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Original Article

Duck Curve Management Using Deep Learning and Optimization Algorithms for Renewable Energy Integration

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Abstract - *The paradox of the duck curve is that more solar and wind power entering the power grid means more duck curves. Efficient Unit Commitment (UC) is crucial for duck curve management, enabling stability and long-term sustainability of the power grid. In this paper, we analyze several approaches using UC to tackle the duck curve problem. After introducing the duck curve phenomenon and its influencing factors, the study reviews current UC strategies, identifying their pros and cons while discussing the conditions under which each strategy performs well. This approach combines Long Short-Term Memory (LSTM), One-Dimensional Convolutional Neural Network (1D-CNN), and a hybrid of both—LSTM-1D CNN and 1D CNN-LSTM—which are applied and compared to predict the day-ahead solar and wind power output. The results show that LSTM-1D CNN outperforms all other techniques, achieving maximum accuracy of 98.64% for solar and 98.87% for wind power. Additionally, three optimization algorithms are used and compared to plan the short-term performance of the power grid: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and a hybrid of both (GA-PSO). The results confirm that GA-PSO surpasses the other methods, achieving the lowest operating cost of $319,876.7. This research can aid researchers, policymakers, and power grid managers create a more efficient and sustainable energy system.*

Keywords - *Unit commitment, Economic dispatch, Deep learning, Duck curve, Solar power.*

1. Introduction

The growing use of renewable energy sources, including solar and wind power, has already created a number of impressive economic and environmental benefits. However, it introduces new challenges for electricity grid management [1]. A common problem that arises is something called the duck curve, which is the imbalance between the amount of power needed and the amount of renewable energy that is readily available. This is due to fluctuations in the availability of renewable energy sources. The duck's back is indeed a bane for the power grid network to arrange sufficient flexible and reliable power generation capacity to meet the peak demand of night-time when the constraint on the supply of renewable energy is greater [2].

Unit Commitment (UC) solutions [3] have been adopted by utilities in the past few years to manage the duck curve and provide a constant supply of energy. That is because UC is what you use to decide what plants should be on and what plants should be off going forward to meet demand. The decision is somehow affected by various factors such as expected power demand, generation cost of that power, and availability of a range of power plants [4]. The challenge is that renewables have to be integrated into the power system through effective UC measures.

Recent developments in machine learning and optimization algorithms have opened up new opportunities to enhance UC strategies, which were previously out of reach. A deep learning-based model has proved its efficacy in forecasting demand for electricity, as well as forecasting renewable energy generation. These contributions can inch towards making more informed decisions about UC by power grid operators. UC optimization algorithms can also be employed for discovering the cost-effective and most efficient UC techniques out of a large number of settings [5].

The duck curve results from daily swings in both renewable energy supply and demand. During the day, renewable energy sources like solar panels and wind turbines can provide a considerable amount of electricity. Usually, the demand for power is low because the majority of people are engaged in work and are not consuming anything. As the sun goes down and people head indoors, the demand for electricity rises sharply, but the availability of green energy dwindles. As a result, more traditional power facilities, such as those that run on natural gas or coal, are needed to fulfill night-time peak demand. Power grid operators are increasingly concerned about the duck curve problem because of the strain it causes on conventional power plants. Power grid instability, including blackouts and other disruptions, can occur when electricity demand exceeds renewable energy supply [6]. Figure 1 illustrates the performance of the solar systems curve for the electrical grid that is more dependent on renewable energy sources.

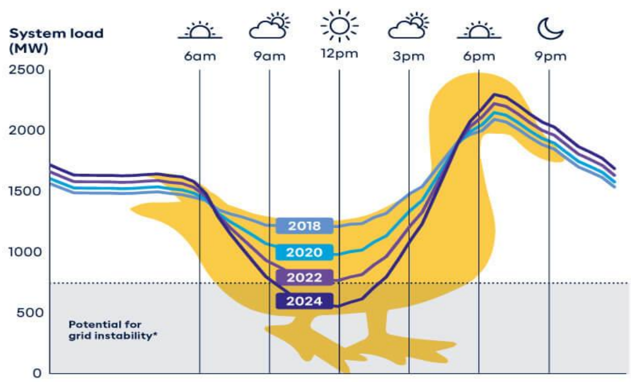

Fig. 1 Solar duck curve behavior [7]

Daily net load reductions occur in a steep downward direction across the day in solar energy-intensive regions. Solar electricity has become commonly accessible throughout the power grid, so the demand for traditional power sources has decreased. The increase in solar energy output during sunrise leads to augmented electricity supply from solar sources. The difference between demand and renewable generation (net grid load) decreases because of this development [8]. During the daytime, the duck curve descent creates operational challenges for power grid operators, who must find ways to handle surplus solar power generation and adjust other generating sources. Some situations need the reduction of surplus energy or its transmission to adjacent energy regions. The duration requires flexible resources and effective unit commitment procedures to maintain reliable grid stability. The evening period shows a substantial upward trend on the duck curve. The day becomes darker as solar power production decreases, but increasing household use leads to fast conventional power generation increases. The fast-growing net load creates excessive strain on the power system because it needs quick corrective actions to meet elevated load requirements. The unsatisfactory management of fast ramp-up operations may trigger power grid instability, drive up costs, and sometimes force usage of either inefficient or environmentally detrimental backup power generators. Successfully managing the duck curve requires detailed execution of unit commitment solutions, which can effectively balance variable supply and demand [9]. Integrating renewable power requires a strategy that includes operating traditional unit schedules to match renewable variability, optimizing flexible resources and energy storage, and implementing consumer demand response programs for peak management [9].

Multiple UC strategies exist to handle the duck curve by maintaining sufficient reliable and flexible power generation capacities to satisfy evening peak load requirements when renewable energy levels drop. MILP serves as a typical UC optimization approach to help schedule power generation by considering power grid limitations and transmission capacity and predicted energy load patterns and renewable output [10]. MILP encounters two main drawbacks because it runs extensive computational processes while failing to adapt to alterations in power grid operations.

Different optimization approaches for UC exist, including stochastic programming [5] and Dynamic Programming (DP) [11], as well as heuristic algorithms such as genetic algorithm (GA) [12] and Particle Swarm Optimization (PSO) [11] together with other approaches to handle these constraints. The power generation schedule becomes optimized through stochastic programming since it minimizes expected generation costs while handling uncertain conditions of renewable energy production and electricity consumption. The power system status evaluation through DP provides time-dependent assessments that allow optimization of power generation planning across all time intervals. Heuristics work as rule-based systems to produce UC choices through simple implementable heuristics.

UC strategies have been proposed to handle the duck curve by ensuring sufficient flexible and dependable electricity production capacity is accessible to meet evening peak demand when renewable energy supplies are low. Conventional UC techniques, such as Mixed-Integer Linear Programming (MILP) [10], are frequently used to optimize the power generation schedule under different constraints, such as the availability of various types of power grids, the transmission capacity, and the forecasted demand and renewable energy generation. MILP has been faulted for its computational difficulty and inability to account for the dynamic nature of the power grid.

Studies have proposed many alternative UC techniques, such as stochastic programming [5], Dynamic Programming (DP) [11], and heuristics algorithms, such as Genetic Algorithm (GA) [12], Particle Swarm Optimization (PSO) [11], etc., to address these constraints. For example, stochastic programming is a technique that optimizes the power generation schedule to minimize the expected cost of generation, taking into account the uncertainty of renewable energy generation and electricity demand. DP is another strategy that optimizes the power generation plan by assessing the status of the power system over time and making the best choice at each time step. On the other hand, heuristics are rule-based systems that use simple heuristics to make UC decisions.

2. Research Contributions and Novelty

The study significantly contributes to renewable energy integration science and UC technique investigations through original research outcomes. The research brings forward its main contributions together with the following findings:

- The research evaluates innovative modifications to standard approaches for solving particular challenges related to the duck curve. The research team created predictive forecasting tools which optimize renewable energy supply and demand forecasting by processing real-time data and optimizing control systems. The research examines methods to improve control systems for flexible power generation equipment to reduce duck curve effects.
- The research includes both a comprehensive review and performance assessments of UC techniques GA, PSO and their hybrid version, which focuses on solving duck curve challenges in power systems with high renewable energy penetration. Grid operators, along with policymakers, can use analyzed results to select the optimal UC strategies for implementation.
- Deep learning techniques play an essential role throughout the primary research investigations in this work. The research examines how LSTM and 1D-CNN and their combination models with LSTM-1D CNN and 1D CNN-LSTM improve solar power prediction abilities for optimized UC strategies. This methodology enables power grid operators to build better, cost-effective commitment strategies for managing unpredictable characteristics of renewable energy production.
- The research establishes the necessity for power plants to have flexibility capabilities in managing the duck curve and incorporating renewable energy effectively into electrical grids. Grid operators, together with policymakers, can develop improved methods for improving power generation infrastructure flexibility with the acquired knowledge.

3. Unit Commitment

The operation and planning of power systems heavily depend on unit commitment as a fundamental operational issue. UC develops optimal procedures for starting and stopping generating units during time periods of one day or one week, subject to system limitations and operational requirements. The electricity scheduling process should fulfill power requirements through the lowest feasible production costs. The total operational expenses consist of fuel expenses together with startup expenses, shutdown expenses and pollution-related expenditures.

The UC problem presents significant difficulty because it is difficult to foresee and accurately predict system demand and renewable energy production levels alongside other changing variables. There have been a number of methods and algorithms created to solve the UC problem. The following is the identification of the UC problem [13, 14]:

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

$$\text{Where: } F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \quad (2)$$

Such that:

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

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

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

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

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

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

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

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

$$\sum_{b=1}^{B} \Gamma_{\ell b}\left(\sum_{i \in \Lambda_b} P_{it} I_{it} - (P_{D,t} + P_{EVS,t})\right) \leq F_\ell \quad (11)$$

Equation (1) is an optimization problem where the objective is to minimize the total cost of making and using power to as minimal as possible. It's made up of three parts:

The first part is the generation cost, where $F_{ci}(P_{it})$ is a quadratic cost function of the power output P_{it} of a generator i at time t and I_{it} is a binary variable that shows whether the generator is online (1) or offline (0) at time t. The second part is the cost of starting up(SUC_{it}). The third term is the cost of Shutting Down (SDC_{it}).

Equation (2) defines the quadratic cost function. $F_i(P_i)$ where a_i, b_i, and c_i are coefficients that determine the shape of the curve.

Equation (3) is a constraint that implies the power output of generator i at time t must be between the minimum and maximum power limits. $P_{i,min}$ and $P_{i,max}$.

Equation (4) represents the power balance equation. It states that the total power produced by all generators, wind turbines $P_{W,it}$, and photovoltaic panels $P_{PV,it}$, must equal the total power used by loads $P_{D,t}$ and losses $P_{L,t}$.

Equation (5) ensures that in order for a generator to be switched on, both it must have been off in the preceding time step and the difference between its current and prior states must be positive.

Equation (6) ensures that the thermal power source can be switched off if it is on at the end of the preceding time step and that the difference between the present and prior states is positive.

Equations (7) and (8) are known as ramping limitations, which limit the rate at which a generator's output electrical power may vary between two-time steps,

Minimum reserve is shown in Equation (9) where $O_{R,it}$ is the reserve available from generator i at time t and $O_{R,t}$ is the total reserve needed at time t.

The necessary spinning reserve is shown in Equation (10), where $S_{R,it}$ represents the spinning reserve of generation i at time t and $S_{R,t}$ represents the total spinning reserve required at time t.

Equation (11) represents the transmission line constraint, which ensures that the transmission lines' power flows do not exceed their capacity limits. The constraint takes into account the power injections from various buses and units, which are weighted by the line flow distribution factors. This constraint assists in maintaining the reliability and stability of the power grid by comparing the total power flow to the transmission line's capacity. Where b is the index for the number of buses, ℓ is the transmission lines index, $\Gamma_{\ell b}$ line flow distribution factor for transmission line ℓ due to the net injection at bus b, F_{ℓ} the transmission capacity on the transmission line ℓ and Λ_b refers to the index set of units at bus b.

4. Methodology

The initiation of solving the duck curve problem through UC begins by precisely forecasting solar power generation levels. The UC system will deliver its best results when solar energy production forecasts show precise accuracy levels. Multiple deep learning methods, including Long Short-Term Memory (LSTM), 1D Convolutional Neural Networks (1D-CNN) and hybrid LSTM-1D CNN, allow researchers to conduct accurate prediction testing.

4.1. Forecasting Models

4.1.1. Long Short-Term Memory for Solar Prediction

The recurrent neural network structure known as Long Short-Term Memory (LSTM) proves effective at identifying time-based patterns in time series information. Research teams have widely applied LSTM for time series forecasting and use it to predict solar power production levels.

The LSTM model effectively evaluates complex solar energy production relations between weather conditions, cloud cover, and daily time cycles [15].

The LSTM architecture includes three distinct gate types which are input gates alongside forget gates and output gates according to reference [16]. The system of gates within LSTM memory cells allows the model to make decisions about what information to remember or forget through the information flow, as illustrated in Figure 2.

LSTM memory cells receive their new input quantities through the input gate mechanism. A sigmoid function uses current input together with previous output values of the LSTM memory cell to regulate the gate operations.

The input gets discarded when the sigmoid output approaches zero values. When the sigmoid output approaches one the entire input becomes retained [16].

LSTM controls the preservation of the previous memory cell state through its forget gate, which determines the amount used in the current time step. The forget gate operates through a sigmoid function, which takes both the current input and prior output of the LSTM memory cell as its inputs.

A near-zero sigmoid output result indicates that the entire previous state will be maintained. The previous state becomes fully deleted when the sigmoid output approaches one value [16].

The output gate decides which portions of the memory cell's current state will be available at the following time step. The output gate of LSTM memory cells depends on two functions, sigmoid and hyperbolic tangent, which process both current inputs and previous outputs together.

The hyperbolic tangent function transforms the LSTM output range, while the sigmoid function specifies the parts of the memory cell state that should be released [16].

Through these gates, the LSTM architecture controls the duration that data remains stored and forgotten when performing solar power forecasting. By implementing these gates, the model can detect complex data patterns, including multiple time frames from daily to weekly cycles and seasonal patterns together with nonlinear variable interconnections.

The general principle behind LSTM gates works as a vital element of the LSTM network and demonstrates exceptional success in solar demand forecasting [17].

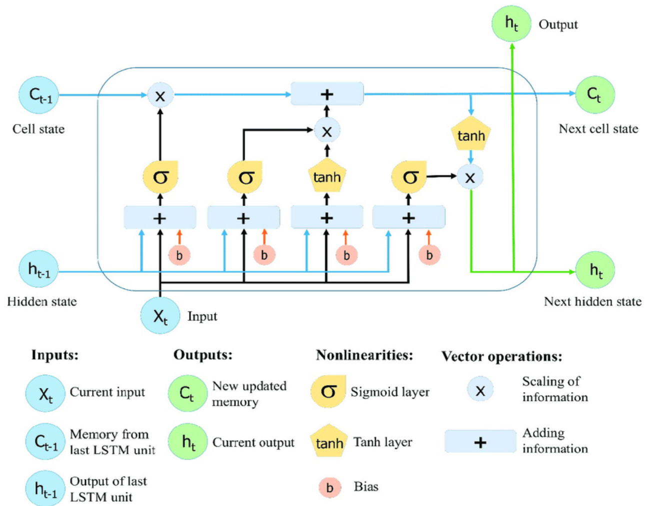

Fig. 2 LSTM architecture [18]

4.1.2. 1D Convolutional Neural Networks for Solar Prediction

1D Convolutional Neural Networks (CNNs) demonstrate effective utilization for solar power forecasting, according to research [19]. These networks employ convolutional layers to extract features from time-series data instead of how LSTM models utilize memory cells for dealing with long-term dependencies.

The convolutional layers generate a feature map with data regional patterns through their filter sliding operation on the input data. Pool layers reduce the data's dimensionality while simultaneously boosting computational speed by downsampling the feature map [20]. The visual depiction of 1D CCN architecture appears in Figure 3.

The 1D CNN model employs solar power forecasting through the learning process of future energy production from historical solar energy output data coupled with weather observations. The 1D CNN architecture enables the detection of nonlinear variable relationships while identifying patterns that occur at daily, weekly, and seasonal time frames in the data.

Among the advantages of 1D CNNs is their capability to operate on irregular time-series data sets that contain missing values and irregular time period measurements without requiring imputation or interpolation techniques. The effective training of big data sets through parallel computing makes 1D CNNs suitable for large-scale applications.

The selection of hyperparameters requires greater attention during 1D CNN tuning because these models demonstrate sensitivity to the chosen parameters. One disadvantage of 1D CNNs is that they normally fail to duplicate the long-term dependency recognition capabilities of LSTM models. The use of 1D CNNs has delivered promising outcomes for solar power forecasting as the industry relies heavily on this technique for the foreseeable future [21].

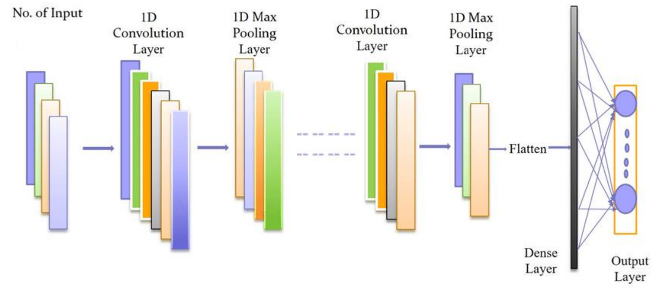

Fig. 3 1D CNNs architecture [22]

4.1.3. Hybrid LSTM-1D CNN for Solar Prediction

The hybrid implementation of LSTM-1D CNN architecture in solar power forecasting allows the benefits of both architectures to work together effectively. The method utilizes strengths from different architectures to create dependable and accurate predictions because it addresses each design limitation [23].

The hybrid LSTM-1D CNN methodology accepts historical solar power production data combined with weather data along with relevant additional details as its input. Preprocessing techniques working on this data sequence normalize values while cleaning up information and eliminating noise and untypical points. The hybrid model accepts preprocessed data for processing and prediction functions.

The hybrid model contains two essential components: the LSTM network and the 1D CNN network. The LSTM network processes data dependencies and time-based information within the dataset. The LSTM network contains memory cells that receive input data and use their data to process information through selective remembering and forgetting methods over time. The LSTM network transforms learned temporal characteristics from the input data into hidden states, which become part of its output sequence [24].

The identification of local patterns and nonlinear relationships in the collected data makes use of the 1D CNN network. After receiving hidden states from the LSTM network, the 1D CNN network applies convolutional and pooling layers multiple times to extract local features. An array of feature maps that display the learned input data patterns and nonlinear relationships produces the 1D CNN network's output [24].

In the last prediction step, both LSTM network outputs and 1D CNN network outputs are sent to a fully connected layer. The fully connected layer forecasts future solar power production through the acquired features from the integrated networks [24].

Multiple advantages exist for the hybrid LSTM-1D CNN architecture compared to individual LSTM or 1D CNN systems. Both the 1D CNN network extracts local patterns from nonlinear data, while the LSTM network demonstrates expertise in detecting long-term dependencies in temporal information. Implementing both network types within a single hybrid model enables accurate forecasting because both short-term and long-term data patterns are detected by the merged networks. The hybrid model functions effectively by managing unpredictable time-series data without requiring imputation or interpolation, and it is less impacted by hyperparameter tuning than solitary models [24]. Figure 4 illustrates hybrid LSTM-1D CNN architecture.

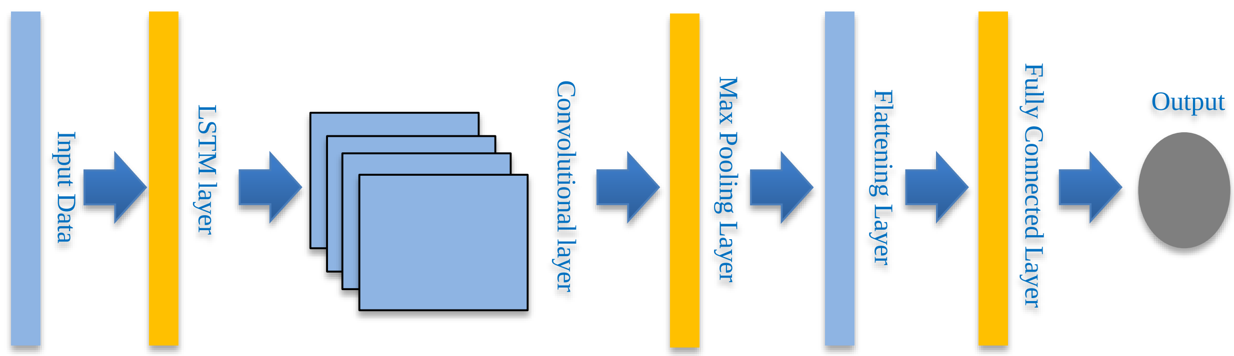

Fig. 4 Hybrid LSTM-1D CNN architecture [25]

4.1.4. Hybrid 1D CNN-LSTM for Solar Prediction

The hybrid 1D CNN-LSTM model demonstrates proven effectiveness, according to [25]. The model incorporates both CNNs and LSTM network benefits. The transformation of solar data series into a time series allows 1D convolutional operations to enhance CNN performance in spatial pattern extraction. The CNN module running in the hybrid model detects local patterns and features embedded within solar data. The capability of LSTM networks extends to the exact identification of extended patterns while recognizing patterns based on time sequence information. The hybrid model uses CNN outputs to link them with its LSTM components. The model achieves greater task complexity through this design. The link between these network types functions through two methods: feeding CNN output values directly to LSTM inputs or merging CNN features with LSTM initial data for processing. The description of these methods is as follows below. Solar data analysis becomes more effective using the hybrid model that integrates CNN spatial feature extraction capabilities with LSTMs time modeling abilities, according to [25]. The hybrid 1D CNN-LSTM model demonstrates proven effectiveness, according to [25]. The model incorporates both CNNs and LSTM network benefits. The transformation of solar data series into a time series allows 1D convolutional operations to enhance CNN performance in spatial pattern extraction. The CNN module running in the hybrid model detects local patterns and features embedded within solar data. The ability to detect both lengthy patterns and temporal dependencies makes LSTM networks highly expert at their task. The hybrid model uses CNN outputs to link them with its LSTM components. The model achieves greater task complexity through this design. The link between these network types functions through two methods: feeding CNN output values directly to LSTM inputs or merging CNN features with LSTM initial data for processing. The description of these methods is as follows below. Solar data analysis becomes more effective using the hybrid model that integrates CNN spatial feature extraction capabilities with LSTMs time modeling abilities, according to [25].

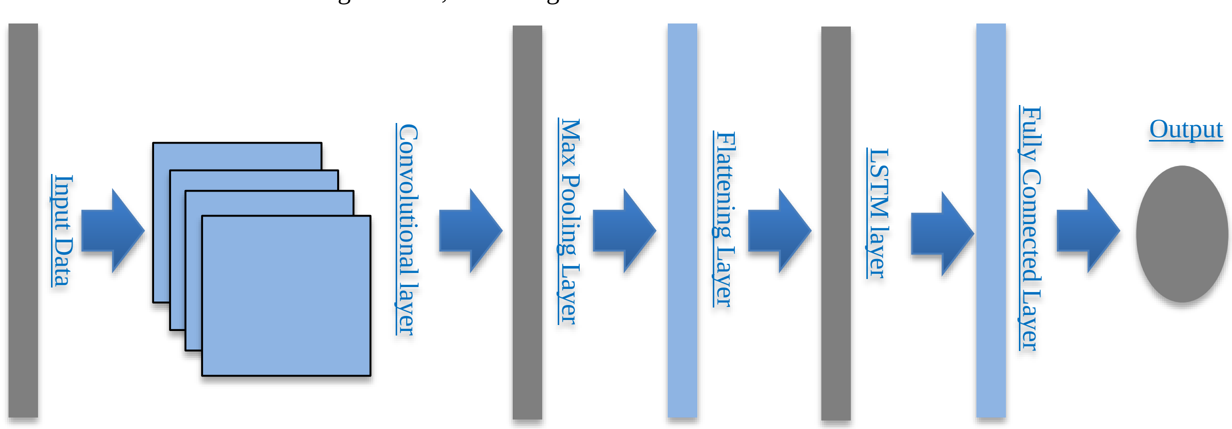

Fig. 5 Hybrid 1D CNN- LSTM architecture [25]

4.2. Optimization Models

Using UC theory, metaheuristic optimization methods like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) can be applied to the duck curve problem. Combining GA and PSO in a hybrid GA-PSO algorithm uses their distinct mechanisms for searching the solution space to increase the likelihood of better optimization results [26].

Here is a rundown of how UC methodology can be applied to GA, PSO, and GA-PSO to solve the duck curve problem:

- Initialization: Create a random set of UC schedules to start with.
- Fitness Evaluation: Use the solar power forecast and energy demand to figure out how well each unit's commitment schedule fits.
- Select the best UC schedules from the population to be the parents of the next generation.
- Reproduction: Use genetic operators to make new UC schedules for the next generation in GA. In PSO, the speed and location of particles should be changed based on the best solution found so far.
- Mutation: Change at random some of the genes in the unit commitment schedules in GA. To encourage exploration in PSO, make random changes to the speed and location of particles.
- Replace: Replace the worst-performing UC schedules with the new ones.
- Termination: Repeat steps 2–6 until a termination criterion is met, such as a maximum number of generations, convergence to a good solution, or running out of computing resources.

Since GA and PSO each have their own unique set of advantages and disadvantages when it comes to solving optimization problems, a hybrid GA-PSO algorithm may take advantage of these differences for enhanced efficiency. PSO excels at capitalizing on the search space around promising solutions, while GA excels at exploring the space and discovering various solutions [26]. The hybrid algorithm, a combination of GA and PSO, can strike a balance between exploration and exploitation and, perhaps, prevent becoming trapped in local optima. However, the performance of the hybrid algorithm is problem- and setting-specific and requires careful evaluation and tuning.

4.3. Working Structure

The working structure of this study can be summarized as follows:

Step 1: Data collection and preprocessing: The first step is to gather the data required for solar power generation, demand, and wind power. This data is then preprocessed and cleaned to ensure it is in an analysis-ready format.

Step 2: Solar power forecasting: The next step is to forecast solar power generation using deep learning techniques such as LSTM, 1D-CNN, hybrid LSTM-1D CNN and 1D CNN-LSTM. Based on past data, these models are trained on the collected data and can accurately predict future solar power generation.

Step 3: Once the forecasts for solar power, wind power, and load demand have been finalized, the UC can be optimized so that it can meet the anticipated demand at the lowest possible cost. The goal is to find the most cost-effective way to meet customer needs, and GA, PSO, and GA-PSO are three algorithms that can help with that.

Step 4: Lastly, it is critical to test and evaluate the performance of the improved UC strategy. To do so, we need to examine the plan's efficacy, efficiency, and cost-effectiveness. If the initial results are not satisfactory, it may be necessary to try again using different parameters or models.

Follow these steps to apply the proposed methodology to the IEEE 39 Bus Test System to solve the duck curve problem using UC, deep learning techniques for solar power forecasting, and GA, PSO, and GA-PSO for optimization.

This can be done by applying the proposed methodology to the IEEE 39 Bus Test System. The case study has the potential to offer useful insights into the efficacy of the proposed methodology and can also be used to identify areas for further research and improvement.

5. Case Study

The IEEE 39-bus test system is a renowned power system test case that has garnered significant utilization among power system researchers. The system is a model of a real-world power system with 39 buses, ten generators, and 46 transmission lines, as shown in Figure 6.

In this study, five thermal generators are utilized on buses 30, 31, 32, 33, and 39. In addition to two wind farms on buses 34 and 37 and three solar farms on buses 35, 36, and 38.

As illustrated in Table 1, the data for unit commitment in the IEEE 39 Bus Test System typically includes information on the generators, such as their capacities, minimum and maximum power limits, ramp-up and ramp-down rates, and startup and shutdown costs.

Moreover, the historical load demand, wind power, and solar power used for training the forecasting models were taken from [27].

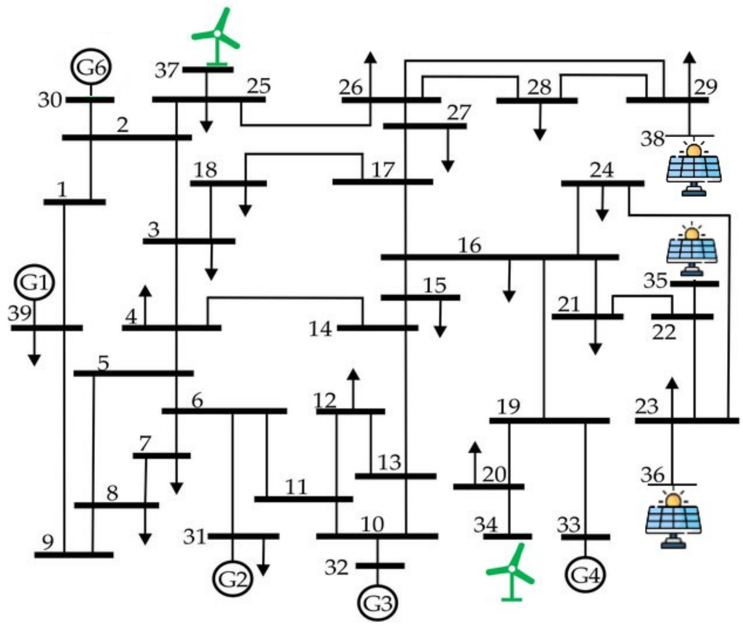

Fig. 6 IEEE 39 bus test system

Table 1. Thermal generators data [28]

Unit NO.	Bus	Pmin (MW)	Pmax (MW)	Min ON	Min Off	Ramp Limits	Cost Coefficients			Startup Costs	Shut Down Costs
							a	b	c		
1	30	15	120	2	2	50	370	22.26	0.712	350	150
2	31	15	120	2	2	80	480	27.74	0.079	400	170
3	32	10	100	3	3	100	660	25.92	0.412	500	500
4	33	10	100	4	4	80	665	27.27	0.22	60	0
5	39	5	70	3	3	50	670	27.79	0.00173	60	120

Table 2. A Comparison between the forecasting techniques

Model	Accuracy	MSE	RMSE	MAPE
LSTM	97.26 %	0.00070925	0.026633	0.037516
1D CCN	94.04 %	0.00023565	0.015349	0.058924
LSTM-1D CNN	98.64 %	0.00021643	0.014713	0.016136
1D CNN-LSTM	67.32 %	0.02184616	0.033650	0.078592

6. Results and Discussions

6.1. Day Ahead Solar Power Forecasting

The findings, which are presented in Table 2, offer a comprehensive comparison of the four used deep learning methods of forecasting with regard to the particular solar prediction task. The LSTM model achieves low values of MSE, RMSE, and MAPE, which indicates that its predictions are accurate and precise. The LSTM model's accuracy is high, coming in at 97.26%. The accuracy of the 1D CNN model is slightly lower at 94.04%, but it performs very well in terms of MSE and RMSE. The LSTM-1D CNN hybrid model outperforms the others with an accuracy of 98.64% and the lowest values for MSE, RMSE, and MAPE. These results indicate that the model's predictions are accurate to a higher degree and with fewer errors than the others.

On the other hand, when compared to the other techniques, the 1D CNN-LSTM model demonstrates relatively poorer performance overall, with lower accuracy and higher error metrics. These findings shed light on the efficacy of LSTM-based models, particularly the hybrid LSTM-1D CNN model, in accurately forecasting solar variables. This, in turn, contributes to the optimization of the integration of solar energy and provides support for the decision-making processes involved in renewable energy systems.

Figures 7 - 10 show the forecasting model's accuracy performance, representing the difference between the actual and forecasted values of the tested sets. Moreover, table 3 represents the day-ahead forecasted values of the solar system in addition to the load demand and wind energy, which will be used for the UC optimization model as explained in section 6.2.

The same forecasting techniques were applied to the load demand and wind power. The results show that the hybrid LSTM-1D CNN outperforms the other methods in terms of accuracy and the other metrics with an accuracy level of 98.35% and 98.87%, respectively.

Table 3 displays the projected power values for 24 hours, broken down by hour. The load values indicate the entire power demand on the grid, whilst the wind and solar power values represent the expected power output from those sources.

Figure 11 depicts the net load (load minus wind power minus solar power) over the course of the day, revealing a distinct duck curve form. The curve's lowest point comes in the middle of a sunny day when solar power is strongest and load is lowest. This is because solar electricity can meet a considerable amount of the power demand during this time.

The peak of the curve occurs in the evening when the load is at its peak, and solar power is no longer accessible. At this time, the grid must rely on alternative power sources to supply demand, such as natural gas or coal-fired power plants.

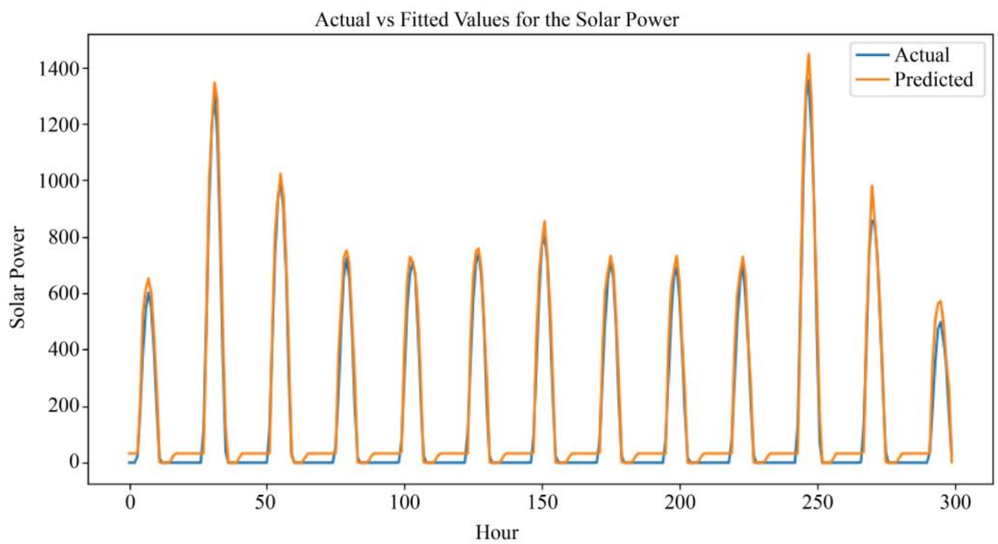

Fig. 7 LSTM accuracy performance in forecasting the solar power

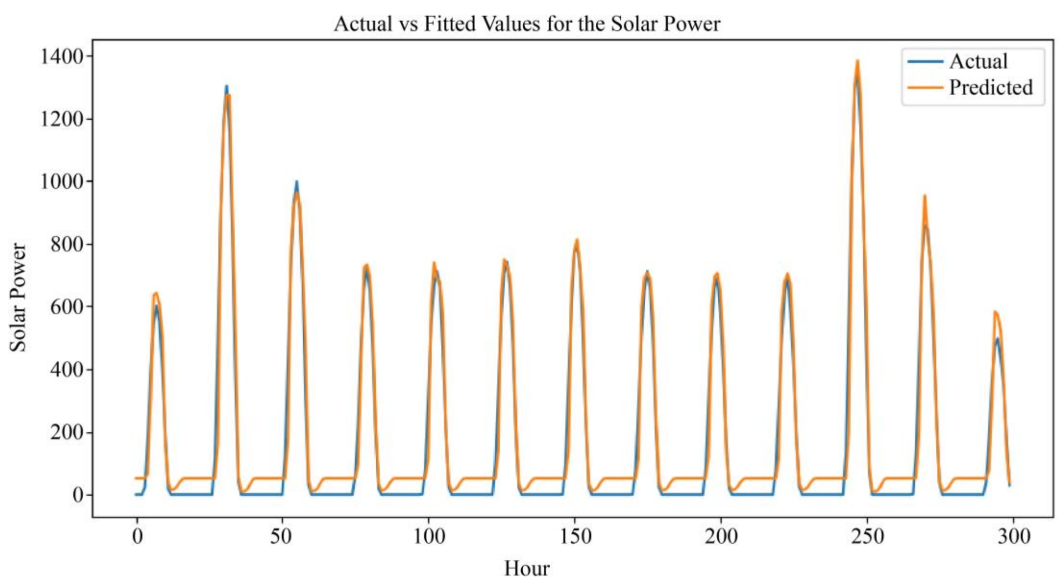

Fig. 8 1D CCN accuracy performance in forecasting the solar power

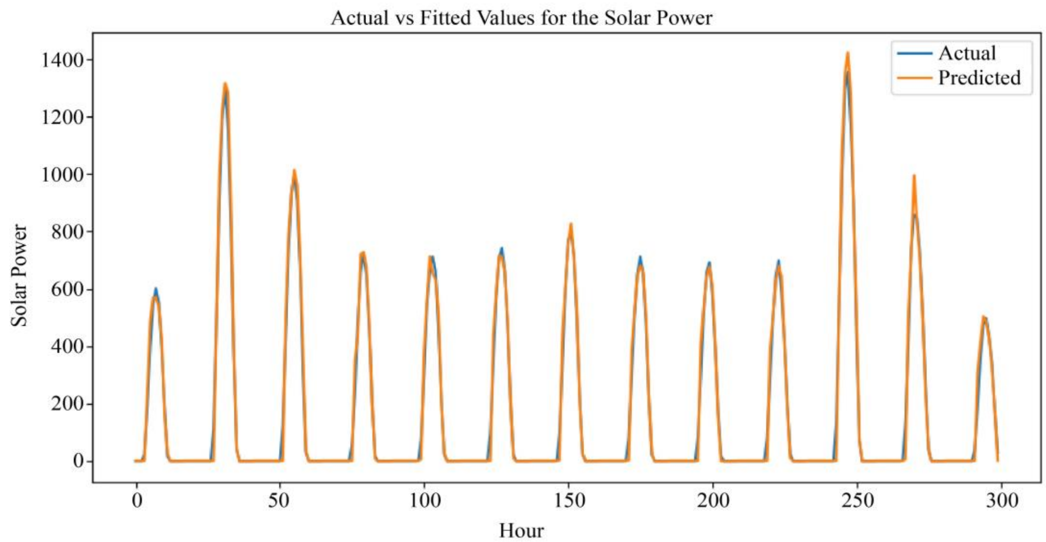

Fig. 9 Hybrid LSTM-1D CNN accuracy performance in forecasting the solar power

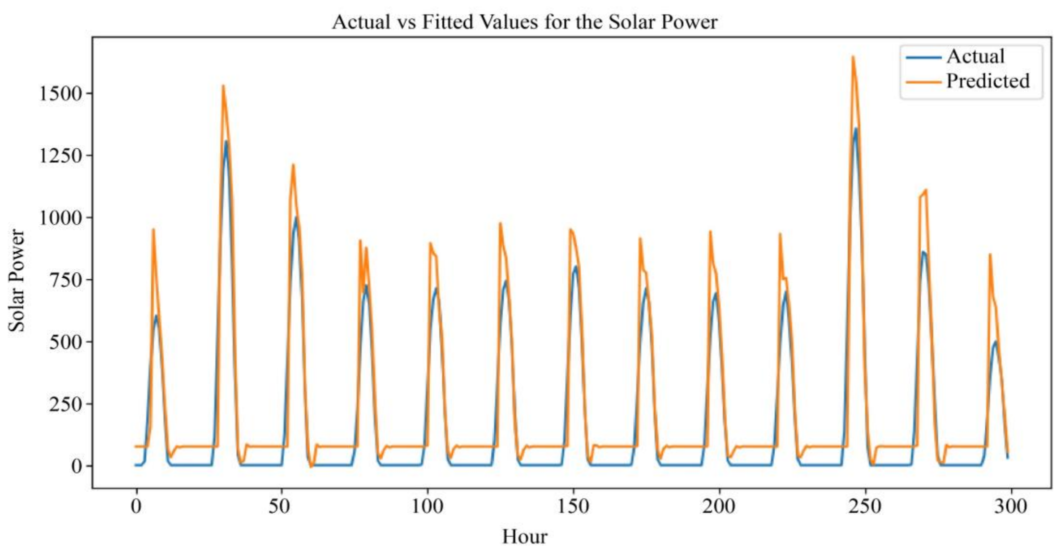

Fig. 10 Hybrid 1D CNN-LSTM accuracy performance in forecasting the solar power

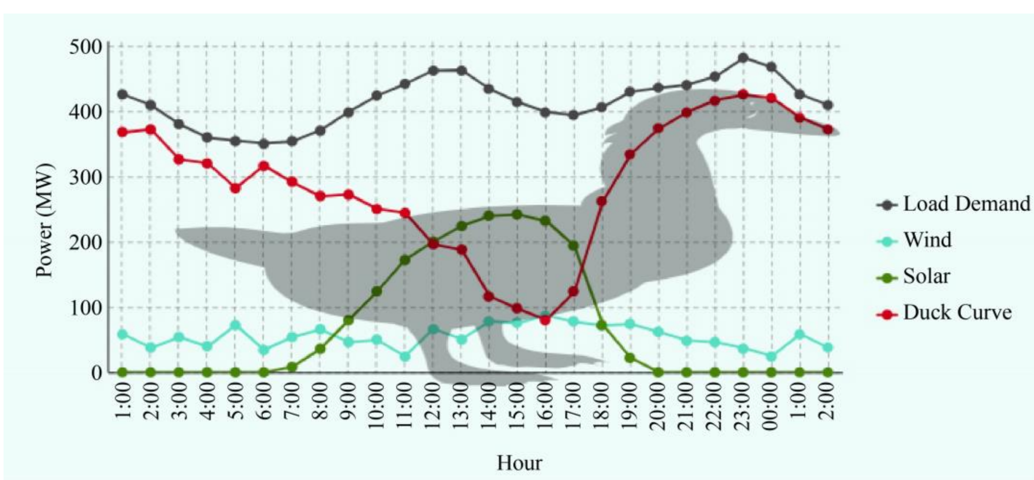

Fig. 11 The duck curve problem representation

Table 3. Day ahead predicted power values

Hour	Load (MW)	Wind Power (MW)	Solar Power (MW)
1	426.18	58.48	0
2	409.68	37.32	0
3	380.32	53.79	0
4	359.88	39.27	0
5	355.10	72.55	0
6	351.26	34.40	0
7	353.82	53.91	8.2
8	371.19	65.53	36.0
9	399.34	46.22	80.2
10	423.91	49.59	123.6
11	442.12	24.69	172.8
12	462.72	66.39	200.2
13	463.38	50.94851	224.4
14	434.20	78.26047	239.6
15	414.34	75.25145	241.8
16	399.26	87.02105	232.0
17	394.24	77.29366	193.4
18	406.50	71.91527	73.0
19	430.33	74.05596	21.8
20	435.84	61.79108	0
21	440.95	48.95232	0
22	453.60	46.22508	0
23	482.36	36.92015	0
24	467.60	24.83013	0

6.2. UC Optimization Models

To deal with the duck curve problem, the input powers of the load, wind, and solar power are predicted and shown in Table 3. Three different optimization techniques, GA, PSO, and a hybrid GA-PSO are used on the IEEE 39 Bus test system to solve the UC problem and figure out the best way to schedule the generating units.

Table 4 compares the operational costs of resolving the UC problem using the GA, PSO, and GA-PSO hybrid optimization techniques. The results are presented for each hour and the overall cost for the entire 24-hour period. The costs are expressed in dollars ($) for the 24 hours.

The GA-PSO hybrid technique, followed by the PSO technique and the GA technique, has the lowest operational cost for solving the UC problem, according to the results shown in the table. The total cost of the GA-PSO hybrid technique is $319,876.7, which is lower than the total costs of $324,099.07 and $327,739.2693 for the PSO and GA techniques, respectively.

The fluctuation in electricity demand regularly leads to predictable changes in operational costs over the course of the day. As a result, the prices are at their peak in the wee hours of the morning (between 1-4) and late at night (between 17-23) and their lowest in the middle of the day (between 12-16). In addition, the hourly costs decrease (between 7-17) as a high percentage of renewable sources is integrated with the grid. However, all three methods share the same basic cost structure.

Table 4. A comparison between the operational costs of different optimization techniques in solving the UC problem

Hour	GA	PSO	GA-PSO
1	19174.09	18961.13	18714.1
2	18583.93	18377.52	18138.1
3	15620.75	15447.25	15246.0
4	15282.12	15112.38	14915.5
5	12989.32	12845.05	12677.7
6	15230.79	15061.62	14865.4
7	13546.48	13396.02	13221.5
8	12235.12	12099.23	11941.6
9	12344.75	12207.64	12048.6
10	11195.07	11070.73	10926.5
11	10864.95	10744.28	10604.3
12	8302.17	8209.96	8103.0
13	7974.92	7886.34	7783.6
14	4770.34	4717.36	4655.9
15	4144.94	4098.90	4045.5
16	3584.49	3544.68	3498.5
17	4706.61	4654.34	4593.7
18	11222.12	11097.48	10952.9
19	15496.77	15324.65	15125.0
20	18825.33	18616.23	18373.7

21	20172.85	19948.79	19688.9
22	21387.19	21149.64	20874.1
23	25158.56	24879.13	24555.0
24	24925.57	24648.72	24327.6
Total Costs ($)	327739.2693	324099.07	319876.7

The outcomes of the UC problem for the IEEE 39-Bus test system using the PSO-GA hybrid approach are shown in Table 5. The units of wind and solar power that were committed for a 24-hour period are shown in the table, along with the hourly units of the five generators (P1-P5). The values in the table represent the optimization problem's decision variables, i.e., the number of units committed for each generator in each hour to meet demand while minimizing cost.

In Table 5, during hours 19-20, the UC fixed the duck curve problem by committing all five available units to generate electricity. This ensured that there was enough generation capacity to meet the sudden surge in demand for electricity during this period. By continuously adjusting the number of committed units based on the demand and availability of different generation sources, the UC can help address the challenges posed by the duck curve and ensure a reliable and stable electricity supply. Moreover, the best description of the committed units can be shown in Figure 12 and how the duck problem was fixed.

Table 5. UC for IEEE 39-bus test system using PSO-GA

Hour	Committed Units							P1	P2	P3	P4	P5
	U1	U2	U3	U4	U5	Wind	Solar					
1	1	1	1	1	1	1	0	32.7	120.0	52.0	94.3	70.0
2	1	1	1	1	1	1	0	33.6	120.0	53.7	97.4	70.0
3	1	1	1	1	1	1	0	26.1	120.0	40.7	73.2	70.0
4	1	1	1	1	1	1	0	25.2	120.0	39.1	70.1	70.0
5	1	1	0	1	1	1	0	25.5	120.0	0	71.0	70.0
6	1	1	0	1	1	1	0	33.5	120.0	0	97.0	70.0
7	1	1	0	1	1	1	1	27.6	120.0	0	77.9	70.0
8	1	1	0	1	1	1	1	22.4	120.0	0	61.0	70.0
9	1	1	0	1	1	1	1	22.8	120.0	0	62.5	70.0
10	1	1	0	1	1	1	1	17.6	120.0	0	45.7	70.0
11	1	1	0	1	1	1	1	16.8	116.7	0	43.0	70.0
12	1	1	0	0	1	1	1	16.2	111.6	0	0	70.0
13	1	1	0	0	1	1	1	15.5	105.2	0	0	70.0
14	0	1	0	0	1	1	1	0	49.1	0	0	70.0
15	0	1	0	0	1	1	1	0	31.2	0	0	70.0
16	0	1	0	0	1	1	1	0	15.0	0	0	68.6
17	0	1	0	0	1	1	1	0	47.3	0	0	70.0
18	0	1	0	1	1	1	1	0	120.0	0	65.3	70.0
19	1	1	1	1	1	1	1	25.8	120.0	40.1	72.1	70.0
20	1	1	1	1	1	1	0	34.2	120.0	54.6	99.2	70.0
21	1	1	1	1	1	1	0	40.3	120.0	65.2	100.0	70.0
22	1	1	1	1	1	1	0	45.5	120.0	74.2	100.0	70.0
23	1	1	1	1	1	1	0	59.4	120.0	98.3	100.0	70.0
24	1	1	1	1	1	1	0	58.6	120.0	96.9	100.0	70.0

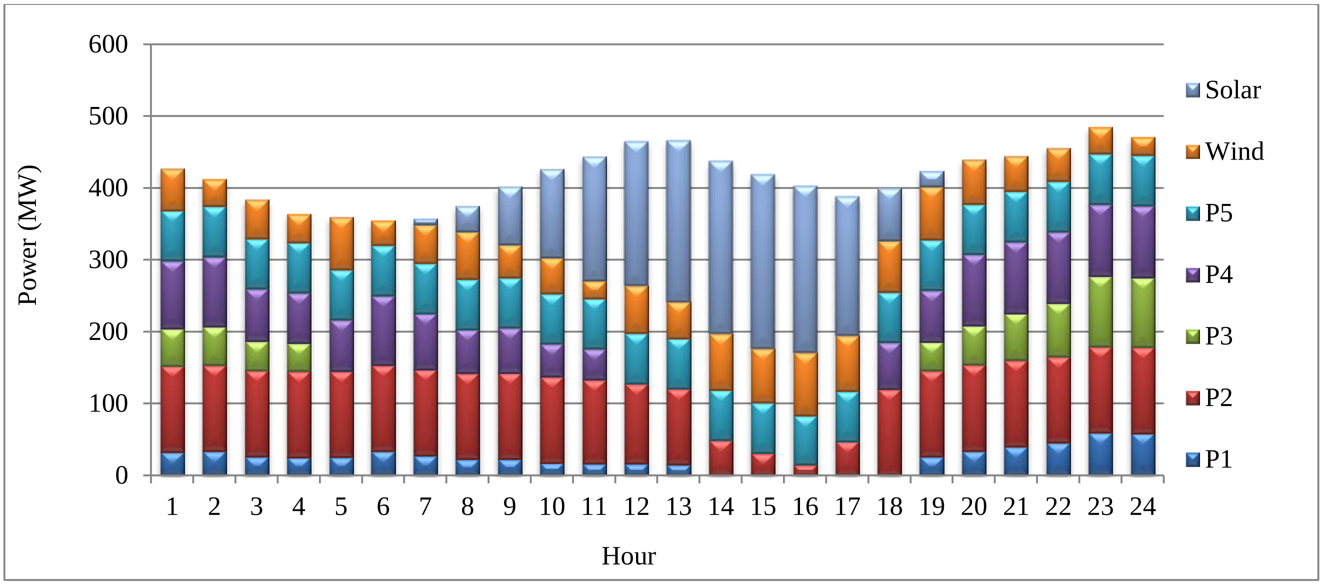

Fig. 12 Units dispatch integrated with solar and wind power

7. Conclusion

Integrating renewable energy sources into the power grid poses a significant challenge in managing the duck curve. Combining unit commitment strategies with techniques for deep learning and metaheuristic optimization can provide effective solutions to this issue. Accurate solar energy production forecasting is crucial for optimal results, and the Hybrid LSTM-1D CNN model has been demonstrated to be exceptionally accurate in this regard when compared to LSTM, CNN, and 1D CNN-LSTM. In addition, the GA-PSO hybrid technique has been determined to be the most cost-effective solution, providing invaluable insights into the optimization of unit commitment strategies for renewable energy integration when compared to GA and PSO. The case study utilizing the IEEE 39 bus test system demonstrates the potential of this methodology and identifies areas for future investigation. The hybrid LSTM-1D CNN model achieves the highest accuracy of 98.64%. The GA-PSO hybrid technique's total cost is $319,876.7, which is less than both the PSO and GA techniques. The UC can help mitigate the effects of the duck curve by adjusting the number of committed units in real time in response to changes in electricity demand and the availability of various types of generation. Successfully managing the duck curve is critical to ensuring a stable and reliable power supply while reducing greenhouse gas emissions.

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