Short-Term Unit Commitment by Using Machine Learning to Cover the Uncertainty of Wind Power Forecasting

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Abstract: Unit Commitment (UC) is a complicated integrational optimization method used in power systems. There is previous knowledge about the generation that has to be committed among the available ones to satisfy the load demand, reduce the generation cost and run the system smoothly. However, the UC problem has become more monotonous with the integration of renewable energy in the power network. With the growing concern towards utilizing renewable sources for producing power, this task has become important for power engineers today. The uncertainty of forecasting the output power of renewable energy will affect the solution of the UC problem and may cause serious risks to the operation and control of the power system. In power systems, wind power forecasting is an essential issue and has been studied widely so as to attain more precise wind forecasting results. In this study, a recurrent neural network (RNN) and a support vector machine (SVM) are used to forecast the day-ahead performance of the wind power which can be used for planning the day-ahead performance of the generation system by using UC optimization techniques. The RNN method is compared with the SVM approach in forecasting the wind power performance; the results show that the RNN method provides more accurate and secure results than SVM, with an average error of less than 5%. The suggested approaches are tested by applying them to the standard IEEE-30 bus test system. Moreover, a hybrid of a dynamic programming optimization technique and a genetic algorithm (DP-GA) are compared with different optimization techniques for day ahead, and the proposed technique outperformed the other methods by 93,171$ for 24 h. It is also found that the uncertainty of the RNN affects only 0.0725% of the DP-GA-optimized UC performance. This study may help the decision-makers, particularly in small power-generation firms, in planning the day-ahead performance of the electrical networks.

Keywords: wind energy; performance; uncertainty; unit commitment; economic dispatch; recurrent neural network

1. Introduction

Unit Commitment (UC) is considered to be one of the most significant remarkable problems in a power system, as it aims to decide the best schedule and the rate of the generating unit’s production in the power system for a specific time interval by facing given forecasted load data [1]. The only optimizing pattern in deciding the UC schedule is the generation cost, which must be minimized over a planning cycle while satisfying all the system constraints resulting from the physical capacities of the generating unit and the network design of the transmission system. Each generator has different limitations—such as maximum and minimum generation limits, minimum down-up time, the ramp rates limit, and so forth.

The UC problem is an integration of two sub-problems. The first one is deciding which generating units to commit, and the second one deals with the generated amount from each committed units. Generating units display different performance characteristics and operating efficiencies, which reflect the needed inputs. Thus, the generation costs
also depend on the output amount from each committed unit, regardless of the option of generating units. Thus, UC problems are solved in two steps. The combination of generators yielding the minimum production cost is then chosen as a schedule for the UC in an hour [2].

The operation of calculating the demanded power from each committed unit for each specific hour predetermined by the schedule for the least possible cost is called economic dispatch (ED). It is a non-linear optimization issue, in which the control variable is the output power of each committed unit, and the determined value must be connected to the power limitation of each unit [3].

UC is considered to be an optimization problem. This research aims to reduce the net present costs concerning several limitations, including system operating, the power balance in the network, unit ramp up, spinning reserve, ramp down limits, unit generation limits, and unit minimum ON and OFF time limits [4]. UC began to be used by researchers in the 1940s. Numerous research papers and studies have examined this field, and numerous methods have been applied to determine the UC problem [5]. Commonly, three methods are applied to solve the UC problem as a complex and non-linear problem. Those techniques can be classified into meta-heuristic, numerical, and hybrid methods [6]. Choosing the best method depends on the power plant units presented in the network and the type of constraints [7].

With the hybrid of large sustainable energy into the power system, the conventional operation and control approaches of UC face the issues associated with renewable energy sources, which may essentially undermine the power system’s security and reliability [2]. Nevertheless, it is expected that the introduction of intermittent power from sustainable energy production facilities will raise the instability of the power system unless a large size of energy storage is installed. Some problems that come with the recent electricity generation changes due to the rising penetration of sustainable energy are the disturbance of the supply and demand balance and stable voltage and frequency changes [8].

On a large scale, the unpredictable and sometimes sporadic nature of wind integration makes day-ahead decision-making challenging. The large-scale expansion of wind power grid penetration has yielded significant economic benefits and large system operation challenges. It is difficult to predict because of the inherent instability and intermittency of wind power generation. Facts indicate that the ability to work with effective decision-integrated wind power has become difficult in recent years [9]. The uncertainty of forecasting the output of wind energy will affect the performance of the UC operation and may cause serious risks to the operation and control of the power system. In this research, a well-known artificial-intelligence-based approach called recurrent neural network (RNN) [10] is being used to forecast the day-ahead performance of the wind energy prelude to be used as the generating unit in the IEEE 30 test bus system, so as to plan the performance of the network operating system by using UC optimization approaches. Moreover, the uncertainty of the RNN method is being analyzed by applying the actual and forecasted wind power in the given network and measuring the performance of the operation of UC in both cases.

2. Research Contributions

The use of renewable energy is growing in the world, and so it is vital to connect to the existing capacity planning processes and operational protocols. The UC and the dispatch mechanism in which the electric power provider operates are taken into account while analyzing wind potential credit in the operational domain. The majority of this study is devoted to the financial aspects of UC in addition to the risk that comes from the uncertainty of wind energy.

This research aims to plan the day-ahead performance of the power system and reduce the uncertainty which comes from wind energy by using reliable forecasting techniques. The following are some important contributions that can be achieved by the end of this study:
• This research may help the electricity supply companies to minimize the operational costs and to have a reliable plan for short-term planning strategies.
• Ensure the stability in the network, since a sufficient number of units will be committed to meet the demand and will help to cut down overall losses or fuel costs by employing the most cost-effective unit; hence, the demand can be provided by that unit functioning at its optimum efficiency.

The novelty of this study is the recourse to machine learning approaches to predict the performance of wind power, so that UC optimization problems can be used. Moreover, the added value brought by the proposed methodology reduces the uncertainty of wind power forecasting, which in turn can provide a more stable and secure power system.

3. Techniques to Solve the UC Problem

For decades, the electricity supply business has tried a variety of approaches to overcome the UC problem. Different implementation strategies are required due to the problem’s sensitivity. One method outperforms the other in terms of computing time and fuel expense. Minor changes in the overall cost can result in large variations in annual fuel costs in a restructured market [5].

Several ways to solve the UC problem have been presented, ranging from simple to hybrid metaheuristic methodologies. Three common approaches were used to solve the problem of UC, namely deterministic methods, metaheuristic algorithms, and hybrid technics [6].

3.1. Deterministic Techniques

The deterministic model of UC situations can be viewed as a subset of the related stochastic expression, in which only a single scenario containing the randomized unit and the process parameter prediction values is evaluated [5]. Popular deterministic methods for solving UC have been used, such as dynamic programming (DP) [11], Lagrangian relaxation (LR) [12], mixed-integer linear programming (MILP) [13], interior point optimization [14], branch and bound [15], and quadratic programming [16].

The study of [11] provides a DP approach for solving the UC issue while taking voltage stability and inequality requirements into consideration. The method created was applied on the IEEE-14 bus test system. The data acquired from this approach were validated using other approaches, and the outcome was judged to be satisfactory. The commitment is constructed in such a way that the overall cost of generating is kept to a minimum.

In [12], the resolution to the UC problem issue is solved utilizing LR and a modified Mendel’s genetic algorithm technique for a standard 10-unit system with a 1-h interval of time across 24 h. The LR method produces a decent optimum solution, but it is susceptible to numerical convergence and solution quality problems.

In [13], the security-constrained UC problem is addressed using a new MILP model. Bus balancing, transmission line constrained flows, and bus voltage angle discrepancies all create transmission constraints. The state of the line is also taken into account. For this, binary parameters for line conditions (active or inactive) are established. In comparison to traditional models, the results achieved cost savings of up to 4.9 percent of the overall producing cost for one day of programming horizon.

3.2. Metaheuristic Techniques

Recently, meta-heuristics methods have indeed been frequently adopted for UC problem solutions due to their potential to handle large-scale difficulties. The most frequently used techniques for solving the UC problem are a genetic algorithm (GA) [17], particle swarm optimization (PSO) [18], a bat algorithm [19], a gray wolf algorithm [20], and a bee colony [21].

In Ref. [17], GA was utilized to solve the UC Problem. The UC challenge was designed with the up and downtime, start-up cost (cold and hot start-up), and manufacturing cost in mind. To calculate the overall cost of generating, the UC schedule and economic dispatch
are determined. Problem-specific functions are employed in the method to improve the solution quality and speed up the problem’s resolution. The GA’s performance is assessed during a 24-h cycle on two IEEE test systems, one with five units and 14 buses and the other with seven units and 56 buses. The findings demonstrate the superiority of GA over other techniques for tackling UC issues.

In Ref. [18], PSO-based heuristic optimization algorithms were utilized to solve the issue of UC. For the UC problem, three PSO methods were demonstrated: Binary PSO, Improved binary PSO, and PSO with Lagrangian relaxation. Overall, the benchmark sets of data and approach demonstrated that the suggested PSO methods are capable of effectively producing higher-quality resolutions in tackling UC problems.

3.3. Hybrid Techniques

Later, efforts were made to develop hybrid approaches, such as hybrids of DP, GA and PSO [22], PSO with Sine Cosine Acceleration Coefficients [23], PSO with gray wolf optimizer [24], and whale optimization differential evolution with GA [25].

In Ref. [22], a hybrid algorithm for DP, GA, and PSO is proposed, to tackle the UC problem in power systems while keeping system security restrictions in mind. Through the aforementioned combination approach, the state of the units (on or off), as well as the economic dispatch, are identified and solved while addressing system security limitations. Resolving with the proposed method brought in more appropriate responses and a more cost-effective customer supply.

4. Identification of the UC Problem

UC is designed to commit and dispatch units before the start of the operational day. The purpose of UC is to reduce the expenses of start-up, shut-down, and operations. Network balance, generator technical needs, and network security are among the constraints [1].

The objective function is the entire production cost over the scheduling horizon, and this must be decreased to obtain the optimal production schedule. The entire production costs include the start-up cost of the operating units and the fuel costs. The start-up cost is a time exponential function in which the generator has been not connected. However, the cost of the start-up in most cases can be considered as a constant. In practice, no costs are associated with the shutting down of the units, but the shutting down costs are included, out of precaution, in the calculation of the total costs. A constant cost may be identified for each generator as the shut-down cost, and this cost is independent of the time the unit has been working before the shut-down [5, 26].

4.1. Objective Function

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

(1)

where \(i\) is the generating unit index, \(t\) is the time index, \(F_{ci}(P_{it})\) is the function of the production cost of unit \(i\), \(P_{it}\) is the power generation of unit \(i\) at time \(t\), \(I_{it}\) is the commitment state of unit \(i\) at time \(t\), \(SU_{it}\) is the start-up cost of unit \(i\) at time \(t\), and \(SD_{it}\) is the shut-down cost of unit \(i\) at time \(t\).

While

\[
F_{ci}(P_{i}) = \alpha_{i} + \beta_{i}P_{i} + \gamma_{i}P_{i}^{2} 
\]

(2)

where \(F_{ci}(P_{i})\) is the cost function, \(P_{i}\) is the output power of generator \(i\) and \(\alpha_{i}, \beta_{i},\) and \(\gamma_{i}\) are the generator \(i\) cost coefficients.
4.2. Constraints

4.2.1. Power Balance

The summation of the output power of the available generators must satisfy the load demand during each time period by taking into consideration the loss of power in the grid as in the following equation [26]:

$$\sum_{i=1}^{NG} P_{it} * I_{it} + \sum_{i=1}^{NW} P_{Wi,t} = P_{D,t} + P_{L,t}$$  (3)

where $P_{Wi,t}$ is the generation of wind power of unit $i$ at time $t$, $P_{D,t}$ is the system demand at time $t$, and $P_{L,t}$ stands for the system’s losses at time $t$.

4.2.2. Power Bounds

Each generator has a minimum and a maximum power, since the generator cannot work below and above them, as in the following equation [26]:

$$P_{i,min} * I_{it} \leq P_{it} \leq P_{i,max} * I_{it}$$  (4)

where $P_{i,min}$ is the minimum power generation of unit $i$ and $P_{i,max}$ is the maximum power generation of unit $i$.

4.2.3. Ramping Limits

No thermal unit can increase or decrease its output power from the current time period to another instantaneously. The operation of increasing the output power is called ramp up, and the operation of decreasing the output power is called ramp down, as in the following equations [26]:

$$P_{it} - P_{i(t-1)} \leq \left[1 - I_{it} \left(1 - I_{i(t-1)}\right)\right] UR_i + I_{it} \left(1 - I_{i(t-1)}\right) P_{i,min}$$  (5)

$$P_{i(t-1)} - P_{it} \leq \left[1 - I_{i(t-1)} \left(1 - I_{it}\right)\right] DR_i + I_{i(t-1)} (1 - I_{it}) P_{i,min}$$  (6)

where $UR_i$ is the ramp-up rate of unit $i$ and $DR_i$ is the ramp-down rate of unit $i$.

4.2.4. Minimum ON and OFF Time

In the activity of generating units, the manufacturer’s specifications or engineering considerations usually require the unit to operate for at least a certain duration of time until shutting down. Similarly, a minimum downtime is enjoined on individual generating units between the successive operations, as in the following equations [26]:

$$\left[X_{on}^{i(t-1)} - T_{on}^{i}\right] * I_{i(t-1)} - I_{it} \geq 0$$  (7)

$$\left[X_{off}^{i(t-1)} - T_{off}^{i}\right] * I_{it} - I_{i(t-1)} \geq 0$$  (8)

where $X_{on}^{i}$ is the ON time of unit $i$, $X_{off}^{i}$ is the OFF time of unit $i$, $T_{on}^{i}$ is the Minimum ON time of unit $i$, and $T_{off}^{i}$ is the Minimum OFF time of unit $i$.

4.2.5. Operating Reserve

It is the available capacity of the power generating to the system during a short interval of time to supply the demand in case of supply distribution or when the generator efficiency goes down, as in the following equation [26]:

$$\sum_{i=1}^{NG} R_{O,i,t} * I_{it} \geq R_{O,t}$$  (9)
where \( R_{O,i,t} \) represents the operating reserve of unit \( i \) at time \( t \) and \( R_{O,t} \) represents the operating reserve at time \( t \).

4.2.6. Spinning Reserve

It is the extra generation capacity that is usable by controlling the output of the generators connected to the grid. This operation is conducted by increasing the applied torque on the turbine rotors, as in the following equation [26]:

\[
\sum_{i=1}^{NG} R_{S,i,t} \cdot I_{t} \geq R_{S,t}
\]

where \( R_{S,i,t} \) represents the spinning reserve of unit \( i \) at time \( t \) and \( R_{S,t} \) represents the spinning reserve at time \( t \).

4.3. Power Losses

The behavior of the network components leads to a lot of effects on the operation system. For example, when the transmission lines are taken into account in the formulation, they show some effects, such as increasing the total generating power demand due to the real power losses. Therefore, it is necessary to take into consideration the consequences of the network elements for finding the optimal solution to verify the system’s security, especially in a large-scale power grid.

Two common methods in UC deal with transmission lines, which are power-flow-based ED and B-coefficient matrix-based ED [27]. The power-flow-based ED method has a convergence risk and is time-consuming; therefore, for real-time applications, it is unsuitable. However, for useful applications, B-coefficient-based ED should formulate more than one frame of B coefficients throughout the specific load cycle, as B coefficients are not constant, but vary depending on the load demand [27]. In this study, the B-coefficient method is used to obtain the losses in the network.

The B-coefficient matrix can be acquired by the traditional power losses formula as shown in Equation (11), which is adopted by Kron and Widely [28].

\[
P_L = \begin{bmatrix} P_{G_1} & \cdots & P_{G_i} & \cdots & P_{G_{NG}} \end{bmatrix} \begin{bmatrix} B_{11} & B_{1j} & B_{1NG} \\ \vdots & \vdots & \vdots \\ B_{i1} & B_{ij} & B_{iNG} \\ \vdots & \vdots & \vdots \\ B_{NG1} & B_{NGj} & B_{NGNG} \end{bmatrix} \begin{bmatrix} P_{C_1} \\ \vdots \\ P_{C_i} \\ \vdots \\ P_{C_{NG}} \end{bmatrix} + \begin{bmatrix} B_{01} \\ \vdots \\ B_{0i} \\ \vdots \\ B_{0NG} \end{bmatrix} + B_{00}
\]

where \( B_{ij} \) is the \( ij \)th component of the coefficient square loss matrix, \( B_{0i} \) is the \( i \)th component of the coefficient loss vector, and \( B_{00} \) is the coefficient loss constant. \( P_L \) is the total of real losses.

5. Wind Forecasting Using a Recurrent Neural Network

5.1. Uncertainty of Renewable Energy Sources

With the entry of renewable energy sources alongside traditional power plants, the total operating costs will be significantly reduced. In the current environment, efforts are being made to maximize the use of renewable resources, and the challenge here is the uncertainty of renewable resources. The most important renewable sources are photovoltaic sources and wind turbines, which have a variable output power due to variable sunlight and wind speed [4]. Forecasting the output of renewable energy is considered to be one of the most important areas of research in the UC problem, where the accuracy of forecasting plays a major role in terms of the reliability and economy of a renewable power network [29].

Forecasting the performance of wind energy has passed through different stages, and there are many methods used in the literature to deal with the problem of the uncertainty of forecasting, such as the statistical seasonal autoregressive integrated moving average [30],
RNNs are a class of models that replicate thinking processes by taking into account historical information throughout the learning process. RNNs are indeed a variation of the feed-forward neural network that is distinguished by the use of feedback from the output of the system to the input. The RNN outcome is influenced not only by this input but also by the network’s former condition, which serves as memory [45]. The RNN architecture includes the input layer \( x_t \), the hidden layer \( s_t \), and the output layer \( o_t \), as shown in Figure 1.

The hidden layer’s nodes are fully connected; the output of the hidden layer is also the input of the hidden layer the following time. \( U \) denotes the weight between the input and the hidden layers, \( V \) denotes the weight between the hidden and output layers, and \( W \) denotes the weight between the current hidden layer and the hidden layer in the future. Weight \( w \) will take the previously suggested state values from the hidden layer and subtract one, which is really the input whenever the state \( x_t \) is altered and placed in the next hidden layer \( s_t \), or when the hidden layer is updated [10]. The following formulas regulate the calculation that performs in an RNN:

\[
{s_t} = f(Ux_t + Ws_{t-1}) \tag{12}
\]

\[
o_t = soft\ max(Vs_t) \tag{13}
\]

Though RNN may theoretically eliminate long-term dependencies, the weight vector will remain to merge with the prior output the longer the time interval step. This situation will result in a diminishing gradient issue or a scenario where the gradient value is the smallest, causing the learning to take longer. There are various components in the RNN design, such as backpropagation through time, the recurrent gate unit, and long-short-term memory (LSTM) [10]. The diminishing gradient issue was fixed using LSTM networks in this paper.

The LSTM is a form of RNN which is good at learning long-term connections. Every neuron in LSTM is considered to be a memory cell, which distinguishes it from standard...
RNN neural networks. The LSTM is a neural network that links previous data to present neurons. The gate input, forget gate, and gate output are indeed the three gates found in each cell [10]. Figure 2 illustrates the LSTM architecture in terms of the three gates that can be found in each neuron.

![LSTM architecture](image)

**Figure 2.** LSTM architecture.

Standard RNNs are unable to learn long-term dependencies due to the vanishing gradient problem. To combat the vanishing gradient, LSTMs were built using a gating mechanism. Recurrent networks of LSTM contain “LSTM cells,” which have an inner recurrence (a self-loop), in addition to the RNN’s exterior recurrence, rather than a unit that effectively applies element-wise non-linearity to the transforming inputs and recurrent units [46]. To grasp what this means, consider how an LSTM calculates a hidden layer:

\[
I = \sigma(x_t U^i + s_{t-1} W^i)
\]

(14)

\[
F = \sum(x_t U^f + s_{t-1} W^f)
\]

(15)

\[
O = \sum(x_t U^o + s_{t-1} W^o)
\]

(16)

In Equations (14)–(16), the input, forget, and output gates are referred to as \( I, F \), and \( O \), accordingly. They have the same formulas, but their parameter matrices are varied. Since the sigmoid function undercuts the values of these vectors between 0 and 1, they are termed by gates. By multiplying with another vector, these gates regulate how much data can travel through. The input gate determines how much of the newly determined state for the current input is allowed to pass. The forget gate regulates how much of the previous state can pass through. Finally, the output gate decides how much of the internal state is visible to the rest of the network (the next time steps and the higher layers).

\[
g = \tanh(x_t U^g + s_{t-1} W^g)
\]

(17)

In Equation (17), \( g \) represents a “candidate” hidden state calculated from the previous and the current input hidden state. The parameters \( U \) and \( W \) in the normal RNN are altered to \( U^g \) and \( W^g \), while the formula remains the same. Rather than using \( g \) as the new hidden phase, like in the RNN, the above-mentioned input gate is used to pick some of it.

\[
c_t = c_{t-1} \circ f + g \circ i
\]

(18)

\[
s_t = \tanh(c_t) \circ o
\]

(19)
In Equation (18), $c_t$ represents the memory of the internal unit. It is the result of multiplying the former memory $c_{t-1}$ by the forget gate and the newly computed hidden state $g$ by the input gate.

RNNs in general can be viewed as a subset of LSTMs. The traditional RNN is defined as having an input gate that is fixed to all 1’s, a forget gate that is fixed to all 0’s, and an output gate that is fixed to all 1’s. There is one more tanh ($\tanh$) that somewhat squashes the output. The gating mechanism is responsible for LSTMs’ ability to express long-term dependency openly. The network learns how its memory should function by learning the settings for its gates. The primary data sources for wind power forecasts are historical observation records from wind farm SCADA system databases. The forecast model used historical measurement records from a SCADA system database from an actual wind power station to build the model. The power forecast result of the model in this work is based on wind speed, and the wind speed factor is a vital aspect in calculating the available power produced. Figure 3, below, represents the physical explanation of the RNN-LSTM model.

![Figure 3](image-url)  
**Figure 3.** The physical explanation of the RNN-LSTM model.

The flowchart in Figure 4 represents the operational explanation of the RNN model. As seen in the figure, the historical wind power data represent the input selection for the model; after processing the input wind power data and making the required normalization, the RNN system, like all artificial neural networks, assigns a matrix of weights to its many inputs before applying a function to those weights to derive a single output. Recurrent networks, on the other hand, apply weights not only to their current inputs, but also to their previous inputs. Then, using two important concepts, they modify the weights allocated to their current and historical inputs. The RNN then trains its nodes by altering their weights in accordance with a small variation of a feedback process called backpropagation. Most crucially, LSTMs can hold onto critical error knowledge long enough to keep gradients fairly steep, and hence training times short. This eliminates the vanishing gradient issue and significantly enhances the accuracy of the RNN-LSTM model.
6. Methodology

In this study, UC is applied to a IEEE 30-bus test system which includes six thermal units plus one wind farm. In the beginning, the RNN approach is used to predict the day ahead of the wind power performance. The accuracy of RNN is being compared with the SVM method in forecasting the wind power performance. Six optimization methods are used to plan the day-ahead performance of the generators, which are DP, MILP, LR,
GA, PSO, and hybrid DP-GA. Finally, the effects of uncertainty of the RNN model are being tested on the performance of the UC operation. Figure 5 characterizes the working procedure step by step.

![Working Procedure Diagram]

7. Case Study

A 30-bus test system is applied for planning the day-ahead performance of the power system. The 30-bus case in Figure 6 is used to explain the proposed methodology. The system includes six thermal generating units and a wind farm. Thermal units lie at buses 1, 2, 5, 8, 11, and 13, respectively. The wind farm lies at bus 15. Table 1 represents the generators' data and operating costs [47,48]. Table 2 represents the loss coefficients of the IEEE 30-bus system [27]. Table 3 provides data about the load demand for 24 h. The used data of this case study are taken from [3]. Table 4 represents historical time series wind power data for one year [49]. The operating reserve and the spinning reserve were chosen to be 0.01 of the load demand.

Figure 5. The working procedure.

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Figure 6. IEEE 30-bus test system with a wind farm line diagram.

Table 1. The generators data.

| Unit | Bus | Pmin (MW) | Pmax (MW) | Min ON Time (h) | Min OFF Time (h) | Ramp up | Ramp down | Cost Coefficients | Start up Cost | Shut down Cost |
|------|-----|-----------|-----------|----------------|-----------------|---------|-----------|-------------------|---------------|---------------|
| 1    | 1   | 15        | 80        | 2              | 2               | 50      | 75        | 0.02              | 15            | 0             |
| 2    | 2   | 15        | 80        | 2              | 2               | 80      | 100       | 0.0175            | 14.75         | 0             |
| 3    | 5   | 10        | 50        | 3              | 3               | 100     | 120       | 0.025             | 16            | 0             |
| 4    | 8   | 10        | 50        | 4              | 4               | 80      | 100       | 0.0625            | 14            | 0             |
| 5    | 11  | 5         | 30        | 3              | 3               | 50      | 75        | 0.025             | 16            | 0             |
| 6    | 23  | 10        | 55        | 4              | 4               | 80      | 100       | 0.0083            | 15.25         | 0             |

Table 2. Loss coefficients of the IEEE 30-bus system.

| Coefficient B | Value  | Coefficient B | Value  |
|---------------|--------|---------------|--------|
| B1            | 0.015751| B24           | 0.036122|
| B2            | 0.004148| B25           | 0.021162|
| B3            | -0.0163430| B26       | 0.037327|
| B4            | -0.0041543| B33       | 0.035597|
| B5            | -0.0070962| B34       | 0.016785|
| B6            | 0.008479 | B35           | 0.00187 |
| B11           | 0.026653 | B36           | 0.01678 |
| B12           | 0.032813 | B44           | 0.04962 |
| B13           | 0.007563 | B45           | 0.023143 |
| B14           | 0.017716 | B46           | 0.034977 |
| B15           | 0.003144 | B55           | 0.013355 |
| B16           | 0.020161 | B56           | 0.014568 |
| B22           | 0.054859 | B66           | 0.054766 |
| B23           | 0.02842  |               |        |
Table 3. Load data for 24 h.

| Hour | Load Demand (MW) | Hour | Load Demand (MW) |
|------|-----------------|------|-----------------|
| 1    | 266             | 13   | 270             |
| 2    | 296             | 14   | 285             |
| 3    | 329             | 15   | 308             |
| 4    | 367             | 16   | 332             |
| 5    | 383.4           | 17   | 346             |
| 6    | 360             | 18   | 341             |
| 7    | 346             | 19   | 336             |
| 8    | 313             | 20   | 325             |
| 9    | 292             | 21   | 304             |
| 10   | 261             | 22   | 282             |
| 11   | 247             | 23   | 261             |
| 12   | 260             | 24   | 231             |

Table 4. Time series wind energy data for one year.

| Hour | Wind Power (MW) Day 1 | Hour | Wind Power (MW) Day 365 |
|------|-----------------------|------|-------------------------|
| 1    | 38.02373              | 1    | 58.48118                |
| 2    | 30.17464              | 2    | 37.32334                |
| 3    | 29.60595              | 3    | 53.79952                |
| 4    | 12.38366              | 4    | 39.27922                |
| 5    | 14.70253              | 5    | 72.55551                |
| 6    | 15.39127              | 6    | 34.4053                 |
| 7    | 23.17681              | 7    | 53.91672                |
| 8    | 19.25512              | 8    | 65.53804                |
| 9    | 19.96631              | 9    | 46.22368                |
| 10   | 21.33149              | 10   | 49.59142                |
| 11   | 11.75611              | 11   | 24.69124                |
| 12   | 2.375202              | 12   | 46.39924                |
| 13   | 1.96187               | 13   | 50.94851                |
| 14   | 4.324661              | 14   | 78.26047                |
| 15   | 5.510049              | 15   | 75.25145                |
| 16   | 6.874369              | 16   | 87.02105                |
| 17   | 11.74694              | 17   | 87.29366                |
| 18   | 9.093303              | 18   | 81.91527                |
| 19   | 12.53907              | 19   | 84.05596                |
| 20   | 10.12221              | 20   | 61.79108                |
| 21   | 19.45207              | 21   | 48.95232                |
| 22   | 21.67068              | 22   | 46.22508                |
| 23   | 32.18356              | 23   | 36.92015                |
| 24   | 32.34231              | 24   | 24.83013                |

8. Results and Discussions

8.1. Testing the Proposed Forecasting Methodology

For forecasting the day-ahead performance of the wind power, the RNN and SVM methods are applied by using the Weka program. Three hundred and sixty-five consecutive days are used to forecast the 366th day. In the beginning, the RNN forecasting method is tested for the 365 given days along with the SVM method, as shown in Table 5. The results show the robustness of the RNN technique, since the average error is less than 5%. Figure 7 shows the divergence between the forecasted wind power using RNN and SVM for the 365th day and the actual wind values.
Table 5. Comparison between the actual and the forecasted wind power using the RNN and SVM techniques.

| Actual Wind Power (MW) | RNN Error (%) | SVM Error (%) | RNN | SVM |
|------------------------|---------------|---------------|-----|-----|
| 58.48118               | 1.924         | 62.423        | 3.94182 |
| 37.32334               | 3.152         | 42.365        | 5.04166 |
| 53.79952               | 2.89          | 49.254        | 4.54552 |
| 39.27922               | 3.294         | 32.365        | 6.91422 |
| 72.55551               | 2.438         | 86.352        | 13.79649 |
| 34.4053                | 4.022         | 37.25         | 2.8447  |
| 53.91672               | 1.923         | 58.365        | 4.44828 |
| 65.53804               | 3.478         | 72.1452       | 6.60716 |
| 46.22368               | 3.4102        | 40.254        | 5.98968 |
| 49.59142               | 2.892         | 56.324        | 6.73258 |
| 24.69124               | 1.43384       | 30.214        | 5.52276 |
| 66.39924               | 3.288         | 62.352        | 4.04724 |
| 50.94851               | 2.476         | 47.3652       | 3.58331 |
| 78.26047               | 2.548         | 71.3256       | 6.93487 |
| 75.25145               | 2.268         | 72.785        | 2.46645 |
| 87.02105               | 1.935         | 84.236        | 2.78505 |
| 87.29366               | 1.079         | 84.365        | 2.92866 |
| 81.91527               | 9.901         | 70.0175       | 11.89777 |
| 84.05596               | 0.092         | 80.985        | 3.07096 |
| 61.79108               | 1.171         | 57.6859       | 4.10518 |
| 48.95232               | 0.761         | 46.358        | 2.59432 |
| 46.22508               | 2.644         | 42.9857       | 3.23938 |
| 36.92015               | 2.422         | 41.6231       | 3.70295 |
| 24.83013               | 1.87213       | 27.691        | 2.86087 |

Average error (%) 2.638% 5.025%

Figure 7. Actual and forecasted wind power using RNN and SVM.

After testing the proposed forecasting techniques, the RNN method is used to forecast the next day, which can be used in the case of the IEEE 30 bus test system. Table 6 shows the day-ahead forecasted wind power in MW using the RNN method.
Table 6. Day-ahead forecasted wind power using RNN.

| Hour | Day-Ahead Forecasted Wind Power (MW) | Hour | Day-Ahead Forecasted Wind Power (MW) |
|------|-------------------------------------|------|-------------------------------------|
| 1    | 48.6582                             | 13   | 41.325                              |
| 2    | 29.6584                             | 14   | 66.254                              |
| 3    | 30.2569                             | 15   | 68.2368                             |
| 4    | 32.2584                             | 16   | 66.5981                             |
| 5    | 64.2658                             | 17   | 68.9862                             |
| 6    | 30.3695                             | 18   | 71.2586                             |
| 7    | 49.2563                             | 19   | 72.02586                            |
| 8    | 55.36985                            | 20   | 52.3697                             |
| 9    | 39.9985                             | 21   | 47.2562                             |
| 10   | 40.2584                             | 22   | 40.3691                             |
| 11   | 18.6985                             | 23   | 29.6859                             |
| 12   | 48.3694                             | 24   | 19.0258                             |

8.2. RNN Uncertainty Effects

In the beginning, UC as an optimization problem is tested using six common methods, which are DP, MILP, LR, GA, PSO, and hybrid DP and GA, as seen in Table 7. The result shows that the minimum hourly costs vary between the six methods, and for 24 h the hybrid DP and GA method outperforms the other methods, taking into consideration the constraints mentioned in Section 4.2. As a result, the DP-GA technique is used for planning the performance of the short-term UC operation for the day ahead.

Table 7. Comparison between six optimization techniques.

| Hour | DP  | MILP | LR   | GA   | PSO  | DP-GA |
|------|-----|------|------|------|------|-------|
| 1    | 3264| 3388 | 3234 | 3217 | 3219 | 3212  |
| 2    | 3985| 4087 | 4140 | 3985 | 3975 | 3978  |
| 3    | 4506| 4648 | 4579 | 4526 | 4521 | 4515  |
| 4    | 5136| 5298 | 5213 | 5100 | 5092 | 5096  |
| 5    | 4858| 4872 | 4885 | 4858 | 4838 | 4847  |
| 6    | 5284| 5346 | 5335 | 5303 | 5314 | 5011  |
| 7    | 4480| 4541 | 4571 | 4497 | 4490 | 4488  |
| 8    | 3875| 3927 | 3947 | 3872 | 3882 | 3867  |
| 9    | 3787| 3817 | 3802 | 3822 | 3755 | 3761  |
| 10   | 3295| 3329 | 3330 | 3297 | 3292 | 3289  |
| 11   | 3399| 3418 | 3423 | 3380 | 3390 | 3391  |
| 12   | 3152| 3210 | 3212 | 3145 | 3151 | 3138  |
| 13   | 3411| 3439 | 3435 | 3423 | 3416 | 3410  |
| 14   | 3258| 3339 | 3306 | 3258 | 3266 | 3260  |
| 15   | 3633| 3655 | 3633 | 3644 | 3591 | 3597  |
| 16   | 3986| 4076 | 3987 | 4003 | 3972 | 3980  |
| 17   | 4173| 4314 | 4213 | 4214 | 4186 | 4172  |
| 18   | 4071| 4211 | 4044 | 4044 | 4045 | 4054  |
| 19   | 4010| 4079 | 4006 | 3975 | 3966 | 3961  |
| 20   | 4161| 4183 | 4165 | 4086 | 4131 | 4104  |
| 21   | 3836| 3879 | 3906 | 3843 | 3837 | 3847  |
| 22   | 3633| 3588 | 3626 | 3635 | 3619 | 3599  |
| 23   | 3433| 3520 | 3460 | 3427 | 3444 | 3440  |
| 24   | 3144| 3283 | 3201 | 3150 | 3163 | 3154  |

Total cost 93,790 95,327 94,653 93,704 93,555 93,171

To analyze the uncertainty effects caused by the RNN predicting technique, the UC optimization is applied in the case of using actual wind power and the forecasted one in the 365th day. Table 8 represents the UC for the IEEE-30 bus test system in the existence of actual wind power for the 365th day, and Table 9 represents the UC schedule for the same system using the wind power for the 365th day forecasted by RNN. As seen from the committed unit schedule in Tables 8 and 9, generators 1, 2, 4, and 6 have the same performance when running in both the actual and he forecasted case. However, generators
3 and 5 have one difference in the commitment performance, since generator 3 at hour 3 is not committing in the case of actual wind power, while in the case of forecasted wind power at hour 3 generator 3 is committing. Moreover, unit 5 at the third hour is committing for the actual wind power case, while it is not running for the forecasted wind power case.

Table 8. UC for IEEE-30 bus test system using actual wind power for the 365th day.

| Hour | Load (MW) | Units Commitment | Output Power (MW) | Cost ($) |
|------|-----------|-------------------|-------------------|----------|
|      | W G1 G2 G3 G4 G5 G6 W G1 G2 G3 G4 G5 G6 |
| 1    | 266       | 1 1 1 0 1 0 1     | 58.481 68.8 80 0 50 0 10 | 3064.9   |
| 2    | 296       | 1 1 1 0 1 0 1     | 37.323 80 80 0 50 0 5 | 3857.7   |
| 3    | 329       | 1 1 1 0 1 1 1     | 53.7995 80 80 0 50 13.7 5 55 | 4138.4   |
| 4    | 367       | 1 1 1 1 1 1 1     | 39.2792 80 80 41.6 50 24.9 55 | 4983.6   |
| 5    | 383.4     | 1 1 1 1 1 1 1     | 72.5555 80 80 31.1 50 18.6 55 | 4714.8   |
| 6    | 360       | 1 1 1 1 1 1 1     | 34.4053 80 80 40.2 50 24 55 | 4986.4   |
| 7    | 346       | 1 1 1 1 1 1 1     | 59.1691 80 80 19.1 50 11.8 55 | 4413     |
| 8    | 313       | 1 1 1 0 1 1 1     | 65.538 80 80 0 50 5 36.2 3711.9 |
| 9    | 292       | 1 1 1 0 1 1 1     | 46.2237 80 80 0 50 5 33.2 3666.4 |

Table 9. UC for the IEEE-30 bus test system using the wind power for the 365th day forecasted by RNN.

| Hour | Load (MW) | Units Commitment | Output Power (MW) | Cost ($) |
|------|-----------|-------------------|-------------------|----------|
|      | W G1 G2 G3 G4 G5 G6 W G1 G2 G3 G4 G5 G6 |
| 1    | 266       | 1 1 1 0 1 0 1     | 57.356 69.9 80 0 50 0 10 | 3081.8   |
| 2    | 296       | 1 1 1 0 1 0 1     | 39.123 80 80 0 50 0 5 | 3888.8   |
| 3    | 329       | 1 1 1 0 1 1 1     | 55.356 80 80 12.7 50 0 55 | 4135.3   |
| 4    | 367       | 1 1 1 1 1 1 1     | 37.985 80 80 42.4 50 25.4 55 | 5004.3   |
| 5    | 383.4     | 1 1 1 1 1 1 1     | 74.325 80 80 30 50 18 55 | 4685.6   |
| 6    | 360       | 1 1 1 1 1 1 1     | 33.0215 80 80 41.1 50 24.6 55 | 4969     |
| 7    | 346       | 1 1 1 1 1 1 1     | 52.8796 80 80 19.7 50 12.2 55 | 4429.6   |
| 8    | 313       | 1 1 1 1 1 1 1     | 63.2586 80 80 0 50 5 38.5 3746.7 |
| 9    | 292       | 1 1 1 1 1 1 1     | 47.8 80 80 0 50 5 31.6 3642.3 |
| 10   | 261       | 1 1 1 1 1 1 1     | 51.0258 80 80 0 50 5 10 3127   |
| 11   | 247       | 1 1 1 1 1 1 1     | 23.2574 80 80 0 50 5 10 3321.4 |
| 12   | 260       | 1 1 1 1 1 1 1     | 64.2158 80 80 0 50 5 10 3282.8 |
| 13   | 270       | 1 1 1 1 1 1 1     | 49.6869 78 80 0 50 5 10 3050.1 |
| 14   | 285       | 1 1 1 1 1 1 1     | 80.254 80 80 0 50 5 10 3050.1 |
| 15   | 308       | 1 1 1 1 1 1 1     | 57.356 69.9 80 0 50 0 10 | 3081.8   |
| 16   | 336       | 1 1 1 1 1 1 1     | 59.1691 80 80 19.1 50 11.8 55 | 4413     |
| 17   | 325       | 1 1 1 1 1 1 1     | 65.538 80 80 0 50 5 36.2 3711.9 |
| 18   | 304       | 1 1 1 1 1 1 1     | 48.9233 80 80 0 50 5 33.2 3666.4 |
| 19   | 282       | 1 1 1 1 1 1 1     | 46.2237 80 80 0 50 5 33.2 3666.4 |
| 20   | 261       | 1 1 1 1 1 1 1     | 36.9202 80 80 0 50 5 33.2 3666.4 |
| 21   | 231       | 1 1 1 1 1 1 1     | 24.8301 69 80 0 50 5 33.2 3666.4 |

Total Costs ($) 89,548.2
For the performance of ED (output power for the committed units), it is usual to find changes in the real power produced at each stage due to the performance of wind power in the case of actual and forecasted values, as shown for generators 1, 3, 5, and 6.

Since the only optimizing pattern in deciding the UC schedule is the generation cost, which is the main objective function of the study besides reducing the uncertainty of forecasting technique, Figure 8 shows the cost performance for 24 h for both actual and forecasted wind power in the UC operation. Moreover, the total production costs for that day in the case of actual wind power equal 89,548.2$, while for the forecasted case it equals 89,483.2$. The results show the effectiveness and robustness of the RNN forecasting technique, since the error in reaching the optimal operational cost is around 0.0725%, which is 65$ for 24 h. Table 10 represents the RNN uncertainty effects on the UC costs.

**Figure 8.** Cost performance for 24 h.

**Table 10.** The RNN uncertainty effects on the UC costs.

| Hour | Costs with Actual Wind Values ($) | Costs with Forecasted Wind Value ($) | Uncertainty (%) |
|------|----------------------------------|------------------------------------|-----------------|
| 1    | 3064.9                           | 3081.8                             | 0.55            |
| 2    | 3857.7                           | 3830.3                             | 0.71            |
| 3    | 4138.4                           | 4113.5                             | 0.60            |
| 4    | 4983.6                           | 5004.3                             | 0.41            |
| 5    | 4714.8                           | 4686.5                             | 0.60            |
| 6    | 4946.8                           | 4969                               | 0.44            |
| 7    | 4413                             | 4429.6                             | 0.37            |
| 8    | 3711.9                           | 3746.7                             | 0.93            |
| 9    | 3666.4                           | 3642.3                             | 0.65            |
| 10   | 3148.5                           | 3127                               | 0.68            |
| 11   | 3299.7                           | 3321.4                             | 0.65            |
| 12   | 2867.5                           | 2900.3                             | 1.14            |
| 13   | 3263.8                           | 3282.8                             | 0.58            |
| 14   | 3080                             | 3050.1                             | 0.97            |
| 15   | 3490.1                           | 3464.1                             | 0.74            |
| 16   | 3668.6                           | 3694.3                             | 0.70            |
| 17   | 3884.4                           | 3870                               | 0.37            |
| 18   | 3888.8                           | 3765.1                             | 3.18            |
| 19   | 3777.3                           | 3778.5                             | 0.031           |
| 20   | 3955.8                           | 3944.7                             | 0.28            |
| 21   | 3820.9                           | 3815.2                             | 0.15            |
| 22   | 3509.2                           | 3527.9                             | 0.53            |
| 23   | 3329.2                           | 3342.8                             | 0.40            |
| 24   | 3066.9                           | 3095                               | 0.91            |
| Total Cost | 89,548.2 | 89,483.2 | 0.0725 |
8.3. Day-Ahead UC Planning

With the forecasted wind power given in Table 6, the UC problem is solved to determine the dispatch units, which are shown in Table 11. As shown, generators 1, 2, 4, and 6 are committed in the whole period, which are the cheapest units, and generators 3 and 5 are committed in the periods (3–7) and (2–20), respectively, which are the highest load-demand periods. The total operating cost for the 24 h in this case is 93,171$, considering the start-up and shut-down costs for each generating unit in addition to the constraints mentioned in Section 4.2. Moreover, between hours 1 and 24 the first, second, fourth, and sixth units are working for the whole period to face the load demand. Figure 9 shows the UC results and power dispatch within the thermal units and the wind.

Table 11. UC using DP-GA for the IEEE 30-bus system.

| Hour | Load (MW) | P_Li (MW) | Wind | Units Commitment | Output Power (MW) | Cost ($)
|------|-----------|-----------|------|------------------|------------------|------|
| 1    | 266       | 1.3       | 1    | 1 1 0 1 0 1      | 48.6582          | 3212 |
| 2    | 296       | 2.315     | 1    | 1 1 0 1 1 1      | 29.6584          | 53.7 |
| 3    | 329       | 3.52      | 1    | 1 1 1 1 1 1      | 30.2569          | 3978 |
| 4    | 367       | 3.82      | 1    | 1 1 1 1 1 1      | 32.2584          | 3958 |
| 5    | 383.4     | 3.9       | 1    | 1 1 1 1 1 1      | 64.2658          | 4515 |
| 6    | 360       | 3.65      | 1    | 1 1 1 1 1 1      | 30.3695          | 4071 |
| 7    | 346       | 3.8       | 1    | 1 1 1 1 1 1      | 49.2563          | 4488 |
| 8    | 313       | 3.72      | 1    | 1 1 0 1 1 1      | 55.3695          | 3867 |
| 9    | 292       | 2.42      | 1    | 1 1 0 1 1 1      | 39.9985          | 3761 |
| 10   | 261       | 2.65      | 1    | 1 1 0 1 1 1      | 40.2584          | 3289 |
| 11   | 247       | 1.83      | 1    | 1 1 0 1 1 1      | 18.6985          | 3391 |
| 12   | 260       | 1.724     | 1    | 1 1 0 1 1 1      | 48.3694          | 3138 |
| 13   | 270       | 2.695     | 1    | 1 1 0 1 1 1      | 41.325           | 3410 |
| 14   | 285       | 2.75      | 1    | 1 0 1 1 1 1      | 66.254           | 3260 |
| 15   | 308       | 3.89      | 1    | 1 0 1 1 1 1      | 68.2368          | 3597 |
| 16   | 332       | 3.365     | 1    | 1 0 1 1 1 1      | 66.5981          | 3980 |
| 17   | 346       | 3.785     | 1    | 1 0 1 1 1 1      | 68.9862          | 4172 |
| 18   | 341       | 3.695     | 1    | 1 0 1 1 1 1      | 71.2586          | 4054 |
| 19   | 336       | 3.524     | 1    | 1 0 1 1 1 1      | 72.02686         | 3961 |
| 20   | 325       | 3.963     | 1    | 1 0 1 1 1 1      | 52.3697          | 4104 |
| 21   | 304       | 3.526     | 1    | 1 0 1 1 1 1      | 47.2562          | 3847 |
| 22   | 282       | 2.365     | 1    | 1 0 1 1 1 1      | 40.3691          | 3599 |
| 23   | 261       | 2.254     | 1    | 1 0 1 1 1 1      | 29.6859          | 3440 |
| 24   | 231       | 2.785     | 1    | 1 0 1 1 1 1      | 19.0258          | 3154 |

Figure 9. The UC and power dispatch in the IEEE 30-bus test system.
9. Conclusions

The main idea of UC is to decide the optimum start-up/shut-down cycle of all units throughout the operating period, with a view to minimizing the overall costs with respect to various generator and system constraints. A steady rise in fuel charges and a rapid fossil fuels depletion have opened the way for the use of renewable sources for power generation. Renewable energy sources are therefore being used and installed with greater eagerness in power systems today. With the deployment of renewable sources, the UC issue becomes more complicated, providing obvious differences in behavioral and technical restrictions on traditional thermal generation systems that need to be resolved, as renewable generation will be integrated in the electrical network.

In this study, UC is applied to the IEEE 30-bus test system, which includes six thermal units in addition to one wind farm. In the beginning, the performance of the RNN approach was compared with SVM in forecasting the wind power, and the result shows that RNN outperforms SVM for short-term forecasting. Then, RNN was used to forecast the day ahead of the wind power performance; the results showed the robustness of the proposed technique. Afterwards, a comparison between six different optimization methods was used to plan the day-ahead performance of the generators, which are DP, MILP, LR, GA, PSO, and the DP-GA method. The result shows that the DP-GA method outperforms the other methods under the forecasted output wind power. With the current concentration on the integration of wind-energy-based power generation into the network, the study provides an effective solution for UC for the systems having wind plants among their generation, and it will help the power utilities in their aim to adopt new tools/solutions while incorporating the wind energy in the power generation billfold.

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Nomenclatures

The following terms with symbols and abbreviations are used in this paper:

| Symbol/Abbreviation | Meaning |
|---------------------|---------|
| CNN                 | Convolution neural networks |
| DP                  | Dynamic programming |
| ED                  | Economic dispatch |
| GA                  | Genetic algorithm |
| LR                  | Lagrangian relaxation |
| LSTM                | Long short Term memory |
| MILP                | Mixed integer linear programming |
| PSO                 | Particle swarm optimization |
| RNN                 | Recurrent neural network |
| SVM                 | Support vector machine |
| UC                  | Unit commitment |
| $P_{it}$            | Power generation of unit $i$ at time $t$ |
| $I_{it}$            | Commitment state of unit $i$ at time $t$ |
| $SU_{it}$           | Start-up cost of unit $i$ at time $t$ |
| $SD_{it}$           | Shut-down cost of unit $i$ at time $t$ |
| $\alpha_i, \beta_i, and \gamma_i$ | Generator $i$ cost coefficients |
| $P_{W, it}$         | Wind power of unit $i$ at time $t$ |
The system demand at time $t$ 

$P_L,t$ The system losses at time $t$

$P_{i,min}$ Minimum power generation of unit $i$

$P_{i,max}$ Maximum power generation of unit $i$

$UR_i$ Ramp-up rate of unit $i$

$DR_i$ Ramp-down rate of unit $i$

$R_{O,t}$ Operating reserve at time $t$

$R_{s,t}$ Spinning reserve at time $t$

$x_t$ RNN input value at time $t$

$s_t$ RNN hidden layer at time $t$

$o_t$ RNN output value at time $t$

$I, W, V$ Weight values

$I$ Input gate

$F$ Forget gate

$O$ Output gate

$g$ Candidate or hidden state

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