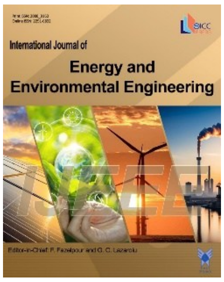

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Research on Cooperative Optimal Configuration of Distributed Energy Storage System and Renewable Energy

Wang Xianchun[1], Gao Lijuan[1,*],Yang Haiyue[1,2],Gao Bing[1],Zhang Kang[1]

[1] *State Grid Hengshui Electric Power Supply Company, Hengshui 053300, Hebei , China*
[2] *Hengshui Electric Power Design Co. , Ltd., Hengshui 053300, Hebei, China*

***Corresponding author:** GaoLijuan179@outlook.com

Original Research

Abstract

The intermittency, volatility, and intrinsic unpredictability of renewable energy sources provide significant problems to the dependable operation of power grids, especially as these sources are becoming widely available. An essential resource for improving the power grid's flexibility, absorbing a large amount of additional energy, and meeting the dynamic demand-supply balance is energy storage. Energy storage is still somewhat expensive, and finding the best way to set it up is the main challenge right now. Distributed generation, a source of grid energy, is becoming more significant in the distribution network as part of the overall trend toward green energy growth. Distributed generating on a massive scale introduces uncertainty and unpredictability, which threatens distribution network dependability and stability. In order to mitigate the negative effects of dispersed generation and maximize the positive effects on distribution network operations, this article investigates the optimal design of energy storage systems. It provides a reasonable analysis of the possibility of collaboration to increase stability and profitability by building a mathematical model of a distributed generating and energy storage system. According to the operational data, distributed generation exhibits seasonal traits, and the scenario reduction approach groups together a collection of common daily scenarios for spring, summer, fall, and winter and clustered using K-means clustering technique. We solve the optimum building planning problem using an objective function and limitations based on the IEEE 33-bus distribution network using Deep Neural Networks (DNNs). Throughout the year, there are four distinct configurations for energy storage. But in order to limit the impact of dispersed generations, it is generally closed. Finally, it suggests some directions for distribution network expansion in the future and summarizes the paper's operations.

Keywords: Cooperative Optimal Configuration, Distributed Energy Storage System, Renewable Energy, IEEE 33-bus; DNN, K-means Clustering

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1. Introduction

In response to the increasing urgency of the climate crisis and the widespread agreement that low-carbon energy is the way to go, an increasing number of nations are taking steps to encourage the growth of renewable energy sources [1,2]. The renewable energy sector is booming, thanks in large part to wind and solar power production, which are helping to meet rising energy demands, improve the energy grid, lessen pollution, and boost economic growth. The intermittency, volatility, and unpredictability of renewable energy sources are unavoidable and strong, and their rising permeability in contemporary power systems necessitates greater standards for safe, stable, dependable, efficient, and cost-effective power system operation. Energy storage is being seen more and more as the perfect technological and financial answer to these problems. Distributed energy storage often allows for the sequencing of electric energy in terms of both time and location, and its charging and discharging processes are analogous to power and load [3,4]. Disruptive, user-friendly, and bidirectionally controlled distributed energy storage is gaining prominence as a means to enhance power system flexibility, incorporate substantial amounts of renewable energy, and meet the ever-changing demand-supply balance. Microgrids, smart grids, and distributed generation all rely on distributed energy storage, which is quickly becoming an acknowledged essential component [5,6]. Not only does it lessen the financial burden of delaying power system infrastructure investment, but it also increases energy efficiency and decreases carbon emissions. Distributed energy storage has become an essential part of all power grids, as seen in Figure 1. Despite our best efforts to improve the efficiency and dependability of power system operations with the integration of renewable energy grids, a number of problems with distributed energy storage continue. Managing energy storage may be a challenge because to its often-dispersed nature, which makes it hard to integrate with traditional equipment and implement seamless control strategy changes. Research on the best ways to set up distributed energy storage for various uses is an essential first step in developing practical and cost-effective solutions for power grids that make use of energy storage. A renewable energy power system's power supply security while operational efficiency can be enhanced through well-planned energy storage systems, which can lead to full energy utilization and reduced distribution network reserve capacity [7,8]. This, in turn, brings about the large-scale convergence impact of distributed energy storage. Location, capacity allocation, and operating strategy are the three most important considerations when designing distributed energy storage systems. In light of this, the optimization goal and configuration method are often chosen in accordance with the needs of various application scenarios, taking into account all relevant technical and economic data. Energy storage remains expensive, and finding the best way to set it up is the main challenge right now. However, the study summary and possible optimization approach for configurations of energy storage systems still do not include a thorough evaluation of technical as well as economic performance. The ability to self-balance power systems might be achieved using this technology [9].

Research objectives

Improve energy efficiency: In order to improve energy efficiency overall, DESS helps to decrease energy waste by preserving and releasing energy when required.
Enhance grid stability: The grid is better equipped to withstand fluctuations in renewable energy output and load demand thanks to DESS, which also increases its resilience.
Reduce costs: The total cost of energy production may be reduced by cooperative optimization, which optimizes the location and scale of DESS and renewable energy.
Increase reliability: When renewable energy output is limited or the grid goes down, DESS steps in to offer a backup power source, making the energy supply more reliable overall.
Reducd environmental impact: Cooperation optimization may lessen the environmental effect and carbon emissions by cutting energy waste and boosting the use of renewable energy sources [10].

Improving the efficiency, reliability, and cost-effectiveness of RE is the ultimate aim of improving distributed storage systems for energy in tandem with RE. This is accomplished by considering a number of factors, such as the following: grid stability, load demand, renewable energy fluctuation, and the ideal size, placement, with operation of DESS and RE sources.

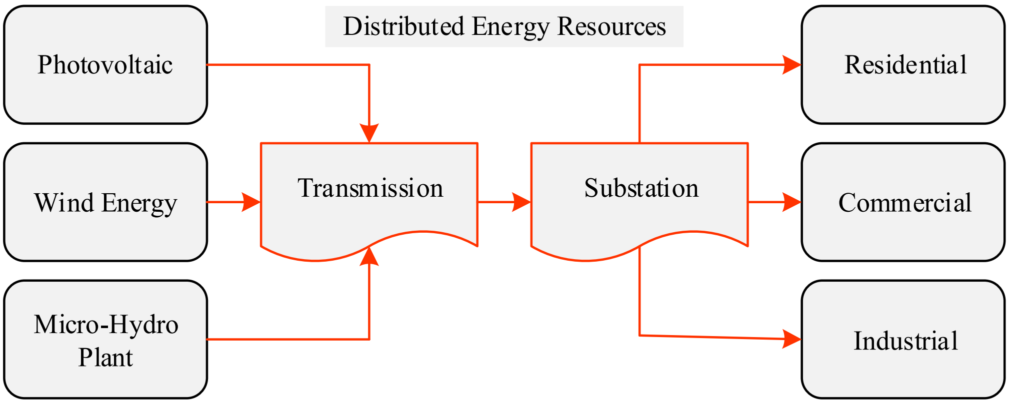

Figure 1. A power grid that uses decentralized energy storage

Table 1. Cooperative Optimization's Crucial Elements

Factors	Cooperative Optimization's Crucial Elements
System-Level Optimization	By optimizing the system as a whole while taking component interactions into account, cooperative optimization seeks to maximize performance.
Load Forecasting	Optimal energy management and charging/discharging methods are made possible by accurate load forecasting, which is essential for DESS and RE operation.
Cooperative Dispatch	When planning power dispatch, the DESS along with RE sources work together to take into account both the present energy demand and the renewable energy sources that are available.
Multi-Objective Optimization	There are usually a number of goals involved in optimizing DESS and RE, including lowering costs, decreasing emissions, increasing dependability, and improving energy efficiency.
Hybrid Energy Storage	In order to meet grid demands and energy storage requirements over a range of time scales, DESS may integrate several energy storage technologies, such as thermal, hydrogen, and batteries.
Grid Stability	By providing auxiliary services like as voltage support and frequency control, DESS may help keep the grid stable, which is especially important when integrating large-scale RE.
Integration of DESS and RE	A more consistent and dependable power supply is achieved by using DESS to control the intermittent characteristics of renewable energy sources, such as solar and wind.

Research aim and scope

Integrating PV and Wind with Distributed Energy Storage: Grid power allows for the discharge of extra solar power at peak demand or at night while solar output is low, in addition to storing excess solar power that is produced during the day.

Optimizing Wind Power Integration: By using DESS, we can maintain a steady power supply by storing surplus wind energy during strong winds and releasing it during low ones.

Cooperative Power Allocation: To optimize the integration of DESS, RE, and additional energy resources to fulfill community energy demands, cooperative optimization may be used to energy systems at the consumer's level [11-17].

An important part of designing and planning distribution networks with many dispersed energy sources is optimizing their capacity configuration. Topics covered in this research include electric car distribution network systems, energy storage, wind farms, solar power plants, and capacity allocation. The method starts by forming four investor groups: electric cars, energy storage, wind power, and photovoltaics. An optimization model is built using non-cooperative game theory to optimize the profits for every investor, taking into account the costs of solar and wind power curtailment and load disruption penalties. Next, the capacity allocation for every participant is improved individually to maximize their earnings. This is done utilizing intelligent optimization techniques and particle swarm optimization settings. Lastly, investigations on distribution network resources allocation are conducted using local electric car load power, average monthly wind and solar production statistics, and other relevant information. Using the model's predictions, we can optimize the distribution network's capacity allocation in a cost-effective and fair way, all while guaranteeing a steady supply and encouraging the efficient integration and use of renewable energy sources [18-20].

What follows is the outline for the rest of the article: Section 2 provides a synopsis of the many power system applications of distributed stored energy, and Section 3 analyses the evolution and use of present-day standard technology. We also provide a brief overview of the current state and potential future uses of distributed energy storage from the perspectives of DG, the grid, and end users. Section 3 uses this information to examine and contrast various modeling techniques and solution methods for improving energy storage system design. In Section 4, the main topics of the study are summarized in a brief manner.

2. Related Work

According to the current electrical framework (reference 21), the main goal for every area is to create a power grid that uses a lot of renewable energy. Renewable energy sources are problematic for the grid due to their intermittency, unpredictability, and volatility. Improving the power system's adaptability and steadiness may be achieved via reasonable optimization of energy storage. However, the majority of regions currently use a cookie-cutter approach to energy storage configuration, which means that standard systems only support standalone new power stations, and that there are significant obstacles to unified scheduling of energy storage between power stations, leading to inefficient use of storage and high operational costs. All of these issues may be efficiently resolved by using the shared energy storage. That research proposes a robust optimum allocation technique to improve the operational mobility, robustness, and economic effectiveness of the system for distributed shared power storage of new energy stations. The first thing to do is to get a bunch of adjacent new energy stations to work together. Then, you may use their distributed shared energy storage approach and play a cooperative game to see who can reap the most financial benefits. The next step is to build a resilient optimal configuration strategy for shared energy storage that takes into account the restrictions posed by the fluctuation of renewable energy sources. Finally, in order to ensure that all members of the alliance get equitable benefits, a profit distribution plan is developed utilizing the Shapley value technique.

The first step is to build a Markov model–based stochastic planning structure to govern the distribution of energy storage capacity. The experimentalists in [22] employ that model, which accounts for the area's renewable energy generation's inherent volatility. Second, considering that regions might reduce their operating costs via cooperation in energy trading, an optimal allocation model of connected multi-region energy storage systems is constructed using Nash bargaining. The alternating direction multipliers method is used to resolve the two linear subproblems that remain after the nonlinear model has been simplified. Finally, the decision outcomes under different situations and schemes are examined using numerical examples. That way, we know the proposed method can set up energy storage capacity correctly and save prices, carbon emissions, along with solar curtailment in every single place.

The researchers in [23] set up a DES system that incorporates a gas turbine, solar panels, ground-source heat pumps, and energy storage. To ensure that ground-source heat pumps and DES devices operate at peak efficiency, they offer an Optimized Zebra Optimization Algorithm. In this study, we build an optimization framework for DES design with energy savings, reduced pollutant emissions, and economic cost savings as our optimization goals. That research confirms that the IZOA algorithm is useful in optimizing DES configurations by examining the mathematical example of a big hotel construction. Distributed energy system development, environmental preservation, and energy conservation may all benefit from the study's research suggestions.

Using an offload approach from mobile edge computing with the best distribution of computational resources, the authors of [24] discuss their work. The second step is to use the best MEC configuration to build a new hierarchical dispatching model. Based on the operating cost of the power system in each area and the total energy consumption of the MEC server, the higher model calculates the computational amount along with output for each distributed unit using the optimum offload technique. Complete accommodation of renewable energy and the area's optimal economic operation are guaranteed by the lower model, which implements EVs and secondary batteries for energy storage within the restrictions of MEC server processing latency. The third part of the paper outlines the suggested screening criteria for the MEC system's computing modes and methodologies for simulating EVs in various regions. The model's efficacy and superiority are lastly confirmed using simulation studies.

Authors of [25] provide a concise overview of the latest research on energy storage applications, modeling methods, and optimum configuration techniques from the perspectives of power production, the grid, and end users. Using that, they may identify where their knowledge of energy storage configuration studies is lacking and where future research should focus. Both present and future improvements and research in the field of energy storage configuration might benefit from such appraisal.

Researchers behind [26] the first step is to build DN-DHN-BESS's distributed cooperative dispatch architecture. The next step is to develop an ideal DHN dispatch model that makes use of the heat storage capacity to offer DN flexible regulating capabilities, all while maintaining a constant flow-variable temperature management approach. The next step is to determine the best BESS and DN dispatch models in order to minimize operating cost. Lastly, a distributed cooperative dispatch approach relying on the alternating direction multiplier is given as a solution for DN-DHN-BESS, that could help them figure out what they don't know about energy storage configuration studies and where to put their research efforts moving forward. A thorough evaluation of energy storage arrangement could be useful for both ongoing and planned advancements in the area.

Substantiating load demand, reducing DG fluctuations, and assisting with frequency or voltage management are the primary areas of interest for DES researchers [27]. Concerning DES's capacity to act as a backup plan, very little study has been carried out. That work examines the DES's capacity to provide a backup plan and suggests a General Algebraic Modeling Systems–solved optimum configuration model of DES for backup plan, taking into account various branch contingencies. The case scenarios of the IEEE 39-bus system confirm the efficacy of the suggested strategy.

Researchers in [28] examine an ideal scaling design for hybrid energy storage linked to independent rooftop solar photovoltaic systems, taking into account the exact use of stored hydrogen and batteries. A temperate-zone office building is the subject of that study's techno-economic analysis. For the purpose of optimizing the suggested distributed renewable energy system's structure and size, a robust optimization tool is used. In terms of reliability, self-sufficiency, total net present cost, and levelized cost of energy, the model optimization outcomes confirm that the hybrid storage system design that utilizes both batteries and hydrogen fuel cells simultaneously outperform the design that only uses hydrogen storage.

The experimenters in [29] proposed a method for optimum allocation of grid-side energy storage that takes static security into consideration by using stochastic power flow modeling under the semi-invariant methodology. One must first construct a stochastic power flow theory for the system based on the probability model for load, wind power, with photovoltaics. Furthermore, the indicators of fault severity and probability are constructed using the two metrics of node voltage with branch power flow. Combine the signals for the probability and severity of faults to create a framework of static security assessment indicators. Next, we take a look at energy storage operators' perspectives to build a model for scheduling grid-side energy storage. The study comes to a close with a simulation study that utilizes the IEEE-30 node system. To address the two-stage operation along with planning problem, an improved genetic algorithm is used. According to the findings, when static security limits were included in the energy storage arrangement, both the probability of failures and their severity were significantly reduced. Simulation results and the case study both point to the possibility that the proposed energy storage allocation strategy may improve the static security of the system.

The authors of [30] introduced a distributed shared energy storage method that aimed to optimize cooperation between the source and the grid. A two-tiered optimal allocation technique is used. First, they lay out a regulatory framework for shared energy storage that accounts for both the power side and the grid. A two-tiered model is constructed for distributed shared battery storage, with the smallest cost of the energy storage system as the upper-tier objective and the lowest daily incorporated cost of operation of the renewable energy stations distributed across the distribution grid as the lower-tier goal. Three, a combination of a double-layer iterative particle swarm approach and tidal calculation is used to tackle the economic operation problem of distribution grid-distributed renewable energy stations along with the shared storage of energy configuration. Finally, a comparison of four scenarios reveals that installing distributed shared energy storage has the potential to lower the net load peak-valley variation by 61% while increasing the initial energy consumption rate to 100%. Additionally, suppliers of shared energy storage who have dispersed their systems have seen positive outcomes.

3. Optimum configuration of DNs and RES

When DG units are integrated into an existing distribution network, it is critical to locate and size them correctly. Here, we'll examine the impacts of DG unit integration on voltage stability, power losses, reliability, the distribution network's voltage description, and the costs and benefits to the economy and the environment. Several goal functions for optimal siting modeling and DG unit size are presented here.

3.1. Distributed grid modeling

There are two possible configurations for energy storage devices in an active power grid system that uses DG (Distributed Generation): centralized and distributed.

Modeling for the production of wind electricity:
The amount of electricity that a wind turbine can generate is directly proportional to the speed of the wind. In this study, the wind is modelled as a random variable using the popular Weibull distribution. How about this for a probability density function?

$$f(v) = \frac{k}{c} \cdot \left(\frac{v}{c}\right)^{k-1} \cdot \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{1}$$

The shape parameter (k) and seale parameter (c) of the Weibull distribution are taken into account here. In the real operating process of the wind turbine, the output PW may be determined according to equation (2), using the distribution-generated random wind speed:

$$f(v) = \frac{k}{c} \cdot \left(\frac{v}{c}\right)^{k-1} \cdot \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{2}$$

Where, $k_1 = \frac{P_r}{v_r - v_i}, k_2 = -k_1 v_i,$ Pr above, vi stands for the fan's rated power, vr for the fan's rated wind speed, and vc for the fan's cutout wind speed.

Modeling the production of electricity from photovoltaic cells:
Light intensity is a strong determinant on the quantity of solar electricity produced. The data show that the variation in light intensity follows a Beta distribution. Here is one way to describe the probability density function:

$$f(r) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \left(\frac{r}{r_{\max}}\right)^{\alpha-1} \cdot \left(\frac{r}{r_{\max}}\right)^{\beta-1} \tag{3}$$

In this context, form variables of the Beta distribution are represented by α and β, while the gamma function is denoted by r $r_{\max}$ is the maximum light intensity, and r represents the current luminance. As seen in equation (4), the photovoltaic output Ps may be calculated in relation to the light intensity:

$$P_s = \begin{cases} r^2 \cdot \eta_s \cdot \frac{S}{r_c} & 0 < r \leq r_c \\ r \cdot \eta_s \cdot S & r_c < r \leq r_0 \\ P_z & r > r_0 \end{cases} \tag{4}$$

Where: η_s where P_z is the rated photovoltaic power, r_0 is the rated light intensity, s is the entire light receiving area of the solar module, and r_c is the threshold constant, which is shown in Figure 2.

The temporal dependence of the system's states or event sequence is not taken into account while sampling in a nonsequential MCS. Consequently, this approach is used to identify a non-chronological state of the system. Alternatively, for reliability of power systems studies, a sequential MCS is the way to go because it can handle the system's sequential operating conditions and incorporate time-correlated events and states like renewable-based producing units' output generation, demand profiles, and customer decisions.

Please be informed that the sizes of the installed DG units are determined by GWO in each iteration. With these values, the power flow evaluation must be conducted for every scenario given by MCS. The scenario that MCS develops can have either a very high load or a very low quantity of wind or solar production. This highlights the significance of the power flow analysis's ability to converge in such cases. Here, we propose an optimum power flow that can manage load shedding, which means that we can drop the lowest amount of load needed to keep a balance among the production of power and the total load if the producing resources aren't enough to cover it. Here is the method for the stochastic framework that determines the best location for DGs:

1. Get all of the input data ready, including things like load, wind speed, and sun irradiation.
2. Curve fit every set of historical information to get PDF parameters.
3. Use MCS to generate samples and scenarios.
4. Launch the GWO and begin the first iteration.
5. Determine the best power flow for each situation using the samples provided by the MCS.
6. Assess both the target function and the restrictions
7. Enhance the solutions by the use of mutation, selection, and crossover.
8. Proceed to Step 5 in the event that the termination requirement is not met.

Installing DG units might be the target function. As mentioned before, other goal functions like voltage stability, total losses, and others might potentially be included. It should be noted that in order for the GWO to optimize the placements and sizes of DG units, it has to include the average cost for every unserved load, which is provided by the OPF after executing the loadshedding method for all scenarios, to the objective function. This will allow the GWO to continue optimizing the unserved loads. With this, we may find a happy medium between the two extremes of unserved load prices and the overall cost of adding DG units.

K-means clustering algorithm

A total of six steps make up the K-means clustering algorithm's method. K, the total amount of clusters, is decided in the first step. There has been a lot of research on K value choosing since it has a substantial impact on the algorithm's output. To help in choosing the K-value, Pham et al. put forth a heuristic. A number of K-value selection procedures were examined by Yuan et al, including the canopy, silhouette coefficient, elbow method, and gap statistic. Six methods for finding the cluster count were laid forth by Kodinariya et al. The centroids are chosen at random in the second step. The distance from each data point to the centroids is determined in the third step. The distance between two points on Earth, as given by Equation (5), is often used in calculations.

$$D_{ik} = \sqrt{\sum_{j=1}^{N^{DM}} \left(x_{if} - c_{jk}\right)^2} \tag{5}$$

where

D_{ik}- is the length in geometric units between the centroid k and data point i;

N^{DIM}- represents the quantity of dimensions;

x_{ij}- lies at data point i's coordinate in dimension j; and

c_{jk}- represents the centroid k's coordinate in dimension j.

In the last step, clusters are formed so that the data points may be aligned with the smallest centroid distance. Equation (2) is used to compute the centroids in the fifth step.

$$C_{fl} = \frac{1}{N_l} \sum_{t=1}^{N_l} x_{tl} \tag{6}$$

where

x_{ij}- stands for the coordinate of data point i in dimension j;

C_{jl}- is located at the center of cluster l in the dimension j,and

N_l- is equal to the quantity of observations in cluster l.

Lastly, the algorithm terminates if the centroid has not been modified; otherwise, it goes back to stage three and starts again.

Load analysis using DNN

There are particular operating requirements and load characteristics for electrical equipment due to the unique internal construction mechanism. Harmonics, RMS, current, power, along with energy consumption are some of the electrical characteristics of the apparatus that change over the course of operation. High harmonics in grid current are a result of new types of rectifiers, frequency converters, as well as electrical devices that have nonlinear properties, which are appearing as a result of the fast advancement of power electronics technology. Televisions, energy-efficient light bulbs, washing machines, and even certain medical devices have nonlinear components. An analysis of harmonic content reveals that most electrical appliances do not exceed 13 orders of odd harmonics and only a handful of appliances exceed 20 orders of harmonics; nonetheless, the harmonic content is minuscule. Almost all of an apparatus's harmonics may be reflected by harmonics of 1-32 orders. Key features for equipment identification include electrical load features, which may be used to categorize equipment into distinct categories based on individual components.

Equipment is often used by users in a certain sequence of times. When the user gets home from work, for instance, a number of electrical equipment in the house will display the estimated usage frequency. Under typical operating conditions, the equipment's power seldom deviates more than a few percent from its rated power. When the working situation changes, however, the power changes dramatically. The internal structure, operating regulations, load characteristics, & powers of electrical devices of the identical kind are quite similar to one another. Because of these features, current waveforms are very consistent in shape, and power variations between states exhibit strikingly comparable regularity. For this reason, we use the electrical equipment's current waveform while power as our gold standard for equipment verification.

A kind of ANN, the MLP has input, hidden, and output layers—a minimum of three—of nodes. With the exception of the input nodes, every node is a neuron that decides whether or not to send the data it receives to the next layer based on an activation function (such as a step, sigmoid, tanh, or ReLU: Rectified Linear Unit). Machine translation software, picture identification, and voice recognition are just a few of the many uses for the MLP, a machine learning solution. Nonetheless, the MLP has issues with diminishing gradient, reasoning with new facts, and processing fresh data. The advent of deep learning allowed us to overcome these challenges. New machine learning approaches, decreased computing cost as a result of graphics processing unit improvement, and image processing technology have all contributed to DNNs' rapid rise to prominence. There has been a lot of research on DNNs as a potential solution to the issue of nonlinear and complicated functions. Furthermore, DNNs learn very well from unlabeled data, which makes them useful in many domains like AI, graphical modeling, optimization, pattern identification, along with signal processing.

To create a DNN, an MLP with just one or two hidden layers is superimposed upon a DNN with several hidden layers.. On the DNN's left side you'll find the input layer. The middle layer consists of L-1 hidden layers. The right half of the diagram shows an output layer. A total of L layers is present. $X = (1, x_1, x_2, \dots, x_d)^T$ is communicated with the input layer, then it communicates with the output layer $o = (o_1, o_2, \dots, o_c)^T$. For that reason, there are d nodes in the input layer and c nodes (not including the bias node) in the output layer. The count of nodes (excluding the bias node) in layer l is represented by n_j. If d is the value of n_0, then the input layer is in the zeroth layer. Here, n_l=c, and the output layer is located on the L-th layer.

As (n_(l-1)+1)*n_l, we get the weights that link layers /-1 and /. The entire mass may be shown using the U^l matrix in (1).

$$U^l = \begin{pmatrix} u^l_{10} & u^l_{11} & \cdots & u^l_{1n_{l-1}} \\ u^l_{20} & u^l_{21} & \cdots & u^l_{2n_{l-1}} \\ \vdots & \vdots & \ddots & \vdots \\ u^l_{n_l0} & u^l_{n_l1} & \cdots & u^l_{n_ln_l-1} \end{pmatrix}, l = 1,2, \dots, L \tag{7}$$

4. Results and discussion

The approach and model for DN wind solar energy storage were tested using an IEEE-33 node system. Using the PSO approach, a complex nonlinear problem was solved. Electricity was generated via wind, solar panels, and batteries as part of the system. A laptop with an Intel Core i7-4600 M processor running at 2.90 GHz is used for the testing. We set the maximum number of particle swarm iterations to 100 to meet the optimization and execution requirements. The control and compensating device for the distribution system has time limits, which is the reason for this. Table 1 displays the DN sensors and their associated parameters.

The reactive power adjustment devices may be found at nodes 7, 24, and 30. Connected to the photovoltaic and energy storage system were nodes 25 and 32. Node 8 was where the wind turbines and batteries were connected. Wind photovoltaic producing equipment is considered an unregulated active power source for the purpose of optimization issue analysis. This is done to show that the two pieces of equipment have a common characteristic: their active power output is unaffected by peak load demand. Additionally, this setup is necessary for the distribution system's operation to be optimally regulated using storage and capacitor banks.

4.1. Case analysis

The test system used for this investigation is a popular IEEE 33-bus radial power distribution system. The current standard IEEE33 node power distribution demonstrator device serves as the basis for this research. Figure 3 displays the system wiring diagram. A few tweaks are applied to the specified parameters. Conversely, nodes 10 along with 31 are linked to wind farms with 500 kW and 1000 kW capacity, respectively. Nodes 21 and 24 are connected to two thermal power plants, respectively.

During the calculation, the following factors were considered: a charge/discharge efficiency of 90% for the energy storage system, a starting capacity of 20% for the SOC, an allowable minimum of 10% and an allowable maximum of 90%, an annual interest rate of 4.9% for the energy storage system, the coefficients for the annual maintenance cost, and T0□Ⓕ. The optimization area for the presently used wind power is set to 0% to 20%, the optimization step length is 5MW, and the P_s optimization region is configured to employ battery types 0 to 200MWh, which is given in Figure 4, and Figure 5.

Figure 6 and 7 shows the photovoltaic output, average every season's statistic on wind power and load. These curves are obtained by grouping the data of a given location using the K-means clustering technique.

According to the demand for electricity, time-sharing tariffs are divided into several periods: peak (11:00–15:00 and 18:00–21:00), normal (8:00–10:00, 14:00–17:00, and 22:00–24:00), valley (1:00–7:00), and interruptible load (112:00–21:00). Parameters pertaining to the distribution network and users are shown in Table 2. Energy storage equipment's primary characteristics are shown in Table 3.

4.2. Performance analysis

4.2.1. *Power loss computation*

Evidence suggests that DGs installed close to load centers may reduce distribution networks' actual and reactive power losses.

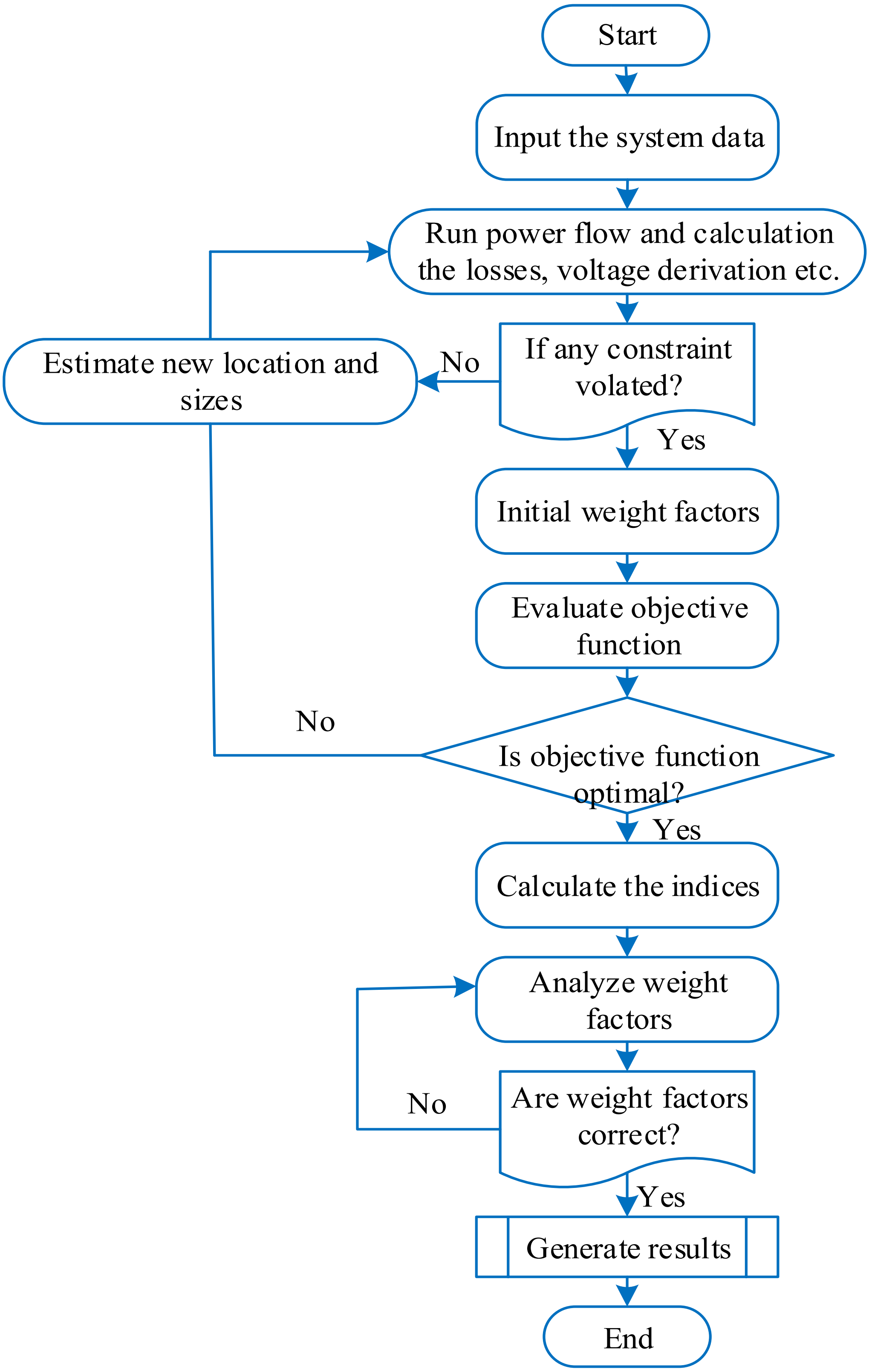

Figure 2. Optimum Configuration for Wind and Solar PVs

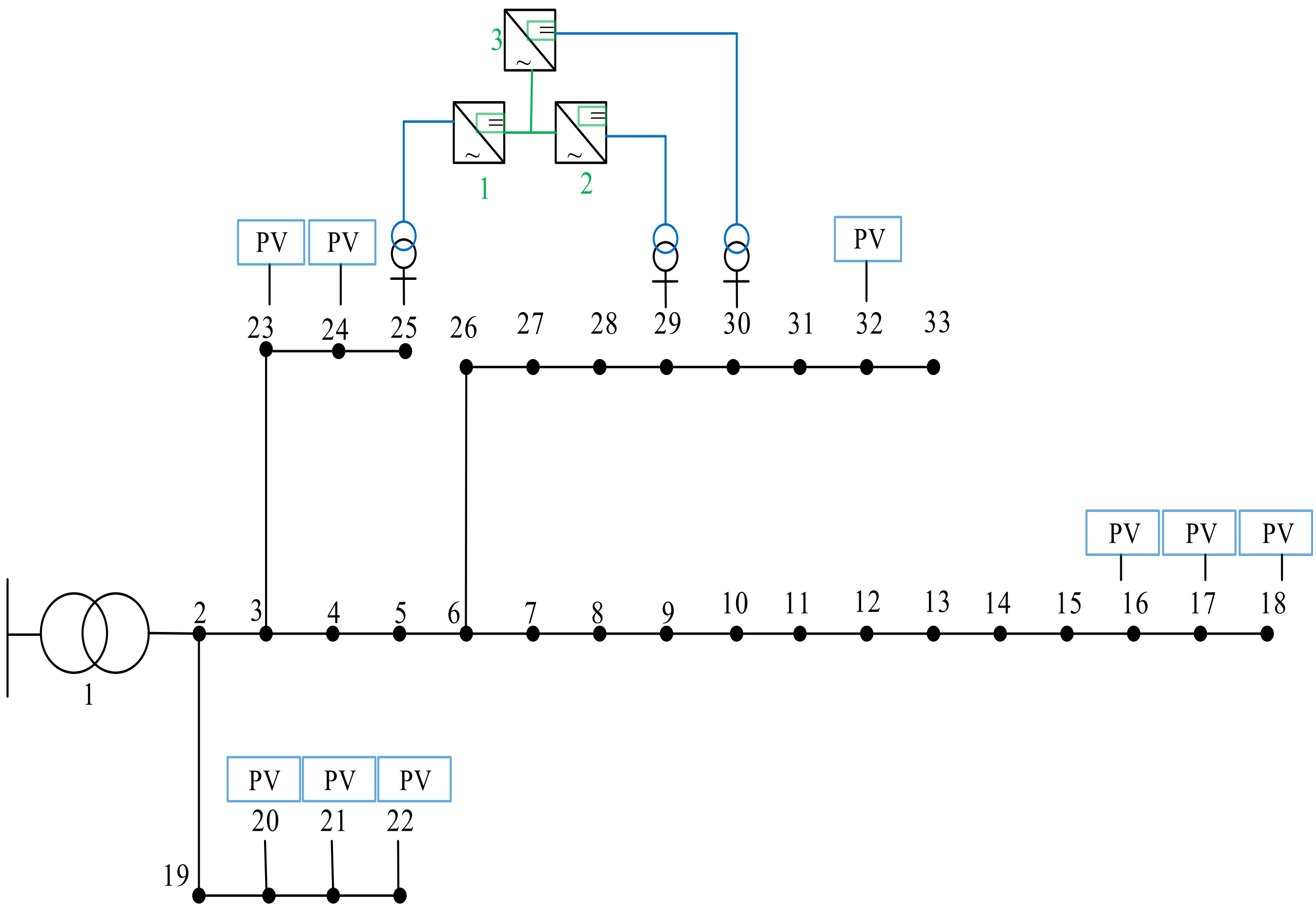

Figure 3. IEEE Bus 33 Model

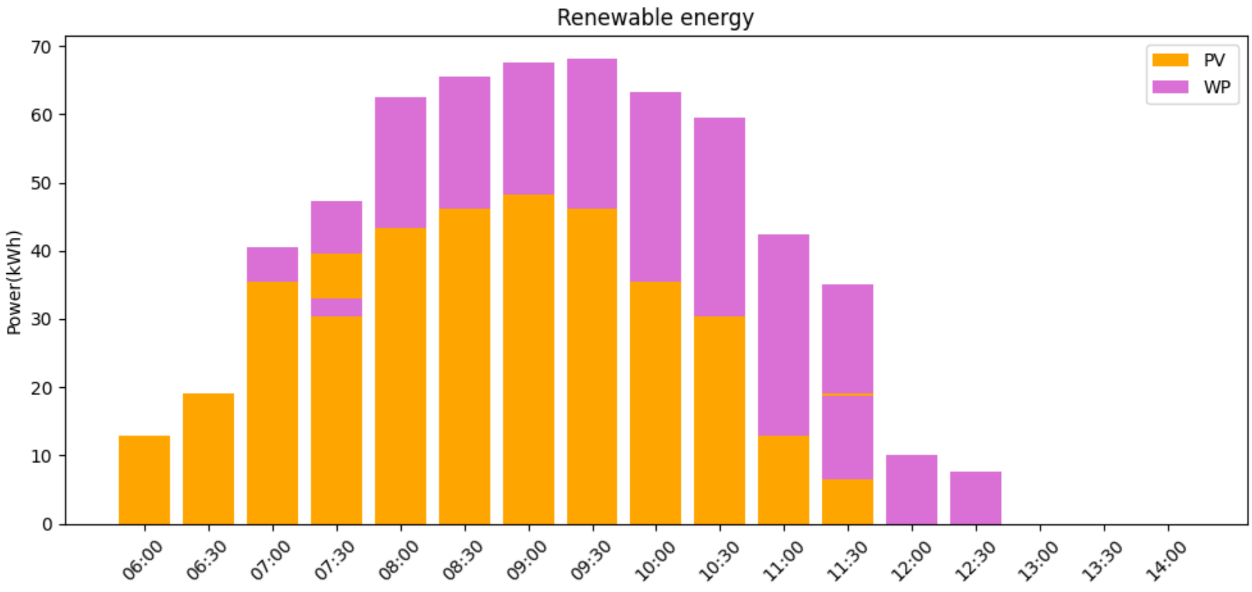

Figure 4. Generated Power using PV and WT

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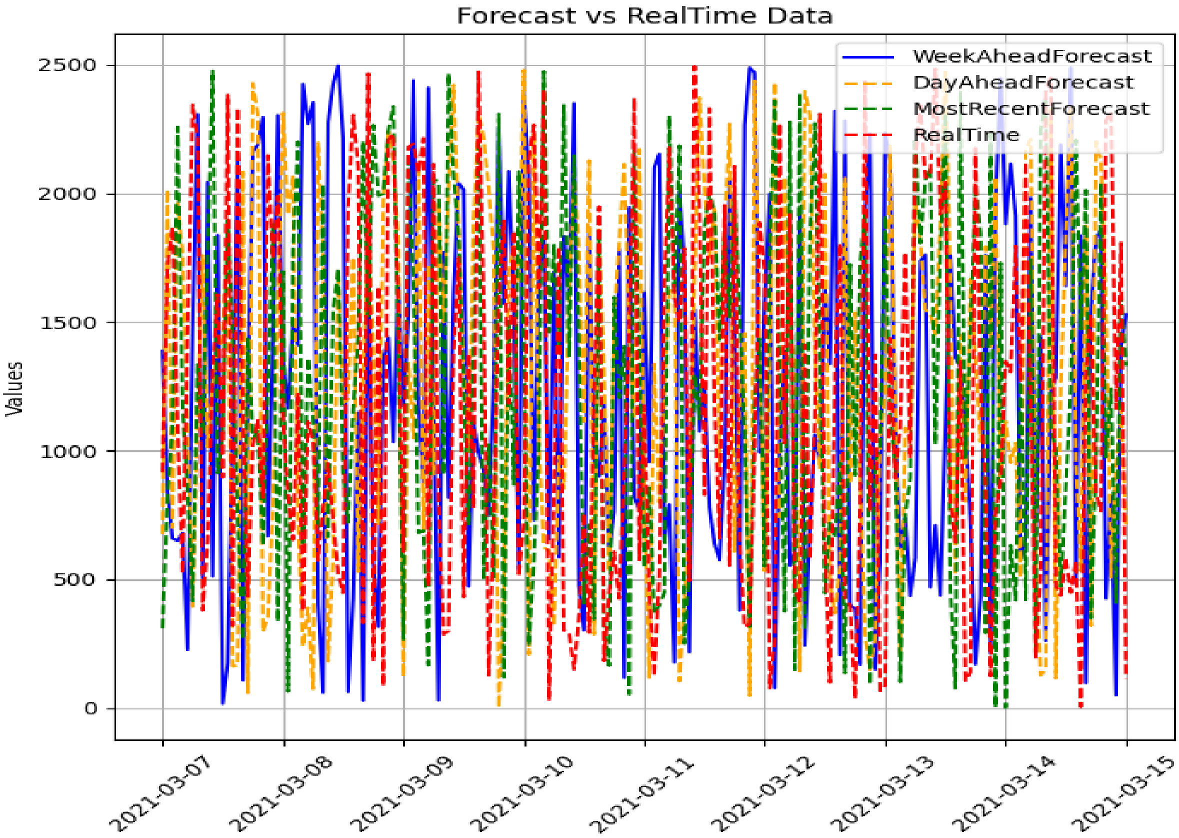

Figure 5. Generated and Real-Time Data

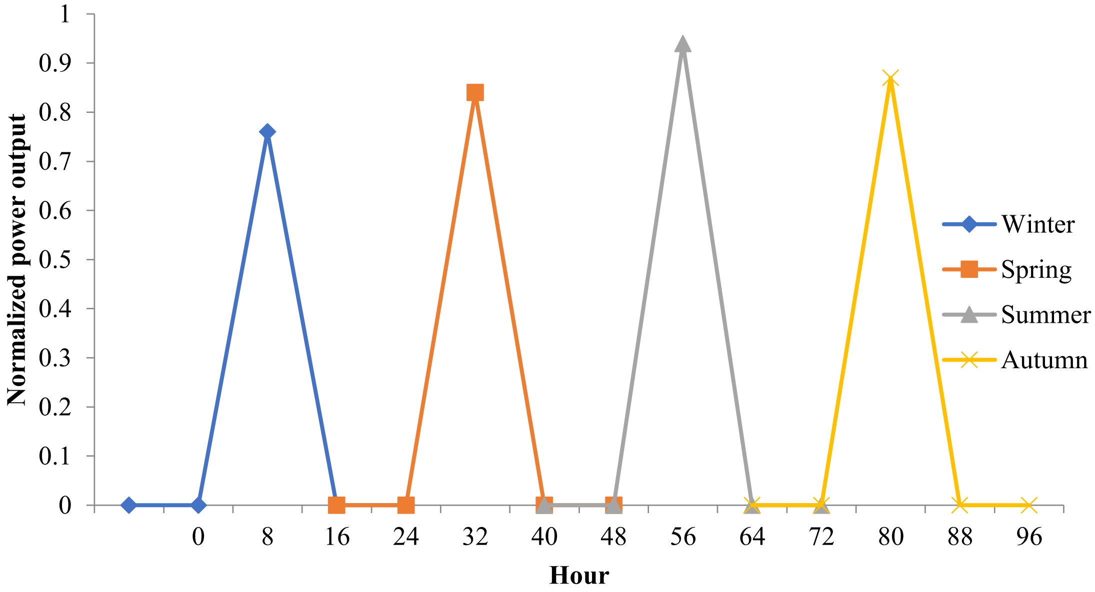

Figure 6. Seasonal output of PV

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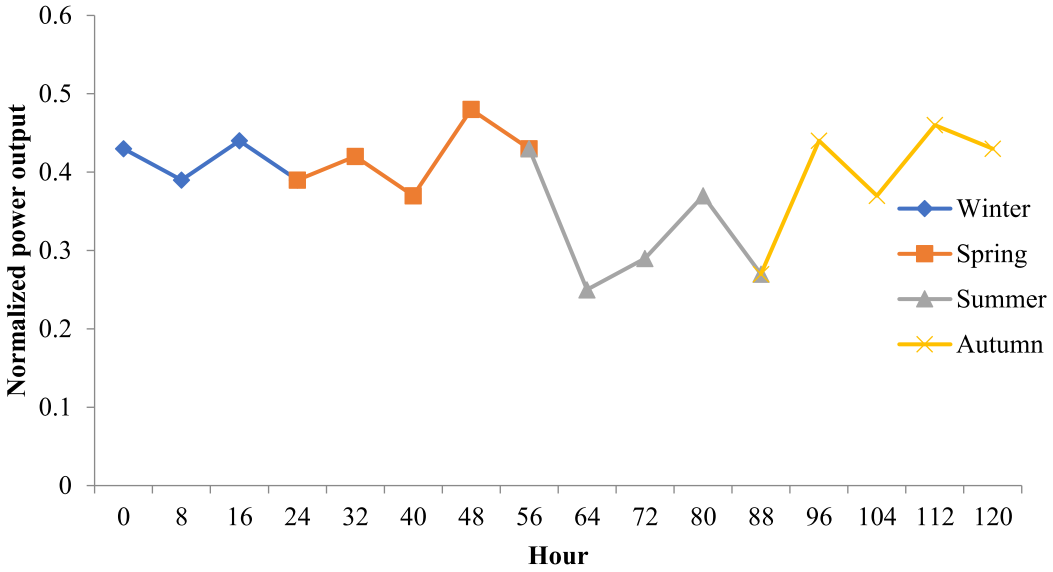


Figure 7. Seasonal output of WT

Table 2. Characteristics pertaining to DG

Parameters	Set
Investment on wind power /(yuan/kWh)	6500
Investment cost /(yuan/kWh) for photovoltaic units	8700
Cost of gas maintenance and operation /(yuan/kWh)	0.6
Federal subsidies for wind power in yuan /(yuan/kWh)	0.4
Electricity sales price for Clean Energy in yuan/(yuan/kWh)	0.7
Gas-fired power cost /(yuan/kWh)	0.8
Investment cost /(yuan/kWh) of gas capacity	4900
Wind power and photovoltaic operating and maintenance expenses /(yuan/kWh)	0.5
Subsidies for solar energy according to /(yuan/kWh)	0.45
Value of emissions of carbon to the environment in yuan/t	29
The cost of carbon /(yuan/t)	15

Table 3. Data pertaining to the distribution network and the user

Variables	Set
Node voltage upper limit in p.u.	1.17
Minimum allowable node voltage/p.u.	0.90
Maximum power output per branch in MW	9.88
Power grids set the pricing that distribution firms buy electricity /(yuan/kWh).	normal:0.60 valley:0.40
Selling price of electricity by distribution firm /(yuan/kWh)	normal:0.80 valley:0.50
Rate of Interruptible Load Subsidy /(yuan/kWh)	0.5
Expenses for network loss divided by /(yuan/kWh)	0.8

The removal of power losses is heavily dependent on the position and size of DG units, according to several studies, the majority of which were mentioned before. As a consequence, usually the best spot for a distributed generator (DG) is the one where its capacity and placement in the network cause the least amount of power loss. When it comes to reducing power losses, the DG allocation technique is almost identical to the capacitor allocation approach. The key distinction between the two procedures is that DG units affect both reactive and actual power, while capacitor banks only affect reactive power. It has been shown that in networks where power losses are high, a small unit DG linked strategically to the network may significantly reduce power losses. The precise loss formula, which depends on the network's operating parameters, gives the losses in a distributed system as (1)

$$P_L = \sum_{I=1}^{n} \sum_{J=1}^{n} a_{lf}\left(P_l P_J + Q_l Q_J\right) + b_{lf}\left(Q_l P_J - P_I Q_J\right) \quad (8)$$

where:

$$\begin{aligned} a_{tj} &= \frac{r_{tf}}{V_t V_f} \cos\left(\delta_t - \delta_f\right), \\ b_{tf} &= \frac{r_{tf}}{V_t V_f} \sin\left(\delta_t - \delta_f\right), \end{aligned} \quad (9)$$

In each bus, P and Q represent the net real power as well as reactive power injection, r_ij denotes the line resistance among buses i and j, and V and δ stand for the voltage or load angle at respective buses. Furthermore, we find details on the two firms' test datasets and assessment criteria that were used to implement the suggested strategy. This analysis also takes into account the experimental setting and its outcomes. To evaluate the accuracy of the prediction made by the suggested approaches, four commonly used performance measures were utilized: RMSE, CVRMSE, MAE, R^3, and MAPE.

$$\begin{gathered} \mathrm{MAE} = \frac{1}{n} \times \sum_{i=1}^{n} \left(|y_i - \hat{y}_i|\right) \\ \mathrm{RMSE} = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2} \\ \mathrm{CVRMSE} = \frac{\mathrm{RMSE}}{\bar{y}_i} \times 100 \\ R^2 = 1 - \frac{\mathrm{SSE}}{\mathrm{SST}} = 1 - \frac{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2}{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \\ \mathrm{MAPE} = \frac{100}{n} \times \sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \end{gathered} \quad (10)$$

Between equations (9) and (10), the variables y_i, $\hat{y}_i$, n, $\bar{y}_i$, SSE, and SST stand for the following: real value of sample i, anticipated outcome of sample i, testing data, mean of predicted values, and total sum of square. Lastly, in order to assess the suggested approaches, we also used the time it took to do the computations.

Discussion

The focus of the simulations in this investigation was on steady-state power flows under peak loading conditions. Because of the high-power flows across the distribution system, the peak loading state significantly affected the system's power loss compared to other loading circumstances. It is possible to classify the methods used to find the best energy storage design into two broad categories: conventional optimization algorithms and intelligent optimization algorithms.

Programming in linear form, nonlinear programming, arithmetic coding, hybrid programming, with and without restrictions, etc. are examples of structural issues often addressed by traditional optimizing procedures. Theoretical analysis of computational challenge and convergence is possible corresponding to the aforementioned technique due to its relatively stable characteristics and clear structural details. Whenever dealing with small-scale, single-objective issues, many classic optimization methods fall under the category of convex optimization. These algorithms possess the distinctive global optimum advantage, which is both simple and dependable. Nevertheless, configuration models for optimal energy storage allocation are frequently multiple-purpose and nonlinear mathematical representations because the variables that are considered in this context are typically continuous variables that pursue either one or more objectives, and because the constraints typically include both linear and nonlinear constraints as well as equality and inequality constraints, among others. Conventional optimization algorithms' calculations become very complicated in such a situation, and their convergence and computation speeds often fall short of what is needed, which is given in Figure 8.

Nevertheless, the vast majority of smart optimization algorithms are heuristics, which lend themselves well to qualitative analysis but defy quantitative proof. Furthermore, the real performance is not controlled since most algorithms are based around random features and their convergence is often probabilistic. Simultaneously, there could be flaws like a single-individual, precocious, or local optimum, and if the data set is very big, finding the answer might be a hassle. Hence, enhancing this kind of method to achieve greater convergence and efficiency in storing energy optimization allotment is still the main focus on present research. The current issues may be effectively addressed by transforming problems with multiple goals into single-objective ones and by linearizing the objective function and constraint conditions, which is given in Figure 9 and Figure 10.

5. Conclusion

When many structures or individuals share energy resources, cooperative optimization may be used for community energy systems. The goal of weather-data-driven cooperative optimization of ESS and RES is to optimize energy systems to their full potential by taking weather patterns into account and making the most of ESS's flexibility and RES's intermittency. In order to maximize efficiency and decrease costs, it is necessary to optimize the functioning, size, and placement of energy storage devices (ESS and RES).

For the purpose of improving the functioning of the ESS and estimating the output of the renewable energy source (RES), the K-means clustering model relies on precise weather predictions such as temperature, solar radiation, wind speed, and others. While keeping the system stable and reliable, our approach enhanced the usage of renewable energy sources. An analysis and summary of the mathematical models and optimization technique pertaining to energy storage setup for several application situations are provided. In future, cooperative game theory model is presented to extend this further.

Table 4. Assessing the efficacy of DNNs in predicting future electric power demands

Metrics	LSTM		GA Model			DNN-K-means-PSO		
MAPE (%)	0.53	0.44	0.14	0.23	−0.04	0.33	0.56	−0.34
R^2	0.5	0.3	0.88	0.96	0	0.86	0.89	0.97
CVRMSE (%)	−0.08	0.22	0.05	0.34	−0.44	0.39	0.56	−0.65
Time (ms)	−0.99	−0.99	12.44	42.87	−29.77	11.22	39.22	−27.7
MAE (MW)	−0.15	−0.55	0.23	0.34	−0.23	0.99	0.66	−0.06
RMSE (MW)	−0.29	−0.33	0.56	0.33	−0.56	0.28	0.99	−0.09

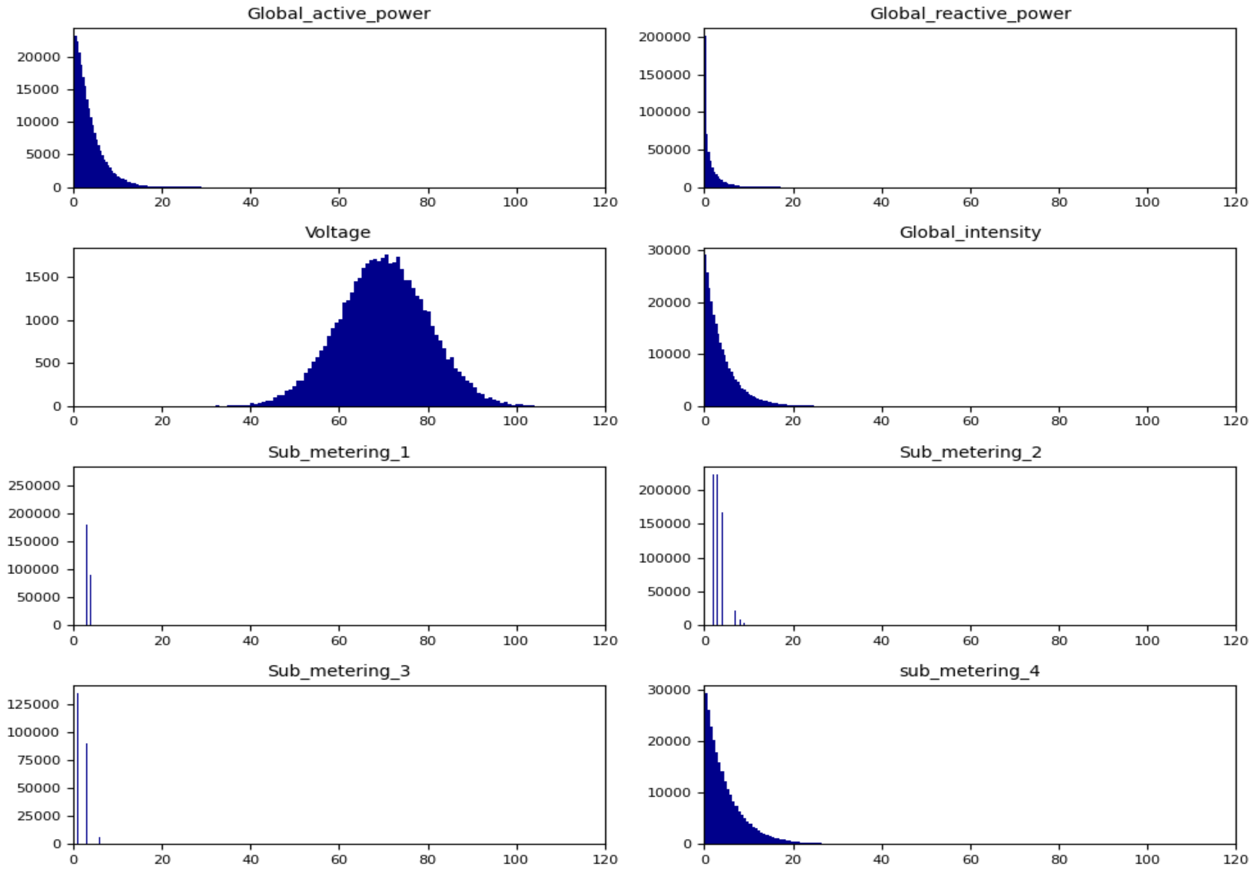
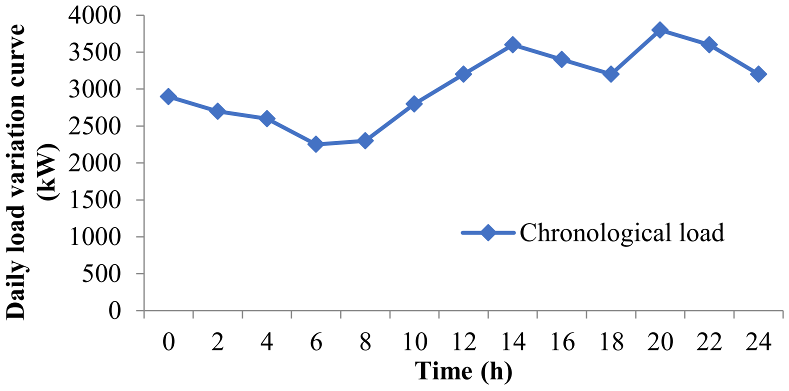
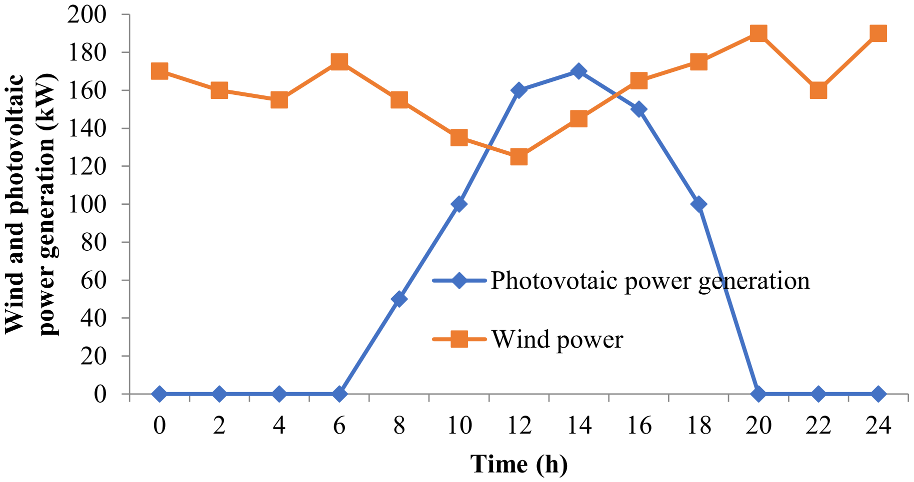


Figure 8. Global Active and Reactive Power Modeling for Different Loads



(a)



(b)

Figure 9. (a) IEEE33 node load timing curve (b) Power generating on a daily basis with wind and solar equipment

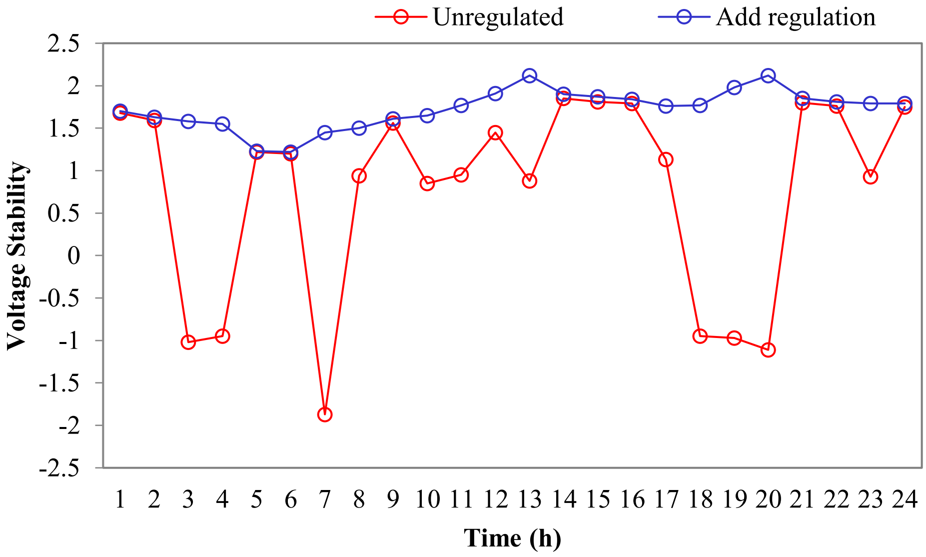


Figure 10. Voltage Stability Analysis

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Declaration:
Ethics approval and consent to participate: Not applicable.
Name of Ethics Committee: Not applicable
Informed consent to participate in the study must be obtained from participants (or their parent or legal guardian in the case of children under 16): Not applicable

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

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All authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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Authors Contribution
All authors contributed to the study conception and design. All authors read and approved the final manuscript.

Availability of data and materials
The data used to support the findings of this study are available from the corresponding author upon request.

Conflict of interests
The authors declare that they have no known competing

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