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Optimization of economic dispatch for distributed generation-based power networks

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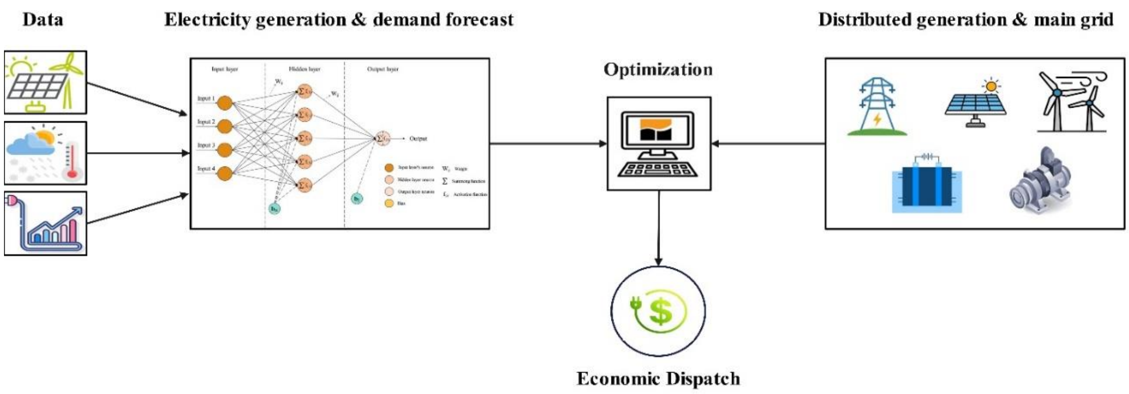
Abstract

The rapid growth in energy demand, along with escalating environmental concerns, highlights the necessity of developing and integrating renewable energy sources into modern power systems. In this context, economic dispatch can play a crucial role in optimizing resource utilization, minimizing operational costs, and ensuring reliable networks. This study provides a renewable-integrated framework using economic dispatching to minimize the total operation cost while achieving optimal utilization of distributed generation (DG) units in the state of Texas. In this study, an Artificial Neural Network (ANN) is employed for forecasting, while the GAMS software is utilized for optimization to perform economic dispatch. In the first stage, an ANN model is developed using historical data from the previous 72 hours to forecast the power output of wind turbines, photovoltaic systems, and electricity demand. The results demonstrated that the proposed model achieved high accuracy, with the Mean Absolute Percentage Error (MAPE) remaining below 5%. In the second stage, a Mixed-Integer Linear Programming (MILP) model was implemented in the GAMS environment to determine the optimal generation mix for each hour of the forthcoming 24-hour period. The optimization results indicated that the total electricity demand for the next day, amounting to 138.93 *MWh*, was supplied through an optimal combination of wind turbines (19.8%), photovoltaic systems (10.9%), gas micro turbines (4.3%), fuel cells (2.5%), and the main grid (62.5%). The total operational cost was calculated to be $18,434, representing an approximate 15% reduction compared to the existing supply scenario relying solely on the main grid.

Graphical Abstract



1. Introduction

One of the leading causes of global warming and adverse environmental consequences is the increasing consumption of fossil fuels, along with the continued reliance on them as the primary energy source. This dependence has not only led to increased greenhouse gases and climate change, but also to air, water, and soil pollution. These undesirable consequences make the need for a transition to sustainable solutions, such as the adoption of renewable energy technologies and efficient energy systems [1]. Various type of renewable energy technologies, encompassing wind, solar, hydro, geothermal, wave, and tidal resources, represent environmentally benign alternatives to conventional fossil fuels. Beyond mitigating adverse ecological impacts, their deployment fosters long-term sustainability, enhances security of energy supply, and facilitates diversification within the global energy portfolio. In the recent decade, electrical energy consumption has increased critically due to population growth and industrialization in the world. According to the International Energy Agency (IEA), global electricity consumption increased by approximately 1,080 *TWh*, nearly twice the annual average growth observed over the past decade [2]. The integration of renewable energy resources with energy storage systems can play a pivotal role in peak load management, ensuring reliable electricity supply while minimizing environmental impacts [3]. However, challenges such as intermittency of renewables and high investment costs in large-scale storage systems remain critical barriers to widespread deployment. The global shift toward renewable energy is driven by multiple factors, including policy frameworks aimed at reducing dependence on fossil fuels, structural transformations in power systems, rapid technological advancements, and growing environmental concerns. Collectively, these drivers have encouraged many countries to accelerate the development and deployment of renewable energy resources, with costs projected to decline further in the future as technologies mature and economies of scale are achieved [4].

As previously discussed, while renewable energy sources offer significant advantages, they are also subject to inherent limitations, most notably production uncertainties and strong dependence on meteorological conditions [5, 6]. These challenges make operational planning, or economic dispatch, even more essential. The integration of renewable energy sources into power systems significantly increases the complexity of coordinating generation units, balancing network loads, and maintaining real-time responsiveness to variations in supply and demand [7]. At the same time, the rise of competitive electricity markets has placed additional pressure on private producers to operate with precise scheduling and well-designed strategies that not only maintain grid stability but also maximize profits. This shift has led to a broad body of research focused on electricity market analysis and cost-minimization strategies. Effective planning is fundamental in electric power systems, as it ensures the secure, reliable, and economically optimized delivery of electricity to end-users. However, there are some challenges that systems may face, such as instability, blackouts, high operational costs, and negative environmental impacts. Effective planning also helps optimize the use of available resources, anticipate future needs, and prevent potential disruptions [8].

Power system planning is typically divided into several levels, each defined by its own time horizon and specific tasks. In general, these levels are categorized as long-term, medium-term, and short-term planning [9]. Long-term planning, with a horizon of two to twenty years, focuses on infrastructure development and the economic evaluation of large-scale projects. Medium-term planning, ranging from several days to about two years, deals with optimizing system operations, scheduling maintenance, and managing resources. Short-term planning, which spans from a few minutes to a few days, is concerned with daily generation scheduling, load management, and responding to demand fluctuations [10].

In this context, economic dispatch in distribution networks has become increasingly important with the growing use of distributed generation resources. Economic dispatch refers to the process of deciding how to operate generation units optimally within a given time horizon. Its main objective is to minimize production costs while improving the efficiency of the distribution system. Advanced dispatching strategies enable the efficient management of distributed energy resources, ensuring optimal performance and the maintenance of supply-demand balance, even under the inherent variability of renewable energy generation [11]. Escobar et al. proposed an optimized dispatching architecture for microgrids with high penetration of renewable resources and storage systems. Their approach combines weather forecasting with battery management to enable stable and efficient energy planning. Tested in both real-world and simulated environments, the system demonstrated strong flexibility and high accuracy in optimizing the control of energy generation and demand [12]. In another study on optimal generation scheduling for power systems with renewable resources, distributed generation, and energy storage, a method based on the Particle Swarm Optimization algorithm was introduced. The approach maximized the use of renewable energy while minimizing network losses, delivering optimal generation schedules and achieving a notable reduction in line losses and the reliance on conventional resources [13]. Shirazi et al. conducted a study on the dispatching of an urban microgrid consisting of a wind turbine, battery storage, and the conventional grid. They optimized system operation using a Mixed-Integer Linear Programming (MILP) model, while load and wind generation were forecasted through deep learning and hybrid models. It was found that the inclusion of battery storage reduced operational costs and significantly improved system resilience [14].

The intermittency and uncertainty of renewable generation add considerable complexity to economic dispatch, since accurate forecasting plays a central role in resource allocation, cost reduction, and maintaining grid stability. To address these challenges, advanced forecasting techniques, including machine learning algorithms and neural networks, can significantly improve prediction accuracy and enable more effective and efficient economic dispatch in systems with high renewable penetration [15]. A review study examined the application of neural networks and machine learning algorithms in forecasting renewable energy generation. The findings showed that these methods, by capturing complex data relationships and production variability, can substantially improve forecasting accuracy [16]. In a study by Waheed et al., deep neural networks (DNNs) were applied in combination with time-series analysis and feature selection for short-term load forecasting. The results demonstrated that DNNs, with their high learning capacity and ability to capture temporal dependencies and uncertainties, significantly improved forecasting accuracy. These models can play a key role in smart grid management, optimizing demand response, and integrating renewable resources into the system [17].

This study proposes a forecasting and optimization framework aimed at minimizing the cost of electricity supply in distribution networks. Historical datasets encompassing consumption patterns, generation profiles, and meteorological conditions are leveraged, while artificial neural networks are employed to accurately predict the next-day demand and generation from available resources. The forecasted data are then integrated into a MILP model implemented in the GAMS environment, which determines the optimal generation mix for each hour of the day. As a case study, the city of Texas was selected due to the availability of reliable and detailed data on consumption, generation, and climate conditions. The proposed system is a hybrid network that includes wind turbines, solar panels, gas microturbines, fuel cells, and the upstream power grid as a backup source.

2. Methodology

The research process consists of two main stages, including forecasting and optimization processes. In the first stage, the input data, including meteorological data, electricity demand, and distributed generation outputs from the past 72 hours, are collected and preprocessed. The proposed model forecasts the next 24 hours of renewable energy generation and electricity demand using an Artificial Neural Network (ANN). In the second stage, the predicted results, along with the cost parameters of distributed generation units and the primary power grid, serve as inputs to the economic dispatch model. A MILP framework is employed to determine the optimal combination of generation resources that meets demand at the lowest possible cost. The MILP framework is developed in the GAMS software.

In this framework, the technical and operational limitations of each distributed generation unit are explicitly incorporated into the model, ensuring that the optimization outcomes are both feasible and reflective. A representation of the research methodology stages is shown in **Fig. 1**, which displays the main steps from data collection to forecasting and finally economic dispatching.

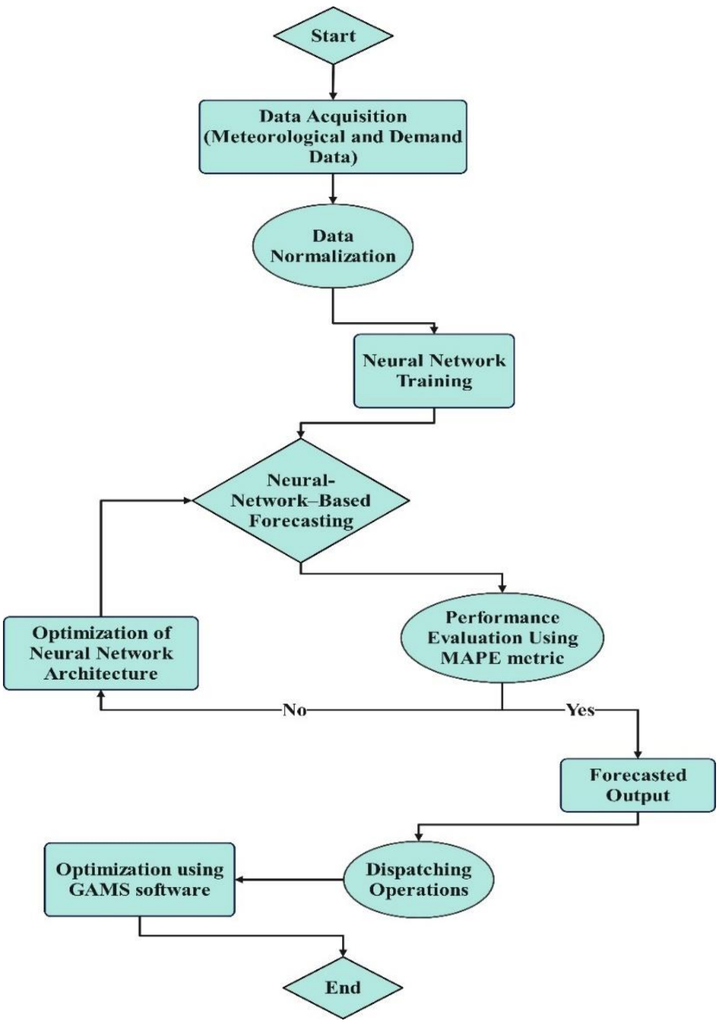


Fig. 1. Economic dispatching flowchart used in this research.

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2.1. Case study

Due to the availability of high-resolution demand-side data, including disaggregated consumption profiles, distributed generation outputs, and comprehensive meteorological datasets, as well as the existence of active distribution networks, the United States was selected as the case study for this research. This choice allows for validation of the proposed model and an in-depth analysis of the economic dispatch framework. Among the U.S. states, Texas was chosen due to its diverse electricity generation portfolio, which encompasses both conventional and renewable energy sources such as solar and wind power. The dataset used in this study includes hourly demand and distributed generation data obtained from [18], along with regional hourly meteorological information collected from [19]. To enhance model scalability and computational, both demand and generation data were downscaled by a factor of 1:10000.

The availability of such data facilitates the detailed analysis of load variations and renewable energy generation patterns throughout the day. Furthermore, the diverse climatic conditions of the state of Texas provide an excellent basis for accurately assessing the influence of weather variations on economic dispatch performance. **Fig. 2** illustrates the average wind speed and solar radiation across Texas.

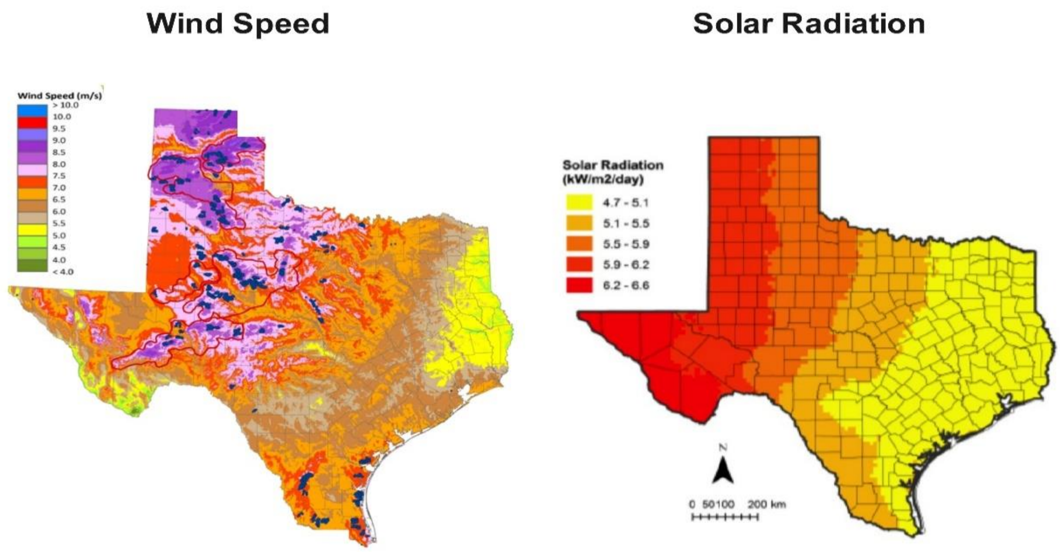

Fig. 2. Average wind speed and solar radiation in across Texas [20, 21].

2.2. Parameters and structure of the active distribution network

In this study, an active distribution network incorporating distributed generation (DG) units, such as fuel cells, gas microturbines, wind turbines, and photovoltaic systems, is examined alongside the main grid. In **Fig. 3**, a schematic diagram of the proposed model is demonstrated. In other words, integrating with the main grid enhances system reliability and mitigates the risk of power supply disruptions when the DG experiences fluctuating or reduced capacity. Economic dispatch represents a key feature of active distribution networks. It involves the optimal allocation of power generation across available resources to minimize overall generation costs and network losses, while satisfying operational constraints and fulfilling load demands. In this process, the dispatch system dynamically allocates the optimal share of each generation resource in meeting the load, based on real-time data collected from both generation units and consumer demand. This approach enhances network flexibility while ensuring the economical utilization of available resources.

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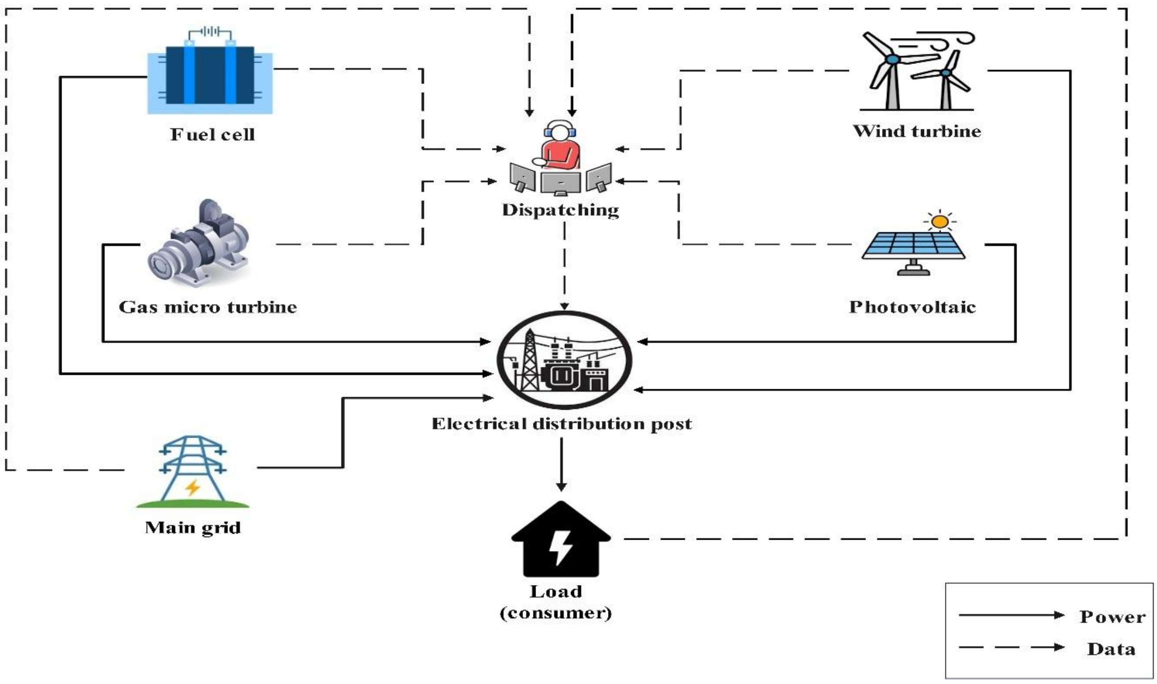

Fig. 3. Structure of the distribution dispatching system and active distribution network components.

The technical specifications and operational parameters listed in Table 1, such as rated capacity, fuel cost, and other performance characteristics, are utilized to accurately simulate the operation of the active distribution network and the proposed economic dispatch model. Furthermore, to account for real network conditions and the cost of purchasing energy from the main grid, an hourly electricity price profile was incorporated into the analysis. The variation of this price over a 24-hour period is illustrated in **Fig. 4.** Incorporating these data enables the model to conduct the economic dispatch process under realistic operating conditions, taking into account the operational costs associated with both the main grid and the distributed generation units.

Table 1. Technical and economic parameters of distributed generation resources.

Source	**Capacity (MW)**	**P_{loss} (%)**	**Life Time (year)**	**Capex ($/kW)**	**$C_{O\&M}$ (%Capex)**	**C_{fuel} ($/kwh)**
Photovoltaic [6]	2	10	20	970	2	0
Wind turbine [22]	2.5	10	20	1,460	1.1	0
Gas micro turbine [23]	0.5	2	20	1290	2	0.003
Fuel cell [24]	0.5	5	10	1000	2	0.015

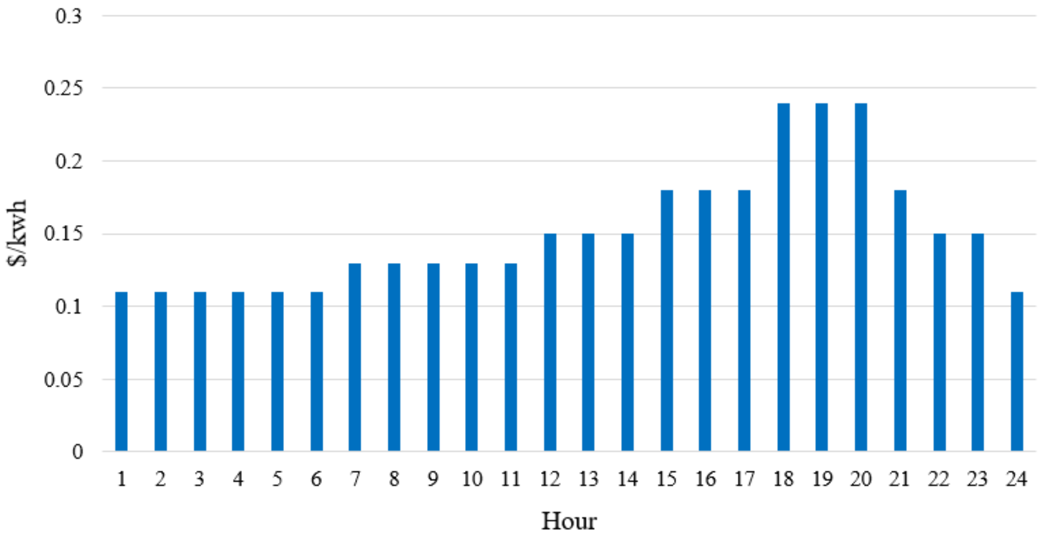

Fig. 4. Hourly price of purchasing electricity from the main grid.

2.3. Artificial Neural Networks

To forecast electricity demand and DG production value for the next 24 hours, an ANN utilized in this study. As demonstrated in **Fig. 5**, the ANN structure consists a single hidden layer with five neurons and uses a sigmoid activation function. The network is capable of learning complex nonlinear relationships between the input parameters (operational and network conditions) and the outputs (generation and demand levels), allowing it to produce accurate short-term predictions. The input and output variables for each parameter are demonstrated in **Table 2.**

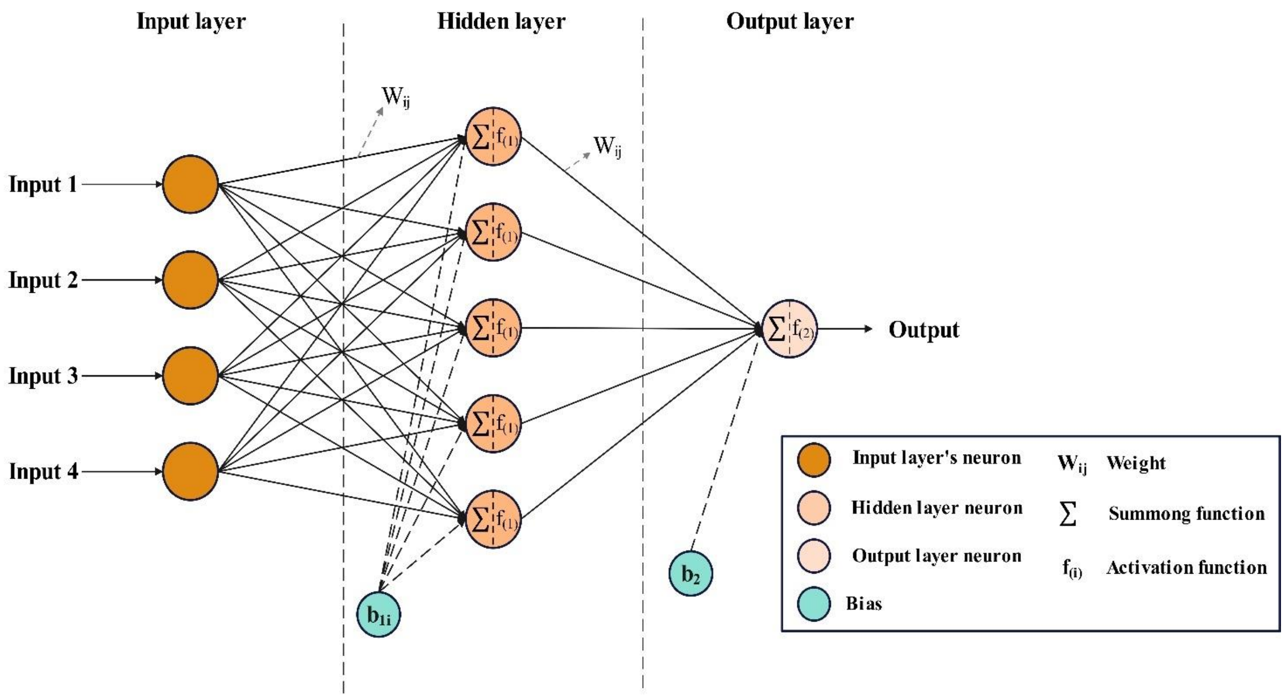

Fig. 5. Structure of the ANN used to predict energy production and demand.

Table 2. ANN inputs and outputs for forecasting production and demand for the next 24 hours.

Category	Inputs	output
Wind turbine	• Wind speed • Gust speed • Temperature • Humidity	Wind energy production
Photovoltaic	• Solar radiation intensity • Cloud cover • Temperature • Humidity	Solar energy production
Electricity demand	• Air temperature • Humidity • Time of day (peak/off-peak) • Electricity price	Electricity demand

Historical data from the previous 72 hours are divided into two subsets, including 80% for training and 20% for testing. The forecasting accuracy is evaluated using the Mean Absolute Percentage Error (MAPE), defined in Eq. (1), which represents the average percentage difference between the predicted and actual values. To minimize the effect of differing data scales and enhance forecasting performance, both input and output variables were normalized to the range [0, 1] using Eq. (2). Normalization helps stabilize the training process and improves the model's predictive accuracy. After forecasting, the predicted outputs are denormalized using Eq. (3) to enable direct comparison between the model predictions and the actual observed data [25].

$$MAPE = \frac{\sum_1^n \left| X_{exp} - X_p \right|}{n X_p} \times 100 \tag{1}$$

$$X_{normal} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2}$$

$$X = X_{normal}(X_{max} - X_{min}) + X_{min} \tag{3}$$

2.4. Optimization and operational constraints of economic dispatching

To determine the optimal operation of distributed generation units and meet the forecasted demand over a 24-hour horizon, the economic dispatch problem is formulated in GAMS using a MILP model. The objective of this model is to identify the optimal hourly generation mix that satisfies the total electricity demand while minimizing the overall operational cost of the system. The objective function, presented in Eq. (4), is defined as the minimization of total operating cost. The model also considers the operational constraints of distributed generation units. Due to hydrogen fuel requirements and storage limitations, fuel cell daily operating time is restricted to approximately 18 hours, with a maximum generation capacity of 500 kW. These constraints are represented in Eq. (5).

Since the operation of gas microturbines is independent of weather conditions, their power generation is not subject to uncertainty. However, it is limited by both power capacity and operation time, similar to other sources. The maximum daily operation of this unit is about 20 hours, with a maximum output of 500 kW, as expressed in Eq. (6). For renewable energy sources, including photovoltaic and wind systems, the main restrictions are determined by installed capacity and weather conditions. The hourly generation of these units cannot exceed their rated capacity and is assumed to remain non-negative. The generation limits for the photovoltaic and wind systems are formulated in Eqs. (7) and (8), respectively.

$$Min\ Cost = \sum_{i=1}^{24} (C_i^G \, . P_i^G) + (C^{MT} \, . P_i^{MT}) + (C^{FC} \, . P_i^{FC}) + (C^{WT} \, . P_i^{WT}) + (C^{PV} \, . P_i^{PV}) \tag{4}$$

$$0 \leq P_i^{FC} \leq 500\ kw, \qquad 0 \leq h_{\ Operation(FC)} \leq 18\ hour/day \tag{5}$$

$$0 \leq P_i^{MT} \leq 500\ kw, \qquad 0 \leq h_{\ Operation(MT)} \leq 20\ \ hour/day \tag{6}$$

$$0 \leq P_i^{PV} \leq 2000\ kw \tag{7}$$

$$0 \leq P_i^{WT} \leq 2500\ kw \tag{8}$$

3. Results and discussion

3.1. Electricity generation and demand forecast results

The results obtained from the ANN model for power generation and demand forecasting indicate that the developed model achieved a high level of accuracy. The network structure consists of an input layer with four input parameters, a hidden layer with five neurons, and an output layer. The sigmoid and linear activation function was selected for the hidden layer and output layer, respectively. Evaluation of the model using the MAPE showed that the forecasting error remained below 5% across all scenarios. This low error rate on test data reflects the high accuracy of the model in short-term forecasting of wind power, solar generation, and electricity demand.

The forecasting results for renewable power generation, including photovoltaic systems and wind turbines, over the next 24 hours are presented in **Fig. 6.** In this figure, diagram (a) illustrates the solar power output, and diagram (b) shows the wind turbine generation profile throughout the day. As illustrated in **Fig. 6a**, solar power generation starts around 8:00 AM, gradually increases, and reaches its peak between 11:00 AM and 4:00 PM. Subsequently, as solar radiation declines in the evening, the output power decreases accordingly and drops to zero during nighttime hours. This trend indicates the correct performance of the model in identifying the daily radiation pattern and converting it into power output. It can also be seen in **Fig. 6b** that wind power generation has relatively mild fluctuations throughout the day. The highest wind output occurs during the early morning hours (1:00–3:00 AM) and around midday (1:00–3:00 PM), reflecting the dynamic behavior of wind patterns in the study region. In the late hours of the day, a gradual decrease in wind power is observed, but the production values remain at an acceptable level. This trend indicates the relative stability of wind in Texas and its high reliability for providing continuous power to the studied network.

Overall, the comparison between the network's test results and actual data shows that the ANN model effectively reproduced the temporal patterns of both renewable sources. The MAPE for wind and solar power forecasting was approximately 4.1% and 3.7%, respectively, confirming the model's high accuracy in short-term renewable energy prediction.

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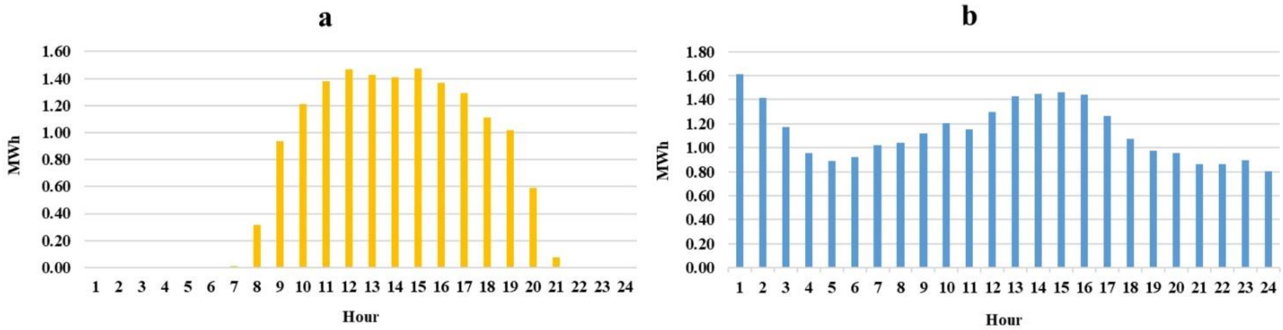

Fig 6. Wind and solar power generation capacity prediction over the next 24 hours.

The results of the electricity demand prediction for the next 24 hours are presented in Fig. 7. As shown, the proposed model successfully reproduces the actual load fluctuation trend with a high degree of accuracy. During the early hours of the day (from 1:00 AM to 6:00 AM), the electricity demand ranges between 4.8 and 5.5 *MW,* reaching its minimum around 5:00 AM. As the day progresses, demand gradually increases and peaks at approximately 7 *MW* between 12:00 PM and 5:00 PM. After this period, a downward trend is observed, with the load decreasing to around 5.6 *MW* during the late-night hours. To assess the model's predictive accuracy, MAPE was calculated for the test dataset, yielding a value of approximately 4.1%. This low error value demonstrates the model's strong accuracy and its ability to effectively learn the nonlinear relationships between inputs and outputs.

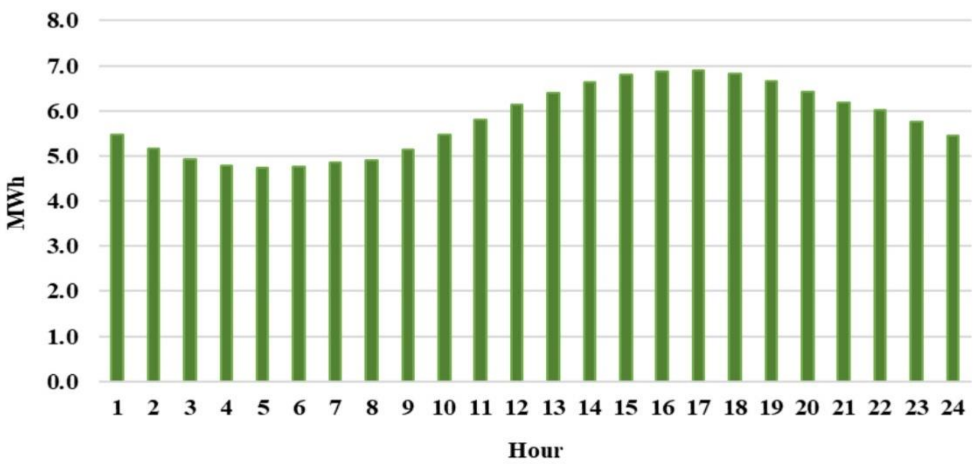

Fig 7. Electricity demand forecasted values over the next 24 hours.

3.2. Optimization results

The results obtained from the MILP optimization model illustrate the optimal utilization strategy of distributed generation resources in response to variations in electricity demand and price over a 24-hour period. The optimal generation mix for each hour of the day is presented in **Fig. 8**. As demonstrated, during the early hours of the day (electricity purchase price ranges between 0.11 and 0.13 USD/*kWh*), the demand is primarily supplied by the main grid, while the contribution of renewable sources remains minimal. Starting around 8:00 AM, with the increase in solar radiation, the PV system begins operation and continues to supply a significant portion of the demand until 4:00 PM. During this interval, solar generation reduces the amount of power purchased from the main grid, thereby lowering the total operational cost. In the afternoon hours (around 3:00–7:00 PM), as the electricity price gradually rises to about 0.24 USD/*kWh*, the optimal dispatch model allocates a larger share of generation to local sources, including the wind turbine, microturbine, and fuel cell. During peak price hours (6:00–8:00 PM), the grid's contribution decreases, and local units play a dominant role in meeting the demand. The fuel cell, constrained by its daily hydrogen storage and operating limits, operates only between 3:00 PM and 9:00 PM, contributing to cost reduction during high-price periods. The wind turbine remains active throughout the day with relatively stable output, effectively reducing dependence on the main grid. Meanwhile, the micro gas turbine, as a controllable and reliable source, operates during most hours and reaches near its maximum capacity during peak load periods.

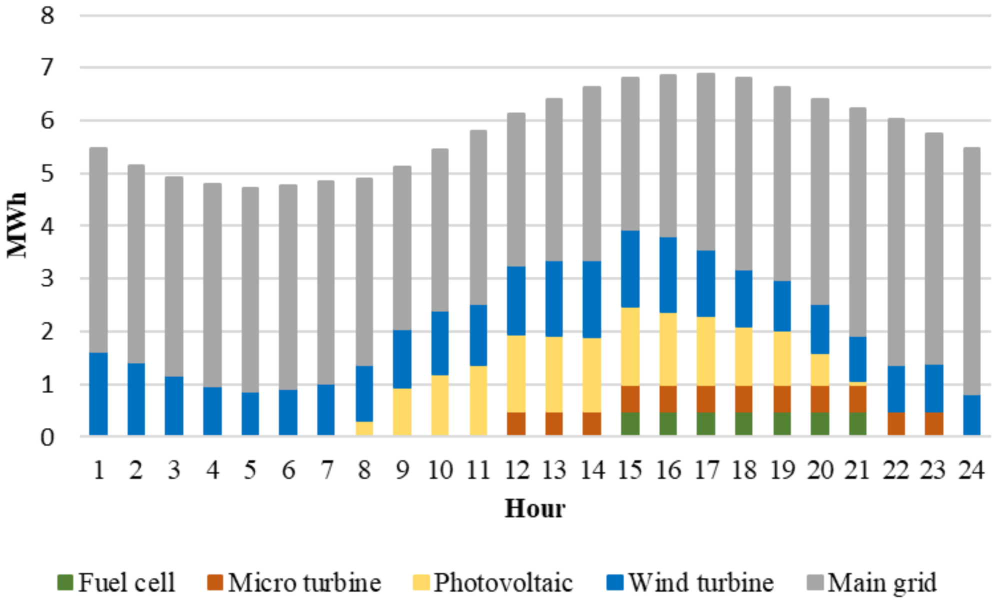

Fig. 8. Optimal utilization pattern of distributed generation resources in the next 24 hours.

According to the results presented in Table 3, the total network demand over the 24-hour period is 138.93 *MWh*. Among various sources, the main grid contributes the largest share, supplying 86.66 *MWh* (62.5%), followed by the wind turbine with 27.22 *MWh* (19.8%), the photovoltaic system with 15.05 *MWh* (10.9%), the microturbine with 6 *MWh* (4.3%), and the fuel cell with 3.5 *MWh* (2.5%). In addition, the total operating cost is calculated to be $18,434. Overall, the results indicate that the proposed model is capable of intelligently determining the optimal generation mix based on variations in load and electricity price. Implementing a renewable-integrated and controllable resource framework contributes to lowering overall operating costs, reducing reliance on the upstream grid, and enhancing the reliability and resilience of the distributed energy system.

Table 3. Optimal hourly generation schedule and total operating costs of distributed generation resources within the 24-hour horizon.

Time (hour)	Fuel cell (MWh)	Micro turbine (MWh)	Photovoltaic unit (MWh)	Wind turbine (MWh)	Main grid (MWh)	Demand (MWh)	Total cost ($)
1	0	0	0	1.61	3.85	5.46	568.9
2	0	0	0	1.41	3.74	5.15	538.3
3	0	0	0	1.17	3.75	4.92	517.6
4	0	0	0	0.96	3.84	4.8	508.9
5	0	0	0	0.87	3.84	4.71	500.7
6	0	0	0	0.92	3.85	4.77	506.3
7	0	0	0.01	1.02	3.81	4.84	588.1
8	0	0	0.32	1.04	3.54	4.9	585.8
9	0	0	0.93	1.12	3.07	5.12	592.9
10	0	0	1.2	1.2	3.04	5.44	623.2
11	0	0	1.37	1.15	3.27	5.79	665.6
12	0	0.5	1.46	1.3	2.87	6.13	763.5
13	0	0.5	1.42	1.43	3.05	6.4	798.4
14	0	0.5	1.41	1.44	3.28	6.63	832.6
15	0.5	0.5	1.48	1.46	2.87	6.81	951
16	0.5	0.5	1.37	1.44	3.05	6.86	970.6
17	0.5	0.5	1.29	1.26	3.33	6.88	996.8
18	0.5	0.5	1.11	1.07	3.63	6.81	1233.5
19	0.5	0.5	1.02	0.97	3.65	6.64	1220.3
20	0.5	0.5	0.59	0.95	3.87	6.41	1228.3
21	0.5	0.5	0.07	0.86	4.3	6.18	1007.5
22	0	0.5	0	0.87	4.66	6.03	847.3
23	0	0.5	0	0.89	4.35	5.74	802.6
24	0	0	0	0.81	4.65	5.46	584.4
Total	**3.5**	**6**	**15.05**	**27.22**	**87.16**	**138.93**	**18434**

4. Conclusion

In this study, a hybrid approach was developed to minimize the power supply cost in active distribution networks by integrating ANN-based forecasting with MILP-based economic optimization implemented in the GAMS environment. The forecasting results showed that the neural network model, consisting of a single hidden layer with five neurons, accurately predicted the temporal behavior of wind power, solar generation, and load demand, achieving an MAPE of less than 5%. The achieved high accuracy significantly contributed to the effectiveness of the optimization process, thereby minimizing uncertainty in the allocation of generation resources. In the economic dispatch stage, the optimization results showed that the total demand for the next 24 hours was 138.93 *MWh*, which was supplied through an optimal combination of renewable resources, local generation units, and the main grid. The main grid contributed the largest share by supplying 86.66 *MWh* of the total demand. Among renewable resources, the wind turbine proved to be the most effective source, generating 27.22 *MWh*, which reflects the strong wind conditions characteristic of the Texas region. The photovoltaic system also played a significant role during midday hours, producing 15.05 *MWh*. Additionally, the micro gas turbine and fuel cell contributed 6 *MWh* and 3.5 *MWh*, respectively, providing support and enhancing network stability. The total operating cost for the 24-hour period was calculated at $18,434. In comparison to the conventional approach, where all demand is supplied exclusively by the main grid, the proposed hybrid framework, combining intelligent forecasting and economic dispatch, resulted in an approximately 15% decrease in total operational costs. Furthermore, the simultaneous utilization of renewable and controllable sources not only reduced dependence on the main grid but also significantly improved the reliability and flexibility of the distribution network. Overall, the results of this study demonstrate that integrating ANNs for prediction and MILP-based models for economic dispatch provides an effective approach for managing active distribution networks with high penetration of renewable energy sources. This method not only enhances the technical and economic performance of the network but also contributes significantly to environmental sustainability by increasing the share of clean energy and reducing greenhouse gas emissions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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