	60.1±2

Impact of Voltage Stability

Voltage stability is a necessary metric for evaluating an approach's ability to maintain voltage within acceptable limits. The instability of voltage is due to the inability of the approach to satisfy the load demand. In critical load conditions, the stability of the voltage should be achieved to facilitate a proper power supply. The comparison of the voltage stability of our proposed approach and the existing approaches with respect to the number of RDGs is illustrated in Figure 10. The voltage stability increases with an increase in the number of RDGs, but the increased number of RDGs results in increased cost of energy; therefore, the optimal number of RDGs should be determined, which is carried out by using MOGEO. The proposed approach possesses high voltage stability in critical load conditions due to the forecasting of load demand. The proper knowledge of the load facilitates proper placement of RDGs in the network, thereby achieving voltage stability. The existing approaches lack prior knowledge of load demand, which reduces their efficiency in determining the optimal location and size of RDGs.

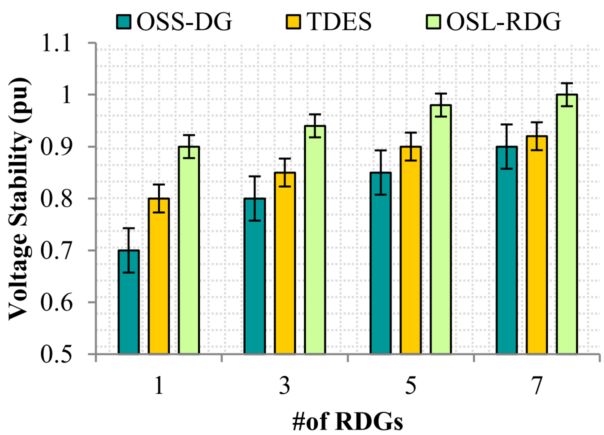

Fig. 10 Voltage stability (critical load)

The numerical comparison of the voltage stability of our proposed OSL-RDG model and existing approaches with respect to the number of RDGs is provided in table.4. In which the proposed model possesses a stability of 0.95pu whereas the existing approaches possess up to 0.86pu. From this, we can conclude that our proposed system is more stable in supplying power to the critical load.

Table 4. Analysis of voltage stability (pu)

Techniques	# of RDGs
OSS-DG	0.83±0.5
TDES	0.86±0.3
OSL-RDG	0.95±0.1

Impact of Voltage Deviation

The voltage deviation is defined as the measure of variation of voltage from the reference voltage, which results in degradation of the performance of the power system. The deviation of voltage is due to the dynamic variation of load demand. In Figure 11, the comparison of the voltage deviation of our proposed model and existing approaches with respect to the number of RDGs is illustrated. The deviation of voltage decreases with an increase in the number of RDGs. The voltage deviation of our proposed approach is less than that of other existing approaches due to the dynamic monitoring of the load. The A2C-GAE is implemented to dynamically categorize the load into critical and non-critical and performing stable supply of power based on the variation of load demand. The existing approaches assume constant load demand, which affects the performance of the system by increasing the voltage deviations. The numerical analysis of the voltage deviation of our proposed OSL-RDG approach and existing approaches with respect to the number of RDGs is presented in the Table.5 The proposed approach seems to have a voltage deviation of about 0.006pu whereas the existing approaches possess up to 0.011pu. The increased voltage deviation of the existing approaches degrades the performance of the power system, affecting the cost of revenue.

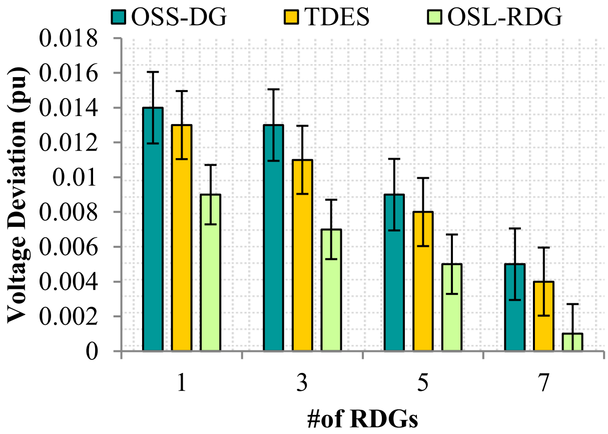

Fig. 11 Voltage deviation (critical load)

Table 5. Analysis of voltage deviation (pu)

Techniques	# of RDGs
OSS-DG	0.011±0.005
TDES	0.009±0.003
OSL-RDG	0.006±0.001

Impact of Forecasting Error

The forecasting error is defined as the difference between the forecasted value and the actual value, which affects the proper estimation of load in the network. The forecasting error is due to the inability to manage the large set of training data. The comparison of the forecasting error of our proposed OSL-RDG model and the existing approaches with respect to the number of RDGs is presented in Figure 12. The forecasting error of our proposed approach is lower than that of the existing approaches due to the consideration of uncertainties in the load demand. The proposed Bi-GRU model forecasts the load demand and weather conditions simultaneously from the time based historical data. The existing approaches possess ineffective forecasting of load, which does not consider the uncertainties and criticality of load, resulting in increased forecasting error.

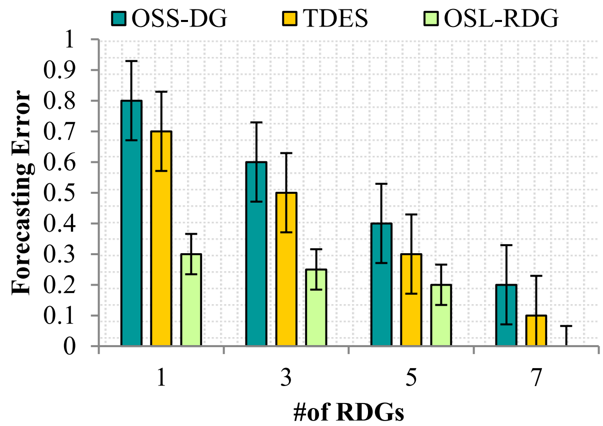

Fig. 12 Forecasting error (critical load)

The numerical comparison of forecasting error of our proposed approach and the existing approaches is provided in Table.6. In which the proposed OSL-RDG approach possesses a negligible forecasting error of about 0.2 on a scale of 0 to 1. The existing approaches possess forecasting error up to 0.5, which affects the optimal sizing of RDG. From this, we can conclude that our proposed work facilitates proper estimation of load, thereby facilitating the optimal placement of RDG in the grid.

Table 6. Analysis of Forecasting Error

Techniques	# of RDGs
OSS-DG	0.5±0.05
TDES	0.4±0.03
OSL-RDG	0.2±0.01

Impact of the Iteration Time

The iteration time is referred to as the time taken to compute the optimization of the size and location of RDG based on several significant factors. The reduced iteration time denotes more efficient optimization of the solution. The comparison of the iteration time of our proposed approach and the existing approaches with respect to fitness value is depicted in Figure 13.

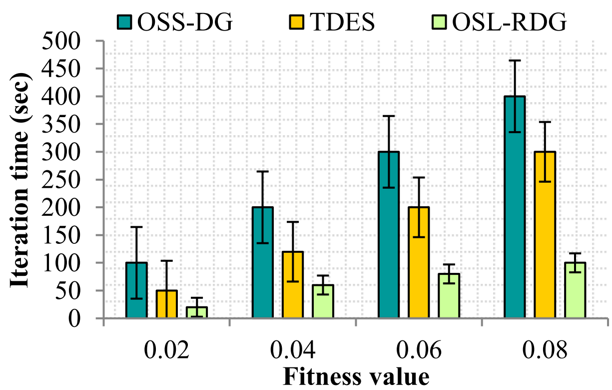

Fig. 13 Iteration time (critical load)

The iteration time increases with an increase in the fitness value. The proposed approach possesses less iteration time even in a critical load condition due to the implementation of MOGEO. The objective functions are defined in an optimal way in order to obtain a higher fitness value. The existing approaches undergo a high iteration time due to the limitation of local optimum, in which the best result in the current set is considered as a solution without considering the global solution. The numerical analysis of the iteration time of our proposed model and the existing models with respect to fitness value is provided in the Table.7 The iteration time of our proposed approach is found to be 65.3 (s), whereas the existing approaches possess up to 250 (s) of iteration time, which degrades the performance of optimal sizing and location of RDG.

Table 7. Analysis of Fitness value

Techniques	Fitness Value
OSS-DG	250±5
TDES	167.5±4
OSL-RDG	65.3±1

4.2.2. Scenario 2: Critical load

Impact of Power Loss

The power loss of our proposed approach in non-critical load conditions is examined here. The non-critical load denotes the load demand from non-industrial and non-commercial applications. The residential load covers most of the non-critical load demand. Figure 14 depicts the comparison of power loss of the proposed OSL-RDG model, considering the non-critical load and the existing approaches with respect to the number of RDGs. The reduced power loss of the proposed approach is due to the proper monitoring of the load and injection of power based on the load demand. The monitoring of load is carried out by using A2C-GAE, in which the dynamic demand of load is considered to categorize the load. The existing approaches lack proper monitoring of load, which increases power loss in the network.

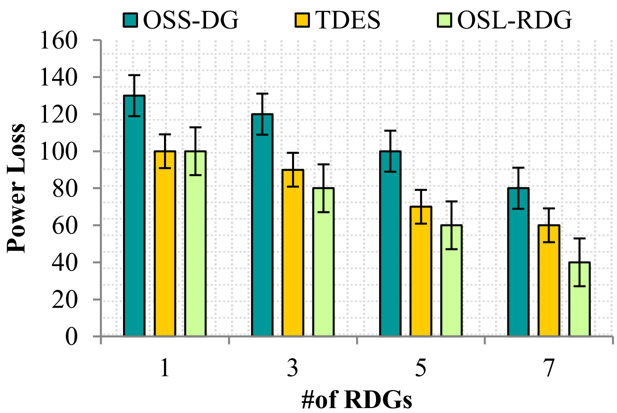

Fig. 14 Power loss (non-critical load)

The numerical comparison of our proposed OSL-RDG approach and the existing approaches in terms of power loss with respect to the number of RDGs is presented in table.8. The power loss of the proposed OSL-RDG model in a non-critical load condition is 70.1 kW, whereas the power loss in a critical load condition is 60 kW. This shows that the proposed approach provides a dynamic power supply based on the criticality of the load, thereby achieving a stable power supply without any shortages. The existing approaches possess up to 107.5 kW due to improper placement of RDG and inefficient monitoring of the load.

Table 8. Analysis of Power Loss

Techniques	# of RDGs
OSS-DG	107.5±5
TDES	80±4
OSL-RDG	70.1±2

Impact of Voltage Stability

The voltage stability of our proposed OSL-RDG approach is examined in a non-critical load condition. The fluctuations in the power generated from wind turbines and solar PV arrays result in instability. This is reduced by the optimal placement of RDG and having prior knowledge of the load. In Figure 15, the comparison of the voltage stability of our proposed approach and existing approaches with respect to the number of RDGs is illustrated.

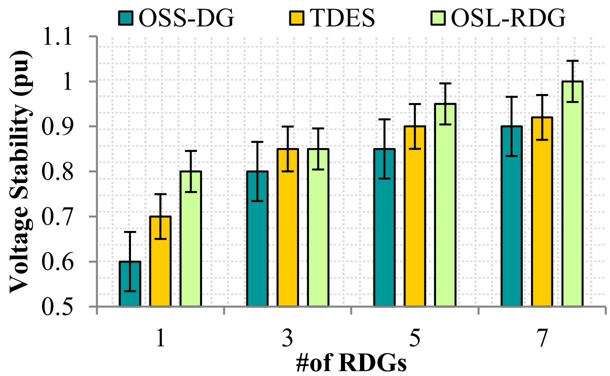

Fig. 15 Voltage stability (non-critical load)

The voltage stability of our proposed model in non-critical load conditions is higher than the existing approaches due to effective forecasting of load and weather, and optimal positioning and sizing of the RDG in the grid based on forecasted load, location characteristics and other significant factors. The existing approaches lack in the effective placement of RDGs, which causes a reverse flow of power. The numerical analysis of the voltage stability of our proposed approach in non-critical load conditions and existing approaches is presented in Table 9. In a non-critical load condition, the proposed approach seems to have a voltage stability of about 0.9 pu, and in a critical load condition, the voltage stability of our proposed model is 0.95pu whereas the existing approaches possess up to 0.84pu. From this, we can conclude that our proposed approach provides high voltage stability even in non-critical conditions.

Table. 9 Analysis of voltage stability (pu)

Techniques	# of RDGs
OSS-DG	0.78±0.5
TDES	0.84±0.3
OSL-RDG	0.9±0.1

Impact of Voltage Deviation

The deviation in the voltage of our proposed model in non-critical load conditions is examined here. The comparison of the voltage deviation of the proposed OSL-RDG model in non-critical conditions and existing approaches is depicted in Figure 16. The voltage deviation of the in non-critical condition is low than other existing approaches due to the optimal placement of RDG in the grid. The optimal placement is carried out by implementing MOGEO, which considers the load demand and other significant factors to obtain an effective solution. The lack of consideration of necessary factors reduced the efficiency of these approaches, resulting in increased voltage deviations.

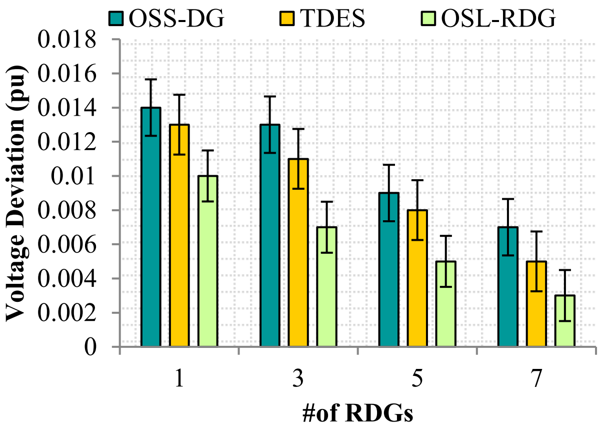

Fig. 16 Voltage deviation (non-critical load)

The numerical analysis of the voltage deviation of our proposed model in non-critical conditions and the existing approaches with respect to the number of RDGs is presented in Table 10. The voltage deviation in non-critical condition is 0.0063pu and in critical condition is 0.006pu whereas the existing approaches possess up to 0.010pu. From this, we can conclude that the voltage deviation of our proposed approach in both critical and non-critical load conditions is less than that of the existing approaches, which means that our approach provides a stable power supply in the grid.

Table 10. Analysis of voltage deviation (pu)

Techniques	# of RDGs
OSS-DG	0.010±0.005
TDES	0.0093±0.003
OSL-RDG	0.0063±0.001

Impact of Forecasting Error

The forecasting error of our proposed approach in non-critical conditions is analyzed. In Figure 17, the comparison of forecasting error of our proposed approach in non-critical conditions and existing approaches with respect to the number of RDGs is depicted. The forecasting error of our proposed approach in non-critical conditions is found to be low due to the implementation of unsupervised learning-based forecasting, in which the trained dataset does not require labelling. The existing approaches execute a supervised learning-based forecasting approach, which makes it hard to label the huge training dataset—the improper training of data results in increased forecasting error, which affects the optimal placement of RDGs.

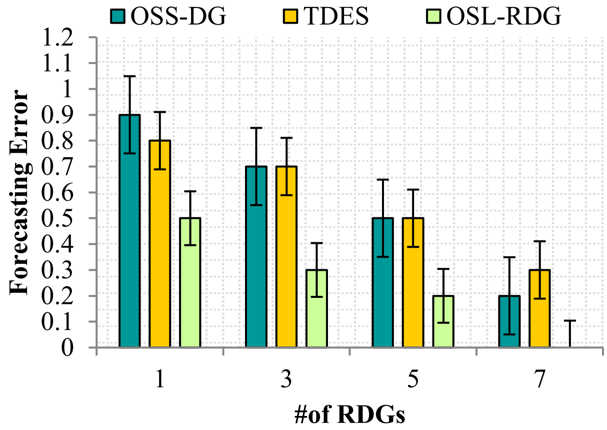

Fig. 17 Forecasting error (non-critical load)

The numerical comparison of the forecasting error of our proposed approach in non-critical load conditions and existing approaches is provided in Table 11. The forecasting error in non-critical conditions is found to be 0.25, and during critical condition to forecasting error is 0.2, whereas the existing approaches possess up to 0.57, which shows that the proposed approach in both critical and non-critical conditions exhibits less forecasting error than existing approaches.

Table 11. Analysis of Forecasting Error

Techniques	# of RDGs
OSS-DG	0.57±0.5
TDES	0.57±0.4
OSL-RDG	0.25±0.1

Impact of the Iteration Time

The iteration time of the proposed model in non-critical load conditions is examined. Figure 18 depicts the comparison of the iteration time of the proposed model in non-critical load conditions and the existing models with respect to fitness value. The iteration time in non-critical conditions is low than other existing approaches due to the implementation of MOGEO, in which the objective functions are defined in a proper manner to achieve fast convergence. The existing approaches lack a proper objective function, and they get stuck in a local optimum.

The numerical comparison of the iteration time of the proposed approach in non-critical load conditions and existing approaches with respect to the number of RDGs is provided in Table.12. The iteration time of our approach in non-critical conditions is 125(s). In the critical load condition, the iteration time is found to be 67(s), whereas the existing approaches possess about 262.5(s) of iteration time. From this, we can conclude that our proposed work converges with increased speed than the existing approaches.

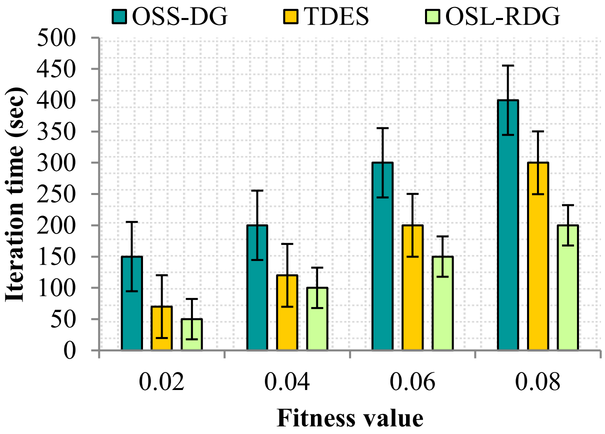

Fig. 18 Iteration time (non-critical load)

Table 12. Analysis of Fitness value

Techniques	Fitness Value
OSS-DG	262.5±5
TDES	172.5±4
OSL-RDG	125±1

4.2.3. Research Summary

The evaluation of the proposed OSL-RDG model is carried out in two different scenarios, namely the critical load condition and the non-critical load condition. The results obtained clearly illustrate that the power loss of the proposed model in both critical and non-critical load conditions is lower than the existing approaches due to the optimal sizing and location of the RDG based on the forecasted load demand and location characteristics. The minimal deviation of voltage and high stability of voltage are obtained due to the dynamic load monitoring and categorization of load based on criticality to facilitate optimal power flow. The minimal forecasting error than the existing approach is obtained due to parallel processing of historical data to achieve accurate forecasting of load demand and weather conditions. The better convergence of our proposed model and the proper defining of the objective function reduce the iteration time of our model, which proves the efficacy of our model.

5. Conclusion and Future Work

The stability and reliability of power flow are challenging factors to be focused in RDG assisted grid environment. The proposed OSL-RDG model achieves the above-mentioned factors by optimal location and sizing of RDG and optimal monitoring of load. Initially, the prior knowledge of the load and weather conditions is obtained by forecasting carried out by Bi-GRU model, in which the parallel processing is carried out to accurately forecast the data. This forecasted data is then utilized to perform optimal placement of RDG, which includes the sizing and location of RDG to reduce the voltage deviation, power losses and maximize the voltage stability. The characteristics of the location considered for optimally placing the RDG. The stability-aware load monitoring is conducted to dynamically categorize the incoming load demand according to the criticality in order to provide optimal power flow in the grid. The simulation of our proposed OSL-RDG model is implemented in MATLAB R2020a, and the validation of our model is performed using the IEEE-33 bus model. The evaluation of our model is carried out with respect to power loss, voltage deviation, voltage stability, forecasting error and iteration time. The discussion of results is performed to conclude that our proposed model is efficient in achieving an optimal supply of power without any shortages. However, the proposed model is validated only on a standard test system and may require testing with real-time, large-scale data; it can be practically useful for improving RDG planning and reducing power loss in real-world power systems. In the future, the model can be enhanced by incorporating real-time data and additional renewable energy sources for better performance. In future, the proposed model will be developed to incorporate more renewable energy resources in order to facilitate improved power flow in a grid environment.

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