Mansoura Engineering Journal

Volume 41 | Issue 1 Article 2

6-30-2020

A Hybrid Dynamic Programming and Neural Network Approach to Unit Commitment with High Renewable Penetration.

Sahar Kaddah
Prof, Electrical Engineering Department, Faculty of Engineering Mansoura University, Egypt, She is the head of Electrical Engineering Department, skaddah@mans.edu.eg

K. Abo-Al-Ez

Tamer Megahed
Electrical Engineering Department Faculty of Engineering Mansoura University

M. Osman
Electrical Engineering Department Faculty of Engineering Mansoura University

Mansoura University
Faculty of Engineering
Mansoura Engineering Journal

A Hybrid Dynamic Programming and Neural Network Approach to Unit Commitment with High Renewable Penetration

إستخدام البرمجة الديناميكية والخلايا العصبية لالتزام الوحدات فى وجود مشاركة عالية من الطاقة المتجددة

S. S. Kaddah, K. M. Abo-Al-Ez, T. F. Megahed and M. G. Osman
Electrical Engineering Department Faculty of Engineering Mansoura University

KEYWORDS
Unit Commitment, Renewable Forecasting, Storage System, Dynamic Program, Neural Network.

الملخص العربي:-البحث يقدم دراسة تفصيلية لمشكلة الالتزام للشبكة الكهربية والتى تحتوي على المصادر التقليدية ومصادر الطاقة المتجددة وكذلك وحدات التخزين. مصادر الطاقة المتجددة تعتمد على مصادر ذات طبيعة عشوائية وهى طاقة الشمس وطاقة الرياح، فمن الضروري إنشاء نموذج للتنبؤ بمقدار الطاقة المتولدة من المصادر المتجددة. تم بناء نموذج التنبؤ باستخدام hybrid Markov للتنبؤ بالإشعاع الشمسي، ونموذج autoregressive integrated moving average للتنبؤ بسرعة الرياح. تم دمج مشكلة الالتزام مع نموذج التنبؤ لمحاكات الطبيعة العشوائية للطاقات المتجددة. الغرض الرئيسى من النموذج المقترح هو تقليل تكلفة التشغيل الكلية والتى تشتمل على تكاليف الوقود وتكاليف التلوث الناتجة من الإنبعاثات وتكاليف الصيانة وتكاليف بدء التشغيل وايضا تكلفة فصل الوحدات. النموذج المقترح يخضع لعدد من القيود، هذه القيود هي قيود النظام والقيود على الوحدات الحرارية والقيود على وحدات الطاقة المتجددة وأيضا القيود على وحدات التخزين. كذلك، تم تعديل معامل الاحتياطي للتغلب على الخطأ فى التنبؤ وأيضا لمحاكات الطبيعة العشوائية للطاقات المتجددة. ولحل مشكلة الالتزام تم إستخدام طريقة خوارزمية بسيطة وسريعة وهى طريقة البرمجة الديناميكية القائمة على الشبكة العصبية.

Abstract **- This paper presents a solution of the unit commitment (UC) problem for an electrical grid, which contains conventional sources and renewable energy sources as well as storage units. To ensure economical with the stochastic nature of renewable sources, it is essential to develop an efficient forecasting model for renewable power generation. Forecasting model was built by using a hybrid Markov to forecast solar radiation, while, autoregressive integrated moving average model is used to predict wind speed. UC problem incorporates with forecasting, the proposed formulation aims to minimize total production cost. The total production cost includes the fuel costs, environmental cost, operation and maintenance cost (O&M cost), start-up cost, and shutdown cost. UC formulation is subject to multi-constraints. These constraints are system constraint, thermal unit constraints, renewable sources constraints and storage unit's constraint. Also, reserve coefficient is modified to overcome the variation and error of renewable source forecasting by developing two new reserves; up reserve and down spinning reserve. The unit commitment algorithm is solved by simple, fast, and accurate optimization technique. So, hybrid optimization technique used to solve UC is dynamic programming based on neural network. The proposed hybrid technique makes the solution faster and more accurate compared with the other techniques. The system under study in this paper is the standard IEEE 30 bus system, with wind speed and solar radiation data of the city of Florida, USA.**

Nomenclature

N	Number of generation units in the system
N_L	Number of transmission lines
g_l	Conductance of transmission line
P_i^t	Real power generation [MW]
U_i^t	State of unit (1 for on and 0 for off)
P_R^t	Real power forecasted from renewable units [MW
D^t	Real power demand [MW]
L^t	Real power losses [MW]
T	Number of hours in the planning horizon
$y(t)$	Wind speed time serie

RECEIVED: 2 OCTOBER, 2015 - REVISED: 30 DECEMBER 2015 – ACCEPTED: 8 MARCH, 2016

$\hat{\sigma}_Y$	Sample variance
$\hat{m}_Y$	Mean of the observed time series
φ_i	Autoregressive coefficients
θ_i	Moving average coefficients
$a(t)$	Gaussian process with zero mean and variance σ_a^2
B	Backshift operator
θ_0	Referred to the deterministic trend term
R^t	Real power spinning reserve [MW]
∇_i, Δ_i	Ramp-down and Ramp-up rates [MW/minute]
P_W^t	Real wind power forecasted [MW]
P_S^t	Real solar power forecasted [MW]
V_w	Wind speed upstream the rotor [m/s]
A_r	An area swept by the rotor [m^2]
$c_p(\lambda)$	Performance coefficient curve for pitch controlled wind turbines
n_{ij}	Transition number between class *i* and class *j*
R_{ij}	Transition rate between class *i* and class *j* [W/m^2/hour]
PDf_t	Probability distribution function of solar radiation
R_s	Solar radiation [W/m^2]
k_1	Characteristic dispersion of the panels
k_2	=-0.47%/C°
T_j	The cell junction temperature [°C]
T_{jref}	Reference temperature of the panels of 25°C
MSR^t	Minimum reserve level to support generator outages and forecast errors
$us\%$, $ds\%$	Renewable generation contributing to up/down spin requirements
US_i^{max}	Maximum up spinning reserve
DS_i^{max}	Minimum down spinning reserve
P_{Ed}^t, P_{Ec}^t	Real power discharged and charged from battery bank [MW]
$C(t)$	Energy stored in the battery bank
Δt	Duration time of discharged/charged interval
η_d, η_c	Discharge and charge efficiency respectively
C_b	Banking-start constant [MBtu/Hr]
t_b	Number of hours the unit was banked [Hour]
C_c	Cold-start constant [MBtu]
t_c	Number of hours the unit was cooled [Hour]
γ	Thermal time constant for generating unit
F_i	Price of fuel used [$/MBtu]
E_p	Emission price [$/ton]
C_f	Fixed start-up cost [$]
m	Operation, maintenance cost coefficient [$/MWh]
$\alpha_i, \beta_i, \gamma_i$	Emission coefficient
a_i, b_i, c_i	Cost coefficient.
D	Normalized load demand
n	Number of neural network pattern
t_{ni}	Target at *i* pattern
O_{ni}	Network's output at i pattern

I. INTRODUCTION

With the increased electrical energy consumption and the shortage of fossil fuel sources, it becomes essential to increase the penetration of on renewable energy sources mainly wind and solar energy. Due to the random nature of renewable energy sources, it is important to install energy storage units to provide power during low levels of generation. With the increased share of power generation based on renewable energy such as wind and solar, the complexity of the unit commitment (UC) problem increases due to the stochastic nature of renewable power. Many recent researches have discussed the issues of UC problems.

Some of recent researches considering the conventional power plants, short term operation and planning as introduced in [1-3]. Environmental/economic power was treated by using a good optimization tools to find suitable operation planning of the conventional units. These units are used fossil fuels which face many problems. Researches [4-7] used the same objective to minimize the environmental/economic operation considering the presence of wind/solar power generation systems and storage units. Although those researches have proposed optimization methods to solve the UC problem considering renewable power plants, they did not tackle the problem of wind and solar power prediction due to variable wind speed profile and solar radiation. But the optimization was solved by treating the intermittent resources as negative loads. There are very limited researches such as in [7] discussed the impact of renewable power forecasting on UC. Author in [7], an optimization strategy was developed to wind park control level that enabled defining the commitment of wind turbines and their active and reactive power outputs. That optimization strategy is solved by using mixed integer linear programming optimization problem based on minimizing the connection/disconnection changes of the individual wind generators for a given time horizon. Short term wind speed forecasts were expressed as power availability. The problem with renewable energies comes from the fluctuating and stochastic nature of the supply that is inherent in its nature. Also the power generation fluctuates independently from demand. So, increasing importance to find suitable control strategy is able to effectively control and manage the energy production in a flexible and proactive way. So renewable power forecasting is very important task to ensure the best use of the power generated from these sources.

This paper introduces a modified UC problem on an electrical grid, which contains conventional/renewable sources and storage units with considerable penetration level of renewable power. The new formulation is aimed to use largest possible proportion of electrical energy to feed the loads from renewable sources, optimal operation cost. Renewable sources is forecasted by using an autoregressive integrated moving average (ARIMA) to forecast wind speed, while a modified Markov chain is used to forecast sun radiation. The ARIMA method is further enhanced by taking into account the non-stationary characteristic of the wind power speed with only few model parameters. In addition, the proposed model does not rely on quantization and thus does not suffer from quantization errors. The modified Markov method used to forecast solar radiation is based on using a hybrid model of two Markov theories; the first one is a Markov estimation method to predict the new data. The predicted data are analyzed by using the second Markov analysis method to find the amount of solar radiation. The new formulation is subject to multi-constraints. These constraints are divided into system constraint, thermal unit constraints, renewable sources constraints and storage unit constraint. Also, a modified reserve is introduced by using two additional reserves; up spinning reserve (USR) and down spinning reserve (DSR) supports the sudden fall and sudden rise in renewable power generation. This is done by making thermal units able to ramp up to support for the reduction in renewable power, and ramp down after sudden increase.

After, building UC model, it is found that the biggest challenge is to find a suitable optimization technique that fits the uncontrolled nature of renewable energy sources. The optimization technique suitable for probabilistic UC formulation should be simple, fast, accurate obtaining the solution and it can deal with any time frame. For this purpose, this paper uses a hybrid optimization technique. Optimization technique is a dynamic programming based on neural network.

The rest of the paper is organized as follows Section 2 introduces UC formulation. Section 3 introduces optimization methodology. Finally, section 4 illustrates numerical case studies.

II. UNIT COMMITMENT FORMULATION

UC involves the period to period ordering of the units on/off in the system to match the anticipated load and to allow a safety margin [8]. The proposed UC formulation used to determine a generating unit schedule aims to minimize total production cost. The total production cost includes the fuel costs, environmental cost, operation and maintenance cost (O&M cost), start-up cost, and shutdown cost [9] as in Eq. 1.

$$\text{Min}\sum_{t=1}^{T}\left\{\begin{matrix}[FC_i^t + EC_i^t + OMC_i^t + SUC_i^t(1-U_i^{t-1})].U_i^t \\ +SDC_i^t(1-U_i^t).U_i^{t-1}\end{matrix}\right\}_{i=1}^{N} \quad (1)$$

Where:-

1. Fuel cost

The generators cost curves are represented by quadratic functions and the fuel cost can be expressed as Eq. 2.

$$FC_i^t = a_i + b_i P_i^t + c_i {P_i^t}^2 \quad (2)$$

2. Environmental cost

The amount of emission depends on various factors such as the type of fuel, level of generation output and the efficiency of the unit. Environmental cost [10] caused by the operation of fossil-fuel thermal units can be expressed as in Eq. 3.

$$EC_i^t = \left\{\left(\alpha_i + \beta_i P_i^t + \gamma_i {P_i^t}^2\right) + \zeta_i \exp(\lambda_i P_i^t)\right\} * E_p \quad (3)$$

3. O&M costs, Start-up cost and shutdown cost

There are other objectives that need to be considered in the UC decision. These objectives are O&M costs as in Eq. 4 and start-up cost as in Eq. 5 [11]. Shutdown cost is considered as a fixed cost [11].

$$OMC_i^t = m.P_i^t.\Delta\text{t} \quad (4)$$

$$SUC_i^t = (C_b.t_b.F_i) + C_c\left(1 - e^{-t_c/\gamma}\right).F_i + C_f \quad (5)$$

This objective function is subject to multi-constraints. These constraints are system constraint, thermal unit constraints, renewable sources constraints and storage unit constraint

2.1 System Constraint

System constraint contains restrictions on the system in general with involving all generating units in the system such as power balance. Power balance constraint as shown in Eq. 6, the total generation equals power demand plus losses as shown in Eq. 7 [12]. That condition of power balance will be easily achieved in the case that all the units used are thermal, but when inserting the renewable units in large quantities the prediction renewable power generating must be constructed.

$$\sum_{i=1}^{N}\left(P_i^t U_i^t + P_{R,i}^t\right) = (D^t + L^t) \quad (6)$$

$$L^t = \sum_{l=1}^{N_L} g_l[{V_x^t}^2 + {V_y^t}^2 - 2V_x^t V_y^t \cos(\delta_x^t - \delta_y^t)] \quad (7)$$

2.2 Thermal Unit Constraints

Most generating stations use thermal units. Each individual unit has its own constraints, which include initial condition, minimum/maximum generation output limits as shown in Eq. 8 [13] and maximum ramp up/down rates as in Eq. 9 and Eq. 10 respectively. Thermal units work for specific time periods [14]. This time depends on minimum up/down time. Despite this, there are some restrictions on the units such as must-run units where, some units must be forced on-line due to the need of reliability and/or economic purposes. And must-off units where, some units are required to be off-line due to maintenance schedule or forced outage, these units can be excluded from the UC decision.

$$P_{i,min}^t \le P_i^t \le P_{i,max}^t \quad (8)$$

$$P_i^{t-1} - P_i^t \le \nabla_i * 60 \quad (9)$$

$$P_i^t - P_i^{t-1} \le \Delta_i * 60 \quad (10)$$

2.3 Renewable Unit Constraint

In renewable generation units electrical power is generated without paying money for operation. Therefore, they should be considered as must run units. Renewable units rely on uncontrollable prime sources, so calculating the output power as Eq. 11 depends on the stochastic behaviour of the renewable source. For this purpose, constraints used for renewable unit are wind forecasting, solar forecasting, and modified spinning reserve.

$$P_R^t = P_W^t + P_S^t \tag{11}$$

Forecasting wind and solar power depends on the statistical information of the individual renewable sources and, the power generation has both lower and upper limits and does not follow a standard probability distribution [15]. So, in this paper wind speed and solar radiation are to be forecasted first.

a- Stochastic Analysis

Artificial neural network (ANN) is used to forecast renewable source [15]. To describe the stochastic nature of the uncertainties by using ANN, it was required a huge number of scenarios. Solving the stochastic problem with these huge sets of scenarios was computationally burden. The motivation of this paper is to search for simple methods of forecasting. There are two simple and accurate types of forecasting methods, namely ARIMA models [16] and Markov models [17].

The purpose of this paper is to study the effect of increasing the renewable energies penetration level on the solution of the UC problem. Therefore, wind farm cannot rely on disconnect when abnormal operation occurs and reconnect wind farms when normal operation has resumed. Consequently, the status of a wind farm over a period of time is a continuous stochastic process. On the other hand, solar units are turned on/off according to the regulating power, which reflects the battery condition. Hence, the generation status of solar units at a specific time instant is a stochastic variable with a certain number of discrete states. Finally, according to the continuous nature of the wind and the discrete nature of solar, the best methods to forecast wind speed is the ARIMA, while solar radiation is predicted using Markov [18].

1- Wind Power Forecasting

There are three time horizons for wind speed forecasting, very short term, short term and medium term forecasting. Very short term is in the range of 0-6 hours, which is more suitable for UC purposes.

As mentioned in the literature, ARIMA is used in wind speed forecasting. The model can predict future values of time series variable by the linear regression between a set of consecutive observations from the time series. The general form of this model is ARIMA(p,d,q) [18] where, AR(p) is the order of the autoregressive part which indicates the number of lagged variables on the relation, MA(q) is the order of moving average part which indicates the number of white noises and I(d) is integration part which difference the time series in the model.

ARIMA processes are a class of stochastic processes used to analyze time series due to Box and Jenkins [4, 6]. The description of the proposed ARIMA model and the general statistical methodology are modified as follows:

- Choose proper transformations of the observed time series. The most common transformations are variance-stabilizing transformation and differencing operation.
- Identification step is to determine the system order from visual inspection of the sample autocorrelation coefficient (ACC) as in Eq. 12 and partial autocorrelation coefficient (PACC) as in Eq. 13 of the observed time series to decide the necessity and the degree of differencing.

$$\hat{\rho}_Y(t) = \frac{\frac{1}{T-t}\sum_{t=1}^{T-t}[y(t)y(T+t)] - \hat{m}_Y^2}{\hat{\sigma}_Y^2}, for\ t = 0,1,\dots T-1 \tag{12}$$

$$\hat{\gamma}_Y(t+1) = \frac{\hat{\rho}_Y(t+1) - \sum_{j=1}^{t}\hat{\gamma}_Y(t,j)\hat{\rho}_Y(t+1-j)}{1-\sum_{j=1}^{t}\hat{\gamma}_Y(t,j)\hat{\rho}_Y(j)} \tag{13}$$

- Calculate the sample ACC and PACC of the properly transformed time series to identify the orders of p and q of the ARIMA model.
- Check the stationary of the time series, if the time series is non-stationary ARIMA is used to reduce the non-stationary this step can be achieved by using integration part to find order of d. where an ARIMA(p,d,q) model of the non-stationary random process $y(t)$ is expressed as Eq. 14.

$$\left(1-\sum_{i=1}^{p}\varphi_i B^i\right)(1-B)^d y(t) = \theta_0 + \left(1-\sum_{i=1}^{q}\theta_i B^i\right)a(t) \tag{14}$$

- Test the deterministic trend term θ_0:-
  -If $d>0$; to decide the necessity of including θ_0 in the model can be omitted unless the sample mean $\hat{m}_z$ of the transformed time series $y(t)$ is significantly larger than its standard error $S(\hat{m}_z)$ [17] as Eq. 15.

$$\boldsymbol{S(\hat{m}z) = \sqrt{\sigma_z^2(1+2\hat{\rho}_z(1)+2\hat{\rho}_z(2)+\cdots+2\hat{\rho}_z(k))/T}} \tag{15}$$

-If $d=0$; the ARIMA(p,d,q) model is reduced to an ARMA(p,q) model [18]. For an ARMA model, θ_0 is related to the sample mean $\hat{m}_Y$ of the process as Eq. 16.

$$\theta_0 = \hat{m}_Y(1-\varphi_1-\cdots-\varphi_P) \tag{16}$$

- After estimate the parameters (p,d,q) the model verification is an important step. It should be normally independently distributed with values, not significantly greater than the confidence interval.
- Finally, predict wind speed for each location then estimate the power generation from wind farm using the wind turbine model as Eq. 17.

$$P_W^t = \frac{\rho}{2} c_p(\lambda) A_r V_w^3 \quad (17)$$

- The algorithm flowchart can be described in Fig. 1.

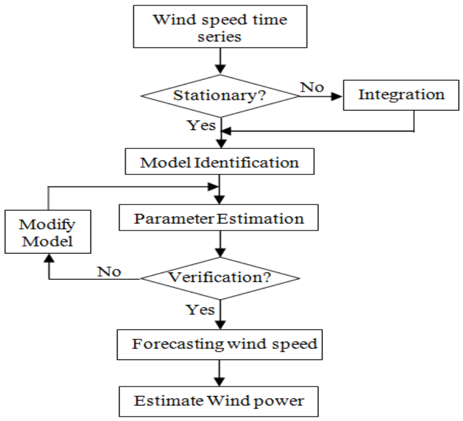


Fig. 1: Algorithm of ARIMA.

2- Solar Radiation Forecasting

The operational status of solar units is largely determined by the stochastic variables of solar radiation. Hybrid Markov analysis are used to present the solar radiation values measured from the site the first one is a Markov analysis method and the second is a Markov forecasting method as shown in Fig. 2. Hybrid Markov models are used to train and recognize sequential data. In a Markov model, each observation in the data sequence depends on previous elements in the sequence. Prediction of the next state and its associated observation only depends on the current state, meaning that the state transition probabilities do not depend on the whole history of the past process. This is called a first order Markov process [18]. First order Markov used to build transition probability distribution matrix of the previous day measured data where solar radiation ranges of interest are divided into [n] classes with different values. The number of parameters of a k^{th} order Markov model is $n^k(n-1)$, which increases exponentially as the order increases. In the k^{th} radiation class R_k is divided into a number of samples observed for each class n_k. The consequent estimated probability of each class P_k. Based on the method in [19] the transition matrix was built, and by using Markov analysis a solution is found in terms of steady-state probabilities α_i, frequencies f_i, and durations d_i of each state of interest. These terms are calculated as shown in the following equation:

$$R_{ij,_{i\neq j}} = \frac{n_{ij}/n}{n_i/n}\frac{1}{\Delta t} = \frac{n_{ij}}{n_k} \qquad i,j = 1,2,\dots\dots n \quad (18)$$

$$\alpha_n \sum_{\substack{i=1 \\ i\neq n}}^{n} R_{ni} = \sum_{\substack{i=1 \\ i\neq n}}^{n} \alpha_i R_{in} \quad (19)$$

$$\sum_{i=1}^{n} \alpha_i = 1 \quad (20)$$

$$f_i = \alpha_i \sum_{\substack{j=1 \\ j\neq i}}^{n} R_{ij} \quad (21)$$

$$d_i = 1/\sum_{\substack{j=1 \\ j\neq i}}^{n} R_{ij} \quad (22)$$

To solve this problem and get next day radiation, the probability distribution functions α_i are used during the training phase, enabling us to get as accurate a model as possible. Then in the prediction step, the Markov forecasting methods [20] is used to estimate the probability of each class's and produce the most probable one. The next probabilities for the current day are predicted based on forward procedure.

$$\alpha_i(t+1) = \sum_{i=1}^{n} \alpha_i(t)\, R_{ij} PDf_t \quad 1 < t < T, i,j = 1,\dots n \quad (23)$$

Also the largest sun radiation can be obtained, which represents peak predicted solar power. The instantaneous solar power can be described as a percentage of the P_{sun}, this percentage are α_i. The state of interest can be obtained through the period of time, which UC is calculated on it.

$$P_{sun} = k_1 R_m[1 + k_2(Te - Te_{ref})] \quad (24)$$

$$P_S^t = \alpha_{\rm i}.P_{sun} \quad (25)$$

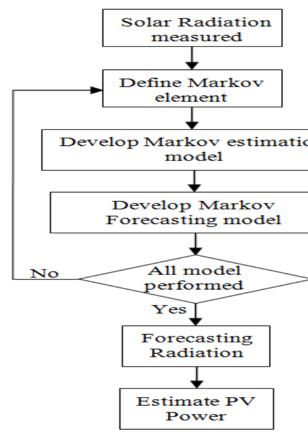


Fig. 2: Algorithm of Hybrid Markov

b- Modified Reserve Requirement

In many power systems, the amount of reserve maintained at any time is just sufficient to cover the loss of the largest generator or a certain percentage of electricity demand. But due to the huge penetration of renewable power and its intermittent nature, its frequent variation may be greater than the reserve allocated [15]. Unfortunately, spinning reserve is very expensive to have and to utilize. So, this paper suggests replacing the reserve by two additional reserves as in Eq. 26. The USR in Eq. 27 supports the sudden fall in renewable power. During a sudden decrease in renewable power, the thermal units should be able to ramp up to support for the reduction in renewable power. The second reserve is the DSR in Eq. 29. This reserve contributes to the sudden rise in renewable power. Whenever there is an unpredictable increase in renewable power, the thermal units should be able to ramp down and should support the after effects of a sudden increase.

$$R^t = \begin{cases} USR^t & \text{sudden decrease in renewable power} \\ DSR^t & \text{sudden rise in renewable power} \end{cases} \quad (26)$$

$$USR^t = \sum_{i=1}^{I} US_i^t \geq MSR^t + us\% * P_R^t \tag{27}$$

$$US_i^t = Min\left(P_{i,max}^t - P_i^t . US_i^{max}\right) \tag{28}$$

$$DSR^t = \sum_{i=1}^{I} DS_i^t \geq ds\% * P_R^t \tag{29}$$

$$DS_i^t = Min\left(P_i^t - P_{i,min}^t . DS_i^{max}\right) \tag{30}$$

2.4 Storage Constraints

In this paper, electrochemical battery is used to store DC power generation from solar farm [21]. This reduces the cost of construction because solar and battery are using the same inverter station to feed the network. Storage units can be considering as reserve to solar farm.

Storage unit is subject to some constraints such as charging period during off-peak load. Discharging occurs when the load is peak. Charging and discharging power are shown in Eq. 31 depend on duration of work and efficiency of battery. Storage algorithm is described in flowchart Fig. 3.

$$\left.\begin{aligned} \text{Discharge: } & C(t+1) = C(t) - \Delta t . P_{Ed}^t / \eta_d \\ \text{Charge } : & \ C(t+1) = C(t) + \Delta t . P_{Ec}^t / \eta_c \end{aligned}\right\} \tag{31}$$

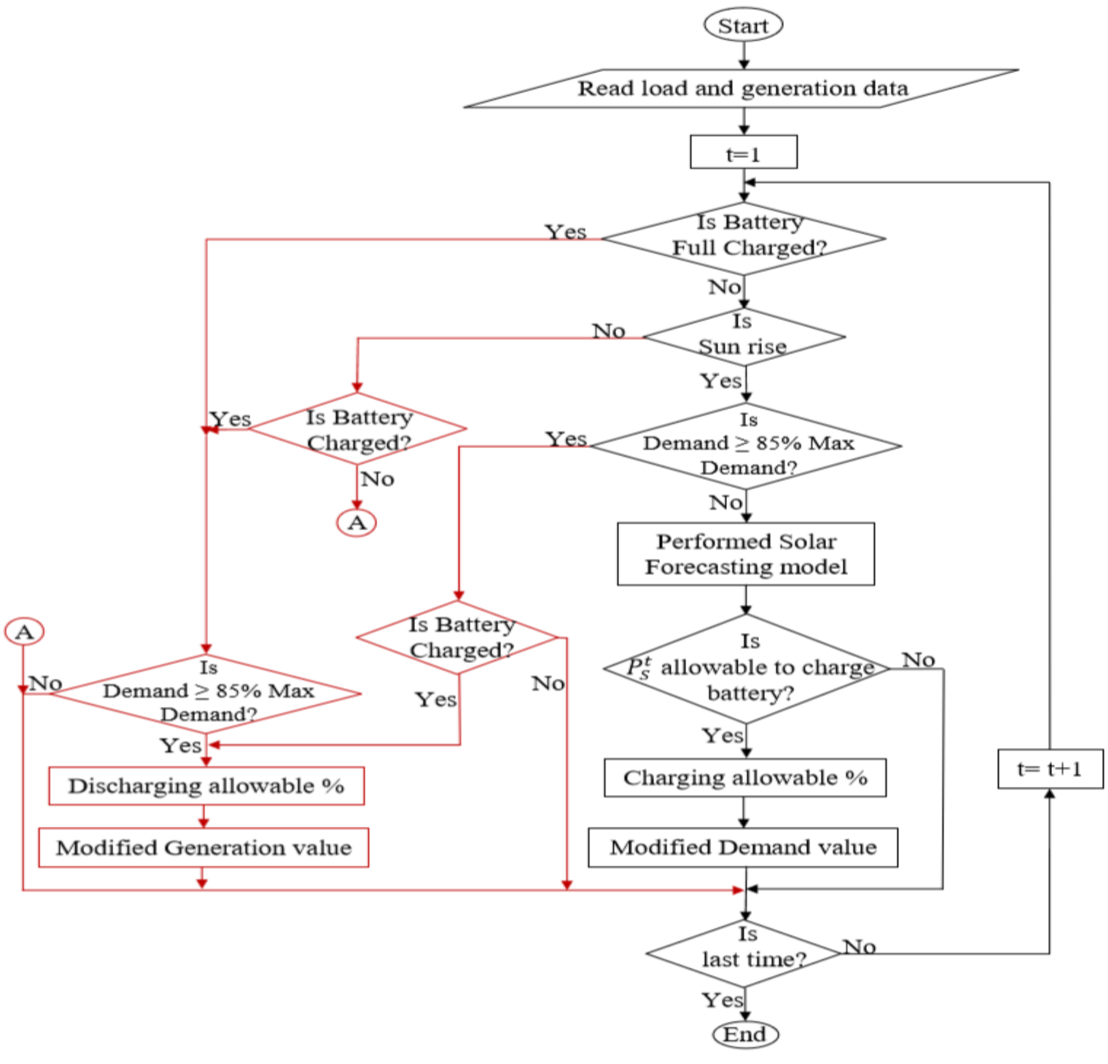


Fig. 3: Storage Model Flowchart

III. OPTIMIZATION METHODOLOGY

After building UC model as described in previous section, a suitable optimization technique should be found that fits the uncontrolled nature of renewable energy sources in order to avoid shortage or surplus of power.

This paper introduced a simple, fast and accurate combination method by using a commonly used optimization method which is the dynamic programming integrated with neural networks. Dynamic programming based on neural network is used to find daily schedule operation units which potentially satisfied environmental and economic objective.

Dynamic program [9] based on forward technique is modified, so it can deal with any time resolution. Therefore, it can be suitable for stochastic behavior of the renewable source. To achieve the greatest benefit from the renewable energy these units are used as must run units. Renewable power is estimated using a forecasting technique based on

ARIMA and hybrid Markov. However, the weather is likely to change during the day of operations and the power supply from renewable energy sources is unlikely constant, a closer look at very short term forecasting is in the range of 0-6 hours may show a renewable power prediction. The prediction uncertainty increases significantly when large amount of fluctuating renewable energy supply is introduced into the power grid. Hence, an intelligent spinning reserves constraint used to handle the uncertainties condition in UC by adding USR and DSR condition. For thermal units since there is a relation between coefficients in linear cost method and quadratic cost method, therefore dynamic programming is modified to estimate the former one (if not given) based on the latter one. This can be done off-line (e.g. least square method) and it would offer more versatility to the program (e.g. using quick dispatch or priority list even if only quadratic coefficients are given). To get schedule operation dynamic program is subject to large number of iterations equal 1000 during optimization horizon. For this, there are many outputs to search for the best solutions among them. The main problem of dynamic technique is slow of optimization so, it takes long time for decision which is the best solution. As the size of a power system increases, more computational effort (CPU time and memory) is required to solve UC. To overcome this drawback this model is modified by inserting neural network.

Neural network application in nonlinear system has increased over the last decade. This is largely due to the proven superiority of this technique. Neural network is a computational paradigm based on mimicking the human brain [22]. Neural network consists of a multilayer feed forward network using back propagation error of learning algorithm. Neural Networks is divided into three sections; Network Architecture, Training details and Network performance.

Network Architecture: is formed by interconnected slabs arranged in a particular manner. Neural network used consist of three feed forward layers including input layer, hidden layer and output layer. All of these layers are fully interconnected with each other by weights. In input layer the number of neurons is equal to number of optimization periods. Load demand is input to neurons which are represented as follows in Eq. 32 [23]. The number of output neurons in the output layer equal to the number of generators that will be committed.

$$D = \frac{D^t - D_{min}}{D_{max} - D_{min}} \qquad (32)$$

Training details: where the network is trained off line to modify the variable connection weights. Back propagation learning algorithm using gradient descent and their corresponding commitment schedules that satisfies all the constraints, is used to minimize error.

Network performance: the trained back propagation network is able to produce the corresponding schedule pattern for the unseen or seen input load profiles. The quality of predictions on unseen data obtained from neural network depends on the number and quality of patterns used for training. Network performance is normally chosen to be the mean square error (MSE) for each pattern on the training set as shown in Eq. 33 [23]. Neural network training algorithm is described in the flowchart Fig. 4.

$$MSE = \frac{1}{P\sum_{i=1}^{P}\left(t_{pi} - o_{pi}\right)^2} \qquad (33)$$

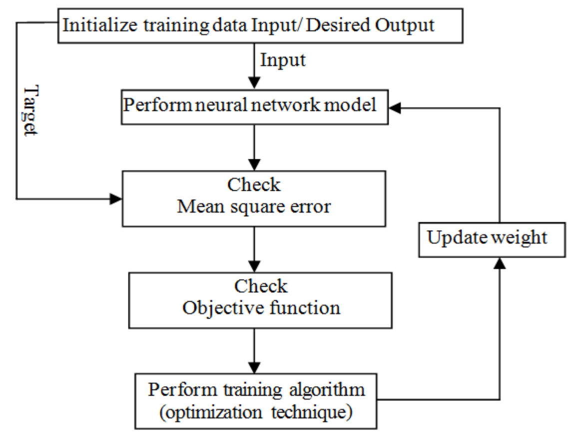


Fig. 4: Neural Network Training Flowchart

The combination between the dynamic program and the neural network is performed as follows: first, a dynamic program is used to prepare multiple UC operation schedules under various load profiles and operation constraints; second, these schedules are used to train the neural network offline. With a good training of the neural networks the best UC schedule is identified within a very short time span.

IV. NUMERICAL CASE STUDY

In this section, a numerical study is presented and the impact of renewable power forecasting as well as the benefit of the optimization approach to minimize operation cost is investigated on a stochastic day-ahead UC model (T=24 h), optimization period (20 minutes) to simulate the nature of renewable energy. The UC models were implemented in Matlab 2010b on a PC with Intel Core™ 2Duo 3.00-GHz CPU and 4.00 GB of memory.

The experiments were conducted on IEEE 30 bus as shown in Fig. 5; renewable data [24, 25] and load curve [26] were conducted on a real power system operated by a local utility company in Florida. The system has 4 convention generators plus wind farms, PV solar units and storage unit with ability 25% [21] from solar farm's capacity. The wind station ability is 275 MW and PV station is 60 MW [27]. The values of total power generation from renewable farms are representing penetration 35%. All data of generators are described in Table 1 [3].

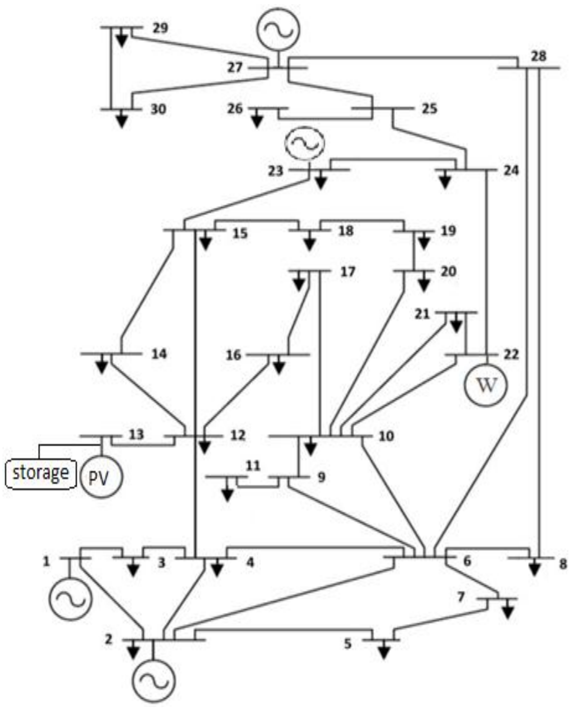


Fig. 5:IEEE 30 Bus Systems.

Table 1: Generators Data.

Coefficient		Thermal unit number			
	Unit No.	1	2	3	4
	BUS	1	2	23	27
Cost	c_i[$/MW^{2}h]	1.0E -4	1.0E -4	5.0E -4	1.0E -4
	b_i[$/MWh]	0.06	0.10	0.05	0.08
	a_i[$/h]	27.0	35.0	29.0	31.0
Emission	α_i[kg/h]	4.091	2.543	4.258	5.326
	β_i[kg/MWh]	-5.55	-6.04	-5.09	-3.55
	γ_i[kg/MW^{2}h]	6.49	5.638	4.586	3.38
P_{min}	MW	5	5	5	5
P_{max}	MW	150	150	150	150

The optimization methodology develops a daily schedule operation for one day {1/12/2013}, where the first step is forecast wind and solar power, and then UC are run in sequence, as described above. The main assumptions for the case study are outlined below.

4.1 wind speed forecasting

Wind speed forecasting by ARIMA is compared with actual wind speed as shown in Fig. 6. It is found that, the percentage of error doesn't exceed 17% in worst interval which speed is less than 4 m/s at time {21:20}. This percentage is acceptable [16], because the difference in power generation in low speed interval is not large. But in high speed interval, the error percentage does not exceed 5% which speed is increased than 6 m/s at time {3:20}, also this percentage is acceptable [16].

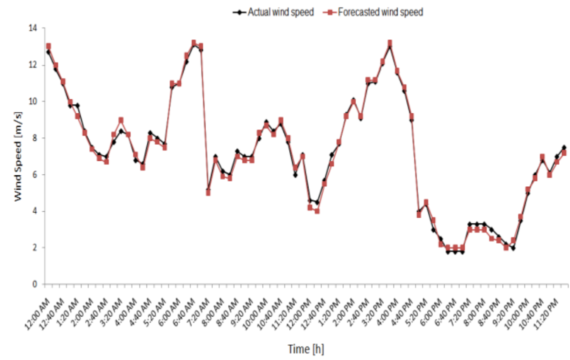


Fig. 6: Forecasted and Actual Wind Speed for Florida.

4.2 Solar Radiation Forecasting

Solar radiation prediction by using Markov can be displayed the following steps. First step: Build transition matrix data which can be set in 5 classes of solar radiation as shown in Table 2. Second step: By using Markov estimate models, predict the new forecasting transition matrix as shown in Table 3. Through new transition matrix and by using Markov analysis, solar radiation curve can be obtained as shown in Fig. 7.

Table 2: Transition Matrix.

$\emptyset_{ij}$	1	2	3	4	5
1	0.9	0.1	0	0	0
2	0.2222	0.5556	0.2222	0	0
3	0	0.25	0.5	0.25	0
4	0	0	0.1176	0.7647	0.1176
5	0	0	0	0.2857	0.7143

Table 3: Forecasting Transition Matrix.

$\emptyset_{ij}$	1	2	3	4	5
1	0.8824	0.1176	0	0	0
2	0.3	0.5	0.2	0	0
3	0	0.0909	0.4545	0.4545	0
4	0	0	0.1379	0.7241	0.1379
5	0	0	0	0.2667	0.7333

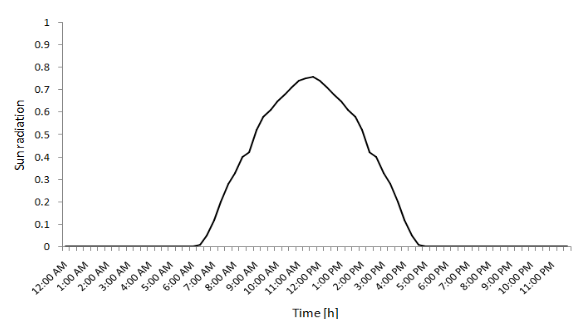


Fig. 7: Sun Radiation for One Day from Florida.

4.3 Storage Unit

Storage units charge from PV farm in the duration of peak radiation. The storage units can be used as a reserve of PV farm in limited mode of the renewable power generation or when the load is peak. Storage unit discharge power during day is displayed in Fig. 8.

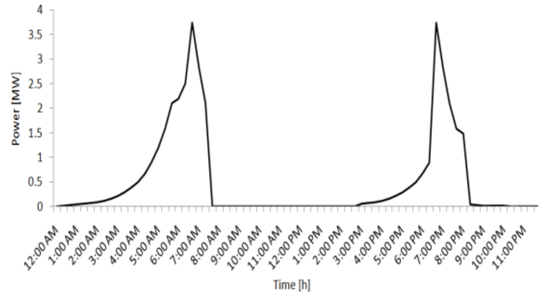


Fig. 8: Storage Unit Power Discharge Curve.

4.4 Commitment Results

Finally, the forecasted renewable power as shown in Fig. 9 is applied in UC to find the optimal total operating cost and emission. This application is done on load demand curve for Florida in winter [26]. With help of load curve and UC algorithm as described in section 2, which are considered for training and generalization of the neural network to find commitment schedules that satisfies all the constraints, training process achieves every two hours. Most of the computation time is spent on training the neural network which can be done off-line well before the actual scheduling. Once the neural network is trained, the actual processing to predict the optimum/environmental commitment schedule for any load profile can be done in a small amount of time. The learning and generalization capability of the neural network hybrid with dynamic programming makes it a faster and more accurate alternative to other existing methods for UC solution of large power system.

Network architecture consists of three-layer feed forward network. Input layer consists of six neurons equal to no. of sources, hidden layer consists of four neurons equal to no. of conventional sources and output layer consists of six neurons. A total of twenty-four patterns were used to train the neural network and six patterns were used for cross validation to monitor the training performance. The computation time to train the network was 3 minutes 33.7 sec on a PC. MSE on the training set after 25 epochs was recorded to be $0.765{*}10^{-4}$.

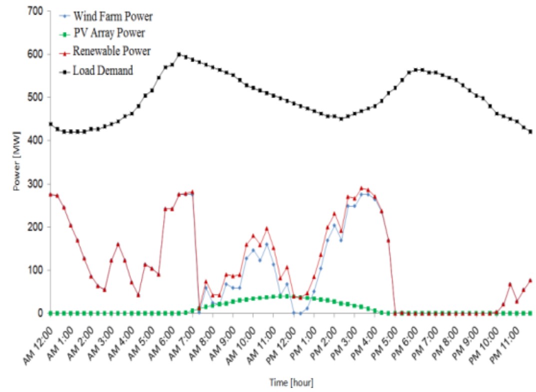
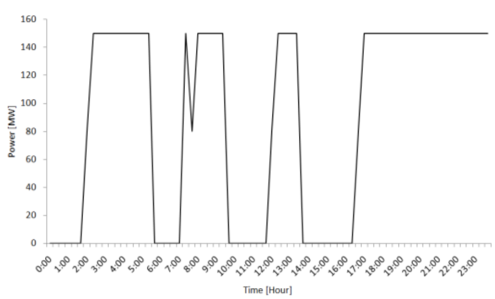
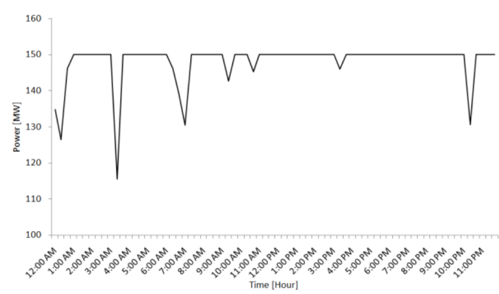


Fig. 9: Renewable Power Generation and Load Demand Curve for Florida in winter

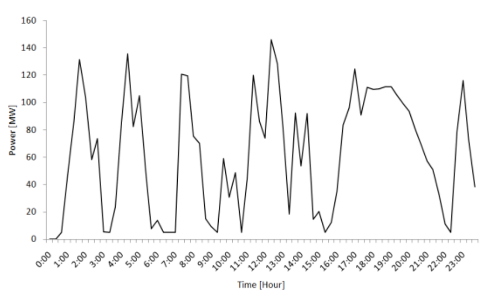
Due to the predominant role from fuel costs in the operation of the system from conventional units, therefore it is important to benefit from the energy generated from renewable units. Fig. 10, displayed the power generation from the convention units. Units' no. 1 and no. 4 contribute the most load feeding.



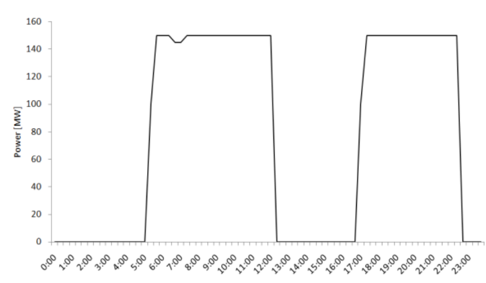
b- Unit no. 2



a- Unit no. 1



d- Unit no. 4



c- Unit no. 3

Fig. 10: Optimal Power Generation of Convention Units.

From Fig. 9 and Fig 10, it is noticed that the power generation from convention units decreased when renewable power generation increased. On the contrary, when the generation of renewable energy is low, the convention units' power generation increased. Therefore, it's a must to insert fast reserve in UC by using fast ramp generation units to utilize all renewable power generation, also to enhance the power system performance against forecasting errors. Spinning reserve is modified by using USR and DSR for unforeseen generator outages by 10% of the load and the reserve for unpredictable fluctuation in renewable power by 10% of the total renewable power generation (us%=10%, ds%=10%). The reserve curve is shown in Fig. 11.

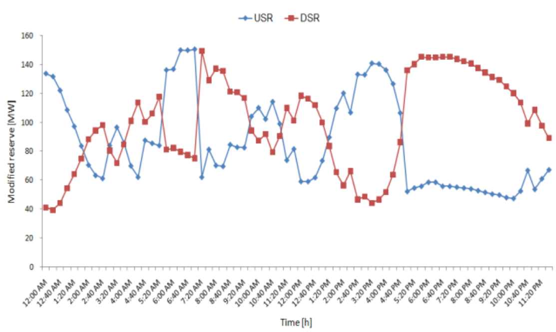


Fig. 11: Modified Reserve Curve.

When renewable power penetration level increases, reserve ratio is increased. This explains the reason why the decrease in the operation cost due to the increase in renewable power. Fig. 12 shows the operation cost curve. Operating cost directly proportional to load, but when there is high participation of renewable energies they reduce the operating cost. From Fig. 9 and Fig. 12 it is noticed that, at 2 AM and 2PM load demand is minimum, but operation cost in 2 AM is more than the cost in 2PM. Because, renewable generation in 2PM is more than the generation in 2AM. Similarly at 6 AM and 6PM the load demand is peak, but operation cost in 6 PM is more than the cost in 6AM.

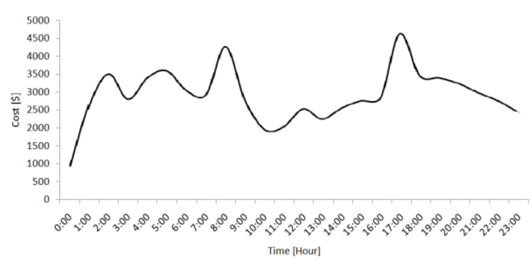


Fig. 12: Operation Cost Curve.

To ensure a minimum of cost, a good predicted system of renewable energy is established. So, the accuracy of power forecast is very important as when the forecasted power is greater than the actual power; this is risk because the short-fall of the power will be compensated from reserve and the deficit may lead to blackout. Also, if the forecasted power is less than the actual power; the excess power can't be utilized and the operation will not be economical. Therefore, the generation of the renewable power is installed to the value of forecasted power by using control.

Also UC solution by using dynamic program supported with neural network is able to find the optimum commitment schedule for any load profile in a small amount of time, assuming the network is well trained. To ensure the accuracy and speed of author's proposed optimization technique, the solution is compared with other optimization technique as shown in Table 4. It is noticed that the runtime for the dynamic programming based on neural network is faster and more economic than solving the UC by other technique and with high resolution.

Table 4: Optimization Technique Comparison.

Optimization technique	Average time for optimization [sec]	Average generation cost [$]
Author's Technique	77	2880
Swarm [28]	84	2895
Interior Point [29]	229	3015
Genetic Algorithm [30]	156	2950
Simulated Annealing [31]	218	3047

V. CONCLUSION

This paper addresses a very interesting problem, namely the optimal operation of power systems using intermittent sources (wind farm and PV array) plus battery storage units. Optimal operation was designed using the UC. The objective function aims to minimize the total operational cost which includes fuel cost, environmental cost, operation and maintenance cost, startup cost and shut down cost. The objective function is also subject to multi-constraints: system constraint, thermal units constraints, renewable sources constraints and storage units constraints.

One of the main objectives of this paper is forecasting wind speed using autoregressive integration moving average and hybrid Markov for solar radiation forecasting. The proposed prediction models accuracy proved to be up to 96%. The second objective of this paper is modifying the reserve to overcome the effect of renewable power variation as well as forecasting error by using up reserve and down reserve coefficients. The third objective of this paper is proposing a new hybrid optimization technique based on dynamic programming and neural network. This proposed optimization methodology is simple, faster and can deal with any time resolution compared to existing methodologies. The proposed solution model is applied on a standard IEEE 30 bus system and the available data of the city of Florida in USA.

REFERENCES

[1] Long Zhao, Bo Zeng, Brian Buckley, 'A Stochastic Unit Commitment Model With Cooling Systems', IEEE Transactions on Power Systems, 2013, 28, 1, pp. 211-218.

[2] Blaze Gjorgiev, Marko Cepin, 'A multi-objective optimization based solution for the combined economic-environmental power dispatch problem', Science Direct, Engineering Applications of Artificial Intelligence, 2013, 26, pp. 417–429.

[3] Serdar Özyön, Hasan Temurtas¸ Burhanettin Durmus, 'Charged system search algorithm for emission constrained economic power dispatch problem', Science Direct, Energy, 2012, 46, pp. 420-430.

[4] S. Nikolova, A. Causevski, A. Al-Salaymeh, 'Optimal operation of conventional power plants in power system with integrated renewable energy sources', Science Direct, Energy Conversion and Management, 2013, 65, pp. 697–703.

[5] Kristof De Vos, Andreas G. Petoussis, 'Revision of reserve requirements following wind power integration in island power systems', Science Direct, Renewable Energy, 2013, 50, pp. 268-279.

[6] Sanjoy Roy, 'Inclusion of Short Duration Wind Variations in Economic Load Dispatch', IEEE Transactions on Power Systems, 2012, 3, 2, pp. 265-273.

[7] Carlos F. Moyano, Joo A. Pecas Lopes, 'An optimization approach for wind turbine commitment and dispatch in a wind park', Science Direct, Electric Power Systems Research, 2009, 79, pp. 71–79.

[8] Pathom Attaviriyanupap, Hiroyuki Kita, Eiichi Tanaka, 'A Hybrid LR-EP for Solving New Profit-Based UC Problem Under Competitive Environment', IEEE Transactions on Power Systems, 2003, 18, 1, pp. 229-237.

[9] Chitra Yingvivatanapong, 'Multi-Area Unit Commitment and Economic Dispatch with Market Operation Components', Doctor of Philosophy, University of Texas at Arlington, May 2006.

[10] S. Goleijani, 'Reliability constrained unit commitment in smart grid environment', Electric Power Systems Research, 2013, 97, pp. 100-108.

[11] X. Xia, A.M. Elaiw, 'Optimal dynamic economic dispatch of generation: A review', Electric Power Systems Research, 2010, 80, pp. 975-986.

[12] A. J. Wood, B. F. Wollenberg, 'Power Generation Operation and Control', 2nd ed, Wiley, New York, 2013.

[13] L.H. Wu, Y.N. Wang, X.F. Yuan, 'Environmental/ economic power dispatch problem using multi-objective differential evolution algorithm', Electric Power Systems Research, 2010, 80, pp. 1171-1181.

[14] Luis Bayón, José M. Grau, María M. Ruiz, 'The Exact Solution of the Environmental/ED Problem', IEEE Transactions on Power Systems, 2012, 27, 2, pp. 723-731.

[15] Venkata Swaroop Pappala, Istvan Erlich, Kurt Rohrig, 'A Stochastic Model for the Optimal Operation of a Wind-Thermal Power System', IEEE Transactions on Power Systems, 2009, 24, 2, pp. 940-950.

[16] Peiyuan Chen, Troels Pedersen, Zhe Chen, 'ARIMA-Based Time Series Model of Stochastic Wind Power Generation', IEEE Transactions on Power Systems, 2010, 25, 2, pp. 667-676.

[17] N. B. Negra, O. Holmstrøm, B. Bak-Jensen, 'Model of a Synthetic Wind Speed Time Series Generator', Wind Energy, 2008, 11, pp. 193-209.

[18] Peiyuan Chen, 'Stochastic Modeling and Analysis of power System with renewable generation', Doctor of Philosophy, Aalborg University, Denmark, January 2010.

[19] A. Testa, 'A Markovian Approach to Model Power Availability of a Wind Turbine', IEEE Lausanne Power Tech, 2007, pp. 642–647.

[20] Ranjit Kumar Paul, 'Forecasting Using Markov Chain', Doctor of Philosophy, Indian Agricultural Statistics Research Institute, New Delhi, Indian, 2012.

[21] City Strategy, 'Solar PV Battery Storage System', Funded by the LGA Solar Councils, August, 2014.

[22] Krishna Teerth Chaturvedi, Manjaree Pandit, 'Modified neo-fuzzy neuron-based approach for economic and environmental optimal power dispatch', Science Direct, Applied Soft Computing, 2008, 8, pp. 1428–1438.

[23] Qiurui Liu, 'An Improved SA-Based BP-ANN Technique for Annual Runoff Forecasting Under Uncertain Environment’, Springer, 2014, pp 1467-1474.

[24] Wind speed data collect from, 'http://www.usairnet.com/weather/maps/current/oregon/wind-speed/'

[25] Stephen Wilcox, 'National Solar Radiation Database 1991–2010 Update: User’s Manual', national laboratory of the U.S. Department of Energy, 2012.

[26] Florida Public Service Commission, 'Review of the 2012 Ten-Year Site Plans for Florida's Electric Utilities', Tallahassee, FL, 2012.

[27] Olmedilla Photovoltaic Park, Spain, 'http://www.solarinsure.com/largest-solar-power-plants'

[28] Divya Ananthan, Prof. S. Nishanthinivalli, 'Unit Commitment Solution Using Particle Swarm Optimisation (PSO)', ijetae, 2014, 4, 1, pp. 512-517.

[29] Milad Tahanan, Wim van Ackooij, Antonio Frangioni, Fabrizio Lacalandra, ' Large-scale Unit Commitment under uncertainty’, Springer, 2015, 13, 2, pp 115-171.

[30] Abookazemi, K., Mustafa, M.W., 'Unit Commitment optimization using improved Genetic Algorithm', IEEE PowerTech, 2009, pp. 1-6.

[31] Dimitris N. Simopoulos, Stavroula D. Kavatza, Costas D. Vournas, 'Unit commitment by an enhanced simulated annealing algorithm', IEEE Transactions on Power Systems, 2015, 21, 1, pp. 68-76.