Renewable Energy and Demand Forecasting in an Integrated Smart Grid

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Renewable Energy and Demand Forecasting in an Integrated Smart Grid

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***Abstract*— The paper presents a framework that realistically simulates a microgrid and forecasts renewable energy and load demand. Electricity spot prices are also forecasted and used by the scheduler to optimize the total microgrid cost per day. The energy storage and conventional supplies are coherently scheduled to meet the demand. Forecasting models described here give an excellent insight to choose the appropriate architecture to safeguard grid stability, smooth scheduling, and energy management. Finally, the results help in a better understanding of the functioning of the smart grid system.**

***Keywords*— Smart Grid, Renewable Energy, Forecasting, Cost Optimization, Scheduling.**

I. Introduction

Conventional Energy resources are draining up steadily. In order to cater to the ever-increasing energy demand, renewable energy sources must be integrated into the grid. However, renewable sources are affected by environmental factors, which can cause fluctuations in power generated. Even the sources' availabilities are subjected to daily or annual cycles (such as solar energy is available only during daytime) [1]. Hence, the agenda of the solution proposed here is to use accurate forecasting models to predict various power & cost values, simulate a realistic microgrid, and integrate it with a cost-optimized scheduler, all the while, ensuring grid stability, smooth-scheduling, and energy management [2],[3]. Day-ahead scheduling is formulated by preparing 288 slots of 5 minutes each, where demand and supply forecasts are matched to make the scheduling decision for the next day [4]. Any deviations on the actual run-day are managed by the spinning operating reserve, which can be a diesel gen-set so that the load demand is satisfied for maximum time intervals without any requirement of load-shedding or islanding [5].

This paper aims to investigate the minimization of microgrid operating cost, by developing accurate forecasting models and optimized scheduling algorithm. The paper is organized as follows: Section II explains the forecasting techniques. Section III describes the scheduling strategies. Section IV depicts the simulation architecture of the smart grid. Section V presents the analysis of results. Section VI concludes the paper.

II. Forecasting Techniques

Accurate forecasting models are essential for the efficient operation, economical, and risk management of a smart grid. The data-set for a region in Germany is collected from different packages present at https://data.open-power-system-data.org/. Forecasting techniques proposed here are classified into the following categories.:

- Spot Price prediction
- Load/Demand Forecasting
- Renewable Energy Forecasting

A. Spot Price Prediction

Conventionally, power sectors are mainly under the government's control, but the establishment of competitive markets and steady privatization has changed this scenario. Globally, electricity is transforming like any other commercial commodity, which has led to an increased number of choices in the market for consumers. Spot prices are used for trading electricity. Accurate forecasting of spot prices is an essential part of optimizing microgrid operation. Spot price is a form of time-series data, exhibiting specific characteristics, like Seasonality, Mean Reversion, Volatility, and Spikes.

A time-series data frame, containing the day-ahead 24 hours spot prices is the feature taken as input to the Recurrent Neural Networks (RNNs) for predicting the next day's spot prices.

Eradicating the vanishing gradient problem of RNNs, Long Short-term Memory (LSTM) versions of RNNs are taken into consideration [6]. The specifications of the LSTM neural network used are shown in TABLE I.

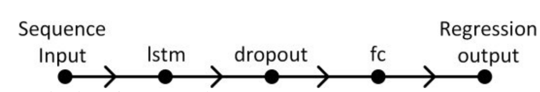

Fig. 1: Network Flow for Spot Price

TABLE I. Network Analysis Parameters for Spot Price

Analysis Result		
No.	***Type***	***Activations***
1	Sequence Input	24
2	LSTM	200
3	Dropout (20%)	200
4	Fully Connected	24
5	Regression Output (Mean-squared-error)	-

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The dataset used is in an hourly format. Therefore, accounting for the one feature, twenty-four(1x24) activations are used for the input layer. The dropout layer helps in removing problems regarding over-fitting. Finally, the output (predicted hourly spot price: 24) is taken from the regression-output layer.

B. Demand Forecasting

Load demand forecasts are remarkably crucial for energy suppliers and other shareholders in power generation, transmission, and distribution. Accurate models for load forecasting are fundamental to the operation and market planning of any power-utility group of companies.

Load forecasting can be broadly classified into three categories [5]:

- Short-term forecasts: forecasts in between one hour to one week
- Medium forecasts: forecasts before a week to a year
- Long-term forecasts: forecasts made more than a year ago.

In this paper, the focus has been made on short-term forecasts. The features taken for load forecasting are shown in TABLE II.

TABLE II. FEATURES FOR LOAD FORECASTING

No.	*Features/Predictors*
1	A day-ahead predicted spot price
2	Temperature (°C)
3	Wind-speed
4	Historical Information of Load-pattern

Depending on the available spot price, the consumers may change plans accordingly so as to pay a lesser amount for electricity bills, thus cutting down the demands when the price is high and vice-versa. Weather features play an essential role in load forecasting. For example, a hot-humid climate can shoot up electricity consumption, and on the other hand, cold weather can lessen the demand. Historical data of the past eleven years are taken into account to accommodate all the variations in load demand. Each of the features mentioned in TABLE II is in the form of a time-series data frame. These are fed as inputs to the RNNs, to predict the next day's load demand. An LSTM version of RNNs is used to capture the seasonality and trends in the time-series dataset. The specifications used for the LSTM network are shown in TABLE III.

TABLE III. NETWORK ANALYSIS PARAMETERS FOR LOAD

Analysis Result		
No.	*Type*	*Activations*
1	Sequence Input	96
2	LSTM	200
3	Dropout (20%)	200
4	Fully Connected	24
5	Regression Output (Mean-squared-error)	-

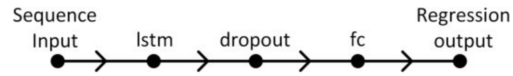


Fig. 2: Network Flow for Load

Since the dataset used is in an hourly format, therefore, accounting for the four features, ninety-six(4x24) activations are used for the input layer. The dropout layer helps to remove over-fitting. Finally, the output (hourly load forecast: 24) is taken from the regression-output layer.

C. Renewable Energy Forecasting

The renewable energy sources used in the proposed model are solar photo-voltaic farms and wind farms. Predictions of solar energy generation are comparatively easier than wind power generation forecasting, owing to a large amount of uncertainty associated with wind-speeds and wind power generations [7]. On the other hand, solar power generations have a proper seasonality on a daily basis and follow a trend annually categorizing under simpler time-series models. Therefore, to prepare a comparative study of forecasting techniques, the power forecast scheme has been described first. An attempt has been made to prepare two similar models approximating the real-life forecasting technique. Finally, a correlative study has been framed, which brings out the better of the two proposed models.

1) Power Forecast Scheme:

The renewable energy forecasting has three stages:

a) Weather Forecasting: Weather data acts as the fuel for the forecasting model that outputs wind-speed and irradiance levels.

b) Simulation of Power: Wind-speed and irradiance forecasts are fed into respective simulation models involving power converter applications. The forecasted values of the wind and solar power are the outputs.

c) Up-scaling to regional levels: The power values from the simulation needs to be up-scaled to operate in a real-life scenario. The up-scaled power is fed to the load flow integrated smart grid model for further analysis.

These stages can be modeled using physical or statistical methods or a combination of both. All the modeling steps may not be explicitly included while forecasting renewable energy sources [5].

2) Proposed Model-1:

Model-1 directly intakes the Numerical Weather Prediction (NWP) forecasts of irradiance and wind-speed from open data platforms. As shown in Fig. 3, the forecasted weather data (here irradiance and wind-speed) are used as predictors/ features for the solar power and wind power forecasting. The models used are medium decision trees and sequential Ls- Boost ensemble techniques, respectively [3]. Finally, the forecasted power values are fed to the load flow integrated smart-grid model.

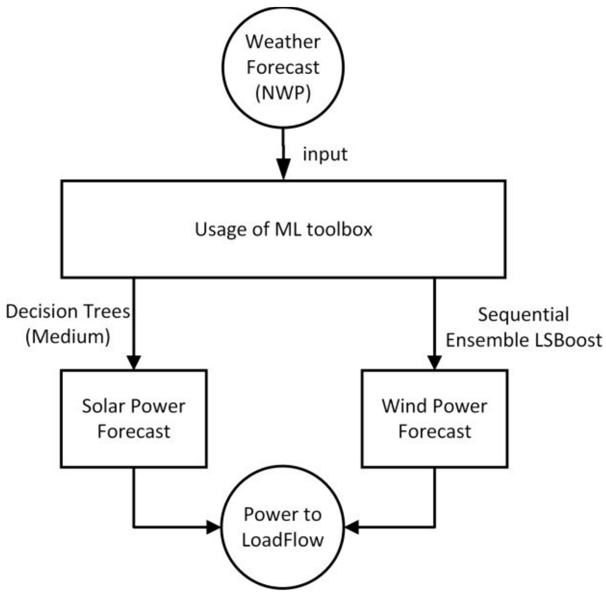


Fig. 3: Forecast Scheme of Model-1

3) *Proposed Model-2:*

Model-2 is a close approximation of the original power forecast scheme. The only difference between the proposed model-1 and proposed model-2 is that the former approach is an end-to-end machine learning proposal, whereas the latter is a hybrid approach taking into consideration machine learning and simulations techniques.

The predictors of input weather data are as shown in TABLE IV, which help in irradiance and wind-speed forecasting.

TABLE IV. WEATHER FEATURES

No.	***Features/Predictors***
1	Precipitation (in mm/hour)
2	Temperature(°C)
3	Snowfall (in mm/hour)
4	Snow Mass (in kg/m^2)
5	Cloud-Cover (as a fraction [0,1])
6	Air-density (in kg/m^3)

The solar irradiance measurement can be formulated using Artificial Neural Network (ANN) as described in [8]. As depicted in Fig. 4, the whole forecasting approach's novelty is to take LSTM versions of RNNs, which provides a better result than the optimizable ensemble(bagging) based statistical weather prediction. Hence the former has been taken forward and used for power forecasting before feeding to the load-flow model. The network analysis parameters used are similar to TABLE III, with the difference in the number of activations for Sequence Input which is 144 (24*6) instead of 96.

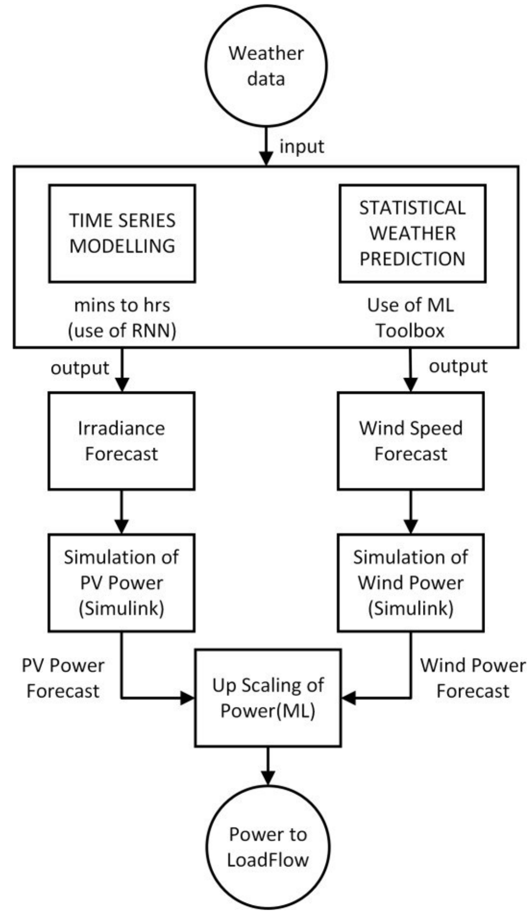


Fig. 4: Forecast Scheme of Model-2

III. SCHEDULING STRATEGIES

Scheduling strategies decides the power share of production units and hence ensures the power flow balance in a microgrid. Two approaches considered are:

A. *Heuristic*

It is a state-flow chart already existing in [4], which takes into account the peak-demand shift using energy storage as a part of the energy management system without any cost optimization. Conditions of the State of Charge (SOC%) limits sufficiently satisfy the requirements of coordination control in energy management logic as shown in Fig. 5.

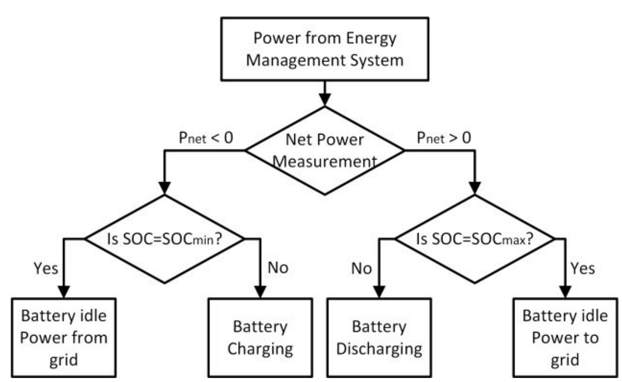


Fig. 5: Heuristic Power Management Logic

B. Linear-programming Optimization

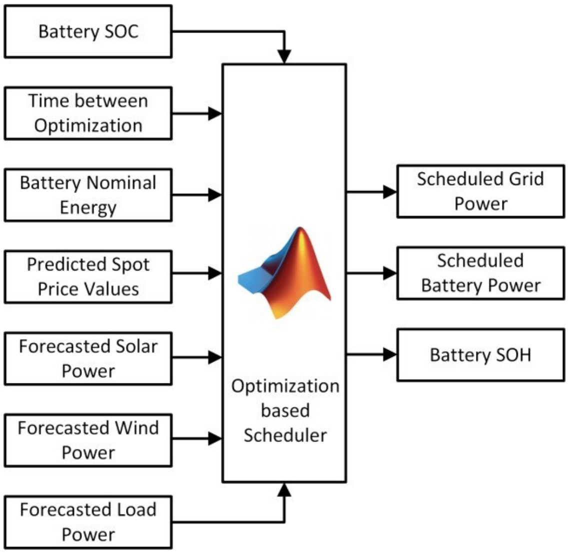


Fig. 6: Inputs and Outputs of Scheduler

In contrast to the standard heuristic approach, our simulation model uses linear-programming based scheduler whose aim is to minimize the microgrid operating cost [9]. It decides to purchase power from grid and charges the Energy Storage System (ESS) during low price periods. This excess ESS power can be used to supply demand during high price periods. If the renewable generation is higher than the load demand, the surplus power will be sold to grid [2]. TABLE V describes the scheduling parameters used.

TABLE V. SCHEDULER PARAMETERS

Symbol	***Description***	***Units***
N	Total number of slots (288)	-
C_{tot}	Total optimized cost	Euros
C_{grid}	Price of grid power per kWh	Euros per kWh
P_{batt}	Power from ESS	kW
E_{batt}	Energy stored in ESS	kWh
P_{pv}	Photo-voltaic Power	kW
P_{wind}	Wind turbine Power	kW
P_{grid}	Power from grid	kW
P_{load}	Power required by load	kW

The objective is to minimize the cost function. The linprog solver form optimization toolbox of MATLAB is used to achieve this [10]. The cost function is described in (1):

$$C_{tot} = \sum_{k=0}^{N} \left(C_{grid}(k). E_{grid}(k)\right) \quad (1)$$

The constraints that define the operation of the system:

a) Energy input/output to the battery:

$$E_{batt}(k) = E_{batt}(k-1) + P_{batt}(k)\Delta T \quad (2)$$

b) Power Balance:

$$P_{pv}(k) + P_{wind}(k) + P_{grid}(k) + P_{batt}(k) = P_{load}(k) \quad (3)$$

IV. SIMULATION OF INTEGRATED SMART GRID

The forecasted data of solar power, wind power and load demand are imported from the proposed model-2 to the Simulink model of smart grid. The scheduled battery power output from the scheduler provides a power reference command to the ESS and ensures a balanced power supply from the sources satisfying the consumer demand. The voltage and frequency levels of microgrid are also synchronized, ensuring stability in all aspects [2].

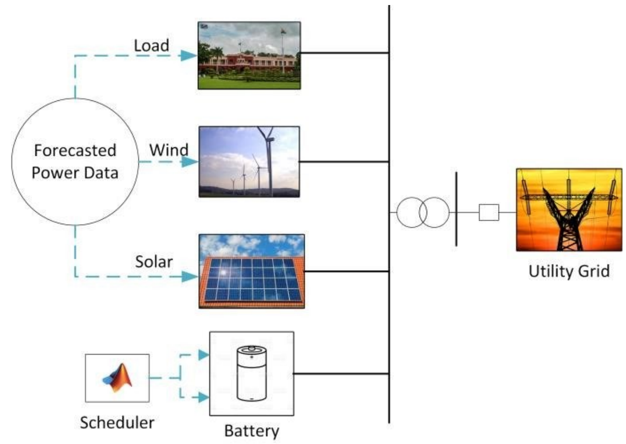


Fig. 7: Scheduler Integrated Smart Grid Model

V. RESULTS AND DISCUSSION

In this section the results of the proposed system namely performance evaluation of forecasting techniques, cost optimization and grid stability are presented.

A. Performance Evaluation of forecasting techniques

The installed solar and wind capacity in December 2004 is 11.18 kW and 141.52 kW respectively. These values increased to 406.36 kW and 490.25 kW in December 2016 respectively. The average load demand per day is 546.62kW. The average spot price value per day is € 35.

TABLE VI and VII shows the comparative study of performances between Model-1 and Model-2. The best model is quantitatively determined by R-squared, mean absolute error (MAE), and mean absolute percentage error (MAPE).

Clearly, Model-2 performs better than Model-1, due to the incorporated LSTM versions. Hence, Model-2 has been carried forward to final micro-grid simulation. The error margins of Model-2 between actual and forecasted values of solar power, wind power load demand and spot price are shown in Fig. 8 for a time frame of one day.

TABLE VI. FORECASTING PERFORMANCE OF MODEL-1

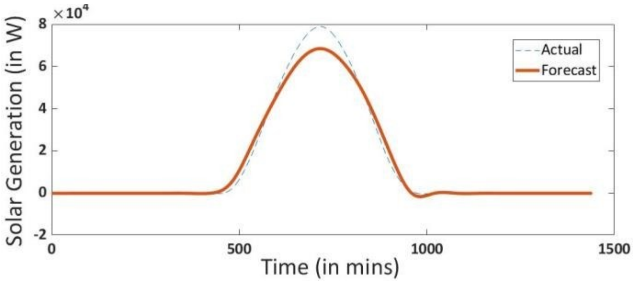
Power Sources	**Model-1**		
	R-Squared	***MAE***	***MAPE***
Solar Power	0.93	1.79	11.95
Wind Power	0.8	30.10	23.87

TABLE VII. FORECASTING PERFORMANCE OF MODEL-2

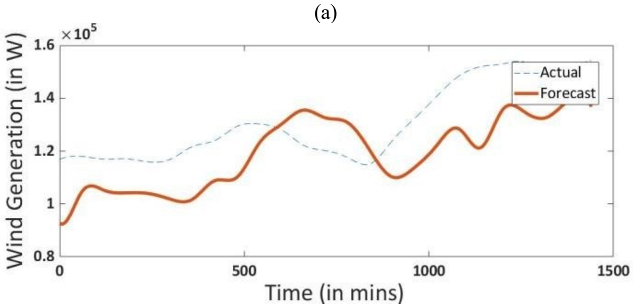
Power Sources	**Model-2**		
	R-Squared	***MAE***	***MAPE***
Solar Power	0.95	1.81	11.9
Wind Power	0.82	28.6	21.76

TABLE VIII. METRICS OF LOAD AND SPOT PRICE FORECASTING

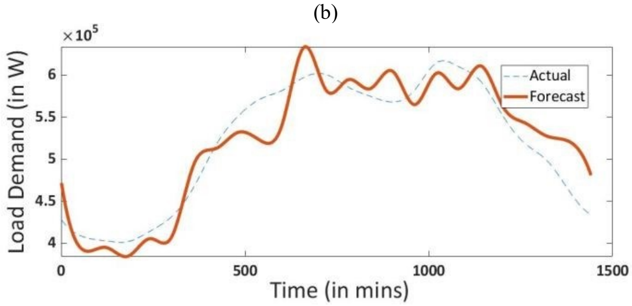
	R-Squared	***MAE***	***MAPE***
Load Demand	0.91	7.89	12.22
Spot Price	0.88	3.98	11.92



(a)



(b)



(c)

Fig. 8: Error Margin between Forecast and Actual values of (a) Solar Generation (b)Wind Generation (c) Load Demand

TABLE VIII shows the evaluation metrics of the forecasted load and spot price values. Although there is significant error involved in the forecasting, comparisons with existing methods included in [7] and [11] show that the proposed methodology works well.

B. Cost Optimization

In the comparative study in Fig. 9, the last hour signifies that the optimization-based cost curve is below the heuristic cost curve, ensuring the minimization of total cost by the end of the day. Hence, the cumulative cost per day to buy power from grid is low when linear programming optimization-based scheduling is used.

- Linear-Programming Optimization Cumulative Cost: € 331.1
- Heuristic Cumulative Cost: € 360.4
- The percentage optimized = 8.11%

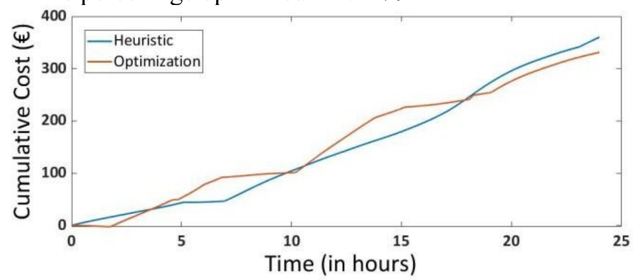


Fig. 9: Cumulative Grid Cost (€)

C. Grid Stability

Fig. 10 shows the voltage synchronization throughout the grid at 5000V, and variations are in the permissible range of ± 5%. Fig. 11 shows the frequency synchronization throughout the grid at 60 Hz and is in the permissible range of 59.95-60.05Hz. Depending on the new SOC % (Fig. 12) and forecasting values (Fig. 8), the balance between load line and all other combined energy sources is achieved as shown in Fig. 13.

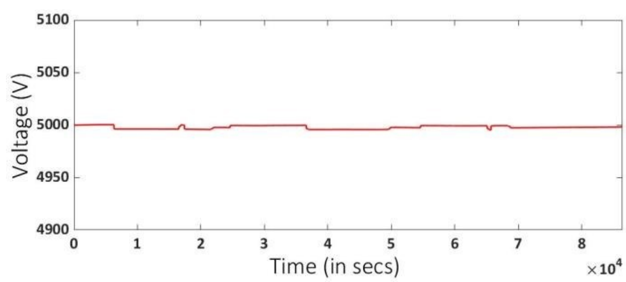


Fig. 10: Microgrid Voltage (Root Mean Square Voltage)

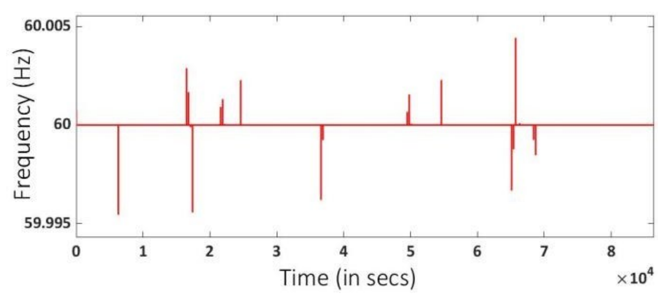


Fig. 11: Microgrid Frequency (in Hz)

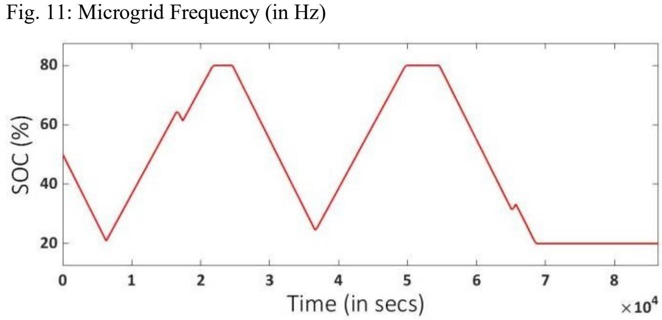


Fig. 12: State of Charge of Energy Storage System

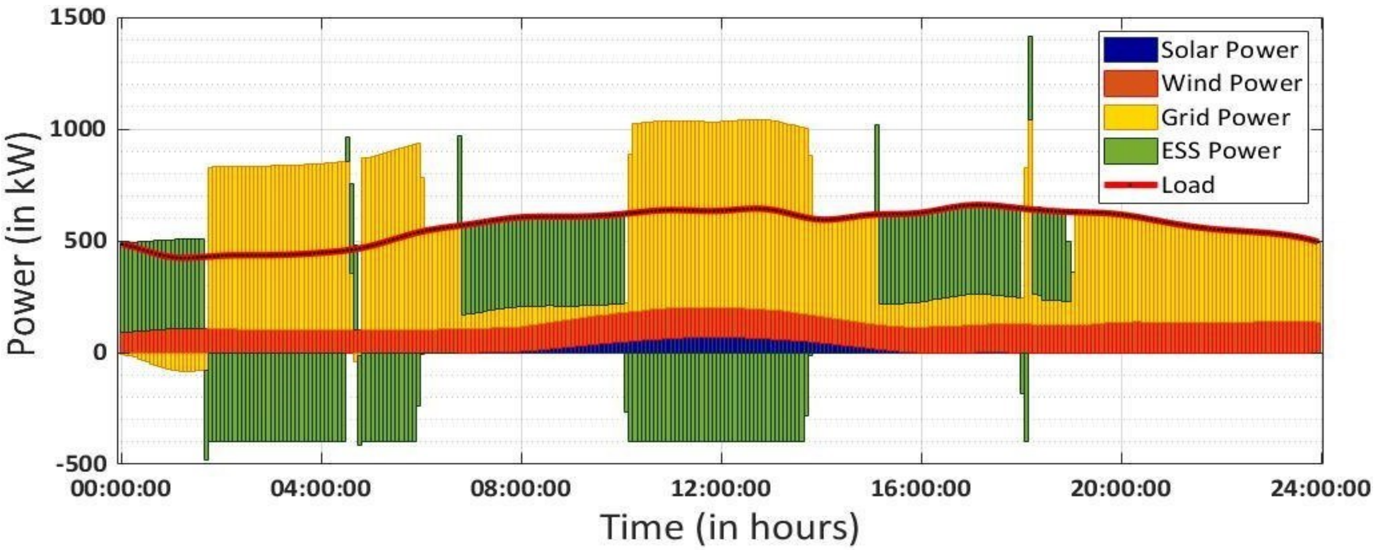


Fig. 13: Day Ahead Scheduled Power Flow in 288 slots

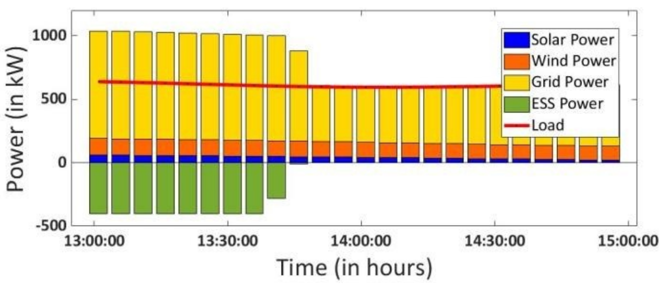


Fig. 14: Scheduled Power Flow in 24 Slots (2 hours)

Fig. 14 is a section enlarged from Fig. 13, spanning over 24 slots (13:00 to 15:00 hours), that helps in visualizing power balance in microgrid according to the (4).

$$P_{batt} \text{ (Scheduled)} + P_{grid}\text{(Scheduled)} + P_{pv}\text{(Forecasted)} + P_{wind} \text{ (Forecasted)} = P_{load} \text{ (Forecasted)} \quad (4)$$

VI. Conclusion

LSTM networks of RNNs are a recently proposed time-series forecasting approach which sufficiently considers the linear as well as nonlinear components of prediction. To comprehensively evaluate this methodology, this paper compares it with a major end-to-end prediction model namely Ensemble learning techniques for the forecasting of the renewable energies. A hybrid approach is taken while considering the LSTMs which forecast irradiance and wind-speed values that are fed to a simulation model to generate the power forecasting values. Therefore, due to the indulgence of LSTM versions into the hybrid model, the best performance is brought out while forecasting power when compared between the proposed two approaches. The linear-programming optimization-based scheduler ensures the best management of power for the microgrid sources and minimizes the total cost by the end of the day. As far as the future scope of the work is concerned, the application of more advanced optimization techniques can improve the percentage of cost optimized during the day thus providing choices to the customers to buy power from grid.

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