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Title: Renewable energy and demand forecasting in an integrated smart grid

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OBJECTIVES

With the escalation of energy demands all over and terror of draining conventional fossil fuels, distributed generation networks were introduced in comparison to the centralized traditional networks. Distributed generation (DG) refers to the production of electricity near the consumption place through renewable energy resources especially wind, solar and so on.

- Problem:- . However, renewable sources are affected by environmental factors, which can cause fluctuations in power generated.
- Solution:- Hence, the agenda of the solution proposed here is to use accurate forecasting models to predict various power & cost values, simulate a realistic micro-grid, and integrate it with a cost-optimized scheduler, all the while, ensuring grid stability, smooth-scheduling, and energy management. Day-ahead scheduling is formulated by preparing 288 slots of 5 minutes, where demand and supply forecasts are matched to make the scheduling decision for the next day.

Existing Research Work

Renewable energy especially wind are intermittent power sources, which have been making significant penetration into the electricity markets in various countries around the world. As a result, the accurate predictions of power generation become increasingly important. Short-term forecasting is critical to the operation of wind turbines and solar panels so that dynamic control can be accomplished to increase the energy conversion efficiency and reduce the risk of overloading.

- A number of time series forecasting methods have been successfully applied to the short-term predictions of power generation. Autoregressive integrated moving average (ARIMA) family is one of the most robust and widely used approach. Included in this family are autoregressive (AR), autoregressive moving average (ARMA), factional ARIMA (fARIMA), and seasonal ARIMA (sARIMA). These models can explicitly reveal the relationship between the inputs and outputs, but they are generally limited in linear forms. Artificial intelligence (AI) and machine learning (ML) approaches are also frequently adopted. The AI/ML models include various artificial neural network (ANN) models such as back propagation (BP) and radial basis function (RBF), support vector machine (SVM), fuzzy logic. In general, the AI/ML models can better handle non-linear relationship and thus are more flexible, but they describe the relationship in implicit ways and sometimes are very computationally intensive. In addition to these single model structures, two new forecasting methodologies are emerging, namely combined forecasting (or ensemble forecasting), and hybrid forecasting. In this section focus has been made on this.
- Apart from forecasting, this project also includes scheduling where linear-programming based optimization is used as an algorithm. Previously, Interior Search algorithms (ISA), Crow Search algorithms(CSA) and gradient descent algorithms served as efficient optimization algorithms to minimize the operating cost.

I. FORECASTING

Forecasting models proposed here can be broadly classified as follows:

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

As can be seen from the below table, Model-1 is an end-to-end machine learning approach while Model-2 is more of a hybrid approach.

	MODEL -1		MODEL -2	
	ACCURACY	Algo	ACCURACY	Algo
SOLAR POWER	93.708	Decision Tree(Medium)	94.56	RNN (LSTM) + Simulink + Linear Regression
WIND POWER	80.2	Ensemble (LSBoost)	82.042	RNN (LSTM) + Simulink + Optimizable Ensemble
LOAD	91	RNN (LSTM)	91	RNN (LSTM)
PRICE	94.8	RNN (LSTM)	94.8	RNN (LSTM)

Spot-Price Prediction

The measures of deregulation and the introduction of competitive markets have reshaped the landscape of traditionally monopolistic government-controlled power sectors. In many countries worldwide, electricity is now traded under market rules using spot and derivative contracts exhibiting seasonality on a daily, weekly and annual basis and abrupt short-lived generally unanticipated price spikes. At the corporate level, electricity price forecasts have become a fundamental input in the energy companies' decision-making mechanism. Electricity price series exhibit certain stylized facts, namely Seasonality, Mean Reversion, Volatility, and Jumps/Spikes. Being a case makes it extremely relevant for modeling spot electricity prices, having a lead time of a few hours/days.

The feature taken into account is the previous day 24 hrs spot-prices, which in turn help in predicting the next day's spot price. Eradicating the vanishing gradient problem of Recurrent Neural Networks (RNN), Long Short-term Memory versions of RNNs are taken into consideration.

RNN MODEL STRUCTURE		
No.	**Type**	**Activations**
1	Sequence Input	24
2	LSTM	200
3	Dropout 20% dropout	200
4	Fully Connected	24
5	Regression Output Mean-squared-error	-

Demand Forecasting

Load forecasting can be broadly classified into three categories:

- 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.

Here, the focus has been made on short-term forecasts.

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

Features Description:-

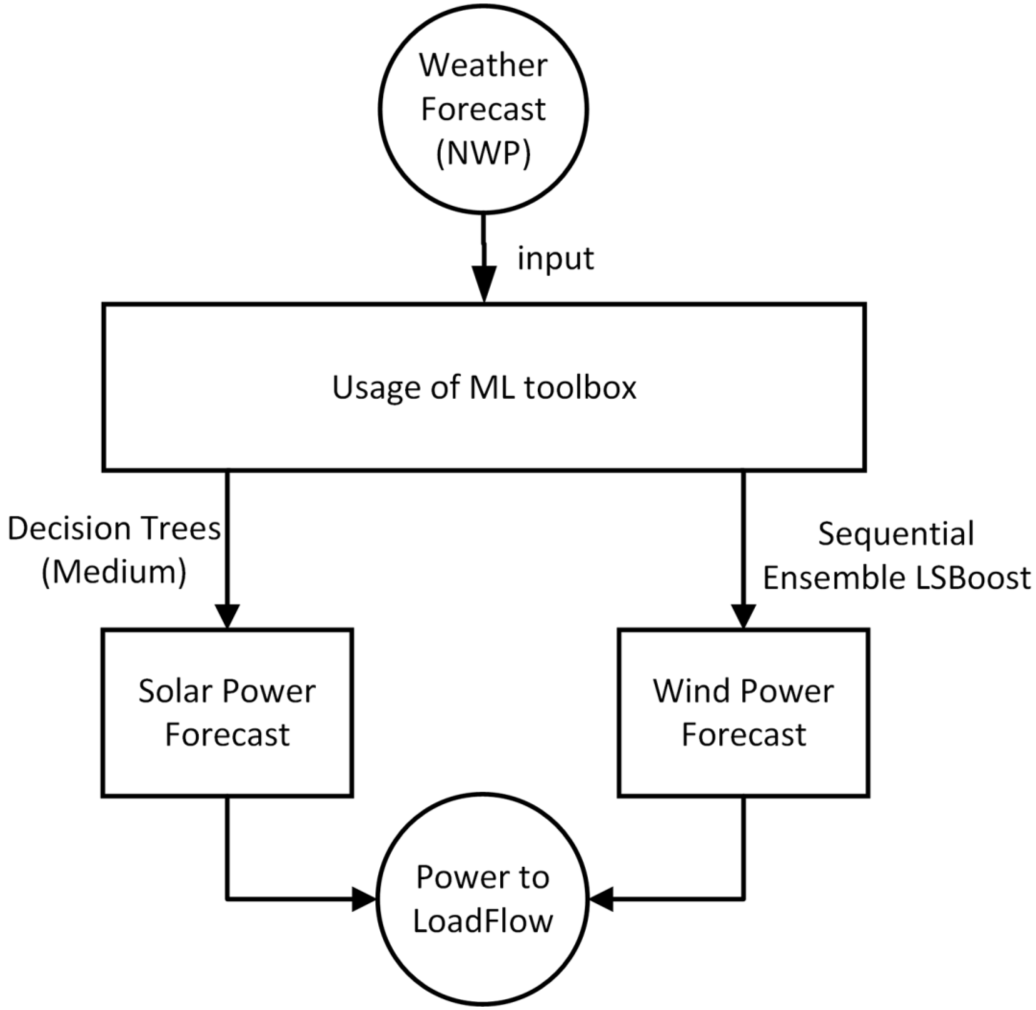
Depending on the available spot-price, the consumers may change plans accordingly so as to pay a lesser amount for electricity bills, thus cutting down the demands when the price is high and vice-versa.

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 is taken into account to accommodate all the variations in load demand. Considering all these features, an LSTM version of RNNs is used to capture the seasonality and trends in the time series dataset.

RNN MODEL STRUCTURE		
No.	**Type**	**Activations**
1	Sequence Input	96
2	LSTM	200
3	Dropout 20% dropout	200
4	Fully Connected	24
5	Regression Output Mean-squared-error	-

Renewable Energy Forecasting

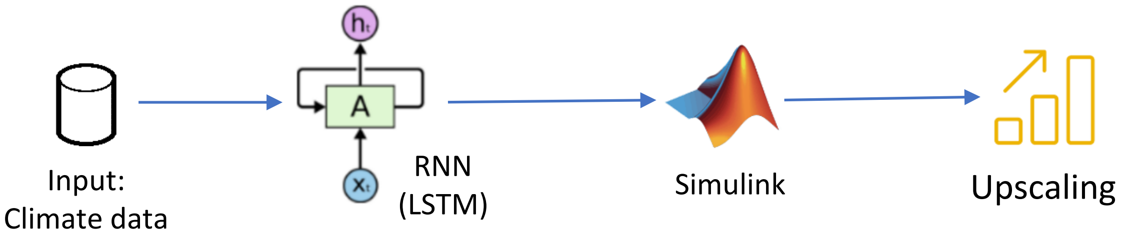


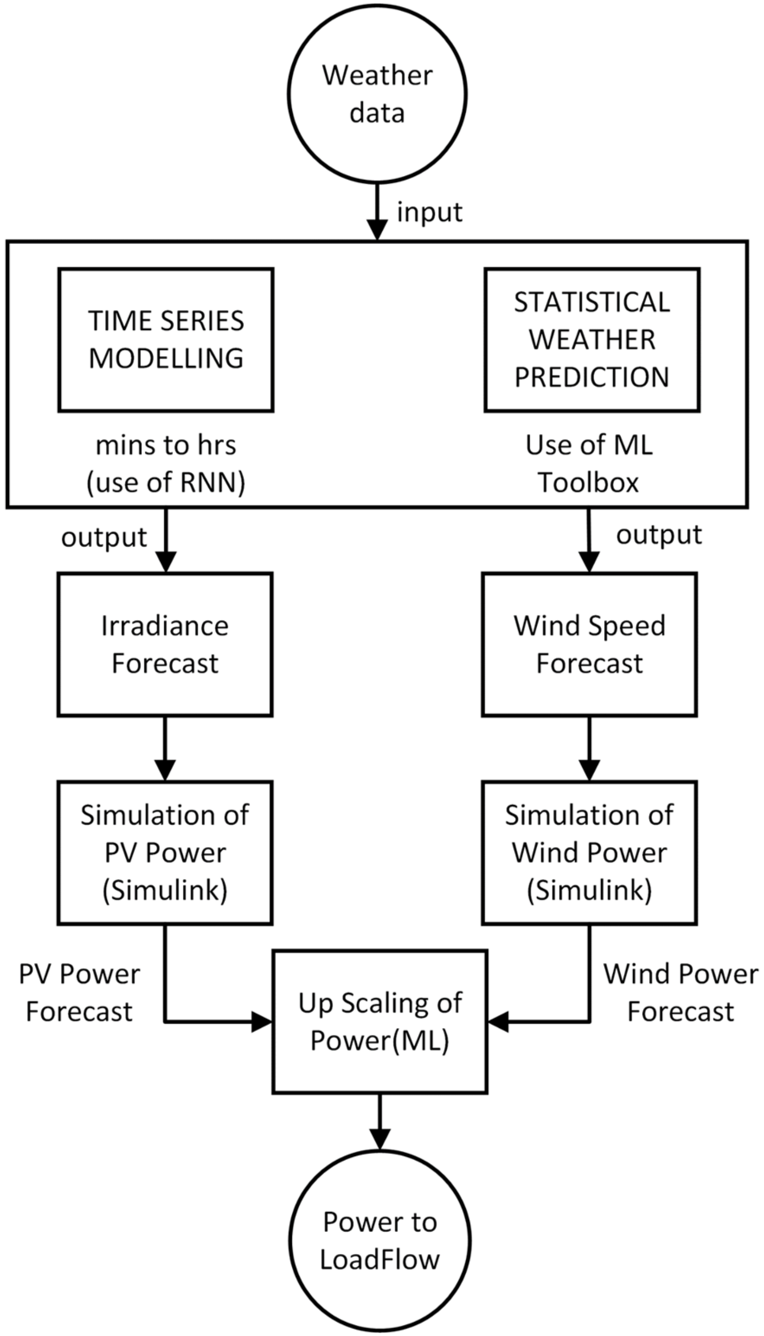
MODEL-1

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)
7	Irradiation (in W/m^2)

MODEL-2

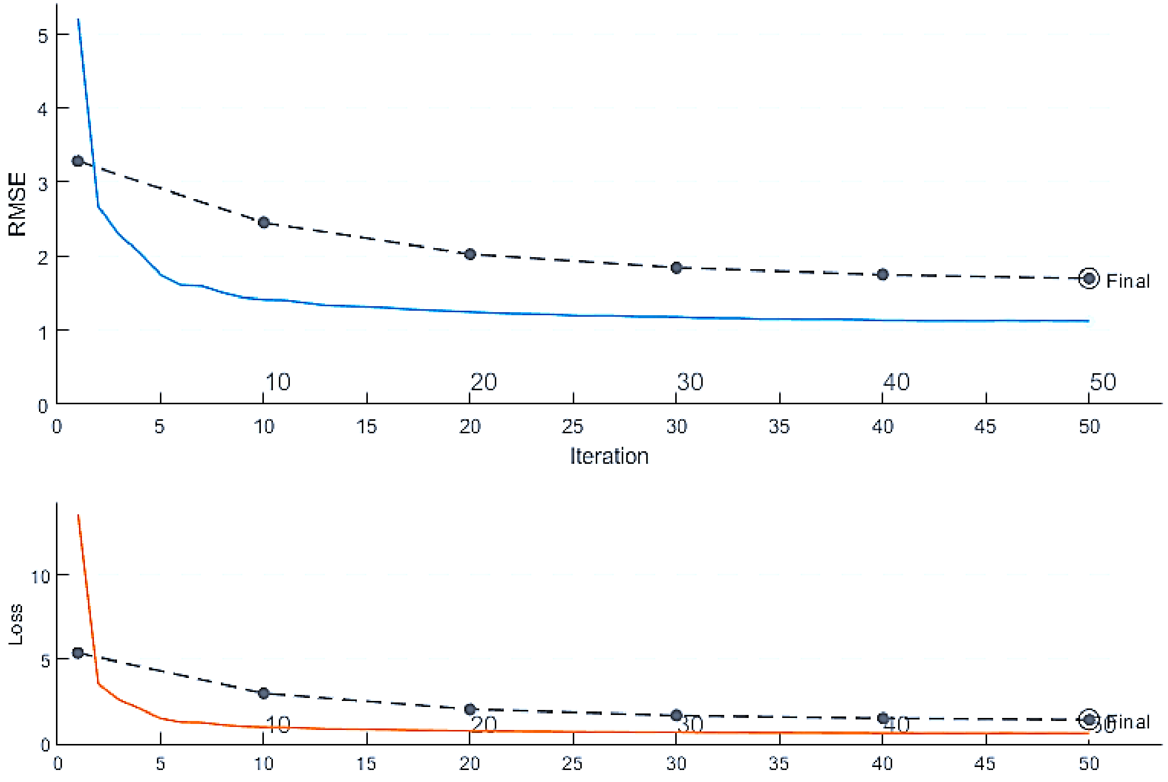
No.	Features/Predictors
1	Precipitation (in mm/hour)
2	Temperature(°C)
3	Snowfall (in mm/hour)
4	Snow Mass (in kg/m^2)
5	Cloud-Cover (as a fraction [0,1])
6	Air-density (in kg/m^3)



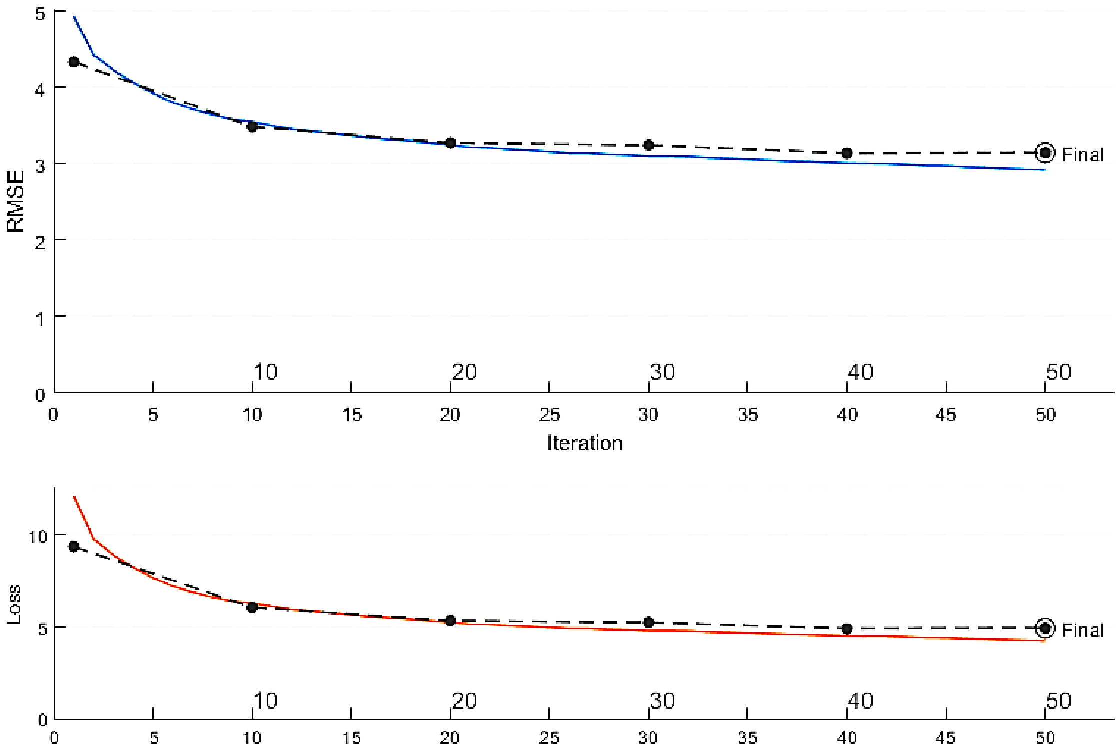


TRAINING LOSS AND ERROR CURVES

Irradiance Forecast

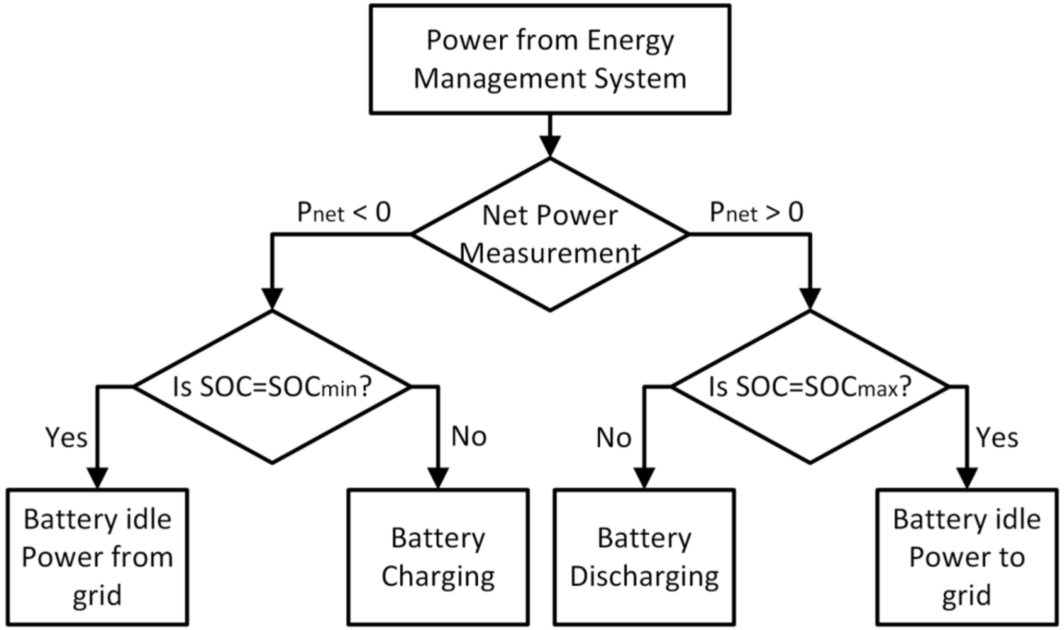


Windspeed Forecast

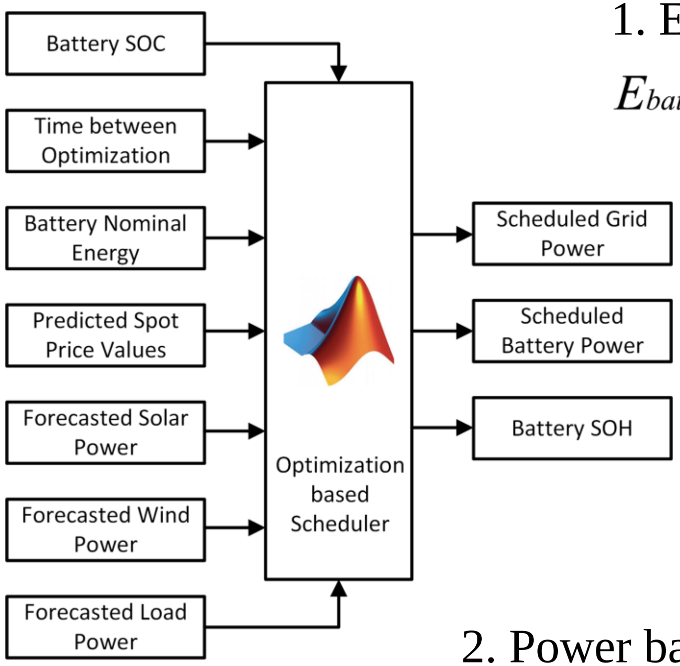


II. SCHEDULING

A. Heuristic Approach



B. Linear-Programming Optimization



1. Energy input/output to the battery:

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

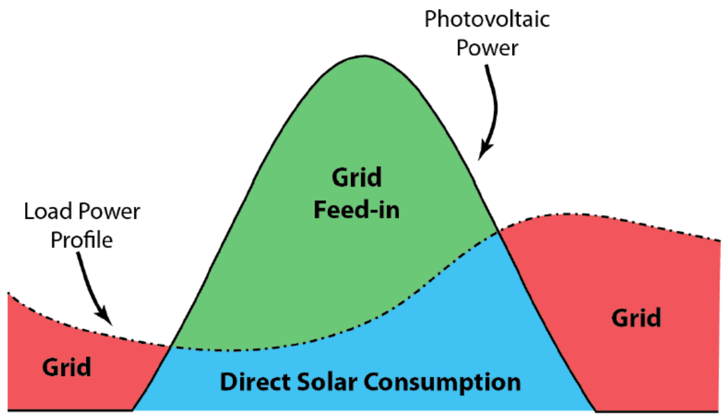
2. Power balance:

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

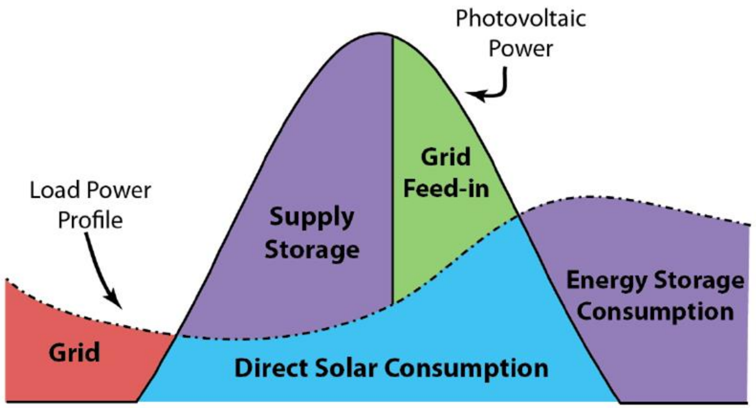
The main objective is to minimize the total cost of variably priced electricity:

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

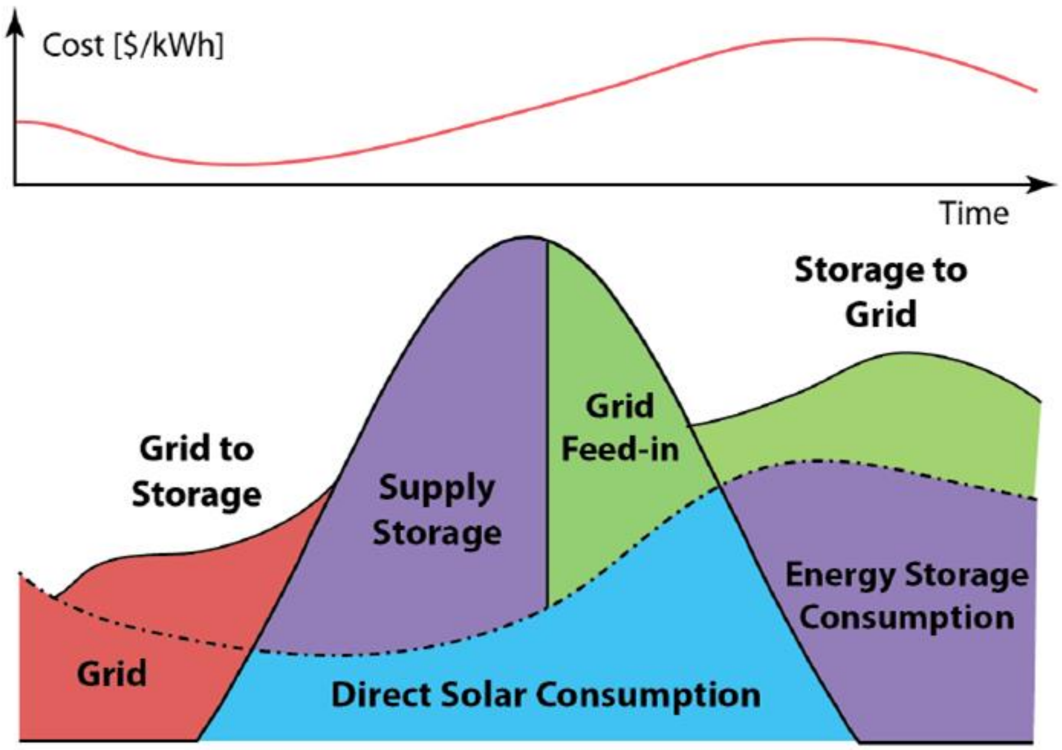
Load-Dispatch Scheduling Strategy



Without considering cost and storage



Without Considering Cost

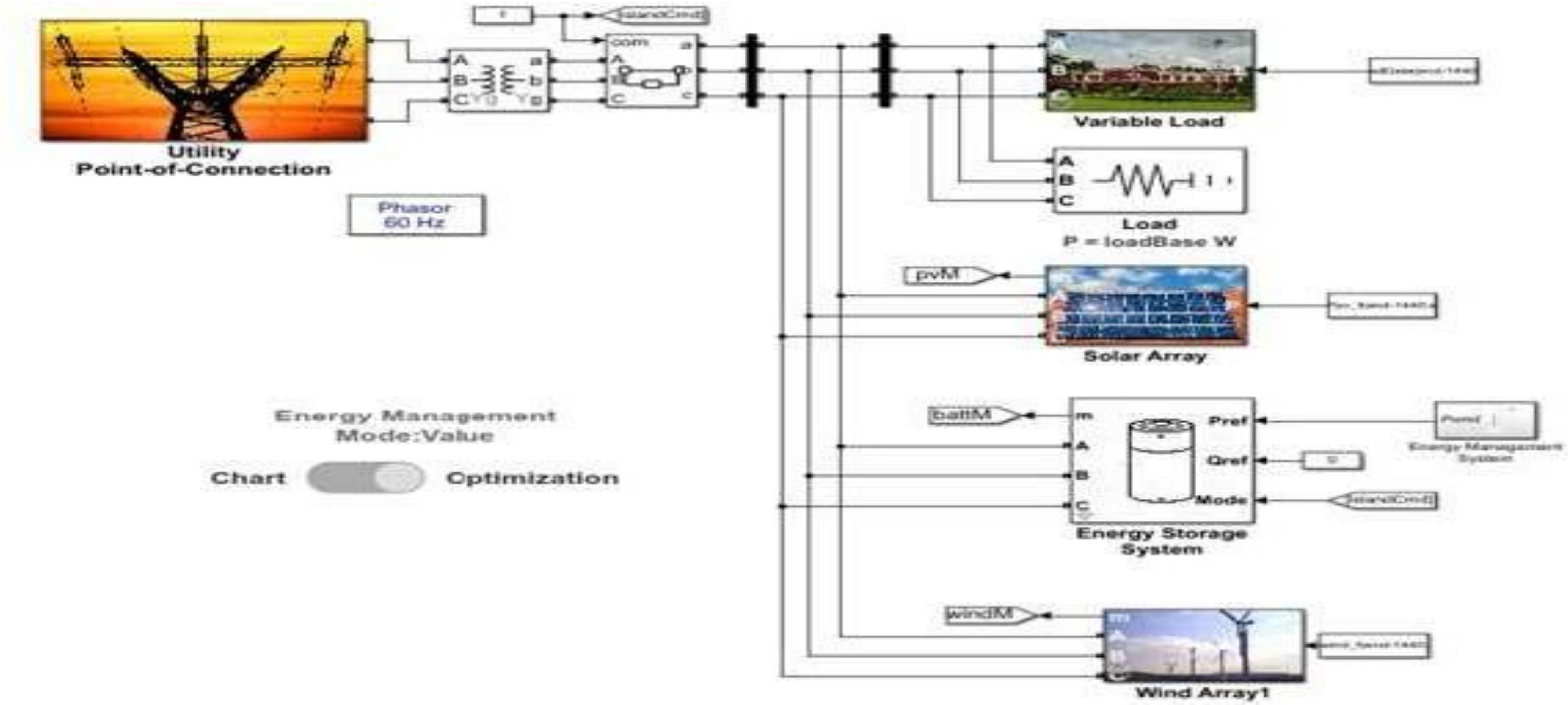


Considering Cost

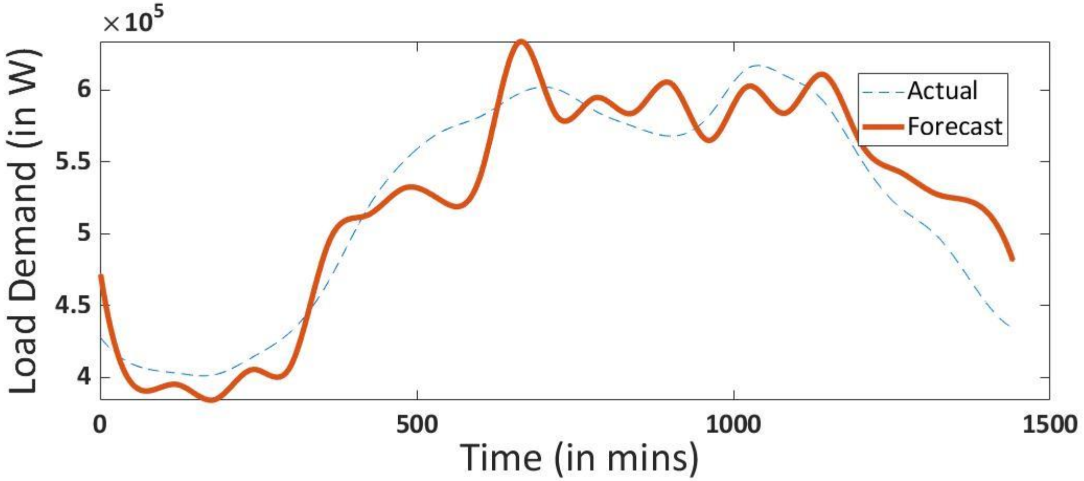
III. Micro-grid

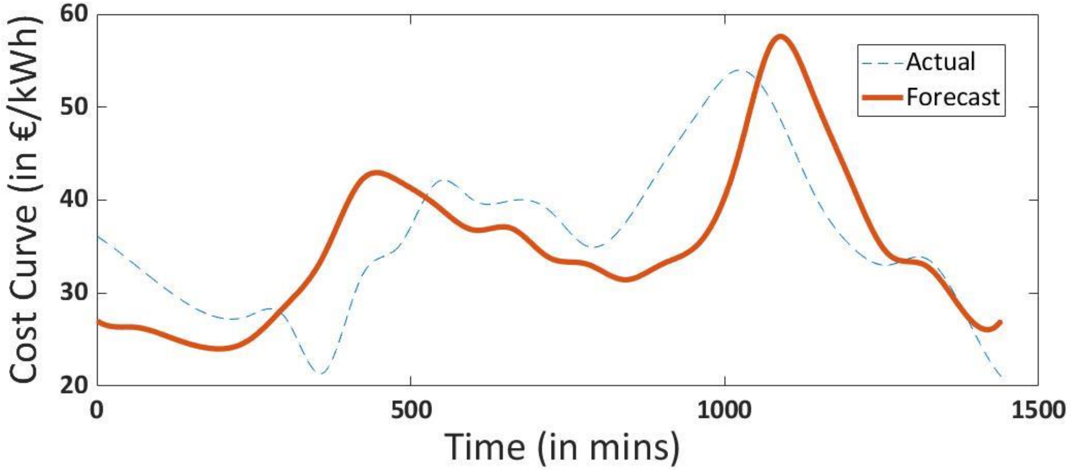
- Microgrid model consists of PV, Wind, Battery (ESS), Grid, Load
- Forecasted power values are fed into PV, Wind & Load
- Scheduling algorithm is integrated at the controller of microgrid
- During simulation scheduling algorithm gives the output of Scheduled battery and grid power values.
- Voltage, frequency of microgrid is synchronized. Power balance is also ensured as demonstrated before.

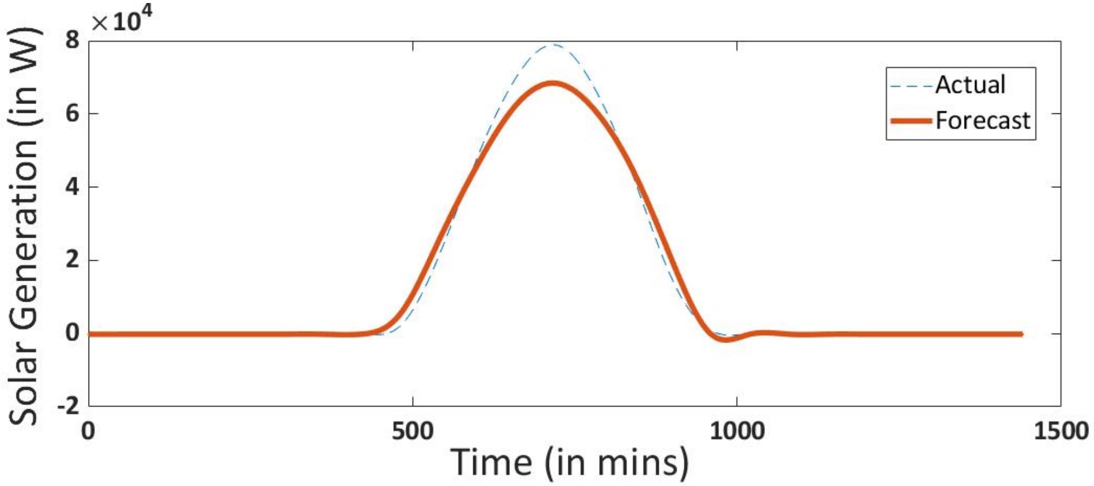
Microgrid Simulink Model

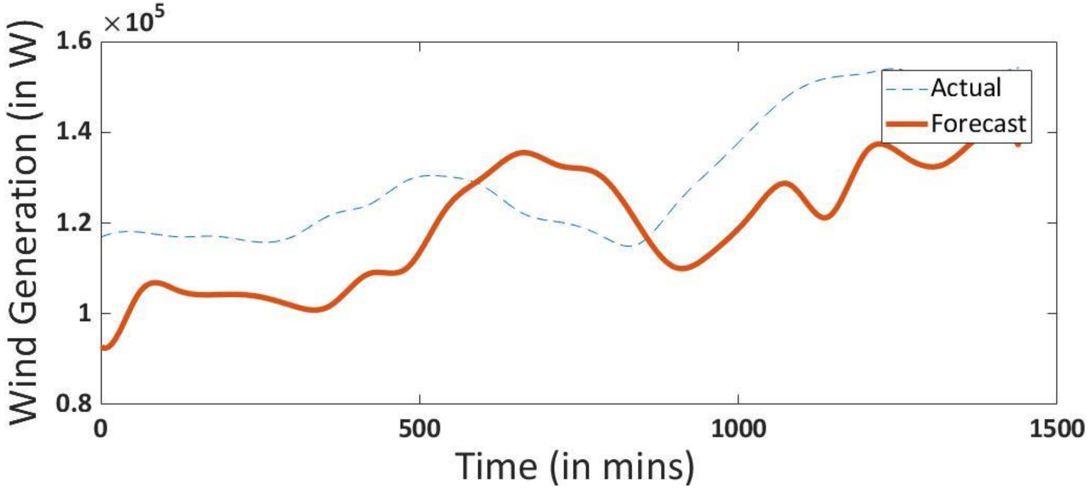


OBSERVATION:
1. Accuracies of Forecasting Models





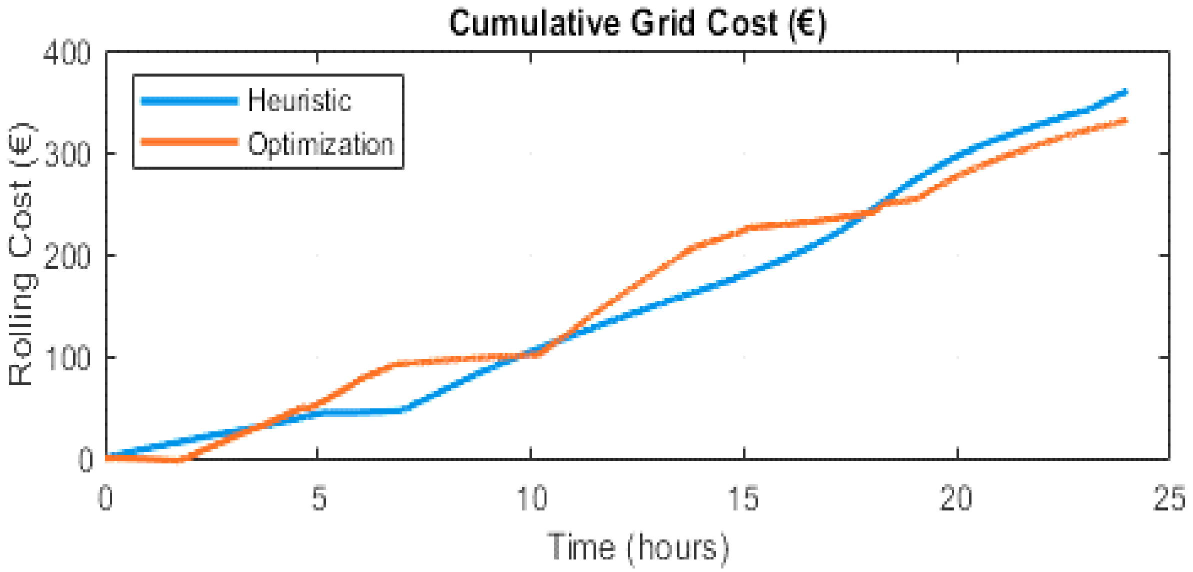




2. Scheduling Cost Comparison

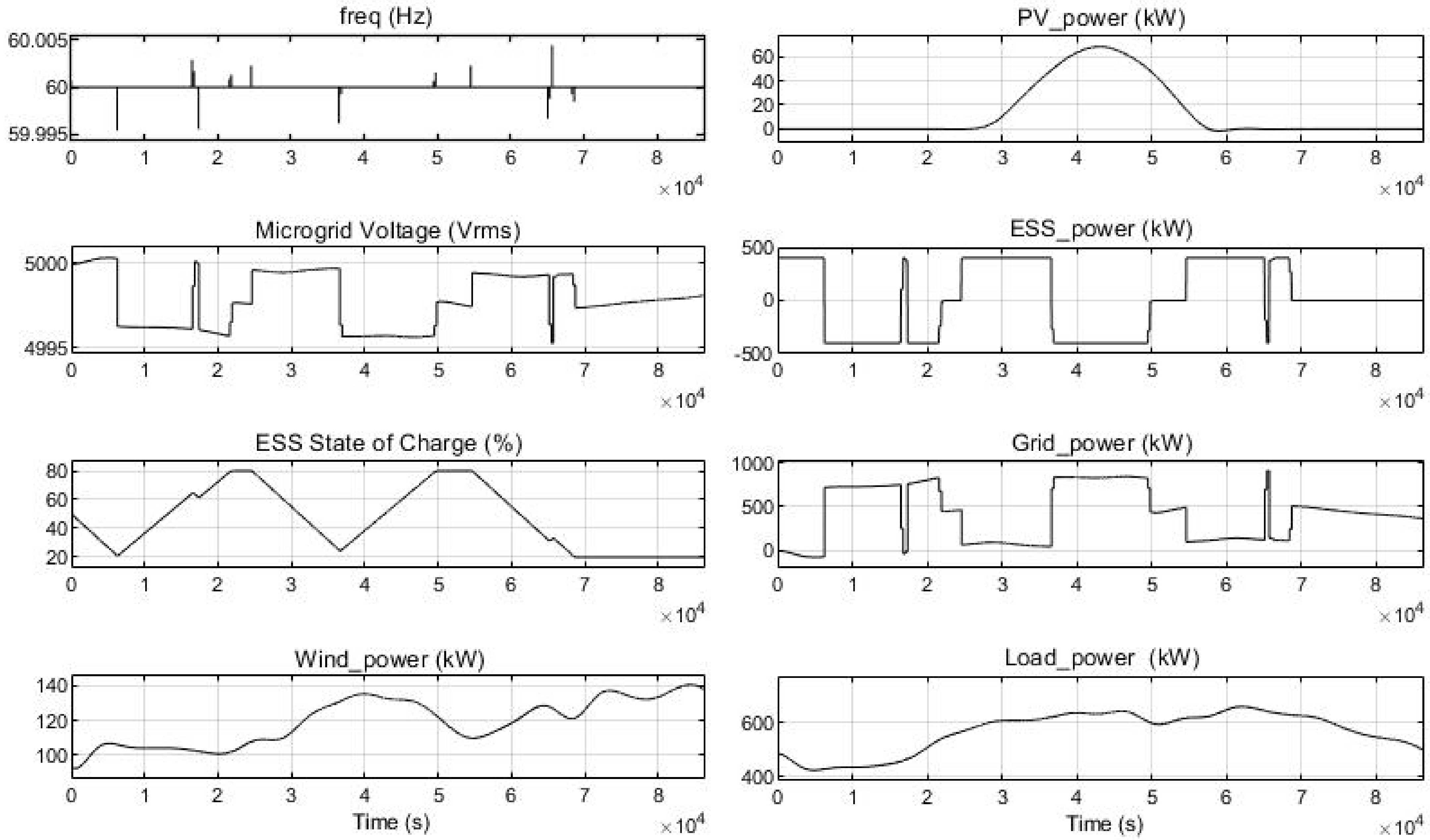
1. Heuristic Cost: € 360.4
2. Linear optimization Cost: € 331.1

Total Cost Optimization : 8%



This Scheduling algorithm is integrated with the microgrid model in Simulink which provides the scheduled battery and grid power values.

3. Final Scope Output



RESULT
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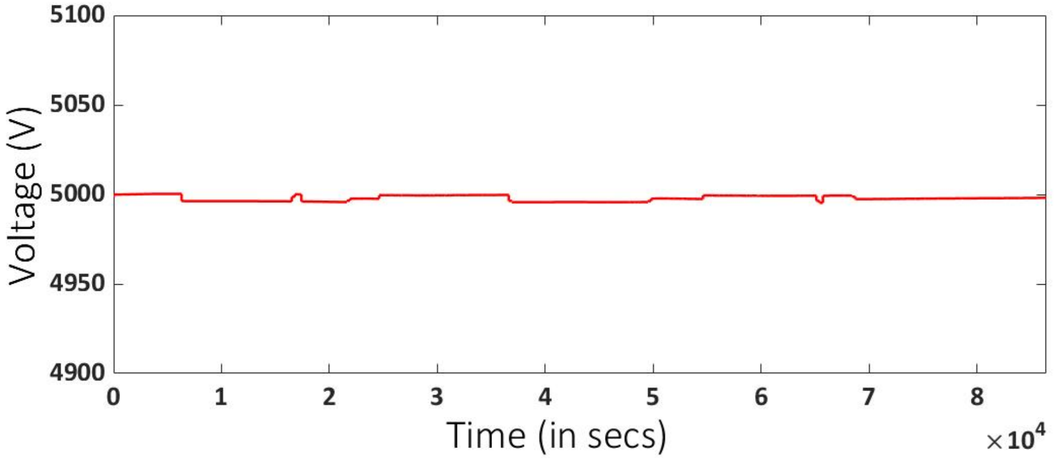
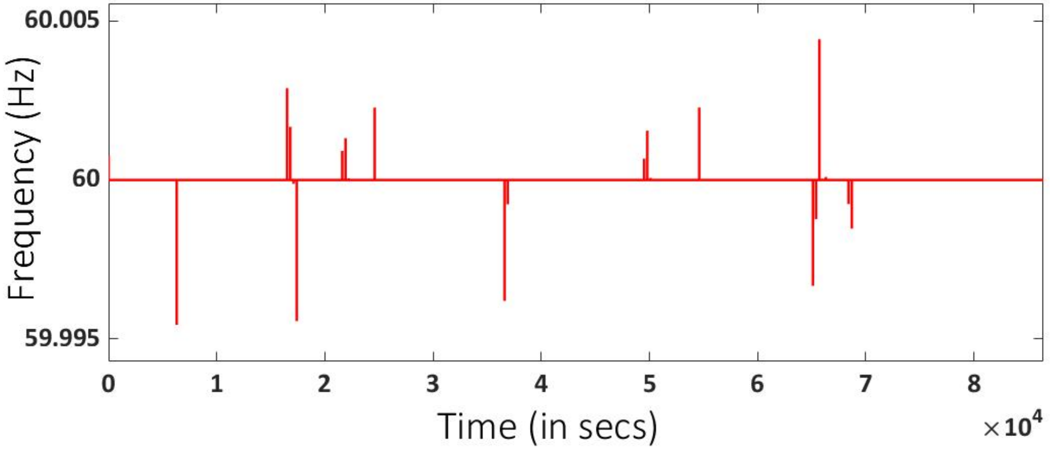
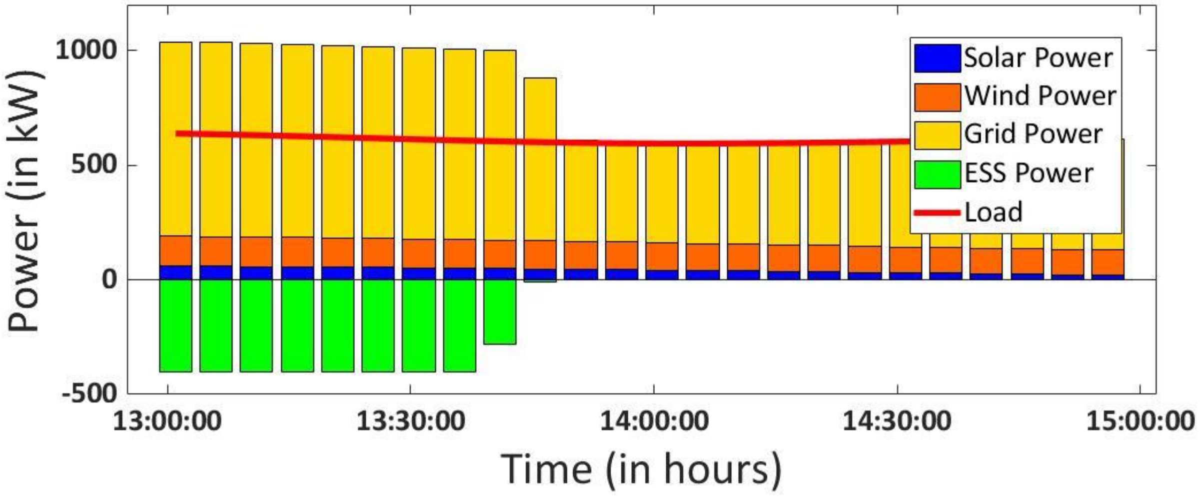
1. Grid Stability :





2. Scheduling Decision Report :



CONCLUSION

The results are extracted in the realization of an integrated smart grid, simulated on a synthetic dataset corresponding to a city in Germany. The architecture is analyzed considering the load variations and balancing them with the energy sources. The simulation is done on a day-ahead basis, taking into account the scheduler's 288 slots and the forecasted values.

However accurate the forecasted values be, there will always remain a tiny percentage of error, which can lead to the power
imbalance. Hence, on an actual day, an operating spinning reserve (can be a diesel gen-set) helps in balancing the mismatch caused due to the slight error percentage in the forecasted and actual values. This helps in the prevention of load-shedding, and thus the continuation of energy supply to meet the load demands is ensured.

THANK YOU