Optimal Power Systems Planning for IEEE-14 Bus Test System Application

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***Abstract*—As renewable energy sources become more prevalent in the grid, grid operators face new issues in maintaining system reliability in the face of changing conditions while also maximizing renewable energy usage. The need for system robustness increases as more renewable energy, such as wind power, is used in the system. In this paper, short-term power system planning and control performance is being investigated; dynamic programming (DP) as a robust optimization technique is being applied to decrease power system operational expenses. The proposed methodology is being tested on an IEEE 14-bus test system. Gated recurrent unit (GRU) and hybrid gated recurrent unit with long short term memory (GRU/LSTM) are two machine learning algorithms being utilized to forecast the performance of short-term wind generation and load demand. The prediction results show that GRU/LSTM outperforms GRU with a mean square error of 0.045 and 0.043 for load and wind prediction, respectively, to achieve the plan of UC with minimum production costs of 508933.8$ for the day ahead.**

Keywords—Unit commitment, uncertainty, forecasting, machine learning, and optimization.

I. INTRODUCTION

The power system is an essential infrastructure that offers clients with an economical and dependable power source. Modern electrical networks have become sizable uncertainty grids in recent years because of the increasing penetration of intermittent energy, the growing load variations produced by electric vehicles, and the regularly fluctuating power demand behaviors. Due to unpredictability variables such as loads, power outputs of renewable energy sources, mechanical power failures, fossil fuel cost, and electricity pricing, the management and planning of power systems are fraught with significant difficulties [1].

Variability and intermittency of renewable energy power outputs are primarily responsible for the unpredictability of generation. The production of renewable energy is highly dependent on continuously changing meteorological conditions, including temperature, wind speed, air pressure, and solar radiation. In addition, the power outputs of a renewable power plant are sequentially connected. Modeling for predicting renewable power outcomes has three difficulties: the forecast inaccuracy of meteorological conditions, the complicated nonlinear interaction between renewable power productions and weather circumstances, and the spatial linkage throughout renewable energy outputs [1] .

Generally, electricity loads exhibit substantial temporal connections can be split into regular and random components. Periodical curves can depict the periodicities of residence, industry, and commerce. The stochastic components indicate the variety of customer behavior, economic strength, manufacturing activities, and crises with temporal fluctuation and geographic spread. The expanding use of electric vehicles and the fluctuating power usage profile would exacerbate the load uncertainty [2]. Moreover, the prices of fossil fuels and electricity affect how much electricity is used and how the power grid works. Valuations of fossil fuels like coal, natural gas, and diesel oil change based on supply, consumption, market sentiment, and the stock share for renewable energy [3].

Unit commitment problem (UC) is a classic optimization technique in which the best schedule for a band of generating units is being found. Optimizing the way electricity is made has many benefits for both market players and end users. But because the problem is so huge and computers can only do so much, this is not an easy process. Because of that, there are a lot of efforts that suggest different ways to find the best solution for this problem. This is an important goal for the advancement of operational research [4]. In the field of mathematical optimization, UC is a basic tool for solving development problems where a group of electrical generators need to be coordinated so that they all produce the optimal amount of electricity. This is done to either meet the energy demand at the lowest cost or make profit from power generation. This may be essential because it's hard to store current on a scale similar to traditional consumption. For every change in consumption, there should be a corresponding change in production [5].

In recent years, higher production from solar and wind power and more price-sensitive demand involvement have made it harder to solve the UC problem. This is mostly because renewable energy sources are hard to predict and vary a lot. It has become important to have a good technique that makes good UC decisions and keeps the system reliable in the face of growing uncertainty in real-time. Aside from that, the progress in renewable energy technology over the past few years has been amazing. Several computer models have been used to make it easier to put renewable energy projects into action, particularly when it comes to choosing and making plans for renewable energy sources [6].

The fact that it is hard to predict how much energy will come from the wind and load demand will affect how well the UC works and may pose serious risks to the way the power system works and controlled [7]. In this research, the performance of short term power system planning and controlling is being studied; a robust optimization technique is being used to minimize the operational costs of the power system, which is dynamic programming (DP). A case study of IEEE 14-bus test system is being used to implement the proposed methodology. Two machine learning techniques are being used to forecast the performance of short term wind power and load demand, which are; gated recurrent unit (GRU) and hybrid gated recurrent unit with long short term memory (GRU/LSTM).

II. Research Contributions

The planet's use of renewable energy is expanding, so it's essential to link to the planning and operating procedures that are already in place. When looking at wind prospective credit in the operational field, the UC and the way the electric power provider sends out power are taken into account. Most of this study is about the financial side of UC and the risk that comes from wind energy's unpredictability. The objective of this study is to use reliable forecasting methods to plan the power study's validity for the next day and minimize the uncertainty that arises from wind energy. Here are some vital aspects that can be learned by the time this research study is over:

- This research could help the companies that provide electricity to lower their operational expenses and come up with a good plan for short-term preparation.
- Make sure the network is stable by making sure there are enough units to satisfy the demands. This will help to cut on overall losses or fuel costs by using the most cost-effective unit, which can then meet the demand by working at its best.

III. Unit Commitment Identifications

UC is made to commit and transmit out units well before implementation day starts. The goal of UC is to cut costs for starting up, shutting down, and operating a corporation. Balance in the network, the technical needs of the generators, and network security are some of the problems [8].

The main objective function is the total cost of production over the planning horizon. To find the best project timeline, this cost must be lowered. The cost of production as a whole includes both the cost to start up the units that do the work and the cost of fuel. The cost to start up is a function of time where the power supply is not linked. The cost of starting up, on the other hand, is pretty much always the same. In practice, there are no costs involved with shutting down the generators. However, the costs of shutting down are added to the final costs as a safety measure. The "shut-down cost" for each power source is a fixed cost that doesn't change no matter how long the unit was running before it was turned off [9].

The objective function is given as in equations 1 and 2 [10]. Moreover, in this study, different constraints are being studied as given in equations 3-10 [10]. In which equation 1 represents the production costs function, taking into account the start-up and shut down costs, equation 2 represents the cost function in terms of the cost coefficients. Equation 3 represents the network power balance; equation 4 represents the generator's power boundaries; equations 5 and 6 represent the generator ramping limits (up and down), respectively, and equations 7 and 8 show the minimum on and of time for each unit.

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

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{2}$$

Such that;

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

$$P_{i,min} * I_{it} \le P_{it} \le P_{i,max} * I_{it} \tag{4}$$

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

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

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

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

Where $F_i(P_i)$ represents the production cost, the generator's power can be represented by P_i and a_i, b_i and c_i are the cost coefficients of generator i, the wind power of unit i can be represented as $P_{W,it}$, $P_{D,t}$ is the load demand at time t and $P_{L,t}$ is the network losses, $P_{i,max}$ represents the maximum generated power of unit i. $P_{i,min}$ represents the minimum generated power of unit i, Where, UR_i represents the ramp-up limit of unit i and DR_i represents the ramp-down limit of unit *i*, X_i^{on} is the ON time, X_i^{off} is the OFF time, T_i^{on} represents the minimum ON time and T_i^{off} is the minimum OFF time for each generator.

IV. Load Demand and Wind Power Prediction

A. Uncertainties

When renewable energy sources are added to traditional power stations, the cumulative cost of running the power stations will go down by a fair bit. In the world we live in now, there are attempts to use renewable resources as much as possible. The problem is that renewable resources aren't always reliable. Photovoltaic options and wind turbines, which get their power from the sun and the wind, are two of the biggest renewable sources [11]. Predicting the outcome of renewable energy is among the most researched topics in the UC issue. The precision of forecasts plays a big role in the consistency and cost of a renewable power system [12].

Predicting the future what well wind energy will work and load demand has changed over time, and there are several ways in the literary works to address the problem of predicting wind future uncertainty and load demand [13]. There are several approaches used; however, machine learning approaches show the outrageously of handling the accuracy issues of predicting such as; GRU [14], long short term memory (LSTM) [15], recurrent neural network (RNN)[13], Support vector machine (SVM) [7], etc.

B. *Gated Recurrent Unit/ Long Short Term Memory*

The LSTM is one of RNNs family, that was proposed by Hochreiter and Schmidhuber [16] to eliminate vanishing or exploding that causes by RNNs gradient algorithm. An LSTM consists of three improved gates: input, output and forget gate that is used to forget any non-important value. In LSTM, the cell has the ability to store, read, write, and delete through gates when its open or close. Yet, a GRU that was proposed by [17] is a marginally more streamlined modification of the LSTM with a novel memory cell. It contains update that includes the input and forget gate into a one single gate and reset gate. Accordingly, the GRU family models is simpler than typical LSTM models and is attractive and popular.

In this paper, our proposed model dubbed GRU/LSTM is an ensemble technique which combines the GRU and LSTM as the final accurate prediction model. A proposed model is used Weighted Average Ensemble (WAE) predictions [18][19] and [20] with GRU and LSTM models. Therefore, The GRU/LSTM model can be seen as an improvement of LSTM and GRU and can be achieved a good performance comparing to LSTM and GRU.

V. METHODOLOGY

Figure 1 depicts the study's working prototype. Furthermore, in figure 2, the study's general work structure is depicted. The study's forecasting process is broken down into the following steps for viewing convenience:

Step1:

The first step is to prepare the data for analysis. Due to the GRU and GRU/ LSTM networks' sensitivity to input scale, Data must be normalized to guarantee that it is all the same. [0, 1] is the starting point.

Step2:

Validation testing: 80% of the freshly reframed data is utilized for training, while 20% is used for testing. The GRU and GRU/LSTM model is trained using predetermined training sets.

Step3:

Predicting future wind power and load demand with GRU and GRU/LSTM model is the purpose of the forecasting process. The testing set created in step 2 contains data that will be useful in the future. Consequently, the testing inputs must be constantly updated to reflect their projected value. Therefore, the best GRU/LSTM model can be used to obtain the results of the matching testing set. The final results can be attained once the output data has been de-normalized.

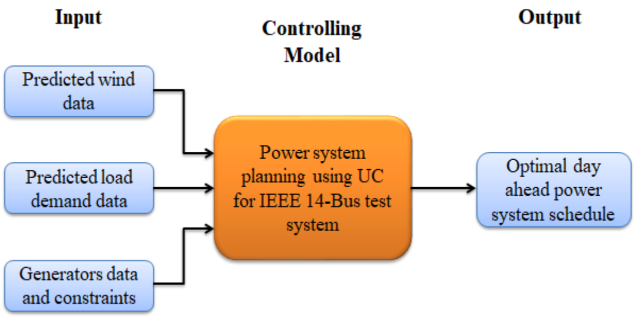

Fig. 1. UC Physical Model.

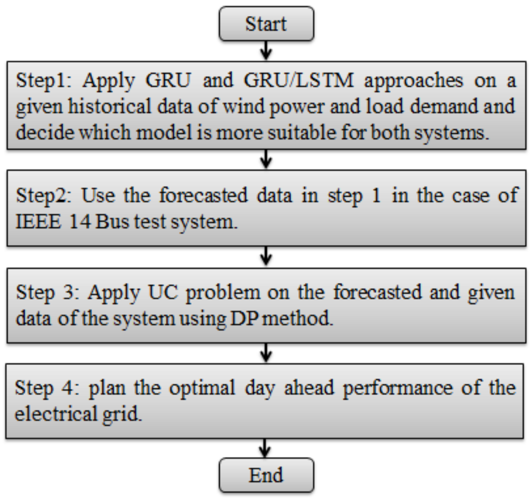

Fig. 2. Working Procedure.

VI. CASE STUDY

A. *IEEE 14-Bus Test system*

In this study, a case of the IEEE 14 bus test system is being used to test the proposed techniques, as seen in figure 3. There are four thermal power plants and a wind farm in the system. The thermal units are on buses 1, 2, 6, and 8. Bus 3 is where the wind farm is. Tables I and II show information about the power plants and how much they cost to run, respectively. The forecasted load demand is given in table V. Moreover, the predicted wind performance is given in table VI.

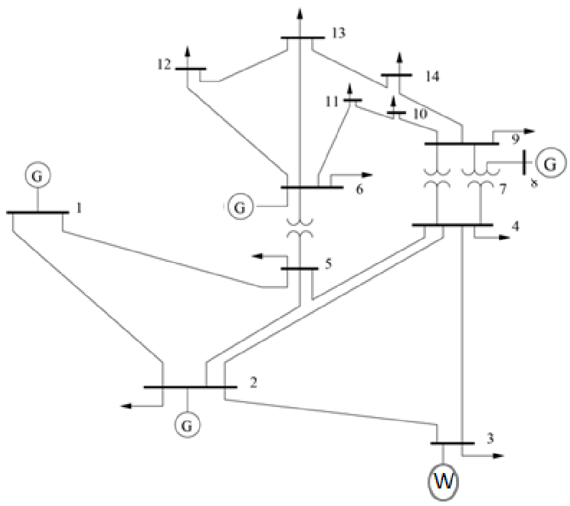

Fig. 3. IEEE 14-Bus Test System.

TABLE I. GENERATORS DATA.

Gen No.	Pmin (MW)	Pmax (MW)	Ramp Up	Ramp Down	Min ON (Hour)	Min OFF (Hour)
1	125	300	50	75	4	2
2	160	500	80	120	5	3
3	175	300	100	150	5	4
4	120	700	80	120	1	1

TABLE II. POWER PRODUCTION COSTS.

Gen No.	a ($)	b ($/MWh)	c ($/MWh^2)	Start-Up Cost	Shut Down Cost
1	1000	16.91	0.00048	350	0
2	970	17.26	0.00031	400	0
3	700	16.6	0.002	1100	0
4	680	16.5	0.00211	0.02	0

B. Load Demand and Wind Power Forecasting

In the case study described, the results reveal that the GRU/LSTM surpasses GRU in terms of mean squared error (MSE) and mean absolute error (MAE) when the number of epochs is fewer than 500. Even with more iterations, GRU/LSTM performs better when the number of epochs is increased. Results in terms of wind energy and load are shown in the tables (III-IV).

The number of training epochs has an impact on the performance of GRU/LSTM and GRU models with fixed architectures since the loss function of these models varies with the training process. Tables III and IV present the findings. A high loss function before the 500th epoch indicates that the proposed models have not yet been adequately trained for the real-world instance. Once the loss function has stabilized, the model can be used to predict future outcomes. On the other side, insufficient training might lead to an overfitting problem, which lowers reliability. The load demand data and wind power data were taken from [21], [22] respectively.

TABLE III. WIND ENERGY PREDICTION RESULTS.

No. of Epochs	GRU Evaluation of Training Data			GRU/LSTM Evaluation of Training Data		
	Loss	**MSE**	**MAE**	**Loss**	**MSE**	**MAE**
10	5.02	5.07	14.7	4.92	4.93	13.03
500	0.19	0.19	2.90	0.17	0.17	2.52
1000	0.1	0.1	1.97	0.09	0.09	1.24
3000	0.05	0.05	1.42	0.04	0.045	1.07

TABLE IV. LOAD DEMAND PREDICTION RESULTS.

No. of Epochs	GRU Evaluation of Training Data			GRU/LSTM Evaluation of Training Data		
	Loss	**MSE**	**MAE**	**Loss**	**MSE**	**MAE**
10	5.07	5.08	14.9	4.95	4.97	14.03
500	0.21	0.21	2.99	0.19	0.19	2.62
1000	0.15	0.15	1.99	0.12	0.12	1.44
3000	0.055	0.055	1.43	0.045	0.043	1.17

As noticed in tables III and IV, GRU/LSTM outperformed GRU method in forecasting the performance of the load demand and the wind power. As a result, GRU/LSTM is being chosen for predicting the day ahead performance of load demand and wind power, as seen in Tables V and VI, respectively, to be applied in the UC optimization model.

TABLE V. DAY-AHEAD LOAD DEMAND USING GRU/LSTM.

Hour	Forecasted Load Demand (MW)	Hour	Forecasted Load Demand (MW)
1	1112	13	1218.12
2	1025.32	14	1275.166
3	1040.012	15	1120.497
4	1014.74	16	1173.007
5	1050.15	17	1073.547
6	1023.85	18	1075.959
7	938.03	19	1079.976
8	1103.19	20	1121.249
9	1045.132	21	1178.559
10	1092.52	22	1312.77
11	1141.05	23	1101.68
12	1202.66	24	1101.24

TABLE VI. DAY-AHEAD WIND POWER PERFORMANCE USING GRU/LSTM.

Hour	Day Ahead Forecasted Wind Power (MW)	Hour	Day Ahead Forecasted Wind Power (MW)
1	51.62	13	46.35
2	35.65	14	69.24
3	70. 69	15	69.23
4	32.25	16	65.59
5	94.28	17	62.98
6	40.35	18	75.86
7	59.23	19	75.06
8	45.85	20	59.37
9	49.95	21	45.22
10	50.84	22	39.31
11	52.65	23	39.69
12	55.34	24	17.08

C. Unit Commitment Strategy

Using the estimated demand for the load that is presented in Table 5 and the amount of wind power that is presented in Table VI, the UC issue can be solved to determine the dispatch units, which are presented in Table VII. As can be seen, generators 1, 2, and 3 are committed throughout the entire period, making them the most cost-effective units. On the other hand, generator four is committed during the time slots (12–16) and (21–22), respectively, making them the times with the highest load demand. In this particular scenario, the overall running cost for one day is 508933.8 dollars, taking into account the costs associated with starting up and turning off each generating unit in addition to the constraints that were discussed earlier. Moreover, the findings of the UC are displayed in Figure 4, along with the power dispatch for the thermal units and the wind. Moreover, the optimal hourly production cost is illustrated in table VIII.

TABLE VII. UC FOR IEEE 14-BUS SYSTEM USING DP.

Hour	G1 MW	G2 MW	G3 MW	G4 MW	U1	U2	U3	U4
1	260.4	500	300	0	1	1	1	0
2	189.7	500	300	0	1	1	1	0
3	169.3	500	300	0	1	1	1	0

4	182.5	500	300	0	1	1	1	0
5	155.9	500	300	0	1	1	1	0
6	183.5	500	300	0	1	1	1	0
7	125	453.8	300	0	1	1	1	0
8	257.3	500	300	0	1	1	1	0
9	195.2	500	300	0	1	1	1	0
10	241.7	500	300	0	1	1	1	0
11	288.4	500	300	0	1	1	1	0
12	227.3	500	300	120	1	1	1	1
13	251.8	500	300	120	1	1	1	1
14	285.9	500	300	120	1	1	1	1
15	251.3	500	300	0	1	1	1	0
16	187.4	500	300	120	1	1	1	1
17	210.6	500	300	0	1	1	1	0
18	200.1	500	300	0	1	1	1	0
19	204.9	500	300	0	1	1	1	0
20	261.9	500	300	0	1	1	1	0
21	213.3	500	300	120	1	1	1	1
22	300	500	300	173.5	1	1	1	1
23	262	500	300	0	1	1	1	0
24	284.2	500	300	0	1	1	1	0

TABLE VIII. OPTIMAL HOURLY PRODUCTION COSTS.

Hour	Cost $/h	Hour	Cost $/h
1	21158.1	13	24086.3
2	19681.7	14	24799.5
3	19256.8	15	20967.8
4	19531.8	16	22742.6
5	18975.9	17	20118
6	19552.8	18	19899.4
7	17499.8	19	20000
8	21094.6	20	21189.4
9	19796.8	21	23283.9
10	20767.6	22	26365.7
11	21743.2	23	21191.7
12	23575.8	24	21654.6

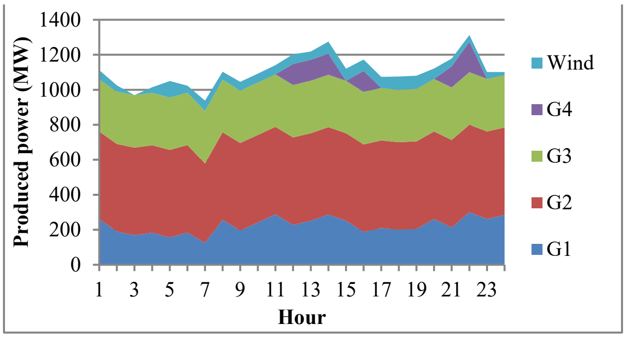

Fig. 4. UC Dispatch for IEEE 14-Bus System.

VII. CONCLUSION

The primary objective of UC is to determine the optimal start-up and shut-down cycle for all units over the whole operating time. This is done with the goal of reducing total costs while taking into account a variety of generator and system constraints. The use of renewable sources for the generation of power has become increasingly viable as a result of both the ongoing rise in the cost of fuel and the rapid depletion of fossil resources. As a result, renewable energy sources are currently experiencing a bigger push toward increased adoption within the power generation industry. As more renewable sources are put into operation, the UC problem will become more difficult to solve because it will present traditional thermal generation systems with new challenges in terms of their behavior and the technical restrictions they face. These challenges must be overcome before renewable generation can be incorporated into the electrical network. Within the scope of this investigation, UC is implemented on the IEEE 14-bus test system. GRU/LSTM was used to forecast the performance of the load demand and wind power.

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