Planning of Hybrid Power Plant Based Smart Grid Using Statistical Approach

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Abstract- *Electricity plays an important role in our daily life activity. Power load (power consumption) and electricity generation in a balanced manner is very important to minimize load shedding, and regular electricity supply specially at the time of peak demand of electricity which is possible only when electricity power plant should be established in a planned way. Long-term demand forecasting in electricity have a vital role in planning of any power plant for regular power supply and it depends upon many factors such as population growth, technology evolution, economic growth, season, weather conditions and the general randomness inherent in individual usage. It is also depends upon the time of day, day of week, time of year, and holidays. Overestimate of long-term demand of electricity leads to financial wastage of investment in the generation of extra power, and underestimate of demand leads to insufficient power generation to fulfill the demand. To overcome from these kinds of problem, in this paper we proposed a novel hybrid long-term forecasting statistical approach for the planning of hybrid power plant based smart grid. Multiple standard long-term forecasting models have been used such as Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA) to make a hybrid technique without depending upon single forecasting model which is applies in traditional long-term forecasting. We have assumed that wind turbines, battery storage and diesel-engines as fundamental components of the hybrid power plant. We have considered power load and weather which can affect performance of wind-turbine in the forecasting calculation.*

Keywords- long-term forecasting, statistical approach, planning, smart grid, MA, AR, ARMA, hybrid power plant, wind turbine, wind energy.

I. INTRODUCTION

Modern world fully depends upon electrical machines and electronic gadgets and their main source of energy is electricity. We use these devices 24x7 in the form of electric bulb, computer, mobile phone, mixer, washing machine, generator, motor etc. from home to office, office to factories everywhere. Power load (power consumption) and electricity generation in a balance manner is very important to minimize load shedding and smooth and regular electricity supply. This can be possible only when electricity power plant/grid should be established in a planned way, which is applicable in both traditional as well as hybrid electricity power plant/grid. Good long-term forecasting plays an vital role for better planning to achieve smooth and efficient electricity generation and power load balancing both in traditional and hybrid power plants/grid.

Traditional power plants have only one kind of power source whereas, hybrid power plants consist of multiple kinds of power sources such as wind turbines (as shown in Fig. 1), solar panels, tidal, wave power devices (i.e. Shoreline devices, Nearshore devices or Offshore devices), diesel engines, power storage etc. In planning of traditional power plant, electricity demand forecasting is only important because it doesn't depend upon other factors such as climate and weather etc. and it produces power constantly w. r. t. power load. But the planning of hybrid power plant is difficult since we have to do electricity demand forecasting as well as power generation forecasting which depends upon weather; hybrid power plant doesn't produce power constantly w. r. t. power load as well as it depends on other factors such as climate and weather etc. Long-term forecasting means forecasting for long duration i.e. several months to several years.

Long-term peak electricity demand forecasting depends upon many factors such as population growth, technology evolution, economic growth, season, weather conditions and the general randomness inherent in individual usage. It is also depends upon the time of day, day of week, time of year, and holidays.

Fig. 1. Wind Plant

Long term forecasting [1], [3]-[6] has higher risk in comparison to short-term planning and forecasting because huge resources, capital and time is invested. Overestimate of long-term demand of electricity leads to financial wastage of investment in the generation of extra power, and underestimate of demand leads to insufficient power generation to fulfill the demand.

To overcome from these kinds of problem in this paper, we are going to propose a hybrid long-term forecasting statistical approach for the planning of hybrid power plant based smart grid.

George Edward Pelham Box (British statistician) said "Essentially, all models are wrong, but some are useful" i.e. a model is not always best for different kind of data for forecasting. But in our research and literature survey we found that research scholars are focusing on a specific forecasting model for long-term forecasting. And we also found that mostly in research papers performance and accuracy of the proposed long-forecasting techniques are evaluated by mean error w. r. t. collected historical data and forecasted data but does not focus on predicted output data accuracy which is the main objective of any kind of forecasting.

Aim of this research is to propose a high accuracy and high performance hybrid long-term forecasting statistical approach for the planning of hybrid power plant based smart grid without depending upon single forecasting model which generally applies in traditional long-term forecasting to achieve the goal of producing sufficient power to fulfill peak electricity demand within the planned duration without overestimation and underestimate.

For the achievement of the aim, our objective is to develop/propose a hybrid long-term forecasting statistical approach for the planning of hybrid power plant based smart grid. We are going to use Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA) standard and popular long-term forecasting techniques with double checking policy for the predicted output data accuracy evaluation. Here, we are assuming that wind turbines, battery storage and diesel engine as fundamental components of the hybrid power plant. We are considering power load and weather which can affect performance of wind-turbine in long term forecasting calculation.

In this paper, in we will discuss hybrid power systems in section II, literature survey of different of research papers, in section III we will focus on limitations of the papers and their solution, further in section IV we will discuss about different methodologies and formulas which are used in the proposed system and old standard systems. In section V problem formulation and proposed system/technique is discussed. After that in section VI experimental result & discussion has been discussed then conclusion and future scope is discussed in section VII. After that literature references are mentioned.

II. HYBRID POWER SYSTEMS

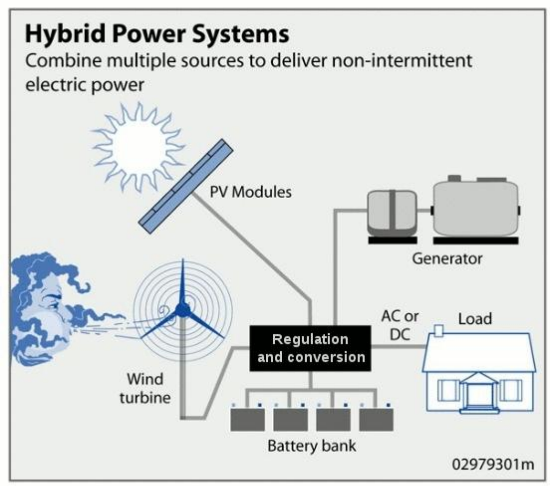


Fig. 2. Hybrid Power Systems

Hybrid power systems/plants (as shown in Fig. 2) use a fossil fuel i.e. diesel or gas as well as renewable energy source as a supplement such as hydro, solar, tidal, wind, wave. Some of them combine renewable sources and battery storage in order to achieve minimum consumption of expensive diesel or oil. However, there is a worldwide trend for natural gas to replace diesel and, with the substantial decline in the cost of batteries, to employ batteries to store surplus power for later use. PV diesel system combines a photovoltaic system with a diesel generator. Combinations with other renewable are possible and include wind turbines.

III. LITERATURE REVIEW

In literature survey we found many research scholars are working on sustainable energy/renewable energy and long term forecasting for the planning of electricity power plant based on hybrid power plant.

[9] Eisa et al. in this paper we studied about lots of statistical analyses are concerned to study the load features and forecasting precision i.e. moving average (MA) and probability plots of load noise. Kuwaiti electric network real daily load data have been taken for the experiment.

[2] Gheisa et al. in this is based on understanding and analyzing the state of art of models applied to electricity long-term forecasts, which is to describe and concern a concise methodology to make a systematic review on academic articles from indexed journals.

[10] Hossein et al. in this paper, two approaches are used for long-term load forecast which are regression method and artificial neural network (ANN). Fuzzy sets are applied to ANN for modeling long-term uncertainties and compared the forecasting results with traditional methods. ISO New England market data have been taken for the experiment.

In the literature review we observed that all research scholars are focusing on a specific forecasting method for long-term forecasting but the reality is "Essentially, all models are wrong, but some are useful" said by George Edward Pelham Box (British statistician) i.e. a model is not always best for different kind of data and for different kind (i.e. short-term, medium-term and long term) of forecasting. In all the above research papers performance and accuracy of the proposed long-term forecasting techniques are evaluated by percentage error i.e. Mean squared error (MSE) w. r. t. gathered historical data and forecasted data but don't focusing on predicted output data which the main objective of any forecasting.

So, in this paper we are going to use multiple standard long-term forecasting models such as Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA) as a hybrid long-term forecasting technique without depending upon single forecasting model which is generally applies in traditional long-term forecasting with double checking policy for the predicted output data accuracy evaluation. We have considered power load and weather which can affect performance of wind-turbine.

IV. METHODOLOGIES

A. Calculate the dailyy wind energy output of a wind turbine system

The wind energy (in W i.e. watt),

$$\text{i.e. } P = \rho A V^3 \tag{1}$$

Where,
P = power (in W i.e. Watt),
ρ = air density (in kg/m^3),
A = swept area of blades (in m^2) given by $A = \pi r^2$ where r is the radius of the blades (in m) and $\pi = 3.1416$ or 22/7,

V = velocity of the wind (in m/s).

Note: The amount of energy in the wind varies with the cube of the wind speed, in other words, if the wind speed doubles, there is eight times more energy in the wind ($2^3=8$). Small changes in wind speed have a large impact on the amount of power available in the wind.

PR = Performance ratio, coefficient for losses (range between 0.5 and 0.9, default value = 0.75) *PR:* PR (Performance Ratio) .

B. Calculate The Air Density

Calculate the saturation vapor pressure at dew point *T*, using the formula

$$\text{i.e. } p = 6.1078 * 10\text{^}[7.5T/(T + 237.3)] \tag{2}$$

Saturation vapor pressure means that the relative humidity is equal to 100%.

Find the actual vapor pressure, multiplying this value by the relative humidity

$$\text{i.e. } pv = p * RH \tag{3}$$

Subtract the vapor pressure from the total air pressure to find the pressure of dry air:

$$\text{i.e. } pd = p - pv \tag{4}$$

Input the calculated values into the following formula:

$$\text{i.e. } \rho = (pd / (Rd * T)) + (pv / (Rv * T)) \tag{5}$$

Where,

pd is the pressure of dry air in hPa,
pv is the water vapor pressure in hPa,
T is the air temperature in Kelvins,
Rd is the specific gas constant for dry air equal to 287.058 J/(kg·K), and
Rv is the specific gas constant for water vapor equal to 461.495 J/(kg·K).

C. Forecasting Models

1) AR(p):*Autoregressive model of order p*

The default AR(P) model,

$$Y_t=c+\Phi_1 Y_{t-1}+\ldots..+\Phi_p Y_{t-p}+\varepsilon_t \qquad (6)$$

By default, all parameters in the created model object have unknown values, and the innovation distribution is Gaussian with constant variance.

2) MA(q):*Moving Average model of order q*

The default MA

$$Y_t=c+\theta_1\varepsilon_{t-1}+\ldots\ldots+\theta_q\varepsilon_{t-q}+\varepsilon_t \qquad (7)$$

By default, all parameters in the created model object have unknown values, and the innovation distribution is Gaussian with constant variance.

3) ARMA (p, q):*Autoregressive Moving Average model of order (p, q).*

The ARMA(p,q) model is

$$yt=c+\phi 1yt-1+\ldots+\phi pyt-p+\varepsilon t+\theta 1\varepsilon t-1+\ldots+\theta q\varepsilon t\text{-}q, \qquad (8)$$

where εt is an uncorrelated innovation process with mean zero.
In lag operator polynomial notation**,** ***Liyt=yt−i.*** Define the degree *p*, AR lag operator polynomial $\phi(L)=(1-\phi 1L-\ldots\ldots-\phi pL_p)$. Define the degree *q* MA lag operator polynomial $\theta(L)=(1+\theta 1L+\ldots+\theta qL_q)$. You can write the ARMA(p,q) model as

$$\phi(L)yt=c+\theta(L)\varepsilon t. \qquad \mathbf{(9)}$$

The signs of the coefficients in the AR lag operator polynomial, $\phi(L)$, are opposite to the right side of Equation 1.
Fractional ARIMA: This type of models is employed when time series exhibits long memory.

Mean squared error (MSE) or mean squared prediction error (MSPE):

i.e. $$MSE = MSPE = \frac{\sum_{t=1}^{N} E_t^2}{N} \qquad (10)$$

V. PROPOSED SYSTEM

Long-term demand forecasting [7] in electricity have a vital role in the planning of any power plant for regular power supply. Long-term peak electricity demand forecasting [8], [9] depends upon many factors such as population growth, technology evolution, economic growth, season, weather conditions and the general randomness inherent in individual usage. It is also depends upon the time of day, day of week, time of year, and holidays.

In this research we have studied about hybrid power plant and observed its dynamic behaviour towards the nature such as effect of the wind pressure, density, velocity etc.

So, it don't produce electricity in constant manner therefore additions power resources (i.e. diesel engine, power storage or other mean of electricity etc.) are required to fulfil shortage of electricity at night, cloudy weather and rainy season for constant and regular power supply to prevent load-shedding.

The uniqueness of the work is it doesn't favour any model in advance and its' double accuracy checking policy in two steps.
We have considering power load and weather which can affect performance of wind-turbine in long term forecasting calculation. We have assumed that wind turbines, battery storage and diesel engine as fundamental components of the hybrid power plant.

We have used multiple standard long-term forecasting models such as Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA) as a hybrid technique without depending upon single forecasting model which is generally applies in traditional long-term forecasting.

A. DATA GATHERING

We have gathered historical power load data in hourly basis of Patna from “Central Load Dispatch, Bihar State Power Holding Company Limited (or BSPHCL), also known as Bihar State Electricity Board (BSEB), Patna, Bihar” and historical weather data in hourly basis of Patna from “National Renewable Energy Laboratory (NREL) website https://maps.nrel.gov/gst-india/” of 01-Jan-2005 to 31-Dec-2014.

B. PRE-PROCESSING

We applied pre-processing in the collected historical data (X) for retrieving relevant data in right format for long-term forecasting and converted the hourly historical data into historical daily data by summation. Then divide the historical data is into two parts for the propose technique into last 5 years i.e. 5*365+1(1 leap year in 5 years) days = 1826 days (X12) data and remaining data from starting (X11).

Here, X=X11+X12 (no. of hours or period difference)

C. MODEL FITTING

we have applied Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA) model one by one on pre-processed historical data (X11) of daily weather (which effects wind turbine performance) and power load for long-term (5 year data X11) forecasting and estimated accuracy of the model by calculating percentage error i.e. MEAN SQUARED ERROR (MSE) by using equation 10 w. r. t. the predicted data of seven days (F11) and last seven days data (X12) from historical data which has been taken before.

D. BEST MODEL SELECTION AND FORECASTING

Select the model which has minimum Avg. of Errors (E) and use the forecasting model to prediction the next 5 years i.e. 5*365+1(1 leap year in 5 years) days = 1826 days (X12).

E. ESTIMATE POWER REQUIRED

Use predicted daily weather parameters (F22) for calculating daily energy (P) which will be produce by one wind turbine then find out, median (PMedian) and minimum (PMin) of the daily energy (P). And assume predicted power load daily data as daily power consumption.

Calculate the maximum of forecasted (predicted) power load with outlier (MP1) and without (MP2) outliers (replace values by median (PMax) which is above median (PMax)) and (ii) is equal to the electricity power required/peak power load next 5 years, which is proportional to required resources for generating sufficient power to fulfil the electricity peak power demand.

F. RESOURCE ESTIMATION

To estimate the resources in next 5 years, divide the MP2 by PMedian and calculate ceiling of the output to find out Number of Wind Turbine (NWT) required in normal condition. Subtract NWT * PMin by MP1 to find out extra power (PExtra) will be required by generators (of capacity PH) or other source of electricity in worse condition. For getting the Number of Generator (NG) required is calculated by dividing the PExtra by PH and calculate ceiling of the output. Block diagram of the proposed technique is shown in Fig. 3.

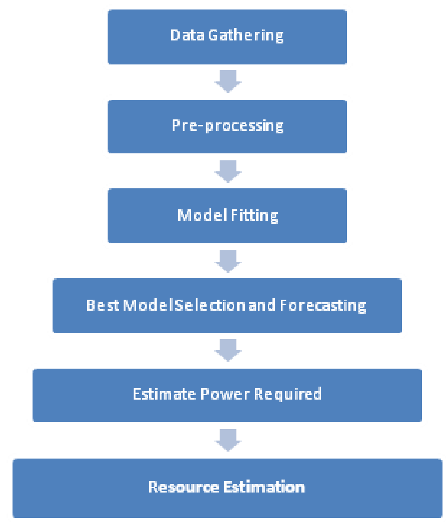


Fig. 3. Block diagram of the proposed technique

VI. EXPERIMENTAL RESULT AND DISCUSSION

A. EXPERIMENTAL SETUP

For the performance and accuracy evaluation of the proposed technique we have gathered historical power load data in hourly basis of Patna (as shown in Table III) from “Central Load Dispatch, Bihar State Power Holding Company Limited (or BSPHCL), also known as Bihar State Electricity Board (BSEB), Patna, Bihar” and historical weather data in hourly basis of Patna from “National Renewable Energy Laboratory (NREL) website https://maps.nrel.gov/gst-india/” of 01-Jan-2005 to 31-Dec-2014 (as shown in Fig. 3, Fig. 8 and Table II). After that the pre-processing procedure has been applied in the collected historical data (X) for retrieving relevant data in right format for long-term forecasting after that converted the hourly historical data into historical daily data by summation. Here, it is assumed that wind turbines, battery storage and diesel engine as fundamental components of the hybrid power plant. Multiple standard long-term forecasting techniques have been used in the proposed technique such as Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA). We have used formula (mention in equation 1) for wind energy measurement which is produced by wind and formula (mention in section 4.1.5 and 4.1.6) has been for estimating power required and resource estimation respectively.

The proposed technique performance and accuracy have been compared with other long-term forecasting techniques i.e. AutoRegressive Integrated Moving Average (ARMA) and Seasonal ARIMA (SARIMA) which are proposed in MA, AR, ARMA. For the performance and accuracy evaluation of the proposed technique data of the last 5 years (assumed as unknown data) (X12) have been taken from historical data; and compared the data with final predicted data (F11) which have come after the forecasting using proposed technique and MA, AR, ARMA using percentage error i.e. MEAN SQUARED ERROR (MSE) from equation. 10.

Here, X=X11+X12 (no. of daily or period difference). Where, X12= F11

B. EXPERIMENTAL EVALUATION

In the literature review we observed that all research scholars are focusing on a specific forecasting method for long-term forecasting but the reality is "Essentially, all models are wrong, but some are useful" said by George Edward Pelham Box (British statistician) i.e. a model is not always best for different kind of data and for different kind (i.e. short-term, medium-term and long term) of forecasting. In all the above mentioned literature review (in Chapter 2) research papers performance and accuracy of the proposed long-forecasting techniques are evaluated by mean error w. r. t. gathered historical data and forecasted data but don't focusing on predicted output data which the main objective of any forecasting. So, in this paper we are going to use multiple long-term forecasting techniques such as Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA) as a hybrid long-term forecasting technique with double checking technique for predicted output data accuracy evaluation.

For the purpose of comparing performance evolution and accuracy of the proposed technique and MA, AR, ARMA we have applied Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA) model one by one on pre-processed historical data (X12) of daily weather which effects the performance of the wind turbine (as shown in Fig. 5.3 to Fig. 5.8) and power load for long-term (5 years, F11=F12) forecasting, and estimated accuracy of the model by calculating percentage error i.e. MEAN SQUARED ERROR (MSE) between predicted data (F11) of seven days and last seven days data (X12) from historical data which has been taken before and the output is noted down.

step 1: we have applied Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA) model one by one on pre-processed historical data (X12) of the daily weather and power load for long-term (5 years, X12) forecasting, and estimated accuracy of the model by calculating percentage error i.e. MEAN SQUARED ERROR (MSE) w. r. t. the predicted data of seven days and last seven days data (F11) from historical data which has been taken before. (step 2) Select the model which has minimum error and use the forecasting model to prediction the next seven days (F22) and estimated accuracy of the model by calculating percentage error i.e. Mean Squared Error (MSE) w. r. t the predicted data of seven days and last seven days data (X2) from historical data which has been taken before and the output is noted down.

Table I results are showing that the proposed system is giving better accuracy and performance in comparison to MA, AR and ARMA and its showing that AR and MA model is best Power Load and Single Wind Turbine Load data respectively among MA, AR and ARMA.

We have used predicted daily weather parameters (F22) for calculating daily energy (P) which will be produce by one wind turbine then find out, median (PMedian) and minimum (PMin) of the daily energy (P). And assume predicted power load daily data as daily power consumption.

Calculate the maximum of forecasted (predicted) power load with (MP1) and without (MP2) outliers (replace values by median (PMax) which is above median (PMax)) and (ii) is equal to the electricity power required/peak power load next 5 years, which is proportional to required resources for generating sufficient power to fulfil the electricity peak power demand.

TABLE I. MEAN SQUARED ERROR (MSE) RESULTS

Techniques	Parameters	Mean Squared Error (MSE)
MA	Power Load	1.359887e+08
	Single Wind Turbine Load	1.178867e+15
AR	Power Load	1.352812e+08
	Single Wind Turbine Load	1.179193e+15
ARMA	Power Load	1.178867e+15
	Single Wind Turbine Load	1.179809e+15
Proposed technique	Power Load (Best Model=AR)	1.352812e+08
	Single Wind Turbine Load (Best Model=MA)	1.178867e+15

For the estimation of the resources in next 5 years, we divided the MP2 by PMedian and calculated ceiling of the output to find out Number of Wind Turbine (NWT) required in normal condition. And we subtracted NWT * PMin by MP1 to find out extra power (PExtra) will be required by generators (of capacity PH) or other source of electricity in worse condition. For getting the Number of Generator (NG) required is calculated by dividing the PExtra by PH and calculate ceiling of the output.

C. UNIQUENESS OF THE WORK

The uniqueness of the work is that it doesn't favour any model in advance.

D. EXPERIMENTAL RESULTS

TABLE II. DAILY WEATHER DATA 2005-2014

	1 Year	2 Month	3 Day	4 DewPoint	5 Temperature	6 Pressure	7 RelativeHumidity	8 PrecipitableWater	9 WindDirection	10 WindSpeed	11
1	2005	1	1	133	463.2664	2.4236e+04	1.1054e+03	38.6991	5.5205e+03	29.0237	
2	2005	1	2	174	467.6501	2.4213e+04	1.1688e+03	51.2093	5.9799e+03	29.4927	
3	2005	1	3	206	508.1395	2.4217e+04	1.1963e+03	35.1990	5.6489e+03	27.5615	
4	2005	1	4	196	525.9292	2.4247e+04	1.0817e+03	42.4400	6.9364e+03	64.9168	
5	2005	1	5	138	440.5342	2.4265e+04	1.1594e+03	23.9406	6.6971e+03	62.9828	
6	2005	1	6	83	441.1212	2.4245e+04	1.0147e+03	20.4098	6.7539e+03	50.4931	
7	2005	1	7	89	446.4703	2.4213e+04	986.8076	29.8203	6.6984e+03	63.9256	
8	2005	1	8	57	414.5241	2.4221e+04	1.0004e+03	18.0971	6.6592e+03	52.2115	
9	2005	1	9	36	405.9328	2.4181e+04	942.5562	22.4180	6.5311e+03	69.0773	
10	2005	1	10	46	407.8003	2.4127e+04	979.4562	24.7815	6.0561e+03	43.5948	
11	2005	1	11	106	460.4944	2.4181e+04	999.1391	37.4315	3.2651e+03	23.3738	
12	2005	1	12	125	444.7124	2.4248e+04	1.1232e+03	28.6480	5.2423e+03	37.6980	
13	2005	1	13	39	414.9581	2.4223e+04	929.2902	22.2739	6.5747e+03	57.7351	
14	2005	1	14	22	408.8021	2.4177e+04	895.2832	23.6770	6.5236e+03	66.6198	
15	2005	1	15	33	432.4527	2.4196e+04	894.1725	25.9088	6.4556e+03	44.6452	
16	2005	1	16	69	483.4369	2.4201e+04	870.0166	25.8143	6.5363e+03	29.2545	
17	2005	1	17	114	498.0554	2.4182e+04	954.3953	45.9714	5.8176e+03	26.3731	
18	2005	1	18	260	478.3523	2.4186e+04	1.4552e+03	53.0313	3.1866e+03	57.2145	
19	2005	1	19	190	426.8680	2.4238e+04	1.4147e+03	31.1442	6.6820e+03	71.4146	
20	2005	1	20	35	396.9335	2.4294e+04	954.1720	19.4623	6.4598e+03	64.3095	
21	2005	1	21	38	434.4721	2.4339e+04	903.4382	25.6432	5.3176e+03	22.5319	
22	2005	1	22	21	479.5105	2.4294e+04	746.0744	33.6404	4.8244e+03	28.6467	
23	2005	1	23	191	394.0762	2.4207e+04	1.4381e+03	48.5736	2.6040e+03	50.5569	
24	2005	1	24	189	419.5820	2.4255e+04	1.4180e+03	42.2057	6.6061e+03	37.1819	
25	2005	1	25	113	421.9343	2.4242e+04	1.1235e+03	47.5529	6.9414e+03	55.5526	
26	2005	1	26	72	448.3601	2.4170e+04	934.8982	49.7276	6.7177e+03	60.8813	
27	2005	1	27	151	493.4018	2.4151e+04	1.0502e+03	44.9865	6.7889e+03	38.9730	
28	2005	1	28	285	486.0957	2.4151e+04	1.4893e+03	60.0152	3.9237e+03	39.7455	

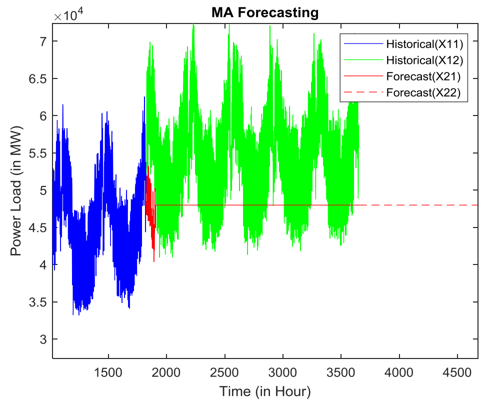
TABLE III. DAILY POWER LOAD DATA 2005-2014 IN MW

	1 Year	2 Month	3 Day	4 PowerLoad	5
1	2005	1	1	4.4028e+04	
2	2005	1	2	5.3466e+04	
3	2005	1	3	5.4208e+04	
4	2005	1	4	5.4264e+04	
5	2005	1	5	5.4081e+04	
6	2005	1	6	4.6661e+04	
7	2005	1	7	4.7235e+04	
8	2005	1	8	4.5511e+04	
9	2005	1	9	5.5184e+04	
10	2005	1	10	5.7307e+04	
11	2005	1	11	5.8560e+04	
12	2005	1	12	5.8474e+04	
13	2005	1	13	5.8566e+04	
14	2005	1	14	5.2355e+04	
15	2005	1	15	4.8245e+04	
16	2005	1	16	5.8467e+04	
17	2005	1	17	5.9948e+04	
18	2005	1	18	5.8795e+04	
19	2005	1	19	5.7755e+04	
20	2005	1	20	5.7055e+04	
21	2005	1	21	5.0759e+04	
22	2005	1	22	4.7386e+04	
23	2005	1	23	5.8278e+04	
24	2005	1	24	5.9675e+04	

We have applied pre-processing to gather relevant data in right format for long-term forecasting using 'Matlab'.

========Power Load==========

========MA==========



1.
2. Result of MA Forecasting for Power Load
3. ARIMA(0,0,80) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	47989	75.434	636.17	0
MA{80}	-0.50736	0.02268	-22.371	7.6143e-111
Variance	3.6743e+07	0.00012773	2.8766e+11	0

Mean squared error (MSE) = 1.359887e+08

========AR==========

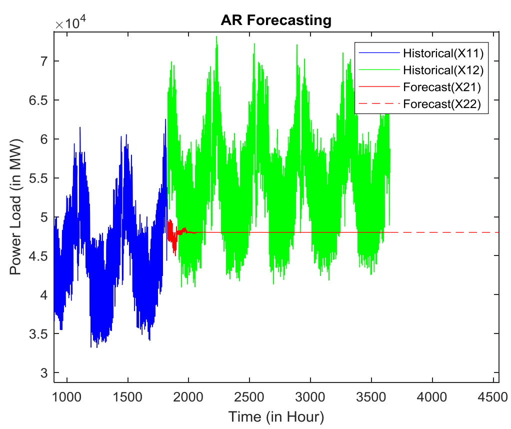


Fig. 4. Result of AR Forecasting for Power Load

ARIMA(80,0,0) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	58034	1188.7	48.824	0
AR{80}	-0.20903	0.024307	-8.5994	8.0111e-18
Variance	3.5687e+07	0.036631	9.7424e+08	0

Mean squared error (MSE) = 1.352812e+08

========ARMA==========

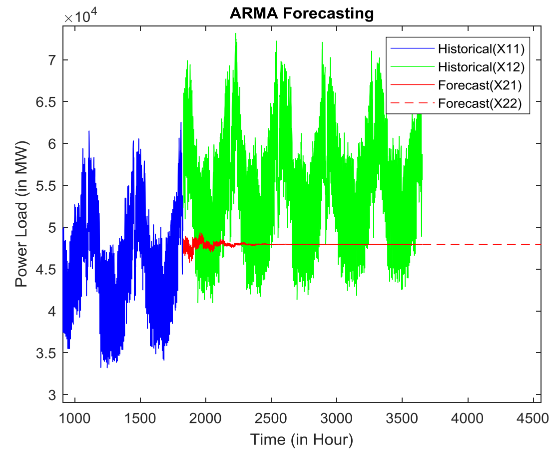


Fig. 5. Result of ARMA Forecasting for Power Load

ARIMA(80,0,80) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	79166	2659.5	29.767	1.0298e-194
AR{80}	-0.65092	0.055737	-11.678	1.6439e-31
MA{80}	0.54545	0.069644	7.832	4.8007e-15
Variance	4.9012e+07	0.49159	9.9701e+07	0

Mean squared error (MSE) = 1.358628e+08

BestModel = AR

========Single Wind Turbine Power==========

========MA==========

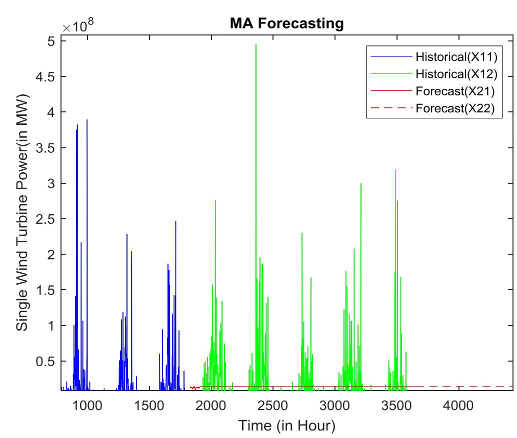


Fig. 6. Result of MA Forecasting for Single Wind Turbine Power

ARIMA(0,0,80) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	1.4012e+07	2.8769e-11	4.8707e+17	0
MA{80}	0.12494	0.0095866	13.032	8.0156e-39
Variance	1.3536e+15	2.6106e-18	5.185e+32	0

Mean squared error (MSE) = 1.178867e+15
========AR==========

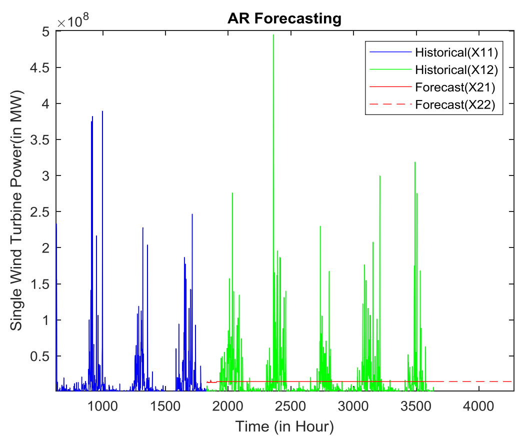


Fig. 7. Result of AR Forecasting for Single Wind Turbine Power

ARIMA(80,0,0) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	1.3095e+07	3.9992e-11	3.2743e+17	0
AR{80}	0.095338	0.0093167	10.233	1.4103e-24
Variance	1.4095e+15	3.1479e-18	4.4776e+32	0

Mean squared error (MSE) = 1.179193e+15

========ARMA==========

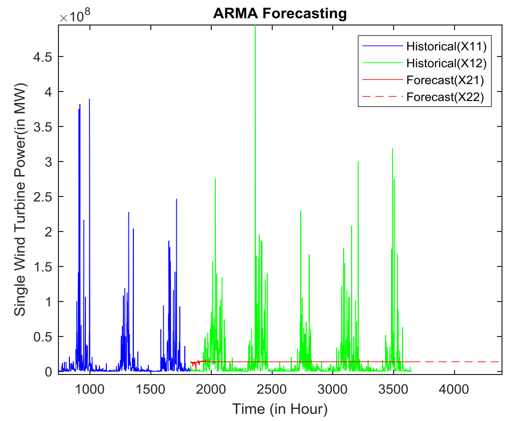


Fig. 8. Result of ARMA Forecasting for Single Wind Turbine Power

ARIMA(80,0,80) Model (Gaussian Distribution):

	Value	StandardError	TStatistic	PValue
Constant	1.7559e+07	1.1194e-08	1.5687e+15	0
AR{80}	-0.26558	0.087035	-3.0514	0.0022779
MA{80}	0.38781	0.090293	4.295	1.747e-05
Variance	1.3833e+15	1.0741e-15	1.2879e+30	0

Mean squared error (MSE) = 1.179809e+15
BestModel = MA
==========RESOURCE ESTIMATION==========
No. of WT = 1
Extra Power Required = 72657.144622 MW
No. of Generator = 72658

VII. CONCLUSION AND UPCOMING WORK

In this paper we have studied about the value of electricity, what is wind turbine, kinds of wind turbine, utilisations and, its pros and cons. We also studied about hybrid power grid, it architecture and working system. In our study we found that long-term demand forecasting in electricity have a vital role in good planning of hybrid power plant for smooth and regular electricity supply especially at the time of peak electricity demand. We have studied about factors that affect long-term peak electricity demand forecasting. These factors are population growth, technology evolution, economic growth, season, weather conditions and the general randomness inherent in individual usage. It is also depends upon the time of day, day of week, time of year, and holidays.

We have seen result of wrong long-term forecasting which may be cause of overestimate of long-term electricity demand which will cause of substantial wasted investment in the generation of surplus power, while an underestimate of demand will cause of insufficient power generation and unmet demand. For the prevention, we proposed a novel hybrid long-term forecasting statistical approach for the planning of hybrid power plant based smart grid.

We have used multiple standard long-term forecasting models such as Moving Average (MA), AutoRegressive (AR) and AutoRegressive Moving Average (ARMA) as a hybrid long-term forecasting technique without depending upon single forecasting model which is generally applies in traditional long-term forecasting. In our study we found that the sustainable energy is a very good option for pollution free efficient electricity production and we studied its limitations. We have assumed that wind turbines, battery storage and diesel engine as fundamental components of the hybrid power plant. The proposed technique will be useful to produce sufficient power to fulfil peak electricity demand within planned duration. We have considered power load and weather which can affect performance of wind-turbine in long term forecasting calculation. In performance evaluation we found the proposed system having better accuracy. The proposed technique will be useful for better planning of hybrid power plant for regular power supply within the planned duration without overestimation and underestimate.

We have used predicted daily weather parameters (F22) for calculating daily energy (P) which will be produce by one wind turbine then find out, median (PMedian) and minimum (PMin) of the daily energy (P). And assume predicted power load daily data as daily power consumption. Calculate the maximum of forecasted (predicted) power load with (MP1) and without (MP2) outliers (replace values by median (PMax) which is above median (PMax)) and (ii) is equal to the electricity power required/peak power load next 5 years, which is proportional to required resources for generating sufficient power to fulfil the electricity peak power demand. For the estimation of the resources in next 5 years, we divided the MP2 by PMedian and calculate ceiling of the output to find out Number of Wind Turbine (NWT) required in normal condition. And we subtracted NWT * PMin by MP1 to find out extra power (PExtra) will be required by generators (of capacity PH) or other source of electricity in worse condition. For getting the Number of Generator (NG) required is calculated by dividing the PExtra by PH and calculate ceiling of the output.

This research work can be enhanced by taking on other factors which can effect long-term forecasting, and by adding other existing and new forecasting techniques in the proposed system.

REFERENCES

[1] Rahul Kumar Agrawal, Frankle Muchahary and Madan Mohan Tripathi, "Long term load forecasting with hourly predictions based on long-short-term-memory networks," *2018 IEEE Texas Power and Energy Conference (TPEC)*, College Station, TX, USA, Electronic ISBN: 978-1-5386-1006-0, Feb 2018.

[2] Gheisa R. T. Esteves, Bruno Q. Bastos, Fernando L. Cyrino, Rodrigo F. Calili, Reinaldo C.Souza, “Long Term Electricity Forecast: A Systematic Review,” *Procedia Computer Science*, Elsevier, Vol. 55, Pg. 549-558, 2015.

[3] Barbara Rossi, "Density forecasts in economics and policymaking," *Els Opuscles del CREI*, Ed. 37, Sept. 2014.

[4] R. Weron, “Electricity price forecasting: A review of the state-of-art with a look into the future,” *International Journal of Forecasting*, Vol. 30, Pg. 1030-1081, 2014.

[5] M. T. Thomé, R. L. Hollmann, and L. F. R. R. S. do Carmo, “Research synpaper in collaborative planning forecast and replenishment,” *Industrial Management and Data Systems*, Vol. 114, Pg. 949-965, 2014.

[6] R. V. Kale, and S. D. Pohekar, “Electricity demand and supply scenarios for Maharashtra (India) for 2030: An application of long range energy alternatives planning,” *Energy Policy*, Vol. 72, Pg. 1-13, 2014.

[7] F.M.Andersen, H.V.Larsen, T.K.Boomsma, “Long-term forecasting of hourly electricity load: Identification of consumption profiles and segmentation of customers,” *Energy Conversion and Management*, Elsevier, Vol. 68, Pg. 244-252, Apr. 2013.

[8] C. H. Wang, G. Grozev, and S. Seo., “Middle-long power load forecasting based on dynamic grey prediction and support vector machine,” *Energy*, 2012; 41: 313-325.

[9] Eisa Almeshaiei and Hassan Soltan, "A methodology for Electric Power Load Forecasting,” *Alexandria Engineering Journal*, Vol. 50, Pg. 137–144, 2011.

[10] Hossein Daneshi, Mohammad Shahidehpour and Azim Lotfjou Choobbari, "Long-term load forecasting in electricity market," *2008 IEEE International Conference on Electro/Information Technology*, Ames, IA, USA, Print ISBN: 978-1-4244-2029-2, May 2008.