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Research Article

Intelligent Controller Design and Fault Prediction Using Machine Learning Model

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In a solar power plant, a solid phase transformer and an optimization coordinated controller are utilized to improve transient responsiveness. Transient stability issues in a contemporary electrical power system represent one of the difficult tasks for an electrical engineer due to the rise in uncertain renewable energy sources (RESs) as a result of the need for green energy. The potential for terminal voltage to be adversely impacted by this greater RES raises the possibility of electrical device damage. It is possible to use a solid state transformer (SST) or smart transformer to address a transient response issue. These devices are frequently employed to interact between RES and a power grid. SST features a variety of regulated converters to maintain the necessary voltage levels. This method can therefore simultaneously lessen power fluctuations and transient responsiveness. In order to improve the quality of RES power injections and the electrical system's transient stability, this work provides a controller design for a solar photovoltaic (SPV) system that is connected to the grid by SST. The optimization of a controller model is proposed by modifying a PI controller taken from a commercial one. With the use of IEEE 39 standard buses, the proposed controller is tested. When evaluating the effectiveness of a suggested controller, it is important to take into account a variety of solar radiation patterns as well as a time delay uncertainty that can range from 425 ms to 525 ms. According to simulation results, the proposed controller can be employed to lessen power fluctuation brought on by unpredictable RES. Additionally, the proposed coordinated regulation of SPV and SST can prevent catastrophic damage in the event of substantial disturbances like a circuit breaker collapsing to expand a power line due to a fault by inhibiting significant voltage cycles within an electronic appliance's rated voltage limit. The results indicate that a transitory stability issue in a modern power system caused by an unforeseen increase in RES may be addressed utilizing the suggested controllers as alternatives.

1. Introduction

Owing to the fact that wind energy is one of the most promising renewable energy sources in the world, it is predicted that wind generation systems will offer ample electricity and have good grid integration [1, 2]. In order to obtain a more stable operation of the controller and increase system efficiency, wind power production systems need more sophisticated, unique, and robust control methodologies. Large amounts of pure, sustainable energy are produced when energy is extracted from water. But so far, only 30% of this energy has been created [3–5]. In comparison to other renewable energy sources, hydropower and especially hydropower facilities are more cost-effective, run more effectively, and are environmentally friendly. Hydropower plants are highly automated and cost-effective to run. To preserve the caliber and dependability of the power source, the major components of the power system must be regularly monitored and safeguarded. The data gathering, monitoring, and protection system handles this responsibility. Turbines need to be safeguarded from abnormal situations as well as short circuits. A failure is a long-term disruption of a system's capacity to fulfil the needed function under certain operational conditions [6, 7]. A defect is an unpermitted deviation of at least one characteristic or characteristic attribute of the system from the accepted or conventional state [8–10].

An enormous amount of prior data (usually more than 100,000 items) is needed to train the decision model, which is a common challenge for machine learning algorithms. This size requires the controller to have robust storage capabilities as well as strong computational capabilities. In a real network, a variety of devices work together to determine if a node is accessible. The controller will have a very significant burden if it monitors and forecasts the state of every piece of equipment on that scale. Selecting a machine learning technique that can train a highly accurate model using less data is essential. At a data amount of less than 5,000, the SVM method has a high efficiency and excellent accuracy, making it ideal for use in real applications.

Since some flaws might cause system failure if they occur frequently, early fault identification is crucial for maintaining system functionality for a long time.

The two main divisions of fault detection techniques are model-based approaches and signal processing-based (feature-based) methods. Model-based techniques are built on the foundations of system modeling and model evaluation. In order to extract information about issues, mathematical or statistical operations are carried out in signal processing-based methods or artificial intelligence (AI) approaches are utilized to appropriately handle signal features. Feature-based methods are more suited for remote monitoring since sensor data may be sent to the processing facility via a number of methods and give in situ observations.

To develop a reliable fault detection algorithm using feature-based approaches, information identifying the state of each observed element is necessary. These facts are gathered via a variety of sensor data. A few examples of the signals that could be used are ultrasonic tests, vibrations, torque, stress, temperatures, electrical output, lubricating oil quality, and centralized management signals.

Research questions served as the basis for the study that is being presented here. They were designed to characterize the pertinent research in terms of publication sources and scientific areas while also examining the strengths and limitations of the most recent machine learning techniques for mechanical fault detection and fault prognosis in manufacturing equipment. Five academic databases were searched for relevant papers, and after applying a set of criteria, the primary studies were chosen.

2. Literature Review

For a 1.5 MW doubly fed induction generator (DFIG) in a grid-connected wind energy conversion system (WECS), the authors in [11, 12] presented optimal design and tuning of fuzzy logic controllers (FLCs) using sophisticated methodologies like the particle swarm optimizer (PSO), the gray wolf optimization (GWO), the moth-flame optimizer (MFO), and the multi-verse optimizer (MVO). The grid-side converter, current regulator, and rotor-side converter of the back-to-back DFIG wind turbine all have FLC scaling factors that are optimized. It is suggested that a multi-objective optimization methodology be used to reduce the steady-state errors of these controllers in order to enhance the dynamic performance of the DFIG wind energy system when variable wind speed circumstances are present. The suggested optimized controller and PI controller are also compared, along with the various FLC optimization strategies employing PSO, GWO, MFO, and MVO. This study's key contribution is its suggestion of a novel control approach for a WECS based on DFIG. Utilizing PSO, GWO, MFO, and MVO algorithms to regulate the d-q element of the stator and rotor currents to manage the active and reactive power of the DFIG will maximize MIMO-FLC transformation matrix. In order to determine the behavior of the proposed controller in the event of a transformation from a low to a high gust, the proposed controller's operation is tested in variable wind speeds. By contrasting the various techniques, it is discovered that the MFO-FLC controller is the best optimized controller and exhibits excellent behavior in these conditions. For the next generation of energy systems, we suggest a revolutionary intelligent fault-tolerant adaptive control methodology in [13, 14]. Based on reliable fault-tolerant control, this design enhances local controllers coupled to energy systems, such as renewable energy-based power producers (FTC). For the monitoring and management of energy systems, this local controller works in conjunction with an area controller. A dual heuristic programming (DHP) action-critic neural network architecture along with a predictive identifier is created with this goal in mind. The area controller's major goal is to communicate with the local controller, supplement local controller, and share information about the grid state in accordance with an ideal control plan. To control reactive power management at the common point of coupling, the controller's effectiveness is tested on a wind-generating system's two-area power grid (CPP). Simulation experiments show that the suggested architecture is capable of enhancing the power grid's stabilization when there are renewable energy resources present. On Pulau Ubin island, an intelligent microgrid with a high proportion of clean and renewable energy resources was designed and put into operation to meet current and projected electrical demand. In the midst of heavily urbanized Singapore, Pulau Ubin is one of the few remaining pockets of "village" life that captures the character of

Singapore in its formative years. The system design has taken into account all potential energy sources, the effectiveness of energy conversion, power demand, and environmental and financial considerations. Electricity is produced using doubly fed induction generators that are fueled by photovoltaic (PV) cells and biodiesel. In order to maximize the utilization of renewable energy sources and to increase battery life, an energy storage system has been suitably sized. Smart grid technologies have been used to optimize energy production, monitor energy usage, handle instant energy flow, preserve electricity performance, and generate fault notifications. These technologies include smart meters, microgrid controllers, and remote monitoring systems with SCADA functions. This project also acts as a testing ground for sophisticated grid control technologies, clean and renewable energy generation, and storage under an intelligent microgrid architecture. The use of these smart grid characteristics to grid-connected microgrids has considerable promise. If this system is implemented successfully, it can serve as an example of sustainable development for many regions of Asia, where almost 40% of the population lacks access to power [15–20]. In this study, PowerFlexHouse, a research center for investigating the technical possibilities of active load control in a distributed power system with a high penetration of renewable energy, is introduced. A study of the software platform on which building controllers can be used is followed by a description of the facility based on a distributed power system (SYSLAB). Finally, this study demonstrates how to create a thermal model predictive controller for this distributed power system's power consumption estimation. Studies on how this intelligent house responds to a hybrid power grid can be done thanks to the PowerFlexHouse's control. With the help of our demand side control study, we intend to significantly increase grid dependability as well as energy efficiency and user power costs [16, 21–24]. Whenever the generator malfunctions and also the machine starts to function as a synchronous motor linked to the electricity grid, the original power source—the motor or turbine—is typically damaged. The proposed protection has been created to prevent this from happening. It becomes necessary to immediately identify these variables in this scenario because the generator turns into an active load, increasing the temperature and seriously damaging the main turbine. In order to prevent reverse power flow and maintain the quality and dependability of supply, this study suggests a novel controller for a neuro-fuzzy system. The fuzzy system network has drawn the attention of numerous scientists and engineers. The modification of the membership function as a reverse mechanism derived from the fuzzy logic controller is this work's novel characteristic. The smart grid is built on a network of smart meters. In this project, wireless sensor network-based Zigbee technology was used to construct smart grid meters. Due to its small battery and low power consumption, the Zigbee network of wireless sensors has more value than other wireless communication systems in terms of providing high-performance measurements. The OPNET simulation is used in this study to depict the Zigbee network. The operating properties of the star, tree, and mesh were understood by parameter analysis based on performance. This strategy is applicable to any network that DG manages. The suggested intelligent protection system intends to improve the availability of the DG units during faults, ensure selectivity of protection, and shorten the time it takes to eradicate problems. Using cutting-edge sensors, a neural fuzzy system, and a Zigbee network, a new protective mechanism is elaborated. By reducing the duration of failure and solving the issue of the system's long-term disconnection, the intelligent algorithm ensures the selectivity of the protection [25–29].

3. Proposed Work

The objective function, which is expressed as the reduction of power loss over a year, can be described as

$$O = \mathrm{MIN} N_d * \left[\sum_{\tau=1}^{M_t} l(S) + \sum_{\tau=1}^{M_t} l_P(W) + \sum_{\tau=1}^{M_t} l_P(\mathrm{SP})\right], \quad (1)$$

where M_t stands for the maximum number of hours in a day and N_d stands for the number of days in each season. S, W, and SP stand for the different seasons of summer, winter, and spring. Figure 1 describes the objective function for the proposed approach.

To produce a stable power supply with maximal voltage stability, which is expressed in equation (1), and the power balance is a significant limitation.

$$G(1)_{ap} - \sum_{k=1}^{n} k_l - \sum_{bh=1}^{nbh} l_{P(bh)} = 0, \quad (2)$$

where $G(1)_{ap}$ represents the grid active power and k_l and $l_{P(bh)}$ are the demand and power loss for the grid, respectively. To ensure voltage regulation, the resistance value at every bus is denoted as

$$\mathrm{Min}_V \leq V_r \leq \mathrm{Max}_V, \quad (3)$$

where Min_V and Max_V represent the lower and upper bounds of the voltage. Bounds of the voltage and also zero phase of angle are calculated as follows:

$$\begin{aligned} \mu_1 &= 0, \\ V_1 &= 1. \end{aligned} \quad (4)$$

Distributed generation is a key tactic for tackling the growing demand for power usage. Numerous earlier studies focused on the ideal power flow in the scattered network, but they did not sufficiently consider the reliability of the distribution network. The structure of demand forecasting in control center is shown in Figure 2.

The distributed generation should be deployed as efficiently as possible, as shown in Figure 3, to reduce power losses and the associated expenses. A variety of factors, including location characteristics, active power loss, voltage stability, voltage variation, load requirements, and DG capacity, impact the placement of distributed generation, which is related to the size and placement of the distributed generation that is appropriate. Accurate forecasting of the load demand is required in order to choose the size and

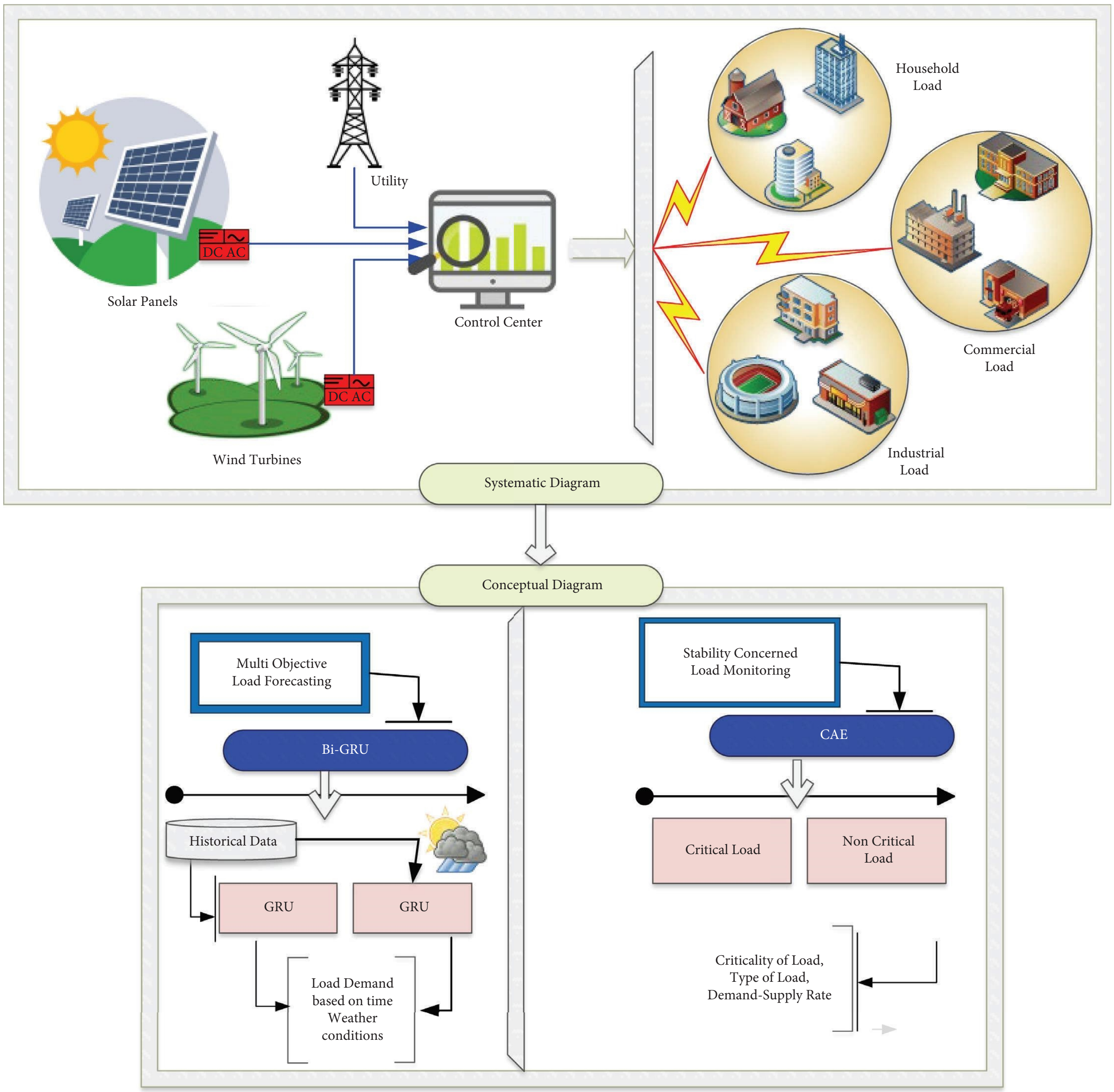

FIGURE 1: System flowchart.

location of the distributed generation. One illustration of a geographic feature is where DG is located. Other examples include the placement of solar power plants depending on local temperature and irradiance and wind turbines based on local wind speed.

(i) The objective function to improve in this article is the position and size of the RDGs, which are determined using a heuristic algorithm.

(ii) The following is a mathematical calculation for optimum sizing, according to solar RDG. The following information is based on the anticipated generation of electricity P_S and the location of SDG.

$$p_{\mathrm{SDGE},i} = n_{s,i} \times p_{\mathrm{SG}}\ \forall i \in d, \tag{5}$$

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. The projected generation rate for the solar RDG is computed as follows if the size and position are optimized.

$$p_{\mathrm{SDG},i} = n_{s,i} \times p_{\mathrm{SDG},R}, \tag{6}$$

where $p_{\mathrm{SDG},R}$ is the discrete size rate of solar RDG.

3.1. Wind Turbine RDG. We can determine the ideal size and position of the RDG wind turbines based on the anticipated rate of power generation P_{WG}, which is shown below.

$$p_{\mathrm{WDGE},i} = n_{w,i} \times p_{\mathrm{WG}}\ \forall i \in d, \tag{7}$$

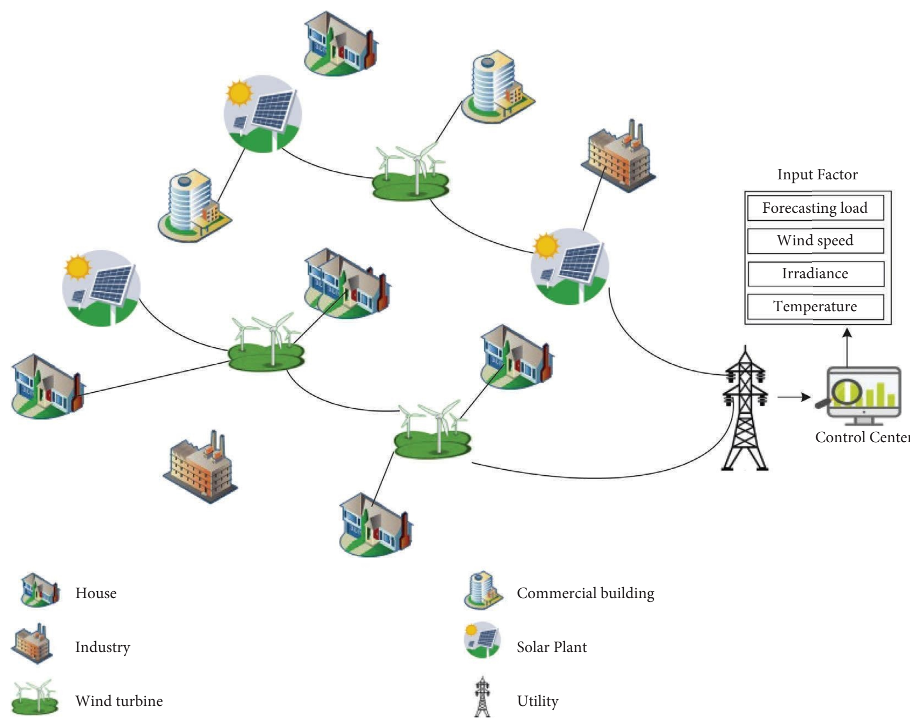

Figure 2: Demand forecasting in control center.

where $N_{w,i}$ and p_{WG} represent, respectively, the quantity of wind turbines and the anticipated power output of the wind turbine. Next, the position and rated size of the WDG are determined as follows:

$$P_{w\mathrm{DG},i} = n_{w,i} \times P_{w\mathrm{DG},R}, \tag{8}$$

where $P_{\mathrm{SDG},R}$ is the discrete size rate of wind RDG. The suggested multi-objective golden eagle optimization (MOGEO) algorithm comprises two phases that are explained in the following in terms of its computational complexity.

3.1.1. Initial Population. The method employs $\mathrm{O}(N_p \times N_d)$ time to initialize each golden eagle's step vectors, position vector, and as memory. This algorithm's main loop accepts $\mathrm{O}(N_p \times N_d \times N_i \times N_o \times N_a)$ as inputs. Finally, we determine that the suggested MOGEO method has a total complexity of $\mathrm{O}(N_p \times N_d \times N_i \times N_o \times N_a)$.

The GEO, which has quick convergence and has proven to be more effective than other meta-heuristic optimization algorithms, performs the task of placing scattered generations in the best possible position. Also, the GEO algorithm is used to accurately find the best solutions for the complex optimization problem discussed above. The golden eagle, which consists of several bird species including hawks and eagles, is the model for this method. The following are some examples of the main characteristics and how they function. It has greater predisposition at the first stage to normalize the transition for the final stage by following a spiral (round) trajectory that restores the search path for the attack. It continues to have propensity to attack and cruise during every flight time. It searches the prey for eagle information. The crowding score (CS) i, which is derived using the crowding distance concept and is defined as follows, is used in MOGEO to assess fitness. The Pareto front value for this distance was calculated between the two values that were closest to each other throughout time using the following formulas.

$$\mathrm{CS}_i = \frac{1}{n} \sum_{j \in J} \frac{\left(f_{i+,j} - f_{i,j}\right) - \left(f_{i,j} - f_{i-1,j}\right)}{f_j^{\max} - f_j^{\min}}, \tag{9}$$

where $f_{i-1,j}$, $f_{i,j}$, and $f_{i+1,,j}$ are the three successive members of the archive which are arranged according to the optimization's objective values and objective functions. The following method is used to calculate a new score based on the roulette wheel procedure. S_i is calculated as follows:

$$S_i = 1 - \mathrm{CS}_i. \tag{10}$$

The following are some examples of the main characteristics and how they function: It has a greater predisposition at the first stage to normalize the transition for the final stage by following a spiral (round) trajectory that restores the straight and searching path for the attack. It continues to have a propensity to attack and cruise during every flight time. It searches the prey for eagle information. At the conclusion of this procedure, the total number of solar and wind RDGs and their positions are determined. Number of iterations, initial conditions, distance scores, and termination criteria of the algorithm are computed. Here, the fitness of the agent is determined while minimizing the losses using a distance-based objective function between two nearby sets of data. The placements of initialized parameters are then modified. If the termination criteria are satisfied, the

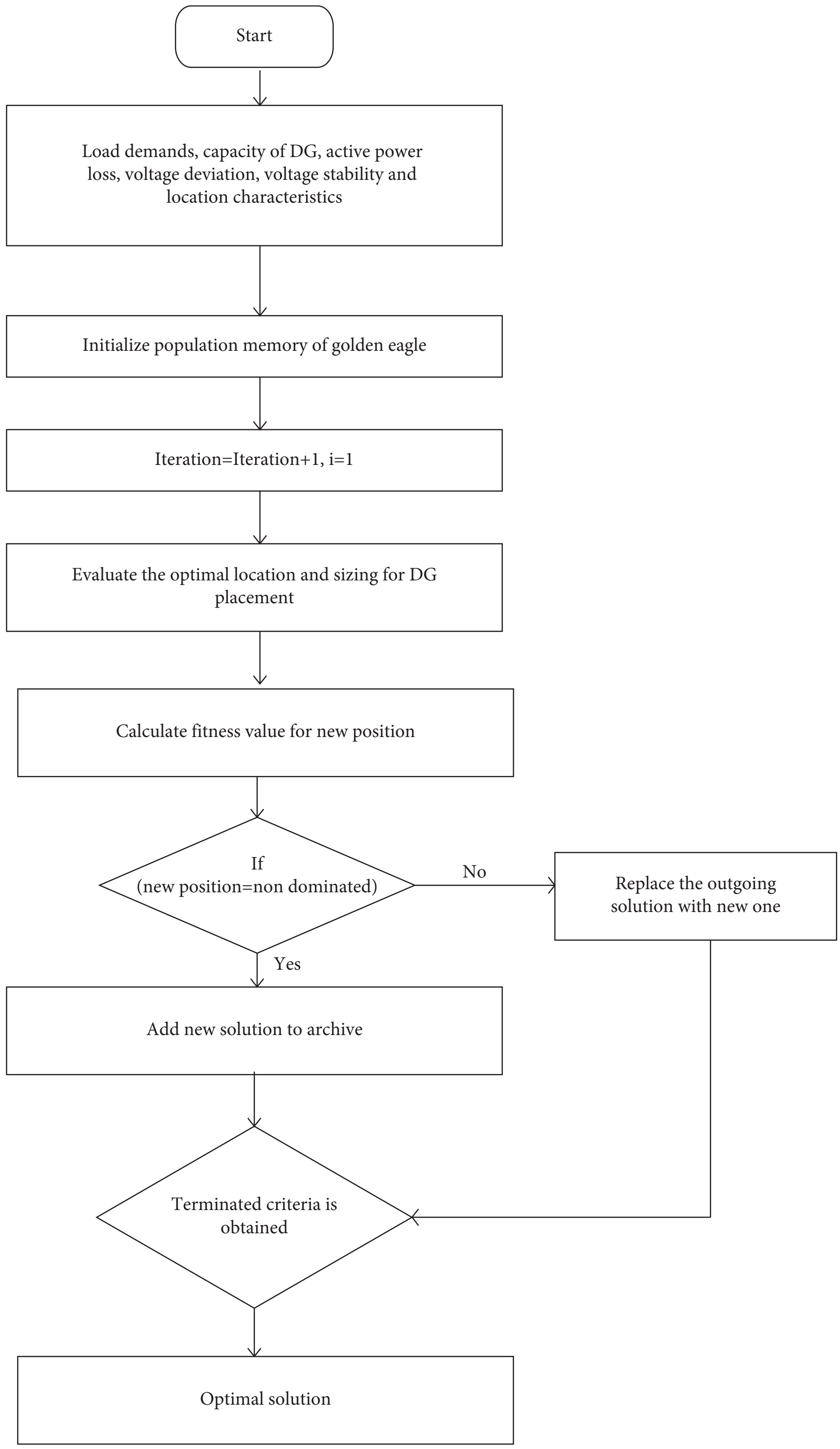

Figure 3: Flowchart for optimization of load demand in control center.

optimal fitness values are preserved; if not, the method is repeated until the best fitness value is reached.

4. Results and Discussion

The word "power loss" refers to the amount of power that is lost during transmission. Reverse power flow is the outcome of distributed generators' ineffective grid placement, which is the source of this. The proposed work is done using MATLAB tool for simulation. In terms of the quantity of RDGs, Figure 4 compares the power loss of our proposed GEO model with that of the existing models. With an increase in RDGs, the power loss is reduced. Our suggested model has a minimal power loss since the RDG is placed optimally taking into account the load demand, RDG capacity, site features, and other important considerations. The MOGEO algorithm is used to decide the size, placement, and number of RDGs. The current methodologies were ineffective at positioning the RDG optimally because they anticipated continuous active and reactive power of the load on the customer side. Additionally, the power flow is not stable when just exogenous influences are taken into account.

Table 1 presents the numerical study of power loss for our proposed GEO model and existing models with regard to the number of RDGs. It is discovered that the suggested model has an average power loss of 60.1 kW, but the existing techniques have a power loss of up to 90.5 kW, which has an impact on the steady power flow to the essential load.

Voltage stability is a crucial parameter for assessing how well a method can withstand acceptable voltage. Voltage instability results from the approach's inability to meet load demand. In severe load situations, voltage stability should be attained to enable proper power supply. Figure 5 compares the voltage stability of our suggested solution and the current approaches in relation to the number of RDGs. Increasing the number of RDGs improves voltage stability, but doing so increases energy costs. As a result, it is important to find the ideal number of RDGs, which can be done using MOGEO. The forecasting of load demand gives the suggested technique great voltage stability in challenging load scenarios. The right placement of RDGs in the network and the achievement of voltage stability are made possible by the correct information of the load. The existing methods are less effective in determining the ideal size and location of RDGs because they lack prior knowledge of load demand.

Table 2 provides a numerical comparison of the voltage stability of the proposed GEO model and the currently used methods in relation to the number of RDGs. The consistency of the suggested model is 0.95 pu, whereas the stability of the previous techniques is only 0.86 pu. This leads us to the conclusion that our suggested method is more reliable at supplying electricity to crucial loads.

The voltage deviation is a measurement of the voltage difference from the reference voltage that has an impact on the functionality of the power system. The voltage divergence is caused by a dynamic variation in load demand. Figure 6 compares the voltage deviation between our proposed model and the existing techniques in relation to the number of RDGs. Less voltage variation occurs when the RDG count rises. Our suggested solution has less voltage damage than other existing systems because of the dynamic load monitoring. Utilizing the A2C-GAE, a steady power supply is offered based on the variation in load demand, with the load being dynamically divided into critical and non-

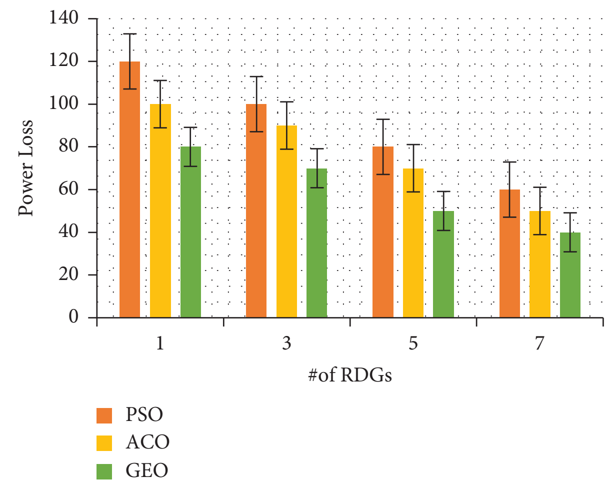

Figure 4: Power loss (critical load).

Table 1: Analysis of power loss.

Techniques	# of RDGs
PSO	90.5 ± 5
ACO	77.5 ± 4
GEO	60.1 ± 2

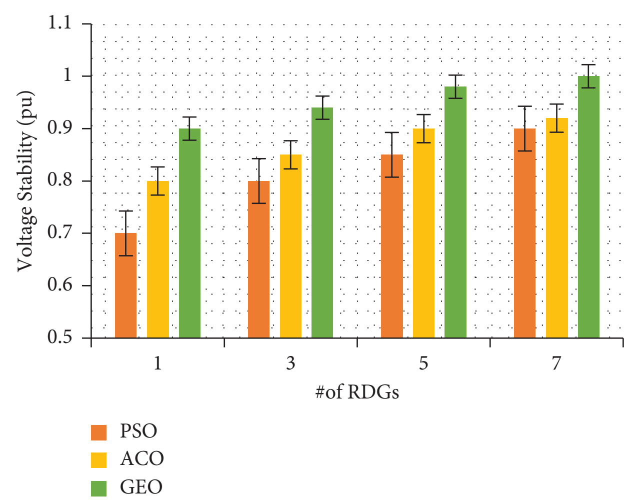

Figure 5: Voltage stability (critical load).

Table 2: Analysis of voltage stability (pu).

Techniques	# of RDGs
PSO	0.83 ± 0.5
ACO	0.86 ± 0.3
GEO	0.95 ± 0.1

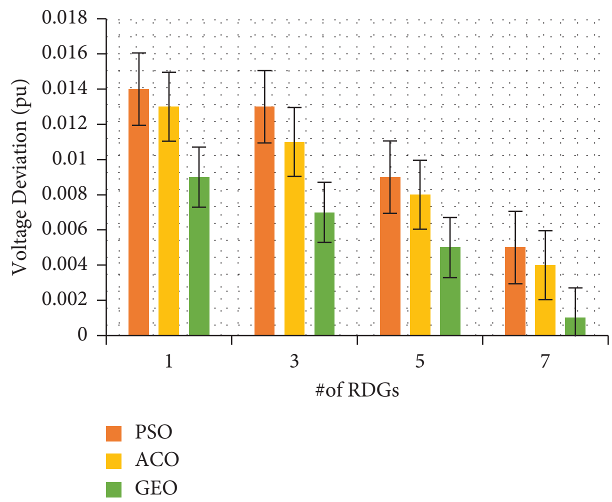

FIGURE 6: Voltage deviation (critical load).

TABLE 3: Analysis of voltage deviation (pu).

Techniques	# of RDGs
PSO	0.011 ± 0.005
ACO	0.009 ± 0.003
GEO	0.006 ± 0.001

critical categories. The present approaches assume a constant load demand, which raises voltage variances and affects system performance.

The voltage deviation with respect to the number of RDGs for both the current approaches and our proposed GEO methodology is numerically analyzed in Table 3. The proposed approach appears to have a voltage deviation of about 0.006 pu, whereas the voltage deviation of the existing methods can exceed 0.011 pu. The increased voltage variation of the current techniques degrades the performance of the power system, increasing the cost of revenue.

5. Conclusion and Future Work

This paper describes the design of a GEO-based controller that will be integrated into a microgrid that is connected to the grid and has the potential to store energy. The controller's goals are to regulate the rate of charge and discharge of the energy storage system (ESS) in order to lower end-user operational costs by running the ESS as an arbitrage device and minimizing power exchange between the main grid and microgrid. By deducting the load, the ESS's charge state, and the cost of power on the market from the available renewable energy, the suggested technique determines the charge and discharge rate of the ESS on a rolling horizon. In comparison to previous controllers with similar objectives, the recommended controller can reduce the energy exchange between the main grid and microgrid and achieve lower operating expenses. The aforementioned initiatives can be advanced using machine learning. A group of clever algorithms known as machine learning is capable of learning the underlying knowledge contained in training data. The resulting decision model serves as direction for more work after the inherent information has been abstracted.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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