Impact of Renewable Resources Forecasting on Unit Commitment Solution of Egyptian Electric Grid

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Abstract

To ensure optimum operation with the stochastic nature sources, it is essential to develop an efficient forecasting model for wind and solar power generation. A hybrid Markov chain is used to forecast solar radiation as it is suitable for modelling discrete process. While, auto regressive integrated moving average (ARIMA) model is used to predict wind speed as a continuous process. Renewable forecasting methods which built in this paper was compared with the other forecasting models and found that the recommended model in this research more accurate, simpler and faster than other models. Wind speed and solar radiation are forecasted at local sites in Egypt. Based on the forecasting outcomes, it would be possible to perform unit commitment to ensure optimal operation with the presence of renewable energy. Unit committed objective for the Eastern Portion of the Egyptian electrical grid is obtained. Also, to overcome the variation and error of renewable forecasting in unit commitment, the reserve constraint is modified to develop two new reserves; up reserve and down reserve.

Keywords: Markov, Auto Regressive Integrated Moving Average, Unit Commitment, and Reserve.

I. Introduction

As a result of increased consumption of electricity and lack of fossil fuel, conventional power stations are unable to feed increased demand. This scenario is common in countries like Egypt, which faces the problem of frequent interruptions of electricity. So, it must set up stations to encounter this problem. The current approach is to generate electricity from renewable sources such as solar and wind. The geographical location of Egypt makes it rich in solar and wind energy in many parts around the country. In the area of Zafarana the average wind speed is 11 m/s [1] with very high capacity factor, this speed is considered to be one of the largest wind speed values in the world [1]. However, the solar radiation remains for about 10 hours a day [2, 3]. Renewable energy penetration in Egypt is less than 0.5% [1] so; it is recommend to increase penetration from renewable energies. When increase the participation rate the network should be restructured to ensure optimal operation. To achieve this, an intelligent, accurate and fast forecasting model for renewable energies must be achieved then provided it with fast unit commitment (UC) tool.

The UC problems are discussed in many researches considering the conventional power plants, short term operation and planning as in [4-6]. In recent researches such as in [7-8], the UC solutions were performed with the presence of renewable generators. Although those researches have proposed optimization methods to solve the UC problems considering renewable power plants, they did not tackle the problem of renewable power prediction due to variable wind speed profile and solar radiation, but the optimization was solved by treating the intermittent resources as negative loads. Currently, there are some researches such as in [9-14], that investigate the impact of renewable power forecasting on the solution of UC problems in modern grids. In [9], the forecasted data were produced by combining a mesoscale weather model with a composite power curve for a number of potential sites for wind power farms. The day-ahead forecasts were generated based on observed forecast errors from four real wind power plants. The problem of this method was that the accuracy of the day-ahead wind power forecast varies from day to day, as the power curve taken is fixed for each location. In [10], forecasting wind power problem was treated using artificial neural network. To describe the stochastic nature of the uncertainties, it was required a huge number of scenarios. Solving the stochastic problem with these huge sets of scenarios was computationally burden. The previous forecasting methods were not accurate and difficult to obtain [9, 10]. Therefore, the motivation of this paper is to search for simple and accurate methods. There are two simple and accurate types of forecasting methods, namely autoregressive moving average (ARMA) models [11, 12] and Markov models [13, 14]. In [11], an ARMA model is directly applied and can be adequate if time series achieves the constant mean over any time interval; while in [12] inserting new factor representing the integration part to develop auto regressive integrated moving average (ARIMA) which converts the time series to stationary. The discrete Markov model is mainly based on a transition matrix [13]. The birth and death Markov model developed in [14] is a simplified Markov model, as it considers only transition rates among two adjacent states. ARIMA models can be applied to continuous stochastic processes on the other hand; Markov chains are suitable for modeling a discrete stochastic process.

The purpose of this paper is to increase the penetration of wind farms, therefore we cannot rely on disconnect and reconnect wind farms when normal operation has resumed. So, it is important to study the stochastic continuous behaviour of renewable source in an electrical power system and their interaction with other generation equipment and loads. 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 and off according to the regulating power. Hence, the generation status of solar units at a specific time instant is a stochastic variable with a certain number of discrete states. Furthermore, the status of the solar unit at different time instants is not independent of each other. Consequently, the status of a solar unit over a period of time is a discrete stochastic process. Finally, Because of the continuous nature of the wind and the discrete nature of sun radiation, the best methods to forecast wind speed is the ARIMA, while solar radiation is predicted using Markov chains.

This paper proposes two forecasting methods using ARIMA to forecast wind speed and modified Markov chain 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 is based on using a hybrid model of two Markov theories; the first one is a Markov analysis method to analysis measured day data then by using the second theory Markov estimation method can predict the current day data. The two forecasting methods incorporate with UC to develop new formulation based on forecasting analysis of renewable sources. This paper also introduces a modified reserve method by using two additional reserves; up spinning reserve (USR) and down spinning reserve (DSR) supports the sudden fall or rise of renewable power and also to overcome the forecasting

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model error. 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. The new formulation in this paper is aimed to use largest possible portion of electrical energy from renewable sources to feed the loads to achieve optimal operation. The new formulation has been applied to the Eastern Part of the Egyptian electrical grid that contains large wind energy in the Zafarana area and a large solar radiation in the Delta region.

The rest of the paper is organized as follows: section II describes the renewable forecasting methods. Section III presents the problem formulation. Section IV presents the algorithm strategy. Numerical examples are provided in Section V. Section VI concludes the discussion.

II. Renewable Power Forecasting

Renewable power generation, such as wind and solar units are relying on uncontrollable sources. So calculating the output power depends on the stochastic behaviour of the renewable source. This section introduces forecasting methods for both types of renewable sources wind/solar to forecast the next wind speed, and solar radiation.

Most of the researchers forecasted wind and solar power. The disadvantage of this method is that it depends on the statistical information of the individual renewable sources and also, the power generation has both lower and upper limits and does not follow a standard probability distribution [10]. But in this paper, due to high penetration and static relationship between wind speed and solar radiation and there power production, so for more accuracy we are forecasting wind speed and solar radiation rather than renewable power and then convert forecasted data to power.

2.1 Wind Speed 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) [12] 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 differencing the time series in the model.

ARIMA processes are a class of stochastic processes used to analyze time series due to Box and Jenkins [15, 16]. 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. 1 and partial autocorrelation coefficient (PACC) as in Eq. 2 of the observed time series to decide the necessity and the degree of differencing.

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

$$\hat{\gamma}_Y(t+1) = \frac{\hat{\rho}_Y(t+1) - \sum_{j=1}^{t}\hat{\gamma}_Y(t,j)\hat{\rho}_Y(t+1-j)}{1-\sum_{j=1}^{t}\hat{\gamma}_Y(t,j)\hat{\rho}_Y(j)} \quad (2)$$

Where: T is a number of hours in the planning horizon; $y(t)$ is wind speed time series; $\hat{\sigma}_Y$ is a sample variance; and $\hat{m}_Y$ is a mean of the observed time series.

- 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:-

$$\left(1-\sum_{i=1}^{p}\varphi_i B^i\right)(1-B)^d y(t) = \theta_0 + \left(1-\sum_{i=1}^{p}\theta_i B^i\right)a(t) \quad (3)$$

Where: φ_i are the AR coefficients; θ_i are the moving average (MA) coefficients; $a(t)$ is a white Gaussian process with zero mean and variance $\sigma_a{}^2$; B is the backshift operator; and θ_0 is referred to the deterministic trend term.

- 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 $S(\hat{m}_z)$ [16].

$$S(\hat{m}z) = \sqrt{\sigma_z^2(1 + 2\hat{\rho}_z(1) + 2\hat{\rho}_z(2) + \cdots + 2\hat{\rho}_z(k))/T} \tag{4}$$

-If $d=0$; the ARIMA(p,d,q) model is reduced to an ARMA(p,q) model [17]. For an ARMA model, θ_0 is related to the sample mean $\hat{m}_Y$ of the process as:-

$$\theta_0 = \hat{m}_Y(1 - \varphi_1 - \cdots - \varphi_P) \tag{5}$$

- 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.

$$P_w^t = \frac{\rho}{2} c_p(\lambda) A_r V_w^3 \tag{6}$$

Where: P_w^t is a real power of the wind [MW]; V_w is wind speed upstream the rotor [m/s]; A_r is an area swept by the rotor [m^2]; and $c_p(\lambda)$ is a performance coefficient curve for pitch controlled wind turbines.

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

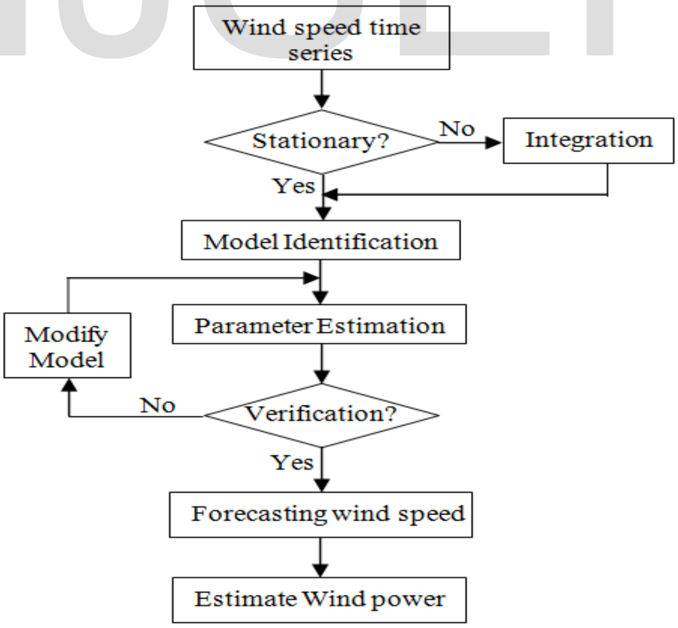

Fig. 1: Algorithm of ARIMA.

2.2 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. 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 [12]. Based on the method in [17] 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:

$$R_{ij_{,i\neq j}} = \frac{n_{ij}/n}{n_i/n}\frac{1}{\Delta t} = \frac{n_{ij}}{n_k} \qquad i,j = 1,2,\dots\dots\dots\dots\dots\dots n \tag{7}$$

$$\alpha_n \sum_{\substack{i=1\\i\neq n}}^{n} R_{ni} = \sum_{\substack{i=1\\i\neq n}}^{n} \alpha_i R_{in} \tag{8}$$

$$\sum_{i=1}^{n} \alpha_i = 1 \tag{9}$$

$$f_i = \alpha_i \sum_{\substack{j=1\\j\neq i}}^{n} R_{ij} \tag{10}$$

$$d_i = 1/\sum_{\substack{j=1\\j\neq i}}^{n} R_{ij} \tag{11}$$

Where: Δt in the field measurement is considered one hour; n_{ij} is transition number between class i and class j; and R_{ij} is a transition rate between class i and class j [W/m^2/hour].

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 an accurate model. Then in the prediction step, the Markov forecasting methods [18] 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.

$$\alpha_i(t+1) = \sum_{i=1}^{n} \alpha_i(t) R_{ij} PDf_t \quad 1 < t < T, i,j = 1,2,\dots\dots\dots n \tag{12}$$

Where: PDf_t is a probability distribution function of solar radiation.

And also, we can get the largest sun radiation, which represents peak solar power from predicting data. The actual 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.

$$P_{sun} = k_1 R_m [1 + k_2 (Te - Te_{ref})] \quad (13)$$

$$P_S^t = \alpha_{\mathrm{i}} . P_{sun} \quad (14)$$

Where: P_{sun} is peak solar power [MW]; k_1 represent the characteristic dispersion of the panels and the value for one panel is included enters 0.095 to 0.105; $k_2 = -0.47\%/\text{C}°$; Te is the cell junction temperature [°C]; and Te_{ref} is the reference temperature of the panels of 25°C; R_m is maximum radiation; and P_s^t is the real power of solar [MW].

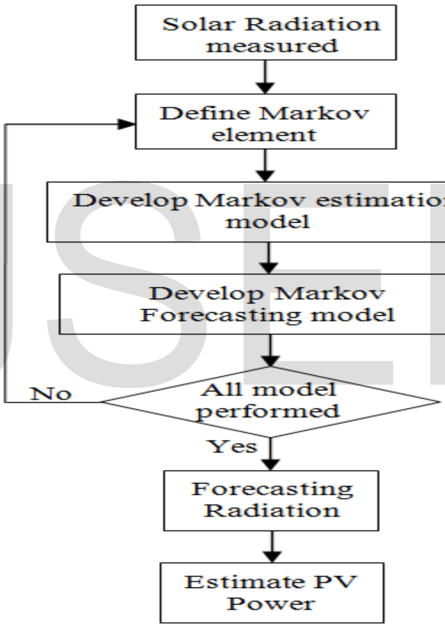

Fig. 2: Algorithm of Hybrid Markov.

III. Unit Commitment Formulation

The objective of power system operation is to supply power from generators to the end users reliably and efficiently, under both normal conditions and expected contingencies. The stochastic nature of the renewable power generation and electrical demand imposes major challenges in power system planning when determining the schedule of the generating units [10]. This schedule can be determined by using UC on a grid, which contains conventional/renewable sources.

The objective in this paper is to minimize the total operation cost by increasing renewable power penetration.

Minimize: $OC_i^t(P_i^t)$ *For i=1,.....M* (15)

Where: M is the number of all units in the system; P_i^t is the real power of the unit i [MW]; and $OC_i^t(\mathrm{P}_i^t)$ is operation cost function [$].

Since the operating costs of the renewable are negligible [10], the total operating cost is given by the sum of the fuel cost as in Eq. 17 and the start-up cost as in Eq. 18 of all thermal units.

$$OC_i^t(P_i^t) = FC_i^t(P_i^t) + SC_i^t \quad (16)$$

$$FC_i^t(P_i^t) = c_i + b_i P_i + a_i P_i^2 \quad (17)$$

$$SC_i^t = (C_b.t_b.F_i) + C_c\left(1 - e^{-t_c/\gamma}\right).F_i + C_f \quad (18)$$

Where: $FC_i^t(P_i^t)$ is the fuel cost function [$]; SC_i^t is the start-up cost [$]; a_i, b_i, c_i cost coefficient; F_i is the fuel price [$/MBtu]; t_b is number of hours the unit was banked [Hour]; C_c is cold-start constant [MBtu]; C_b is banking-start constant [MBtu]; t_c is number of hours the unit was cooled [Hour]; γ is thermal time constant for the generating unit; and C_f is fixed start-up cost [$].

This objective function is subject to multi-constraints. Multi-constraints contain power balance constraint as in Eq. 19, active power loss constraint as in Eq. 21. Also, contains power generation limits as in Eq. 22, minimum-up time, minimum-down time, and crew constrains.

$$\sum_{i=1}^{N}(P_i^t.U_i^t + P_R^t) \geq \sum_{i=1}^{N}(\mathrm{D^t} + \mathrm{PL^t} + R^t) \quad (19)$$

$$P_R^t = P_W^t + P_S^t \quad (20)$$

$$PL^t = \sum_{k=1}^{NL} g_k[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)] \quad (21)$$

$$P_{i,min}^t \leq P_i^t \leq P_{i,max}^t \quad (22)$$

Where: $\mathrm{U_i^t}$ is state of the unit (1 for on and 0 for off); $\mathrm{D^t}$ is real power demand [MW]; $\mathrm{PL^t}$ is a real power loss [MW]; R^t is a real power reserve [MW]; NL is the number of transmission lines; $\mathrm{g_k}$ is the conductance of the K_{th} line that connects buses i to bus j; $\mathrm{P_{i,min}^t}$ is minimum real power capacity [MW]; and $\mathrm{P_{i,max}^t}$ is the maximum real power capacity [MW].

Due to the huge penetration of renewable power and its intermittent nature, its frequent variant may be greater than the reserve allocated. So reserve must be modified by two additional reserves [10]. The up spinning reserve (USR) which 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 down spinning reserve (DSR). 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.

$$R^t = \begin{cases} USR & \text{Sudden decrease in renewable power} \\ DSR & \text{Sudden rise in renewable power} \end{cases} \quad (23)$$

$$USR^t = \sum_{i=1}^{N} US_i^t \geq MSR_t + us\% * P_R^t \quad (24)$$

$$US_i^t = Min\left(P_{i,max}^t - P_i^t . US_{max}^i\right) \quad (25)$$

$$DSR^t = \sum_{i=1}^{N} DS_i^t \geq ds\% * P_R^t \quad (26)$$

$$DS_i^t = Min\left(P_i^t - P_{i,min}^t . DS_{max}^i\right) \quad (27)$$

Where: $US_{i,t}^s$ is up spinning reserve; $DS_{i,t}^s$ is down spinning reserve; MSR_t is the minimum reserve level; $us\%, ds\%$ are renewable generation contributing to up and down spin requirements; and US_{max}^i, DS_{max}^i are the maximum allowable up and down spinning reserves.

IV. Implementation

To solve UC problem based on renewable forecasting, it is must to use simple optimization technique that can deal with any time resolution to simulate the stochastic behaviour of the renewable source. Dynamic program based on forward technique used to solve UC problem. This model is modified, so it can deal with any time resolution, the optimization period every (10 minutes) to simulate the nature of renewable energy. To achieve the greatest benefit from the renewable energy, these units are used as must run units. Renewable power value is calculated 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, modified spinning reserves constraint used to handle the uncertainties condition in UC by adding USR and DSR condition. 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.

V. Numerical Examples

The forecasting problem is simulated with a 26-bus system that represents the Eastern Portion of the Egyptian grid shown in Fig. 3. This system consists of six generators plus a wind farm placed at Zafarana, and solar units are placed in the Delta region. The wind farm is rated at 2000 MW, and PV stations with a capacity of 40 MW at sunny day (1sun=1000W/m^2) consist of 60000 units, each unit generates 0.7 KW at 1sun [20]. The value of total power generation from renewable power represents 46% penetration. The system has two levels of voltage 220/500 KV, bold line represents 500 KV line and other lines is represented 220 KV. Generators data are described in Table 1 [21].

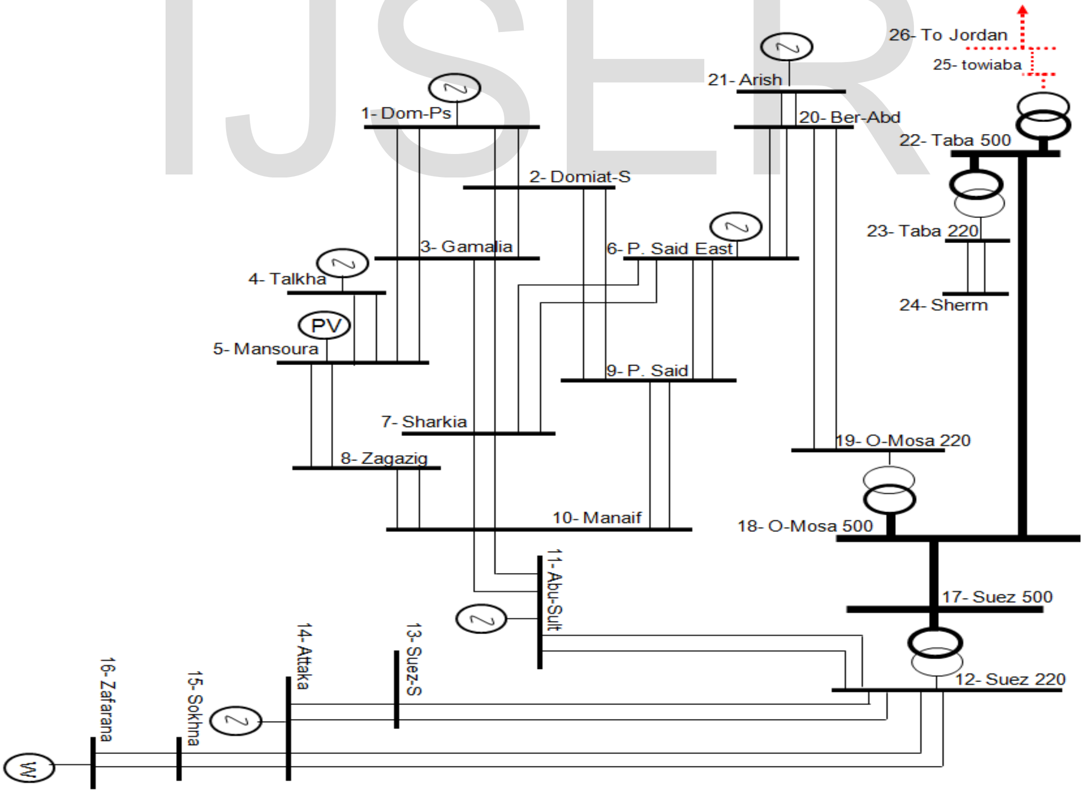

Fig. 3: 26-Bus System, Eastern Portion of the Egypt Grid.

Table 1: Thermal Units Data [21].

Coefficients	Thermal unit number, (*i*)						
		1	4	6	11	14	21

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Cost	c_i [$/h]	240	200	220	200	220	190
	b_i [$/MWh]	7	11	8.5	11	10.5	12
	a_i [$/MW^{2}h]	0.007	0.0095	0.009	0.009	0.008	0.0075
P_{min}	[MW]	100	50	80	50	50	50
P_{max}	[MW]	1125	800	740	600	185	930

5.1 Zafarana Wind speed Forecast Using ARIMA

The wind speed data considered in this paper are relative to a measurement campaign gathering data for 10 min periodically during December 2013. This data collected from Zafarana site, Red sea, Egypt. To verify the accuracy of this prediction model by using ARIMA, the predicted wind speeds were calculated under different cases and is compared with the actual data. Different cases were selected on the basis that it covers all cases of speed intervals (low speed, medium speed and high speed) as shown in Fig. 4, Fig. 5 and Fig. 6, respectively.

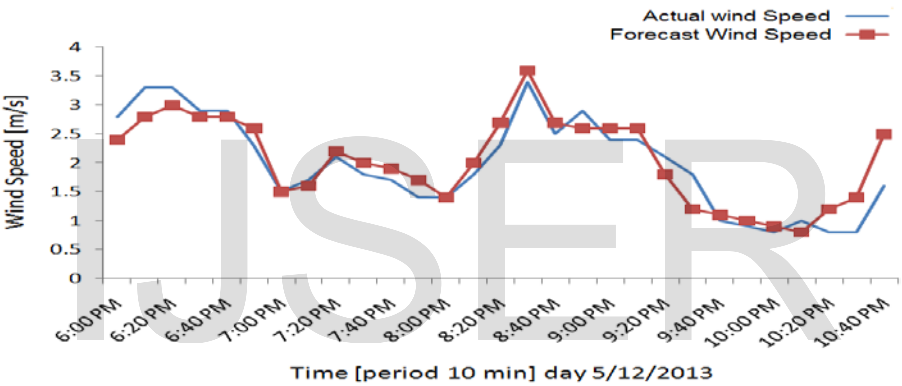

Fig. 4: Low Wind Speed Forecasting.

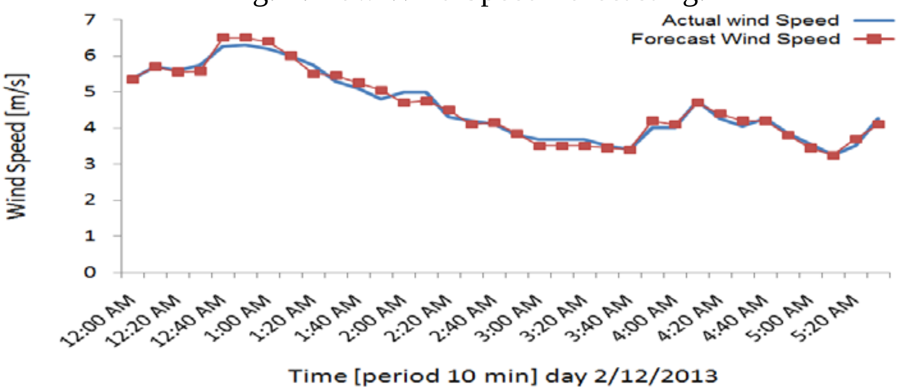

Fig. 5: Medium Wind Speed Forecasting.

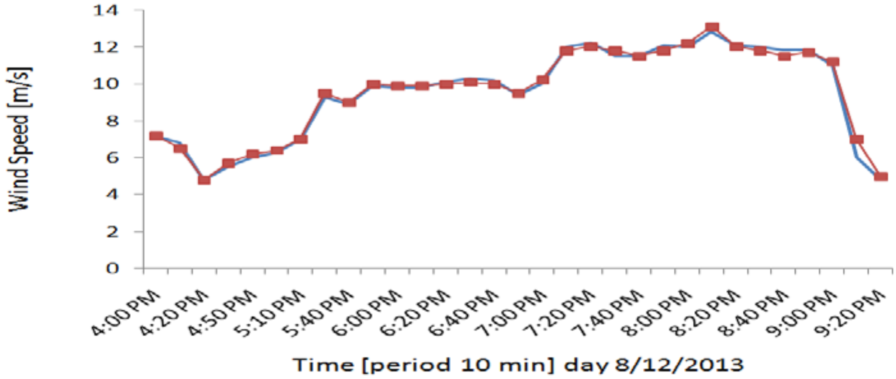

Fig. 6: High Wind Speed Forecasting.

The percentage of the error for the worst case is 20% in the case of low speed at the time (9:30 PM, 10:30 PM), this error doesn't affect as it occurs at small wind speed in which the output power generation is zero. But in case of medium and high wind speed forecasting the maximum error percentage does not exceed 8% such as in medium speed forecasting at the time (2:10 AM), and in case of high speed forecasting at the time (8:10 PM).

Most of the researches dealt with the wind power using two methods. The first method is the simplest way to represent wind power in UC problem, which considers the wind power generated through a small period, e.g. (10 min) is a fixed value and equal to the actual measured value [22]. The second method is developing a number of scenarios for the predicted amount of energy generated from wind farm [23, 9, and 10]. These scenarios are generated using the forecasted data. The mean and standard deviation of the forecast error at every time stage are determined; the scenarios lie within a certain probabilistic confidence interval.

To deduce the best method representing the wind forecasting method in UC, a comparison is held between the three methods listed in the paper; the proposed method described in this paper which built by using ARIMA and the other two methods. The comparison result for medium wind speed is displayed in Fig. 7. However, the result for high wind speed is shown in Fig. 8. The case of low wind speed will be ignored because the generating power is zero.

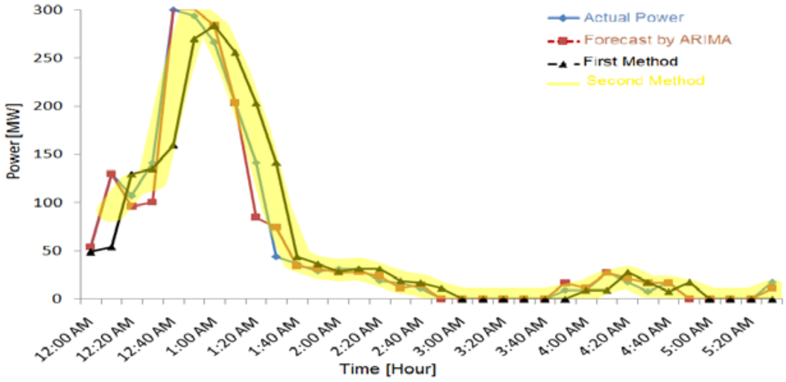

Fig. 7: Medium Wind Speed, Power Generation Comparison.

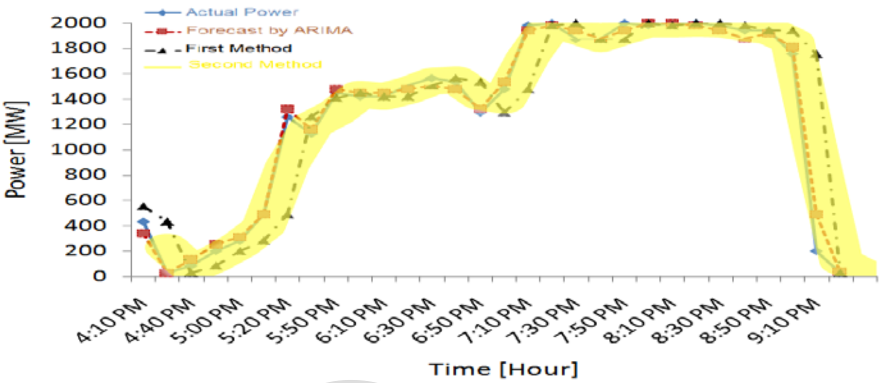

Fig. 8: High Wind Speed, Power Generation Comparison.

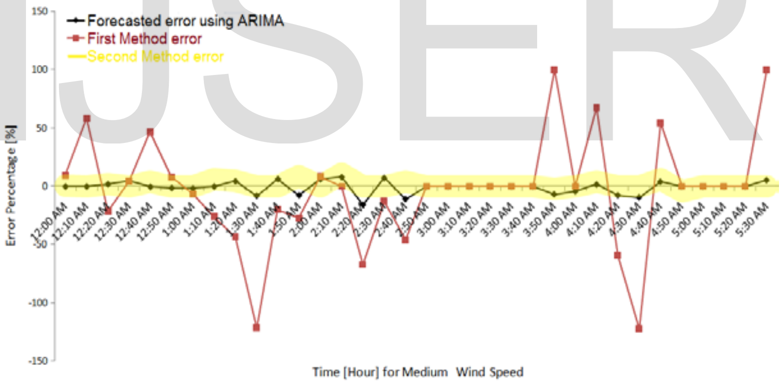

Fig. 9: Medium Wind Speed, Power Generation Error Percentage.

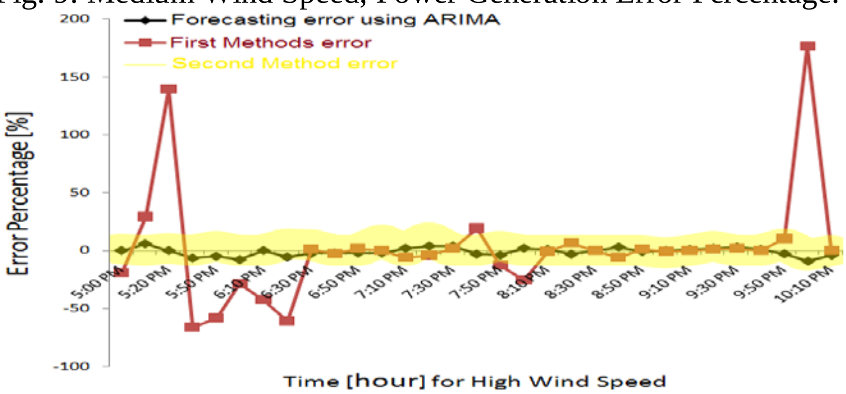

Fig. 10: High Wind Speed, Power Generation Error Percentage.

From Fig. 7 & 8, it is noticed that the forecasted power nearly equals the actual power and doesn't equal the power of both others methods. For example in Fig. 7 at (1:10 AM) the value of power generated from the forecasting model using ARIMA equals actual power. On other hand, the value of power generated from first method is higher than the actual power by 54 MW, i.e. error percentage 26%. However, for the second method the lowest scenario equals actual power and the highest scenario are higher than the actual power by 60 MW, i.e. error percentage 29.5%. And also, In Fig. 8 at (8:00 PM) the value of power generated from the forecasting model using ARIMA is less than the actual power by 20 MW, i.e. error percentage 2%. On the other hand, the value of power generated from the first method is lower than the actual power by 500 MW, i.e. error percentage 25.3%, and the second method ranges from -300 MW to 100 MW from actual power, i.e. error percentage is ranging from 15.1% to 5%.

Fig. 9 and Fig.10 show the forecasting error for three methods during all forecasting interval. It is found that, both the forecasting method using ARIMA and second method gives less value of error, however, the forecasting method using ARIMA is faster and easier for calculation.

Finally, from the above comparison, it is noticed that the result of the proposed technique model by using ARIMA is the closest technique to the actual wind speed. However, the second forecasting technique produces a good forecast but it has a huge number of scenarios. So, it is slow as it causes computational burden and consumes more time.

5.2 Mansoura Solar Radiation Forecast Using Modified Markov

The solar radiation was measured periodically every 10 min during December 2013. This data was collected from Mansoura site, Delta, Egypt. To predict solar radiation by using modified Markov, the following steps are used; first step: Build a transition matrix data that can be set in 7 classes of solar radiation. Table 2 shows the transition rates matrix obtained. The rows represent the i^{th} state, the columns represents the j^{th} state, Transitions rates is defined in events/hour. Second step: By using Markov, estimate models predicting the new forecasting transition matrix as shown in Table 3. This forecasted data represents the next day prediction. Through transition estimate data and by using Markov analysis α_i, f_i, and d_i can be obtained as shown in Table 4 and also the power produced from largest sun radiation

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which equals 0.63 W/m^2. By compensating the largest predict sun radiation in PV Matlab model, maximum power generated from the PV unit can be obtained which equals 26.5 MW.

Table 2: Transition Rates (Event/Hour).

R_{ij}	1	2	3	4	5	6	7
1	0.833	0.167	0	0	0	0	0
2	0.182	0.636	0.182	0	0	0	0
3	0	0.2	0.6	0.2	0	0	0
4	0	0	0.167	0.667	0.167	0	0
5	0	0	0	0.222	0.556	0.222	0
6	0	0	0	0	0.25	0.5	0.25
7	0	0	0	0	0.333	0.333	0.333

Table 3: Transition Estimate Rates (Event/Hour).

R_{ij}	1	2	3	4	5	6	7
1	0.8421	0.1579	0	0	0	0	0
2	0.25	0.375	0.375	0	0	0	0
3	0	0.2	0.5	0.3	0	0	0
4	0	0	0.0541	0.7297	0.2162	0	0
5	0	0	0	0.4118	0.4118	0.1765	0
6	0	0	0	0	0.4	0.2	0.4
7	0	0	0	0	0	0.6667	0.3333

Table 4: Probability, Frequency and Duration for Each State.

State	Steady state probability	Frequency (event/hour)	Duration (h)
1	0.065	0.01	3.84
2	0.041	0.026	0.9
3	0.0775	0.039	1.2
4	0.43	0.116	2.25
5	0.226	0.133	1.05
6	0.099	0.08	0.76
7	0.06	0.04	0.92

There is another method to predict solar radiation [24], which is the representation of solar radiation as a sine wave. But in this method the procedure assumes an extensive surface having uniform slope at each point of calculation, so effects of protruding surrounding terrain are not considered. This reduces the accuracy of the outputs, but the method used by hybrid Markov procedure were taken into account protruding surrounding terrain by inserting new matrix called emission matrix. Generating curve of PV station is represented in Fig. 11.

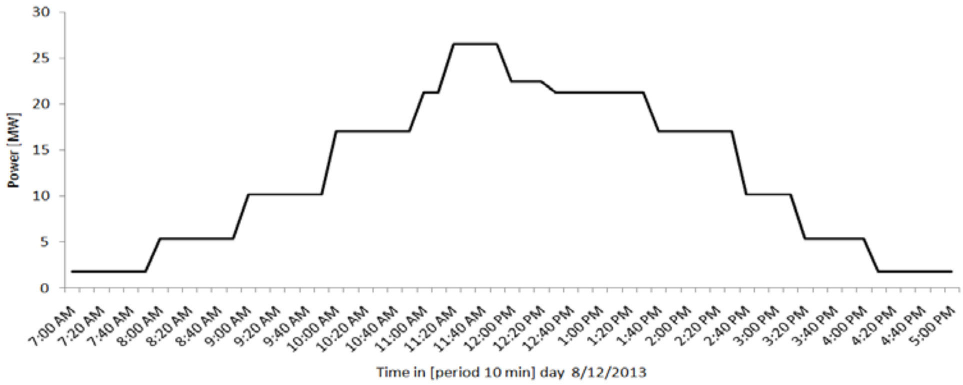

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Fig. 11: PV Station Power Curve.

5.3 Unit Commitment of Eastern Portion of the Egyptian Grid

Finally, the forecasted wind speed by using ARIMA and solar radiation by using hybrid Markov is applied in UC to find the total operating cost as we consider operating cost of renewable source negligible. As the wind power is much greater than the power generated from the sun. Therefore, this application is done in the two cases of wind speeds interval (medium and high). The load curve for both cases is shown in Fig. 12.

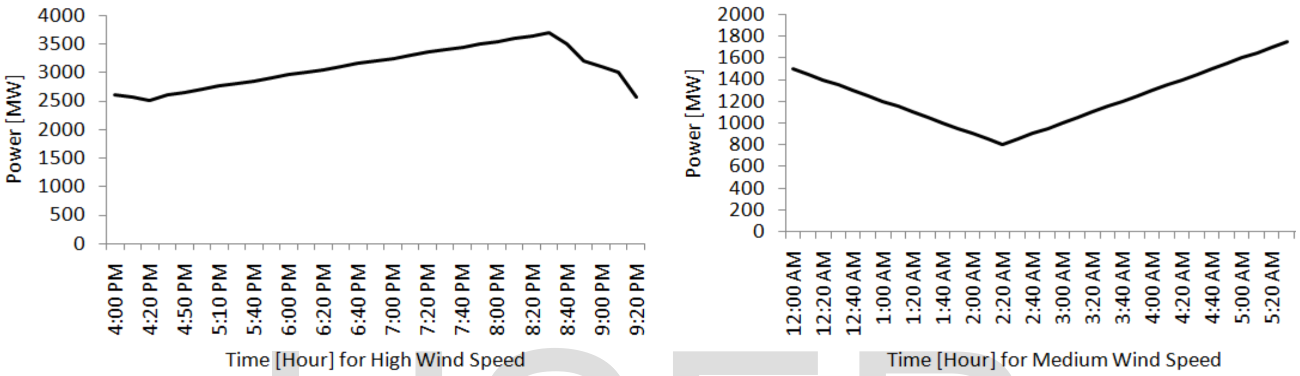

Fig. 12: Load Curve.

In conventional UC, the amount of reserve is just sufficient to cover the loss of the largest generator. But in this study to enhance the power system performance against forecasts errors, spinning reserve is modified 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. 13.

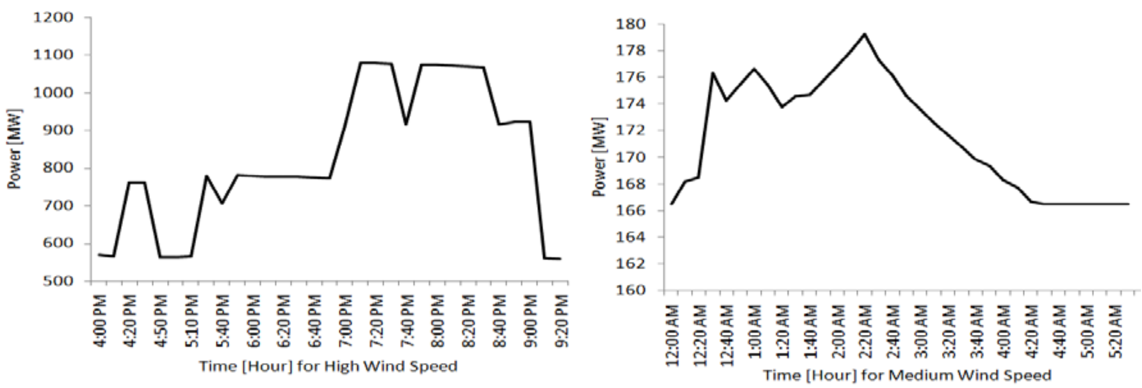

Fig. 13: Modified Reserve Curve.

When renewable power penetration level increase leads to increased reserve ratio. Fig. 14 show the generation cost curve. It is noted that when increasing loads increases the cost of generation.

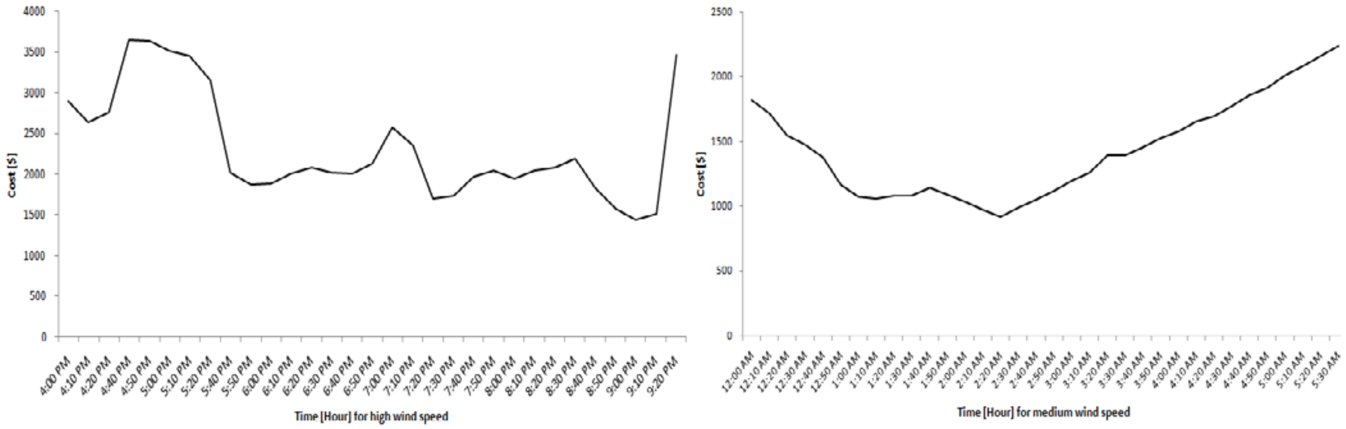

Fig. 14: Generation Cost Curve.

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-fill 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.

Table 5 shows the average value for cost and the percentage of the prediction error. These outputs are calculated for different situations by using ARIMA, first method and second method. Generation cost in the case of ARIMA is less than the other cases; also the prediction errors in the first and second cases are higher than that in the case of ARIMA. Therefore, ARIMA prediction method is more accurate, faster and easier to implement.

Table 5: Forecasting Error and Generation Cost Comparison.

Average / Forecast Case	Medium wind speed interval		High wind speed interval	
	Forecasting Error [%]	Cost [$/h]	Forecasting Error [%]	Cost [$/h]
ARIMA	-0.66473	1438.37	-1.05695	2333.72
First method	-3.39984	1639.13	2.228387	2635.61
Second method	0.9 to -0.5	1540 to 1300	1.1 to -0.7	2560 to 2097

VI. Conclusions

Renewable energy sources have an intermittent nature, which leads to variable power production through the day. With increased penetration level of renewable energy sources in modern electric grids, there is an urgent need to develop an advanced formulation of the unit commitment problem. This formulation requires an accurate and efficient forecasting model for wind and solar power production. This paper proposed a modified hybrid Markov chain to forecast solar radiation, and an improved auto regressive integrated moving average (ARIMA) model to predict wind speed. ARIMA is improved by taking into account the non-stationary characteristic of the wind speed with few model parameters. Markov chain is modified by integrating both Markov forecasting and Markov analysis. The paper presented a comparison between the proposed forecasting methods and the conventional methods, proving that the superiority of the proposed methods in terms of accuracy and ease of application. Two reserve coefficients are added to overcome the error of renewable power forecasting. The up reserve coefficient is used to overcome sudden decrease in renewable power production, while the down reserve coefficient is used to overcome sudden increase of renewable power production. The forecasted wind and solar power are used with the unit commitment problem for the Eastern Portion of the Egyptian electrical grid.

References

[1] Egyptian New and Renewable Energy Association, NREA Annual Report, 2013, *http://www.nrea.gov.eg/annual-english-2012-2013.pdf*

[2] Carsten Hoyer-Klick, Lucien Wald, ' Solar Atlas for the Southern and Eastern Mediterranean', Solar atlas ISES Solar World Congress, Kassel, Germany, 2011.

[3] Taha Ahmed, ' Estimation of Hourly Global Solar Radiation in Egypt Using Mathematical Model', Int. J Latest Trends Agr. Food Sci., 2012, 2, pp. 74-82.

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

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

[6] S. Bisanovic, 'Unit commitment problem in deregulated environment', Electrical Power and Energy Systems, 2012, 42, pp. 150-157.

[7] J.P.Fossati, 'unit commitment and economic dispatch in micro grids', Memoria de Trab. 2012, 10, pp. 83-96.

[8] Ruiwei Jiang, Jianhui Wang, Yongpei Guan, 'Robust Unit Commitment with Wind Power and Pumped Storage Hydro', IEEE Transactions on Power Systems, 2012, 27, (2), pp. 800-810.

[9] J. Wang, A. Botterud, 'Wind power forecasting uncertainty and unit commitment', Applied Energy, 2011, 88, pp. 4014–4023.

[10] Jeanne Andersen, 'Modelling and Optimisation of Renewable Energy Systems', PhD Thesis, AARHUS University, Denmark.

[11] Carlos D. Zuluaga, Mauricio A. Álvarez, Eduardo Giraldo, 'Short-term wind speed prediction based on robust Kalman filtering: An experimental comparison', Elsevier, Applied Energy, 2015, 156, pp. 321–330

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

[13] G. Papaefthymiou, B. Klöckl, 'MCMC for Wind Power Simulation', IEEE Trans. Energy Conversion, 2008, 23, pp. 234-240.

[14] Bryant Le, John Andrews, 'Modelling wind turbine degradation and maintenance', Wiley, Wind Energy, 2015.

[15] 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.

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

[17] Mazaher HAJI BASHI, Akbar EBRAHIMI, 'Markovian approach applied to reliability modeling of a wind farm', Turkish Journal of Electrical Engineering & Computer Sciences, 2014, 22, pp. 287-301.

[18] Ranjit Kumar Paul, 'FORECASTING USING MARKOV CHAIN', Doctor of Philosophy, Indian Agricultural Statistics Research Institute, New Delhi, Indian, 2012.

[19] A. J. Wood, B. F. Wollenberg, 'Power Generation Operation and Control', 3rd, Wiley, New York, 2013.

[20] Olmedilla Photovoltaic Park, Spain *http://solarenergypowerplants.blogspot.com/2010/10/olmedilla-photovoltaic-park.html*

[21] Egyptian Electricity Holding Company Annual Report 2008/2009 *http://www.moee.gov.eg/English/Electric-eng-2010.pdf*

[22] M. Esmaeeli Shahrakht, A. Kazemi, 'Linear Programming Application in Unit Commitment of Wind Farms with Considering Uncertainties', International Journal of Electrical, Robotics, Electronics and Communications Engineering, 2013,7, (2), pp 175-180.

[23] Jianhui Wang, Audun Botterud, 'Impact of Wind Power Forecasting on Unit Commitment and Dispatch', 8th Int. Conf. on Wind Integration Workshop, Bremen, Germany, 2009, pp. 44-51.

[24] Richard G. Allen, Ricardo Trezza, "Analytical integrated functions for daily solar radiation on slopes" science direct Agricultural and Forest Meteorology, 2006, 139, pp 55–73.