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Original Article

Day Ahead Unit Commitment with High Penetration of Renewable Energy Sources and Electric Vehicle Charging Stations

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Abstract *- Unit Commitment (UC) is a power system nonlinear programming with mixed integers issue. As Electric Vehicles (EVs) and renewable energy sources are incorporated into the power system, the UC problem becomes more challenging. With the continued increase of wind and solar-based renewable energy in the utility power system on the supply side, the random features of the supply and demand sides of the power grid will become increasingly apparent, affecting the system's security, stability, and economical operation. In that sense, UC has theoretical and practical importance. The optimal scheduling of thermal, wind, solar, and EV units has been studied. The purpose of optimal scheduling is to minimize unit operating expenses. This study examines how the integration of a large percentage of renewable energy sources like wind and solar affects the effectiveness of short-term power system planning and control in urban areas where EVs charging stations and conventional demand coexist. Particle Swarm Optimization (PSO)is used to minimize the system's operational costs. The IEEE 24-bus test system is used to evaluate the study. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are compared and used to forecast the day ahead performance of the load demand, wind and solar energy, and EVs stations demand to be used in the proposed case study. It has been found that in forecasting the load demand, solar power, and EVs charging demand, LSTM performs better than GRU with MSE of 5.2%, 3.6%, and 8.6%, respectively, and for wind power prediction, GRU outperforms LSTM with MSE of 3.9%. Moreover, the results show the robustness of the proposed methodology with optimal production costs of $340686.*

Keywords *- Deep learning, Economic dispatch, Forecasting, Optimization, Unit commitment.*

1. Introduction

For decades, researchers have been working to develop the UC, a vital component of electric power systems' day-to-day security and economic operation. The UC is a programming concern outlined to optimize the hourly timetables of generation units with load variations under diverse constraints and in divergent conditions to help the electrical companies determine when and which generators should run and at what level to fulfil the energy needs. Power systems are evolving at an unprecedented rate, bringing with them new characteristics that are changing the nature of the UC issues [1]. The UC issue might include different kinds of power units, such as thermoelectric, solar, wind energy, hydroelectric, or nuclear energy stations [2]; each of them has its own unique properties of technical qualities, which are determined by the specific conditions of its production. These units are all electrically connected to one another since each one is generating power to satisfy the needs of a particular power load. Grid balancing, minimum up- and down-time, energy generation restrictions, ramp rate, system reserve, and unit frequency have all been taken into account in traditional methods to the thermal-based UC. This is so because the thermal-based UC affects the unit length [3]. The only type of power generating included in the thermal-based UC is thermal production. According to Abujarad in [4], wind turbines and photovoltaic units add extra prerequisites and generate expenses to the UC because of their inherent variability and intermittent nature, while hydroelectric units that are hydrologically and hydraulically associated with each other present considerable impediments to the UC issue. According to the renewables worldwide status report, it is anticipated that the global proportion of renewable energy sources in the power system will continue to climb, eventually reaching 45 percent by the year 2040 [5]. In recent years, an increase in generation from renewable energy sources and an increase in market price demand involvement has made the UC problem more difficult to solve. This is mostly the result of the unpredictability and the high fluctuation of renewable energy sources. In order to ensure the system's reliability in the face of growing real-time uncertainty, it became important to develop an efficient process that can deliver reliable UC outcomes [6]. The UC problem is fundamentally defined as a nonlinear, non-convex, mixed-integer, and large-scale combinatorial optimization issue with constraints [7]. This mathematical formulation is applicable in various scenarios. The non-convexity arises from the binary nature of the on/off decisions.

Furthermore, the nonlinearity is introduced by the generation cost curves and transmission constraints. The presence of both binary and nonlinear elements necessitates the reformulation of the problem as a mixed-integer combinatorial optimization task. As a result, the complexity of addressing the UC problem is substantially heightened. Because of this, academics have been putting a lot of effort into constructing UC algorithms that are both effective and nearly optimal and that can be implemented in large-scale power systems [8]. The literature has used many optimisation methods to find the best answer to the UC problem. Through processing of a collection of input data, these techniques generate the most effective unit schedule as output. Basic to sophisticated metaheuristic methods have been proposed as ways to tackle the UC problem. A big difficulty in the power sector is the UC issue. Many mathematical approaches have been put up to address this time-dependent problem [4]. Historically, the Lagrangian relaxation method was favored for handling UC constraints [9].

The methods for solving the UC problem are broadly categorized into four classes: Dynamic Programming (DP) [10], Mixed-Integer Linear Programming (MILP), decomposition methods, and metaheuristic methods [11]. Due to their ability to tackle challenges on a massive scale, meta-heuristics methods have been increasingly popular in recent years for the treatment of UC issues. Generally, hybrid approaches, such as memetic algorithms and hybrid ant colony optimization, produce higher-quality answers than traditional approaches. It has been pointed out that applying the Lagrangian relaxation algorithm in conjunction with the Memetic algorithm yields the most successful outcome for solving the UC problem [6]. The types of units that are present in the power plant, as well as the technical limitations of those units, can determine which strategy is the most feasible option.

The use of renewable energy sources like wind and solar electricity has become increasingly common in recent years. The benefits are substantial, and they include minimal economic expenses and zero emissions into the environment. It is for this reason that its implementation has kept pace with the global growth of many countries.

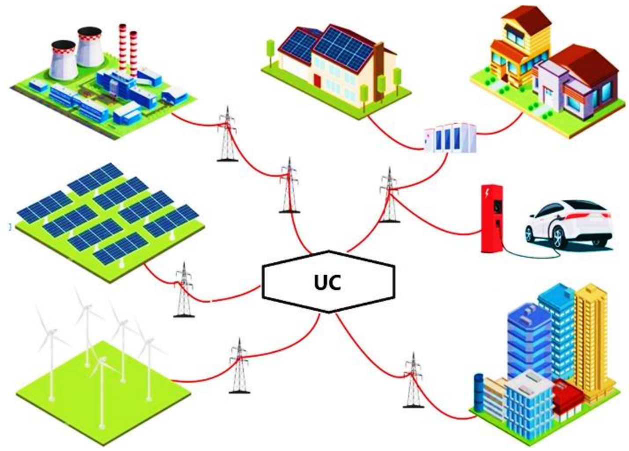

Fig. 1 Integrated power grid in UC planning

While intermittent renewable energy sources have the potential to reduce carbon emissions, the process is riddled with risk. Uncertainties also exist in other power system elements, such as load requirements, generators, and transmission lines (faults and leakages). Uncertainties in forecasting the output of intermittent renewable energy sources, such as wind and solar production, and grid loads may not be taken into account by conventional energy management systems and tools that have been used for generating commitment, dispatch, and market implementation.

These uncertainties present significant risks to the regulation, operation, and reliability of the grid, particularly as the integration of intermittent resources increases. Without a thorough examination of common risks, system operators have limited means to evaluate the probability of issues arising and to implement necessary countermeasures. A computational approach to include these uncertainties and prevent the system's potential dangers is, therefore, urgently needed in the sector. Over the past few decades, the Earth's climate has undergone a dramatic shift. Renewable energy has piqued researchers' attention due to the world's increasing demand for energy and the depletion of conventional energy sources (oil, coal, and natural gas). Since wind power is so readily available, it has become one of the most prominent and frequently used renewable energy sources. Because of advances in technology, wind power has become a vital part of the international power system and may one day completely replace traditional energy resources used for energy generation in the future [12].

The growing usage of wind power has posed numerous operational and strategic issues around the world due to the stochastic character and intermittency of the wind. Wind energy prediction models and procedures have had to be improved in accuracy in order to meet these challenges. Thus, wind power prediction has been studied and refined throughout the last few decades to cope with issues that occurred as wind power became more widely used in global energy systems.

In addition to forecasting wind generation, prediction models help control power networks and arrange electricity markets [12]. Global investors are most interested in solar photovoltaics (PV), and Green Banks are at the front of the low-carbon energy uprising, which will help mitigate climate change impacts while also addressing consumers' priorities. Despite experiencing a decade of rapid expansion, solar photovoltaic (PV) technology continues to exhibit growth, as reported by the International Energy Agency (IEA). This growth has resulted in a total PV capacity of 398 GW, accounting for approximately 2% of the world's total energy production [13].

However, the widespread adoption of solar PV is constrained by the unpredictability of weather conditions and the fragility of infrastructural grids despite the presence of regulations, innovations, and corporate commitments. Forecasting systems, which provide PV power projections across various temporal and spatial horizons, can support the expansion of solar PV and ensure the efficiency of energy transition planning between intermittent and conventional energy sources. As a result, the grid operator can benefit from PV power forecasting since it provides information on the projected energy output of solar PV systems, which in turn facilitates more efficient UC scheduling and planning [13].

Such systems are highly invasive into the real power system asset since PV-produced power is mostly dependent on the weather which is by nature quite unpredictable. The amount of power PV plants produce is influenced by a number of meteorological variables, including solar radiation, air temperature, cloud variation, wind speed, relative humidity and wind speed. Large databases, many input-output observations, inaccurate measurements, and multi-step applications are among the challenging scenarios for PV output power forecasting. However, precise forecasts save management money on penalties for differences in power output. The precision of the forecast may usually be increased by pre- and post-processing historical and projected PV output power. [14].

Notwithstanding these developments, there is still a study gap because of the complexity of the UC problem in modern power networks with increasing renewable energy and EV penetration. The growing need for EV charging and the intermittent and stochastic nature of renewable energy sources produce uncertainties that are intractable by conventional UC methods. Furthermore, the literature lacks many UC optimization models that precisely estimate the supply, load, and demand for EV charging from renewable energy. A variety of PV power prediction techniques have been developed in the literature, which can be categorized into four main groups based on the forecast timeframe. These categories are very short-term predictions, ranging from seconds to minutes; short-term predictions, covering up to 24 to 72 hours in advance; medium-term predictions, spanning from days to weeks; and long-term predictions, extending from months to a year or more. For instance, very short-term predictors are utilized for the control and management of PV systems, power market operations, and microgrid administration. Power system operations, ED, UC, etc., are all managed on short timescales. It is common practice to plan for and perform maintenance on PV plants over a medium- to long-term time frame [15]. Time horizon and time resolution, climate, location, accessibility, and quality of data are the most important aspects influencing the accuracy of forecasters used to anticipate the electricity generated by PV plants.

Moreover, Load forecasting, which primarily relates to anticipating electricity load and energy, is conducted in all segments of the electrical power market, including the generation, transmission, and distribution of electricity. Recent innovations in the electrical system, which have integrated multiple power sources, including renewables, have made load forecasting more challenging.

The widespread adoption of renewable energy sources such as solar, wind, and thermal has ushered load forecasting into a more complex phase. Professionals in the power industry now encounter an increasingly intricate context for analyzing and managing electrical generation, supply, reserves, and demand. This complexity arises from the nonlinearity and non-stationary nature of load performance, necessitating a thorough examination of various factors that directly or indirectly influence the forecasting process. Despite the utility of forecasting methods, achieving reliable predictions remains difficult [16].

On the other hand, EVs have captured the attention of policymakers, car manufacturers, and energy providers alike. Electric vehicles are viewed as a practical response to the problems of declining fossil fuel reserves and increasing pollution. In particular, carbon dioxide emissions are thought to be reduced as EVs gain in popularity [17]. Additionally, the scale of EVs will rise rapidly due to lowering battery prices and government subsidies. However, major challenges are posed to the electrical infrastructure by the increasing charging demand caused by the rapid proliferation of EVs. The reliability of the distribution network is impacted in a number of ways by the EV charging load, including a decrease in power quality and the challenge of optimizing and monitoring grid operations [18]. Research on EV charging load forecasting is conducted to facilitate EV growth and to ensure the power grid is operated economically and reliably [19].

Three primary categories of EV charging load forecasting techniques are presently probability models, time series models, and machine learning models. In the probabilistic modelling approach, future load is predicted by Monte Carlo simulation after probabilistic models of residents' charging and travel behaviour are constructed using statistics and queuing theory. Short-term EV charging load forecasting is currently frequently done with machine learning and time series methods. [17], [20]. This article makes use of some abbreviations, along with their corresponding symbols and abbreviations are illustrated in Table 8. Significant advantages of the growing use of renewable energy sources like solar and wind power include zero emissions and low economic expenses.

Their intermittent and unpredictable character makes their integration into power systems difficult, though. Since wind power is stochastic, wind energy prediction models were developed to help with power network management and market structure. In the same vein, by offering estimates of PV power generation, solar photovoltaic (PV) forecasting systems support energy transition planning. With the addition of renewable energy sources, load forecasting, which is essential for production, transmission, and distribution, has grown more difficult. Furthermore, the electrical infrastructure is being challenged by the growth of EVs, which makes accurate EV charging load projections necessary to guarantee stable and economical grid operation. This work provides a new answer to the problems presented by contemporary power systems by integrating sophisticated forecasting techniques into the UC problem, therefore building on the results of previous research.

2. Research Contributions and the Novelty of the Study

In response to issues like global warming, rising carbon emissions, rising demand for high-quality power, and running out of fossil fuels, countries are required to boost the number of renewable energy sources in their electricity networks. Using renewable energy sources in a wide range, on the other hand, can cause power systems to run into some serious problems. One of these problems is that the shapes of the renewable energy sources generation and load are not the same. For example, solar power plants make the most electricity at noon, but the peak load can even happen at night. This can be negative in two ways.

First, the operator will have to cut down the amount of energy coming from renewable sources because the consumers may be getting all of their power from thermal generation units that can't ramp down any further or fast enough. Also, this mismatch can cause the power to go out during peak times. Moreover, when a large number of EVs are linked to the grid, the initial and operating costs will rise dramatically if the EV load is added to the traditional load as a pure charging load.

The financial implications of UC and the uncertainty in estimating renewable energy sources, load, and EV charging station demand are the primary centres of this analysis. With the help of an accurate forecasting technique, this study will help planners foresee tomorrow's power system performance. Here are some useful outcomes that may emerge from this research:

- This study has the potential to aid energy supply firms in reducing operating expenses and developing trustworthy short-term planning strategies.
- Ensure network reliability since an adequate number of units will be dedicated to meet demand; consequently, the most cost-effective unit, which can satisfy demand while minimizing losses and fuel costs, will be used to fulfil it.

The novel aspect of this research was exploiting machine learning techniques to forecast the next day's performance of renewable energy sources, load, and EV charging station demand, all of which could be used in the UC optimization process. Furthermore, the suggested model can provide a more stable and safe power system by lowering the prediction uncertainty.

3. Problem Formulation and Unit Commitment Identifications

3.1. Objective Function

The main objective of the UC is to reduce operating costs, which include fuel costs as well as starting and shutdown costs [21].

$$Min \sum_{i=1}^{NG} \sum_{t=1}^{NT} [F_{ci}(P_{it}) * I_{it} + SU_{it} + SD_{it}] \quad (1)$$

$$F_i(P_i) = \alpha_i + \beta_i P_i + \gamma_i P_i^2 \quad (2)$$

where the fuel cost for generating units is represented by the first term, startup costs are represented by the second term, and the shutdown cost is represented by the third term. $F_i(P_i)$ is the cost function, and α_i, β_i and γ_i are the generator i cost coefficients. Several constraints must be met during the optimization process, including:

3.1.1. Generator Limitations

Because the generator cannot operate lower or above certain power levels, each generator has a minimum and maximum power output. The following equation illustrates this concept:

$$P_{i,min} * I_{it} \leq P_{it} \leq P_{i,max} * I_{it} \quad (3)$$

3.1.2. System's Power Balance

In order to ensure that the total output power of all of the available generators is sufficient to meet the load demand over the course of each time period, the following equation must be used, which takes into account the amount of power that is lost in the grid.

$$\sum_{i=1}^{NG} P_{it} * I_{it} + \sum_{i=1}^{NW} P_{W,it} + \sum_{i=1}^{NPh} P_{Ph,it} = P_{D,t} + P_{EVS,t} + P_{L,t} \quad (4)$$

In this study, the generating units comprise thermal solar systems, power stations, and wind farms as renewable energy sources. Additionally, the consumption term encompasses demand from EV charging stations, load demand, and power losses within the grid.

3.1.3. Minimum ON and OFF Time

Generating units must usually be operated for a minimum of a predefined duration of time before being shut off, either by engineering considerations or by the manufacturer's specifications. Comparably, as the following equations illustrate, each generating unit must have as little downtime as possible between each subsequent operation:

$$\left[X_{i(t-1)}^{on} - T_i^{on}\right] * \left[I_{i(t-1)} - I_{it}\right] \geq 0 \quad (5)$$

$$\left[X_{i(t-1)}^{off} - T_i^{off}\right] * \left[I_{it} - I_{i(t-1)}\right] \geq 0 \quad (6)$$

3.1.4. Ramping Limitations

Thermal units cannot instantly increase or decrease their electricity production when transitioning between time periods. The process of gradually increasing output power is termed "ramping up," while the gradual reduction of output power is termed "ramping down," as demonstrated in the following equations:

$$P_{it} - P_{i(t-1)} \leq \left[1 - I_{it}\left(1 - I_{i(t-1)}\right)\right]UR_i + I_{it}\left(1 - I_{i(t-1)}\right)P_{i,min} \quad (7)$$

$$P_{i(t-1)} - P_{it} \leq \left[1 - I_{i(t-1)}(1 - I_{it})\right]DR_i + I_{i(t-1)}(1 - I_{it})P_{i,min} \quad (8)$$

3.1.5. Spinning Reserve

Once the output of the generators connected to the grid has been regulated, the extra producing capacity can be used. The following equation illustrates how more torque is applied to the turbine rotors to accomplish this procedure:

$$\sum_{i=1}^{NG} R_{S,it} * I_{it} \geq R_{S,t} \quad (9)$$

3.1.6. Operating Reserve

As in the following equation, it is the power plant's ability to temporarily meet demand in the case of supply distribution or when the unit efficiency decreases:

$$\sum_{i=1}^{NG} R_{O,it} * I_{it} \geq R_{O,t} \quad (10)$$

The operating system is affected in a variety of ways by the network component's activity. For instance, when transmission lines are considered during formulation, some consequences are visible, such as an increase in the total demand for generating power as a result of real power losses. In order to discover the best method to check the system security, particularly in large-scale power grids, it is vital to evaluate the effects of the network elements. Table 1 shows a summarized comparison between different optimization techniques that have been studied recently.

Table 1. Comparison between different optimization techniques in solving uc problem

Ref.	Used Methods	Time Horizon	Model Description and Outcomes
[24]	GA, SFLA	Short-term	To address UC, GA is applied. The UC problem was formulated after taking into account the costs of production, startup (both hot and cold), and downtime. GA outcomes are compared with SFLA. The results show how GA is a better solution to the UC problem than the other methods.
[25]	DP, PSO	Short-term	This paper contrasts the DP and PSO methods for solving the UC problem in the microgrid main power management system and reducing fuel costs and carbon dioxide emissions. Based on the simulation results, it is clear that the PSO method is superior to the DP method in terms of solving UC problems.
[26]	PSO–GWO, PSO, DP, LR	Short-term	This paper solves a single-area UC problem using a novel PSO technique. Suggested NPSO and hybrid PSO–GWO algorithms have successfully evaluated the standard IEEE bus system. The outcomes are for 14-bus, 30-bus, and 10-generating unit models. Using NPSO outperforms conventional algorithms.
[27]	PSO, Lambda Iteration	Short-term	The PSO approach was implemented in the IEEE 30 bus system, which resulted in a reduction in the cost of fuel. The effectiveness of the PSO Method is demonstrated by comparing its results with those obtained using the Lambda Iteration Method.
[28]	DP, PL-GA, PL-PSO	Short-term	This study compares the results of the PL-PSO, PL-GA, and DP approaches for scheduling thermal units while incorporating renewable energy sources. The results show that PL-PSO is capable of finding a good solution in a reasonable amount of time and has a high chance of convergence.
[29]	ACS, AS, DP	Short-term	As a case study, an IEEE 30-bus system was simulated, and optimal thermal UC of power systems was performed using an ant colony system (ACS). When compared to the AS and DP approaches, the ACS strategy performed better.
[30]	BGWO, PSO, GA	Short-term	The Binary Gray Wolf Optimization (BGWO) method is investigated in the context of UC with regard to load consideration and wind power prediction uncertainties. Two standard algorithms, PSO and GA, are used to compare the outcomes. When compared to two other methods, the results demonstrate that the BGWO method performs better.

Two widely used UC approaches are power flow-based ED and B-coefficient matrix-based ED for transmission lines. Convergence risk and time commitment make the power flow-based ED technique inappropriate for real-time applications.

Since B coefficients vary according to the load demand, more than one frame of B coefficients must be created during the particular load cycle for B coefficient-based ED to be effective [22]. The network losses in this research are determined using the B-coefficient approach.

Equation (11) from the conventional power losses formula, used by Kron and Widely [23], illustrates how to obtain the B-coefficient matrix.

$$P_L = \begin{bmatrix} P_{G_1} & \cdots & P_{G_i} & \cdots & P_{G_{NG}} \end{bmatrix} \begin{bmatrix} B_{11} & B_{1j} & B_{1NG} \\ \vdots & \vdots & \vdots \\ B_{1i} & B_{ij} & B_{iNG} \\ \vdots & \vdots & \vdots \\ B_{NG1} & B_{NGj} & B_{NGNG} \end{bmatrix} \begin{bmatrix} P_{G_1} \\ \cdots \\ P_{G_j} \\ \cdots \\ P_{G_{NG}} \end{bmatrix} + \begin{bmatrix} P_{G_1} & \cdots & P_{G_i} & \cdots & P_{G_{NG}} \end{bmatrix} \begin{bmatrix} B_{01} \\ \cdots \\ B_{0i} \\ \cdots \\ B_{0NG} \end{bmatrix} + B_{00} \quad (11)$$

4. Day Ahead Forecasting Models

4.1. Forecasting Models

Due to the intermittency of power production by renewable sources, it is essential to have an efficient electricity prediction in order to achieve effective energy monitoring and planning. Scholars have created a variety of forecasting techniques for load prediction and renewable energy sources based on the features of these factors, such as the speed of the wind, solar irradiance, temperature, etc.

The use of deep learning for energy forecasting, whether it is wind energy, solar energy, or load, typically proceeds in three primary processes, as shown in Figure 2. The initial step of the data analysis process is the data pre-processing step.

During this step, the input data is extricated and normalized, and it is also separated into the testing, validating, and training datasets. Following this, model training is carried out in order to construct forecasting models that are valid and acceptable. In the final step, forecasting is carried out by utilizing the trained model, and the results are frequently presented.

The most widely used deep learning model architectures, which are mentioned here, are those which are highly suggested for demand foresting at Wind, Solar, load, and EVs stations.

In the literature, various forms of Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and their hybrid models are commonly used. The technical aspects of these models' internal workings and how they're trained are discussed in the following sections.

Recurrent Neural Networks (RNN) are a family of artificial neural networks used specifically to model sequential or time-series data. An intrinsic temporal information present in time-series data is invisible to a simple neural network.

A time-step edge offers a sense of time to RNNs, which are reinforced over basic neural networks. A neuron forms a cycle of connections to itself by means of recurrent edges that connect the succeeding phases. These self-connected loops represent the many time stages.

The fundamental construction of a recurrent unit is depicted in Figure 3. Every hidden unit has a connection to a hidden phase vector (h_t) that begins at the start stage with a value of zero.

That has a similar length as the number of inputs, and it keeps the beneficial data that has been computed and seen in the previous run. The hidden vector at the instance of time ($t-1$) is recalled by the hidden state using the feedback links when the hidden state is accessed at the time instance (t).

In this manner, the hidden state vector from the time instance before this one is combined with the present input, which is x_t, in order to do the calculation, it is necessary to determine the hidden state at the time instant (t).

As a consequence of this, the last output ($\hat{y}_t$) is affected not only by the information that is currently being entered but also by the information that has been stored in the past. The following equations provide a mathematical representation of the process:

$$h_t = f(W_{hx}x_t + W_{hh}h_{t-1} + B_h) \quad (12)$$

$$\hat{y}_t = f\left(W_{yh}h_t + B_y\right) \quad (13)$$

Where $f(.)$ is the activation function, W_{hx} is the weight matrix between the input and the hidden layer, and W_{hh} is the weight matrix between the hidden layer and itself from previous time steps. The bias vector can be represented by B_h and B_y. LSTM networks are an advanced form of RNNs that have shown useful in predicting time series. It has been observed that RNN networks, because of the vanishing gradient and the gradient explosion problem, are unable to deal with long-term correlations in data. Indeed, Sepp Hochreiter and Jürgen Schmidhuber's development of LSTM networks has eliminated this problem [32]. By including memory gates and cells, which control the network's data flow, the LSTM structure solves the problem of a vanishing gradient.

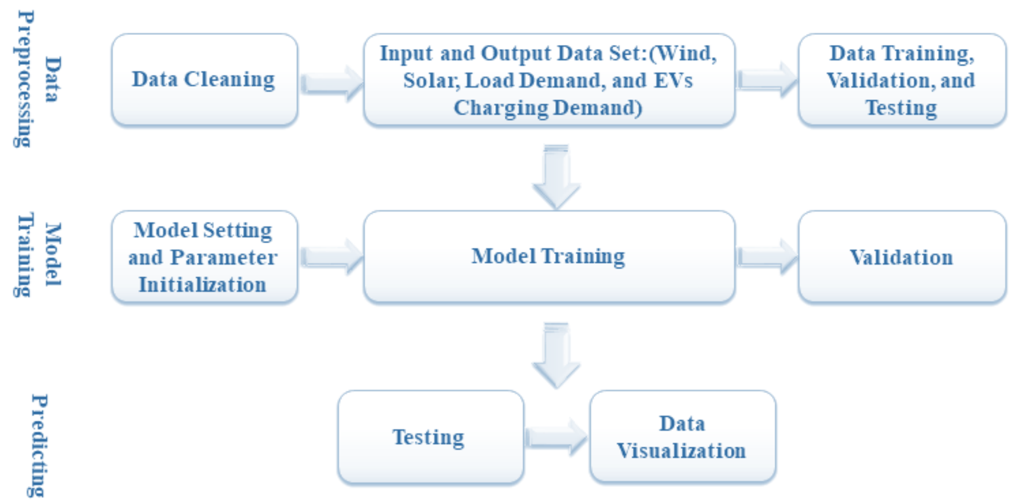

Fig. 2 Predicting Flowchart for Wind, Solar, Load Demand, and EVs Charging station demand using deep learning techniques [31]

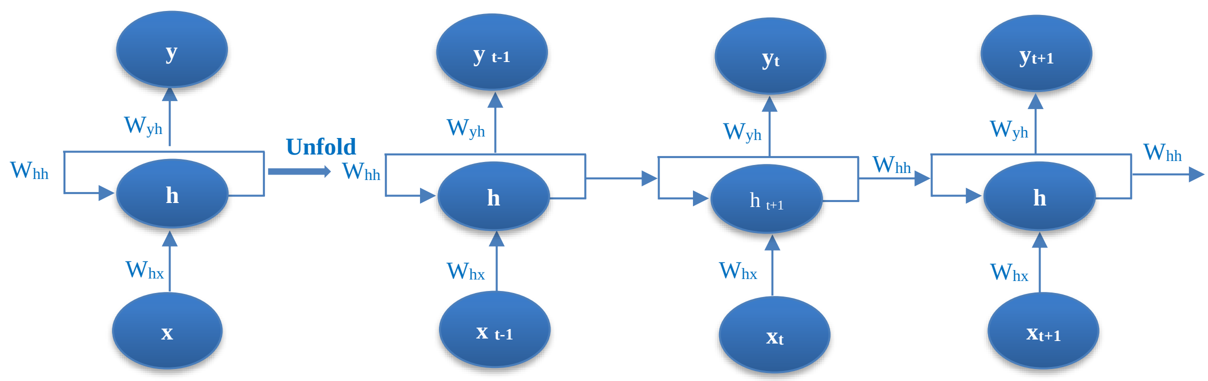

Fig. 3 RNN folded and unfolded structure [31]

The fundamental structure of an LSTM cell and how data propagates through the LSTM network are depicted in Figure 4. It consists of the following gates: a forget gate, an input gate, and an output gate. Following is a list of the mathematical expressions that can be used to represent their method of operation.

$$f_t = \sigma(W_{fh}h_{t-1} + W_{fx}x_t + b_f) \quad (14)$$

$$i_t = \sigma(W_{ih}h_{t-1} + W_{ix}x_t + b_i) \quad (15)$$

$$\tilde{c}_t = \tanh(W_{\tilde{c}h}h_{t-1} + W_{\tilde{c}x}x_t + b_{\tilde{c}}) \quad (16)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \quad (17)$$

$$o_t = \sigma(W_{oh}h_{t-1} + W_{ox}x_t + b_o) \quad (18)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (19)$$

At time *tt*, the input, recurrent data, and output of each cell can be represented by x_t, h_t, and o_t respectively. The forget gate is denoted by f_t and c_t represents the state of the LSTM cell. The network weights are represented by W_i, $W_{\tilde{c}}$, and W_o the operator '.' denotes the element-wise multiplication of two vectors and b_f, b_i, and $b_{\tilde{c}}$ are the system's biases.

The input gate is responsible for deciding which new information can be registered in the cell state and which data can be produced based on the current state of the cell whenever the cell state is updated. The forget gate is able to decide what information from the current state of the cell can be forgotten about and stored elsewhere. When the forget gate, denoted by f_t, is set to a value of 1, and it stores this information, but when it is set to a value of 0, it deletes all of the data. According to the findings, the most important components are the forget and output gates, and the findings also showed that the performance of the network would suffer greatly if either of those components were removed. In addition, the number of parameters as well as the computational cost, can be decreased without causing a major decrease in the network's overall performance by making small adjustments to the connected input and forget gates. As a result of the enormous capabilities it possesses, LSTM has emerged as the central component of deep learning and has been used in a wide range of endeavors. One of the most popular RNN versions, the gated recurrent unit (GRU), was developed by Cho et al. (2014) [33].

GRU can identify long-term relationships in data and tries to solve the basic RNN's vanishing gradient issue. Given that both LSTM and GRU have comparable working mechanisms and architectures, they can both be seen as variations of one another.

GRU uses a gating method to control the information flow, much like LSTM. The input and forget gates are combined into one update gate in GRUs. GRU, in contrast to LSTM, only has two gates: an update gate and a reset gate. These two gates determine what historical material should be erased and what information should be kept that is still useful. The following is a description of the mathematical terms used to describe how a GRU operates.

$$r_t = \sigma(W_{rh}h_{t-1} + W_{rx}x_t + b_r) \tag{20}$$

$$z_t = \sigma(W_{zh}h_{t-1} + W_{zx}x_t + b_z) \tag{21}$$

$$\tilde{h}_t = \tanh(W_{\tilde{h}h}(r_t \cdot h_{t-1}) + W_{\tilde{h}x}x_t + b_z) \tag{23}$$

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{24}$$

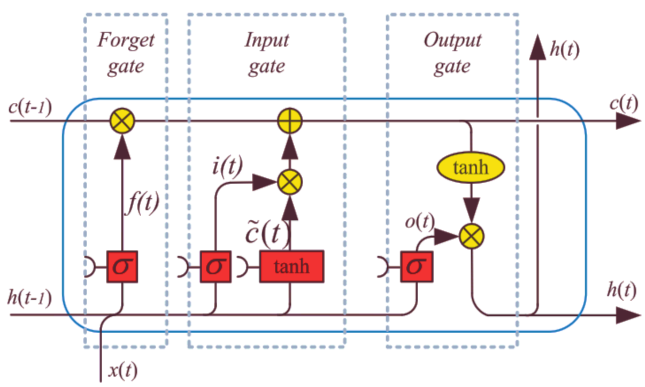

Fig. 4 LSTM Structure [34]

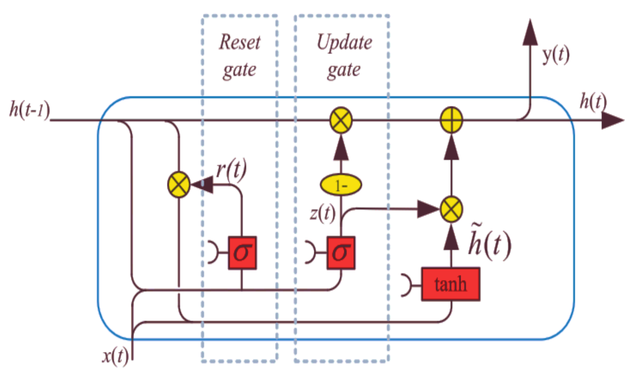

Fig. 5 GRU Architecture [34]

The GRU cell simplifies the LSTM model by combining the input and forgets gates into a single update gate, thereby reducing the number of required parameters. In a GRU cell, there are only two gates: the update gate and the reset gate.

This design allows for the conservation of a single gate signal along with its associated properties. Essentially, the GRU functions as an LSTM with a combined forget gate. However, a single GRU cell is less effective than a full LSTM due to the presence of only one gate. Figure 5 illustrates the GRU structure.

4.2. Forecasting Model Evaluation

The purpose of an efficiency evaluation is to assess the level of essentiality; that's the case. There are a number of points in model creation where the performance evaluation is useful. Some examples of this kind of evaluation include testing the model as it is being trained, evaluating how well it does in the face of unknown conditions or data, and comparing different models.

Performance comparison, however, is complicated by factors such as the length of time over which forecasts are made, the specifics of the models used, and the climatic circumstances at each site. For example, Comparisons between observed and forecasted sun irradiation are used to determine how well a forecasting system is doing [32].

4.2.1. Mean Absolute Error (MAE)

The value of this evaluation technique is ascertained by averaging the absolute discrepancies between the actual and expected values. Every disparity in the data is given equal weight in this method.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |\hat{y}_i - y_i| \tag{25}$$

4.2.2. Mean Square Error (MSE)

This metric is calculated by taking the difference between the actual and predicted values, squaring it, and then averaging these squared differences.

Larger discrepancies are penalized more heavily by this metric.

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (\hat{y}_i - y_i)^2 \tag{26}$$

4.2.3. Root Mean Square Error (RMSE)

It is applied in prediction model accuracy measurement. It has to be ascertained by considering the square root of the mean squared variances between observed and predicted values.

This is the reason RMSE is well acknowledged as a crucial component of performance assessment measurement.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (\hat{y}_i - y_i)^2} \tag{27}$$

5. Methodology

5.1. Prediction Model

The methodological approach consists of doing a comprehensive literature analysis in order to locate the previously published studies on the subject of energy forecasting that make use of big data and deep learning.

When conducting a literature review, it is necessary to consult a wide variety of data sources in order to compile relevant information. A search strategy that involves the use of certain keywords is required for this. The essential parts of the conference proceedings and the articles published in peer-reviewed journals are parsed out with the use of search items located in a variety of databases and publications.

A discussion of some of the pertinent book chapters follows. This research takes into account relevant industry reports in the realm of energy prediction utilizing big data and deep learning as well.

The data on wind, solar, and load production that was generated in France between January 1, 2013, and December 31, 2016, and was obtained from the Transparency platform of the Figshare database, is utilized in this analysis. These data are used in this investigation, and 80% of the data in this set is used for training purposes. The remaining 20% is used as the sample for the test.

Changes on an hourly basis can be seen in these statistics. The input values, such as the current date, are used by the machine learning algorithms to determine the output value, which is the total amount of power. There have been concerted efforts made to find a connection between the day and the amount of power.

As shown in Figure 6, rolling deep learning-based short-term forecasts of wind energy, solar energy, and load demand—including EV charging station consumption involve the following steps:

Step 1: Train deep learning models using historical wind power, solar energy, and load demand data, including EV charging station consumption.

Step 2: Tests for constant values, physical minimum and maximum limits, and missing data identification can help to remove anomalies from the training data. Following completion of all quality checks on the training data, the average of the four most recent timestamps has been used to fill in the missing values. The model-building procedure then uses pre-processed training data to educate the model on how to spot patterns in the data.

Step 3: If there was a last intraday update less than 24 hours ago, update the training data with real energy production data from the chosen source. The intraday prediction schedule is updated as a result of this step, forcing the forecast model to find new patterns.

Step 4: An evaluation of the prediction model's efficacy is performed by comparing the predicted output of the selected model with the measured values of power generation and consumption in the system.

Step 5: When comparing the anticipated output power values with the actual system power levels, the typical comparison matrices such as MAE, MSE, RMSE, and accuracy are utilized to make the comparison.

5.2. UC Model

Uncertainties are factored into the calculation in some kinds of UCs, including the ones described in this study. The use of stochastic UC has been approved. This is the approach that should be taken in order to apply fuzzy analysis to UC.

It is assumed a few different situations, each of which has a certain probabilistic model, then minimize the expected value of the expense multiplied by each frequency. The objective function of the optimization problem was displayed by equations (1) and (2).

One of the heuristic optimization methods that is derived from the social-psychological theory is known as Particle Swarm Optimization (PSO), which was initially presented to the public by Kennedy and Eberhart.

Through the process of adaptation, it has been discovered that PSO is capable of addressing problems with nonlinearity and non-differentiability, as well as those with many optima and large dimensionality. It is easier to implement than other optimization algorithms and has the ability to provide high-quality solutions that have steady convergence characteristics. These are only two of the many benefits it offers over its competitors [33].

When it comes to the resolution of UC problems, one of the most appealing aspects of using PSO algorithms is how quickly they converge numerically and how simple they are to implement. In addition, the PSO algorithms that have been proposed can simply be expanded in order to handle a new profit-based UC problem in an environment that is competitive. UC arranging online plans for generators in a power system to fulfill demand is essential to its safe, effective, and economical everyday operations. Clashing demands for supply security at low cost hinder this.

Given enough computing time, a sustained study has yielded optimal methods. Figure 7 represents the proposed methodology for this study, starting from forecasting the day ahead system parameter to be integrated with the planning system.

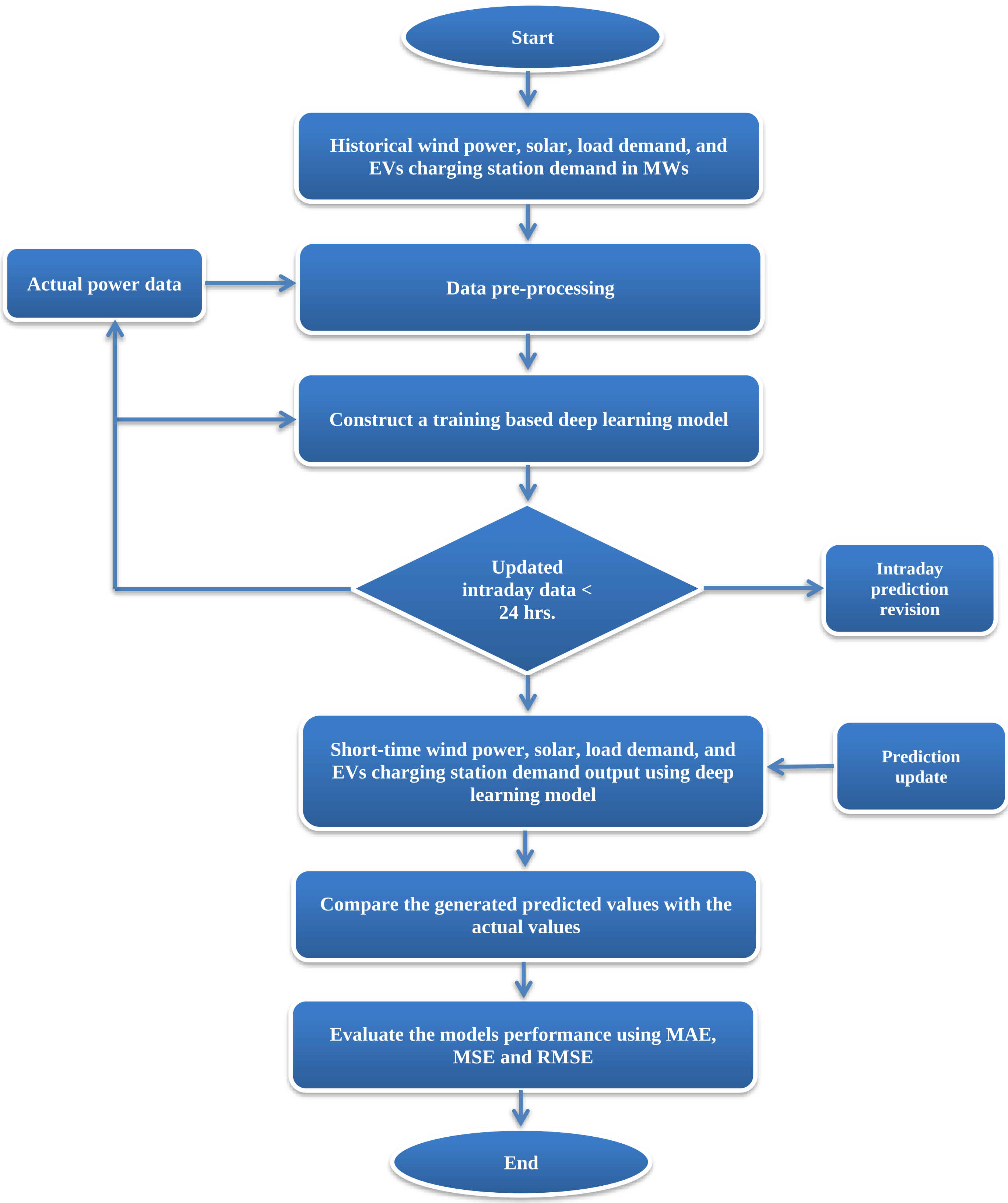

Fig. 6 Deep learning techniques forecasting flowchart

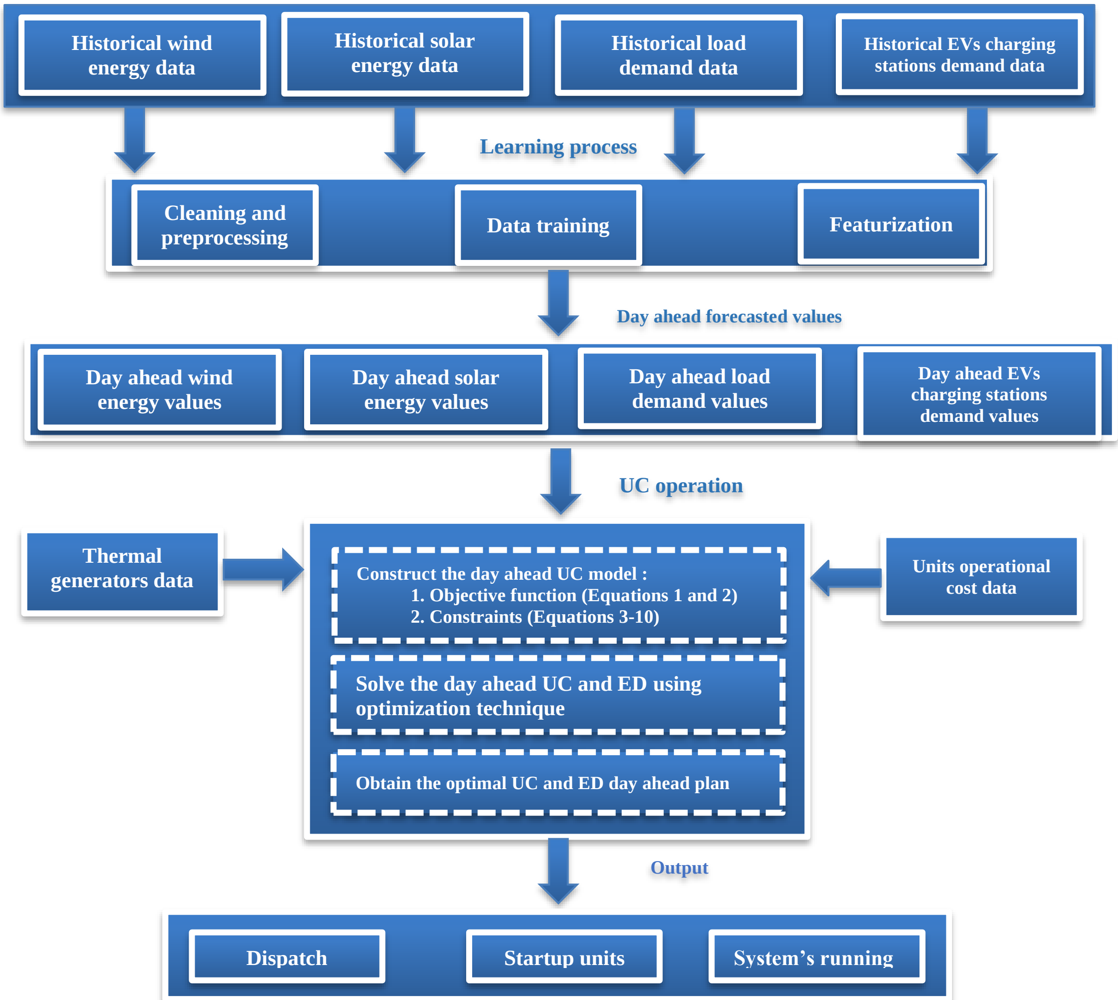

Fig. 7 Flowchart of the integrated UC optimization problem

6. Case Study

For the purpose of planning the power system's day-ahead performance, a 24-bus test system is utilized. The proposed methodology is explained using the 24-bus system that can be seen in Figure 8. The infrastructure has ten thermal generating units, in addition to a wind farm, a PV Station, and electric vehicle charging stations that are dispersed among the load buses. The buses numbered 1, 2, 7, 13, 15, 16, 18, 21, 22, and 23 each have one thermal unit. The wind farm is located on bus 8. Bus 19 has the PV station.

The data concerning the generators and their operating costs can be found in Table 2. The wind, solar, and load demand data were collected in France during 2013-2016 [35]. For EVs charging demand, data is collected in real-time by many charging stations that are participating in the energy Pilot under the SOFIE EU project (GA n.779984) [36]. Figure 9 summarizes the historical energy data for the load demand, including the EVs charging demand in addition to the used sources of renewable energy.

7. Results and Discussions

7.1. Numerical Simulations

The LSTM and GRU algorithms, implemented in Python, are used to predict the next day's performance of the load demand, EV station demand, wind power, and solar power. The results of the previous three years are averaged for use in making predictions about the upcoming day. Table 3 represents a comparison between the performance of the two forecasting methods in terms of MAE, MSE, and RMSE as the most reliable evaluation methods. As illustrated, for load demand, solar power, and EVs charging demand, LSTM outperforms GRU.

However, in the case of predicting the performance of day ahead wind performance, GRU performs better than LSTM. As a result, the forecasted wind values have been taken from the GRU model, and the other predicted values have been taken from the LSTM model, which is shown in Table 4. Because PSO is used for effective unit commitment optimization, advanced forecasting models (LSTM and GRU) that improve accuracy by capturing temporal dependencies and non-linear patterns, and thorough scenario analysis to account for the intermittencies of renewable energy sources are integrated, the study achieves better results than state-of-the-art techniques. With an ideal production cost of $340,686, the model solves a crucial difficulty that is sometimes disregarded by conventional techniques. Modern power systems find the method more successful because of its mix of sophisticated forecasting, strong optimization, and comprehensive system integration, which leads to increased accuracy, dependability, and cost efficiency.

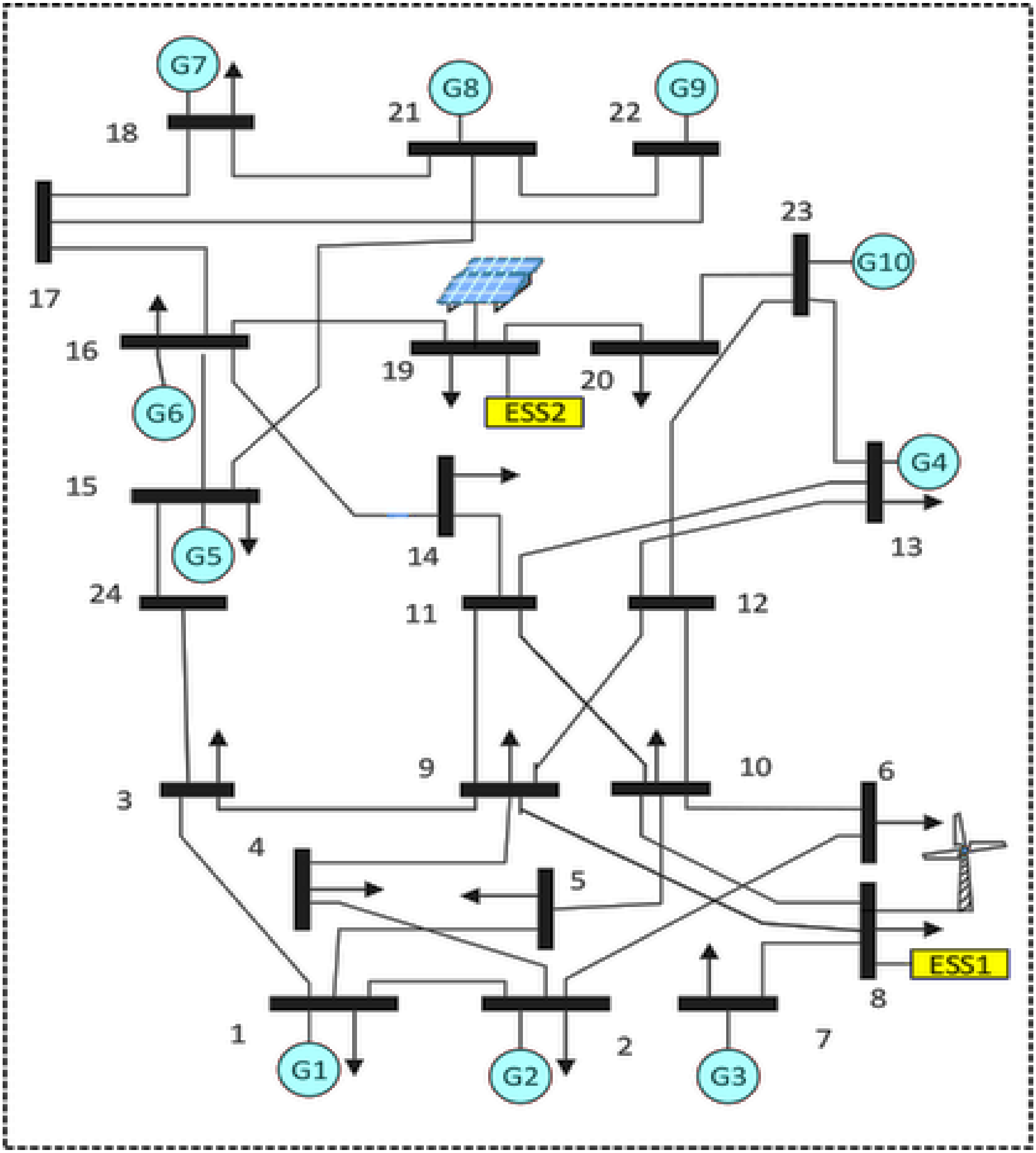

Fig. 8 IEEE 24 Bus test system single line diagram [37]

Table 2. Thermal units data [27]

Unit	Bus	Pmin (MW)	Pmax (MW)	Min ON (h)	Min OFF (h)	Ramp up	Ramp down	Cost Coefficients			Start up cost	Shut down cost
								α	β	γ		
1	1	125	700	8	8	50	75	1000	16.19	0.48	4500	0
2	2	160	750	3	3	80	100	970	17.26	0.31	5000	0
3	7	175	800	5	5	100	120	700	16.60	2	550	0
4	13	120	600	5	5	80	100	680	16.50	2.11	560	0
5	15	100	750	6	6	50	75	450	19.70	3.98	900	0
6	16	160	700	3	3	80	100	370	22.26	7.12	170	0
7	18	160	850	3	3	75	50	480	27.74	0.7	260	0
8	21	160	800	1	1	100	80	660	25.92	4.13	30	0
9	22	260	500	2	2	75	80	665	27.27	2.22	30	0
10	23	360	900	1	1	100	50	670	27.79	1.73	30	0

Table 3. A comparison between three evaluation methods for LSTM and GRU

	LSTM			GRU		
	MAE (%)	MSE (%)	RMSE (%)	MAE (%)	MSE (%)	RMSE (%)
Load Demand	5.2213	0.3736	6.1122	6.0914	0.4833	6.9519
Wind Power	4.0621	0.2998	5.4753	3.9311	0.2801	5.2924
Solar Power	3.6049	0.3908	6.2513	3.8597	0.4379	6.6105
EVs Charging Stations Demand	8.6508	1.5263	12.3543	8.9311	1.59762	12.6396

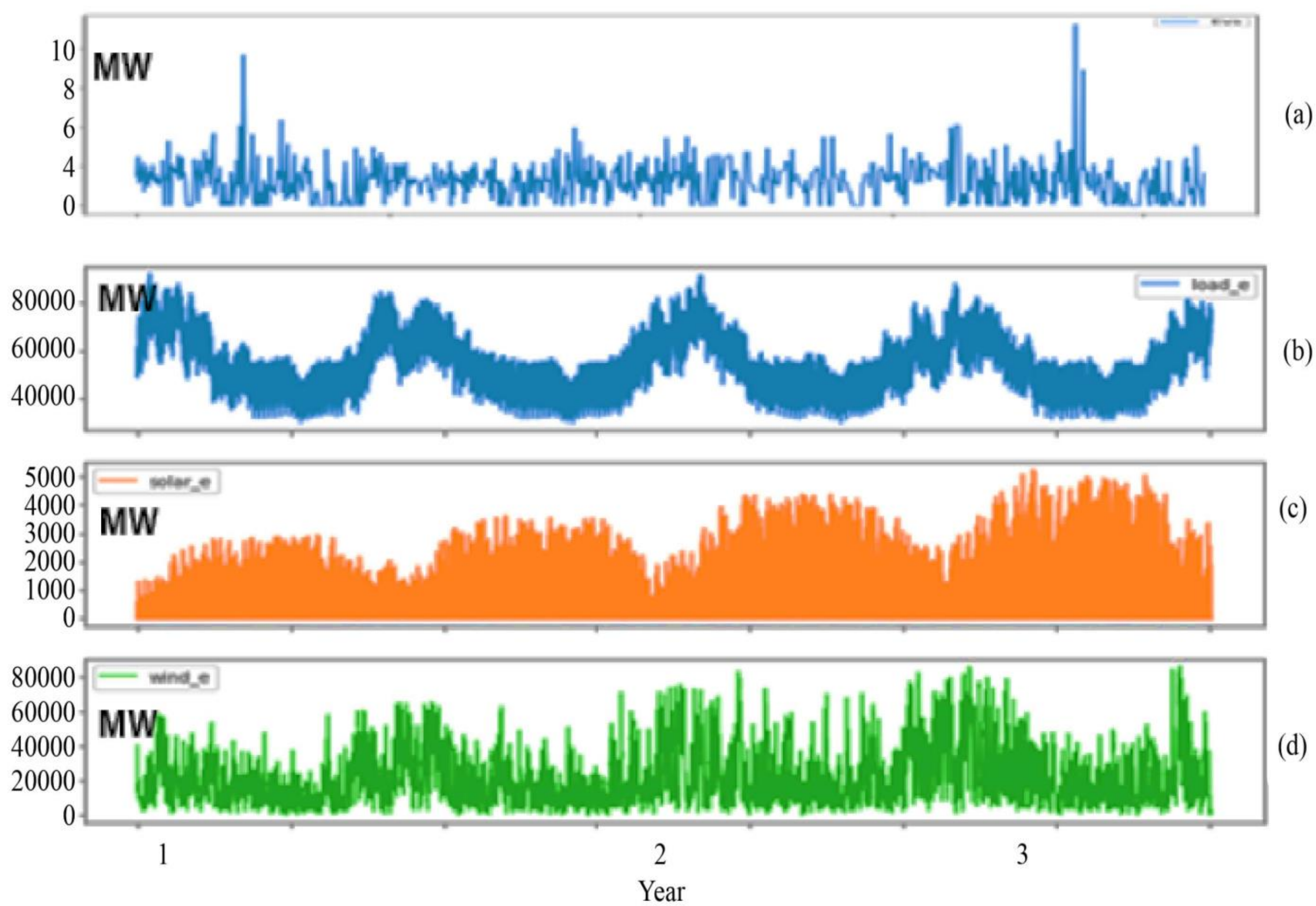

Fig. 9 Historical data for (a) EVs Energy demand, (b) Load demand, (c) Solar energy production, and (d) Wind energy production

Table 4. Day ahead performance of the UC input parameters

Hour	Load Demand (MW)	Wind Power (MW)	Solar Power (MW)	EVs Charging Stations Demand (MW)
1	4991.6797	221.07263	0	9.6344
2	4761.3414	223.11922	0	10.908
3	4527.0934	226.53581	0	9.104
4	4475.0633	228.67395	0	10.646
5	4677.3004	230.20168	0	9.955
6	4969.782	231.53938	8	8.909
7	5103.3207	230.57283	43. 214	8.873
8	5106.823	230.90744	85.23564	9.793
9	5073.3035	229.79712	120.36545	10.244
10	5140.014	226.16425	185.28214	11.851
11	5256.504	220.88106	573.5594	11.082
12	6630.692	215.33221	843.61835	9.593
13	6019.0906	210.35564	912.8525	9.207
14	5656.2246	207.77528	810.895	9.812
15	5375.035	207.13455	641.68146	10.312
16	5131.441	207.51205	411.3378	11.593
17	4997.6023	210.09018	159.26357	10.915
18	4985.5008	212.45564	0	11.446
19	5005.2035	215.67271	0	10.209
20	5044.8273	219.76074	0	10.136
21	5075.1004	224.25682	0	10.098
22	5136.32	227.58528	0	9.987
23	5161.663	230.50513	0	9.665
24	5112.965	232.38008	0	11.775

7.2. Different Scenarios

7.2.1. Case 1: Integrated UC with 100% Renewable Energy Sources for IEEE 24-Bus System

As recommended in the literature PSO algorithm proved its efficiency in solving the UC problem, so in this study, PSO is being applied to solve the problem of the IEEE 24-bus test system with high penetration of renewable energy sources to achieve the main objective of UC in reducing the production costs as explained in equation 1 and 2. The UC issue can be resolved by using the forecasted demand for the load, the level of wind power, the performance of photovoltaics, and the EVs charging demand, all of which are presented in Table 5, to determine the dispatch units, which are presented in Table 5. This makes the problem solvable. The information in Table 5 reveals that generating units 2, 3, 7, and 10 are utilized continually, making them the most cost-effective option. Even though the load demand is greatest between the hours of 7-16 and 19-24, generators 1, 4, and 8 are already scheduled to be in use during those hours. In addition, generator nine is required to make a commitment because the greatest load demand occurs during the time period 12-13. Taking into account the constraints outlined in equations (3-10) results in a daily running cost of $340686 in this particular scenario. This includes the costs that are connected with the beginning and ending operation of each generator. In addition, Figure 10 displays the UC results as well as the power dispatch for the thermal units and the Renewable sources. Moreover, the optimal cost of production per hour is shown in Table 6.

7.2.2. Case 2: UC for the IEEE 24-Bus System Excluding Wind Farms and Incorporating EV Charging Stations

It simulated the economic impact of including solar electricity and electric vehicles in the planning of the power grid. The weather significantly impacts the output of power generated by solar power.

The total cost, charge cost, and unit cost were all attainable by acquiring the interval number solution set due to the interval nature of the solar power price. The results of the simulation in case 2 show that the unit dispatch and commitment will be higher, and the total cost of production for the following day will increase by $12,253.

7.2.3. Case 3: UC for the IEEE 24-Bus System Excluding Solar Farms and Including EV Charging Stations

The financial repercussions of incorporating EVs and wind power into the power system's scheduling have been analyzed and modeled. The amount of energy that wind farms can produce varies greatly with the changing of the seasons. This demonstrated that even while the unit's production curve would vary due to the unpredictable nature of wind power output, electric car charging and discharging could nevertheless mitigate power load changes and accomplish peak-load shifting. Based on the simulation results for case 3, we can see that there has been a shift in unit dispatch and commitment and an increase in total production cost of $14804.3 for the next day.

7.2.4. Case 4: UC for the IEEE 24-Bus System Excluding Wind and Solar Farms and Including EV Charging Stations

In order to study the economic impacts of integrating electric vehicles (EVs) into the power system without including integrating renewable energy sources, the final scenario solely featured UC integration with EV charging stations. According to the findings for Case 4, the daily total cost for Case 4 is determined to be $367057.6.

7.3. A Comparison Between the Scenarios

The economic consequences of including different renewable energy sources and EV charging stations in the electricity system are brought to light by the outcomes of these scenarios, as illustrated in Table 7. Where, the cheapest overall manufacturing cost ($340,686) of Case 1, which uses just renewable energy sources, illustrates the financial advantages of combining solar and wind power with electric vehicles.

The cost of losing the contribution of wind power is shown in the $12,253 increase in manufacturing cost in Case 2, which includes solar power and electric vehicles but not wind farms. A little higher rise in production cost ($14,804.3) in Case 3, which leaves out solar farms but includes wind power and electric vehicles, suggests the somewhat greater economic significance of solar power in this configuration than in Case 2. The highest overall production cost ($367,057.6) of Case 4, which leaves out wind and solar farms but includes EVs, highlights the substantial cost reductions that may be achieved by integrating renewable energy sources into the electrical system.

8. Future Scope

It is vital to integrate Levelized cost of energy calculations in UC issue models for future study because it is anticipated that the proportion of generation from renewable sources will increase in the near future. Furthermore, there is a significant opportunity to explore the prospect of extending the abilities and expanding the models for additional generating sources such as biomass and waste to energy, which might also include recoupment in terms of lowering both the cost and the pollution in an integrated grid setting.

In a similar vein, the conceptual models of other potential energy sources, such as hydrogen storage, need to be investigated. In addition, since having certainty is the most important aspect of having a solid strategy, developing better methodologies for forecasting is absolutely necessary for the research that will be done in the future.

Table 5. UC for IEEE 24-Bus test system using PSO

Hour	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
1	0	1	1	0	0	1	1	1	0	1	0	750	800	0	0	700	850	800	0	895.6
2	0	1	1	0	0	1	1	1	0	1	0	750	800	0	0	700	850	800	0	674.7
3	0	1	1	0	0	1	1	1	0	1	0	750	800	0	0	700	850	800	0	442.9
4	0	1	1	0	0	1	1	1	0	1	0	750	800	0	0	700	850	800	0	394.9
5	0	1	1	0	0	1	1	1	0	1	0	750	800	0	0	700	850	800	0	597.4
6	0	1	1	0	0	1	1	1	0	1	0	750	800	0	0	700	850	800	0	881.3
7	0	1	1	0	1	0	1	1	0	1	0	750	800	0	750	700	850	672	0	360
8	0	1	1	0	1	0	1	1	0	1	0	750	800	0	750	0	850	800	0	898.6
9	0	1	1	0	1	0	1	1	0	1	0	750	800	0	750	0	850	800	0	833.6
10	0	1	1	0	1	0	1	1	0	1	0	750	800	0	750	0	850	800	0	844.9
11	0	1	1	0	1	0	1	1	0	1	0	750	800	0	750	0	850	800	0	580.6
12	1	1	1	0	1	0	1	1	1	1	700	750	800	0	750	0	850	800	500	490.1
13	1	1	1	0	1	0	1	0	1	1	700	750	800	0	750	0	850	0	500	360
14	1	1	1	0	1	0	1	0	0	1	700	750	800	0	750	0	850	0	0	862.6
15	1	1	1	0	1	0	1	0	0	1	700	750	800	0	750	0	850	0	0	757.1
16	1	1	1	0	1	0	1	0	0	1	700	750	800	0	750	0	850	0	0	745.3
17	1	1	1	0	1	0	1	0	0	1	700	750	800	0	750	0	850	0	0	862
18	1	1	1	1	1	0	1	0	0	1	700	750	800	600	750	0	850	0	0	407.6
19	1	1	1	1	1	0	1	0	0	1	700	750	800	600	750	0	850	0	0	421.3
20	1	1	1	1	1	0	1	0	0	1	700	750	800	600	750	0	850	0	0	456.3
21	1	1	1	1	1	0	1	0	0	1	700	750	800	600	750	0	850	0	0	481.7
22	1	1	1	1	1	0	1	0	0	1	700	750	800	600	750	0	850	0	0	537.9
23	1	1	1	1	1	0	1	0	0	1	700	750	800	600	750	0	850	0	0	560.4
24	1	1	1	1	1	0	1	0	0	1	700	750	800	600	750	0	850	0	0	513.8

Table 6. Production costs per hour to maximize efficiency

Hour	Production costs ($)	Hour	Production costs ($)
1	14061.4	13	14736.6
2	13464.9	14	13837.3
3	12839.1	15	13552.3
4	12709.3	16	13520.6
5	13256.2	17	13835.6
6	14022.6	18	14480.8
7	14508.7	19	14517.8
8	14204.5	20	14612.2
9	14028.9	21	14680.8
10	14059.5	22	14832.5
11	13345.9	23	14893.4
12	16767.5	24	14767.6

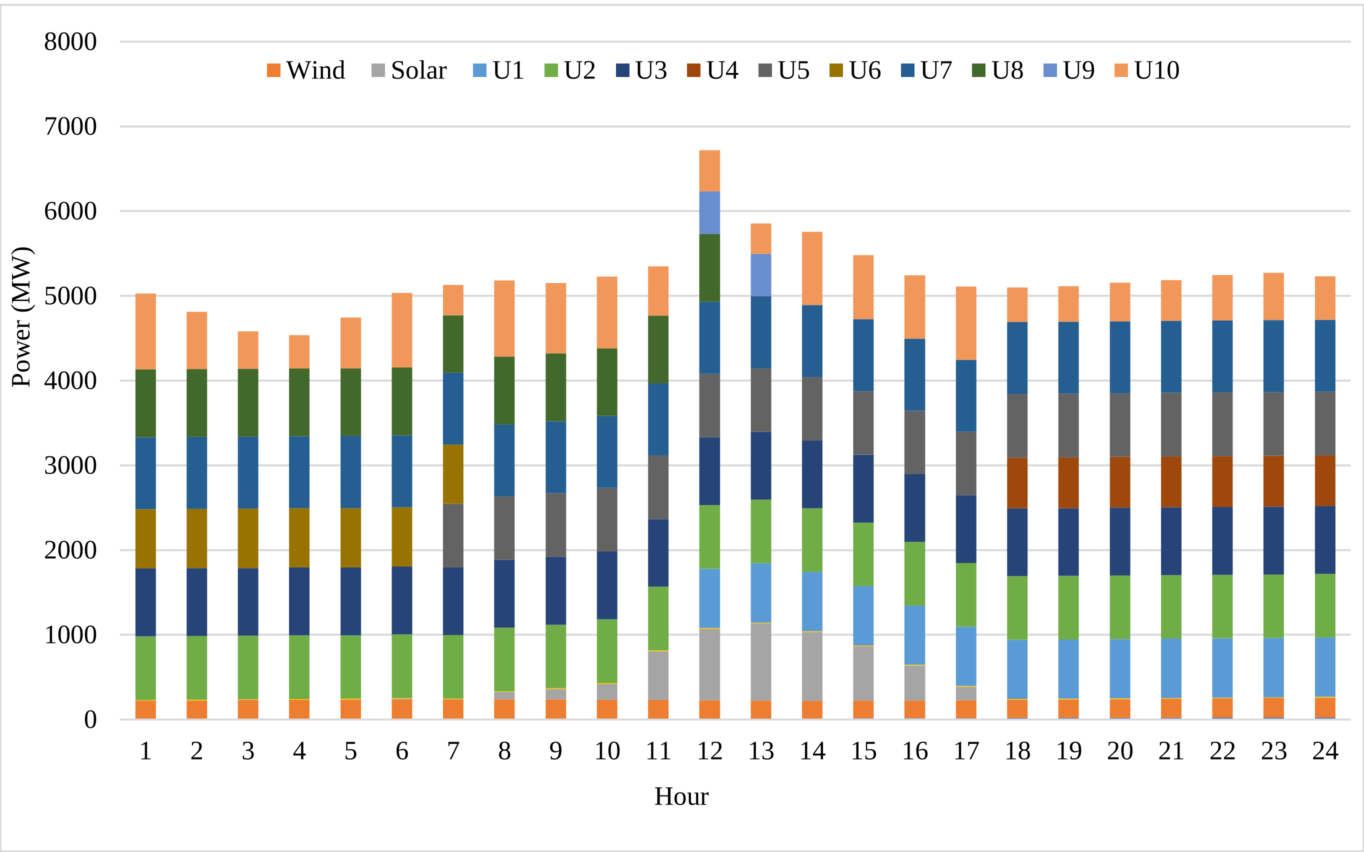

Fig. 10 Units dispatch integrated with solar and wind power

Table 7. A Comparison between the four cases

Scenario	Total Production Cost ($)	Additional cost Compared to Case 1 ($)	Notes
Case 1	340,686	-	Base case including EV charging stations and integrated solar and wind electricity.
Case 2	352,939	12,253	Higher cost because EV charging and solar electricity are not included; wind power is.
Case 3	355,490.3	14,804.3	Higher price because solar power is not included; wind power and EV charging are.
Case 4	367,057.6	26,371.6	Highest cost because it just covers EV charging and leaves out solar and wind electricity.

Table 8. Definitions with characters and abbreviations that are employed in this article

Abb.	Definition	Abb.	Definition
UC	Unit commitment	$P_{W,it}$	Wind power at time t
EVs	Electric vehicles	$P_{Ph,it}$	Solar power, at time t
PSO	Particle swarm optimization	$P_{D,t}$	Load demand at time t
LSTM	Long short-term memory	$P_{EVS,t}$	Electric vehicles demand at time t
GRU	Gated recurrent unit	$P_{L,t}$	Power losses at time t
DP	Dynamic programming	T_i^{on}	Minimum ON time
MILP	Mixed-integer linear programming	T_i^{off}	Maximum OFF time
PV	Photovoltaics	UR_i	Ramp up limit for generator i
IEA	International Energy Agency	DR_i	Ramp Down limit for generator i
ED	Economic dispatch	$R_{S,t}$	Spinning reserve at time t
GA	Genetic algorithm	$R_{O,t}$	Operating reserve at time t
LR	Lagranigian relaxation	W_{ih}	weight matrixes
ACS	Ant colony system	f_t	status of the LSTM's cell at time t
BGWO	Binary Gray Wolf Optimization	c_t	status of the LSTM's cell at time t
RNN	Recurrent neural networks	o_t	output of each cell at time t
$F_i(P_i)$	Cost function	h_t	recurrent data at time t
α_i, β_i and γ_i	The generator i cost coefficients	x_t	Input data at time t
SU_{it}	Startup cost of generator i at time t.	b_s	systems bias
SD_{it}	Shut down the cost of generator i at time t.	r_t	Reset gate status at time t
$P_{i,min}$	Minimum output power of generator i	z_t	Update gate status at time t
$P_{i,max}$	Maximum output power of generator i		

9. Conclusion

The UC issue in the power system can be thought of as a nonlinear programming mixed integers problem. The UC issue becomes more complicated as renewable energy and EVs become more widely incorporated into the power system. With the increasing penetration of variable renewable energy sources like wind and solar into the utility power system, the impact of random characteristics on both the supply and demand sides of the power grid on reliability, stability, and profitability will become more apparent.

Aside from its theoretical merits, UC also has real-world applications. To that end, we studied the optimal ways to coordinate the usage of thermal, wind, solar, load demand, and EV units. Optimal scheduling seeks to minimize per-item manufacturing costs. This research looks at how the presence of recharging stations for electric vehicles and conventional demand in urban areas can affect the efficiency of short-term power system planning and control in the presence of high penetration of renewable energy sources like wind and solar. The interplay between these elements is the focus of this investigation. In order to reduce the overall power consumption of the system, PSO is used. The study is analyzed by use of a 24-bus test system developed by the IEEE. The proposed case study makes use of LSTM and GRU to forecast the next day's performance of the load demand, wind and solar energy, and the demand at EV charging stations. LSTM is superior to GRU in predicting the demand for load, solar electricity, and electric vehicle charging. However, GRU outperforms LSTM when it comes to forecasting the day ahead's wind performance. The GRU model was used to obtain the expected wind speeds, while the LSTM model was used to obtain the other projected variables. The results validate the proposed approach and show that $340686 is the optimal cost of production. Moreover, different scenarios were generated to explain the high intermittencies of renewable energy effects on the power system planning and control and the operation costs.

Funding Statement

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Availability of Data and Materials

The used data was taken from the IEEE database and mendely, as shown in references [35] and [36].

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