# P-Q Control of Photovoltaic Generators using LSTM based Load Forecasting

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*Abstract*— **In this paper, a power system is designed where real and reactive power have been controlled of the photovoltaic generators tied with the BUET power plant generators. When there is enough solar power to meet a local load, the PV active power output can be adjusted in the load-following mode. The loads that will be fed by controlling PV arrays have been forecasted based on previous 4 years' data. Load prediction has been done using LSTM method.**

***Keywords—microgrid, photovoltaic, load-following, LSTM***

## I. INTRODUCTION

Nowadays, electricity plays a vital role in national economic and social development. Moreover, Solar photovoltaic (PV) technology holds paramount importance in the pursuit of sustainable and renewable energy systems. Accurate load forecasting and efficiently uses oof PV can help power companies to secure electricity supply and scheduling and reduce waste since electricity is difficult to store. The global pursuit of sustainable and resilient energy systems has necessitated innovative approaches to seamlessly integrate renewable sources into the power grid. In this context, solar photovoltaic (PV) generators emerge as pivotal assets, capable of not only providing a clean and abundant energy supply but also dynamically responding to the fluctuating demands of contemporary power grids.

Traditionally, power systems have been designed around a stable base load, with supplementary sources adjusting to meet varying demands. However, the increasing penetration of renewable energy sources, particularly solar PV, introduces variability and intermittency challenges. To address this, our paper proposes a novel system design where PV generators are strategically employed to meet fluctuating loads through a load following mode.

The novelty of this innovative approach lies in the utilization of Long Short-Term Memory (LSTM) networks for load forecasting. LSTM, a type of recurrent neural network (RNN), excels in capturing temporal dependencies and patterns in time-series data. By integrating LSTM-based load forecasting, our system aims to predict load variations with high accuracy, allowing the PV generators to dynamically adjust their output to meet the anticipated demands.

This paper reaches into the details of load following with PV generators, exploring the comparison between load forecasting precision and real-time control strategies. The incorporation of LSTM-based forecasting not only enhances the predictability of load fluctuations but also enables proactive and responsive adjustments, ensuring optimal utilization of solar energy resources while maintaining grid stability.

Furthermore, our study addresses the broader implications of this integrated approach, encompassing environmental benefits, economic considerations, and the overall sustainability of power systems. As solar PV technology continues to advance, the proposed system offers a scalable and adaptable solution for mitigating the challenges associated with load variability, thus paving the way for a more resilient and renewable energy landscape.

In conclusion, this paper contributes to the evolving discourse on renewable energy integration by presenting a comprehensive framework that optimizes the use of solar PV generators in load following mode. By leveraging LSTM-based load forecasting, our approach seeks to usher in a new era of intelligent and sustainable power systems capable of meeting the demands of an ever-changing energy landscape.

## II. METHODOLOGY

We are intending to design a micro grid system where 2 generators are connected to feed a load. One generator is Gas-generator and another is a Solar Array Generator (Photovoltaic Generator). This design is done to feed the load by sharing power supply between this two generators. Gas-generator is designed to feed the base load of the micro grid and Solar Array Generator is designed to supply the fluctuating loads of the micro grid. So, both real and reactive power flow control mechanism is needed to balance power generation and consumption. Figure-1 is a overall schematic of the designed model.

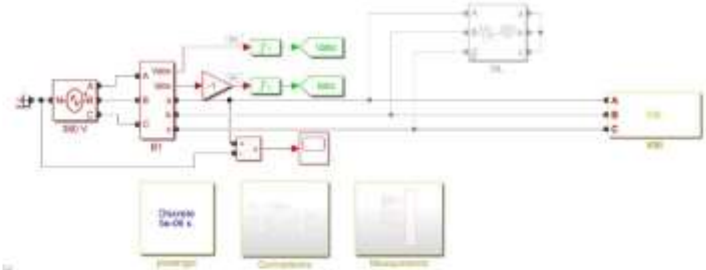

Figure-1

Let, Gas-generator is supplying a certain P and Q. We need some extra P and Q to balance the load demand. Extra power should be supplied by the Photovolatic Generator. Firstly, supplied power from the Gas-generator is measured by using three phase voltages and current flow from the Gas-generator as well as voltage magnitude, frequency and phase angle (wt) are measured from the abc Voltage. Then, Vdq is calculated from Vabc and wt and Idq is calculated from Iabc and wt.

Formulas of calculating power from direct axis and quadrature axis voltage and current are –

$P = V_d\, I_d$ (1)

$Q = V_q\, I_q$ (2)

When Vd is a constant, P is proportional to Id and Q is proportional to Iq.

Now, the difference between the required power and supplied from the Gas-generator power (for both real and reactive power) is measured and passed through a PI controller with suitable tuning (as figure - 2). So, referance direct axis current, Id_ref is obtained which is used for generating required real power according to eqution-1. Similarly, reference quadrature axis current, Iq_ref is obtained which is used for generating required reactive power according to eqution-2. In figure-2, it is designed for only real power (P) control method to observe effects. Required real power, P is modeled here as a step function to see whether the real power generation can follow the required real power level or not.

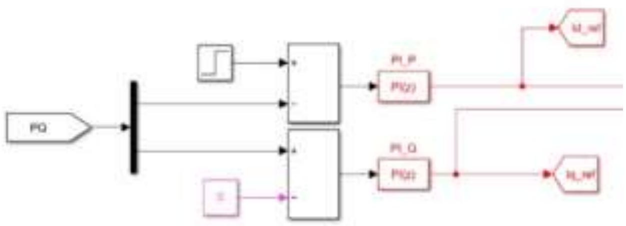

Figure-2

Using the Id_ref, Iq_ref, Vd, Id and Iq values, required PWM signal is generated to operate Inverter for converting DC power of the Photovoltaic Generator to 3 phase AC power.

Main control mechanism is in the generating block of PWM signals. First, a reference sinusoidal signal is needed to produce and compare with a triangular wave for PWM generation for 6-pulse inverter operation.

Reference Signal Generation:

$V_d = E_d + 2\pi f L I_q + error$ (3)

$V_q = E_q - 2\pi f L I_d + error$ (4)

From reference Vd and Vq, abc sequenced referance voltage is produced and normalized. Then compared with a triangular wave for PWM generation (as Figure-3).

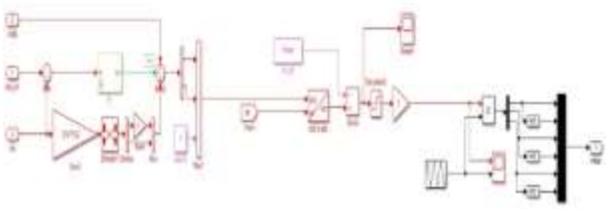

Figure – 3

Photovoltaic Generator is taking irradiance as its input and generating DC power (parameters: (Voc = 980V , Pmax = 350 kW). In PV generator characteristics curve is shown. A 6-pulse inverter is operated to produce AC Voltage for supplying required amount of Real and reactive power. Produced AC voltage and current contains a lot of harmonics and a RL filter is used to remove harmonics and it is connected to the grid (Figure-4).

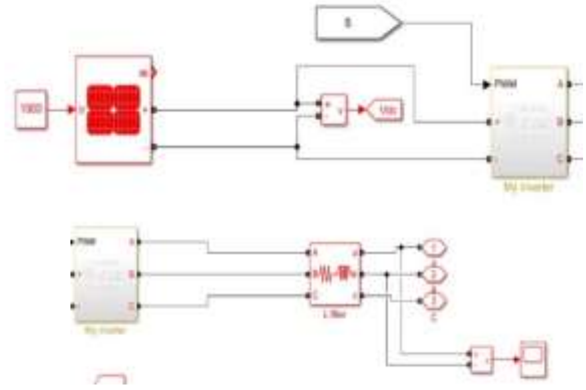

Figure – 4

For forecasting purposes, artificial neural networks have been used widely. Neural networks identify the features, or variables, that affect whatever outcomes you deem important, whether its classification, reconstruction, or prediction with regression. That is, the neural networks feed their results into other algorithms. During training, the guesses made by the network are tested against ground-truth results, and the error that results is used to adjust the network's coefficients. Those coefficients, or weights, are the numbers that amplify or dampen the signal of any given feature.

In our project, we used these three types of neural networks:

- Convolutional Neural Network (CNN)
- Long Short-Term Memory (LSTM)
- Feed Forward (FF)

From the plot of hourly load demand of 03/03/2022 the bell shape nature of load data is clearly visible.

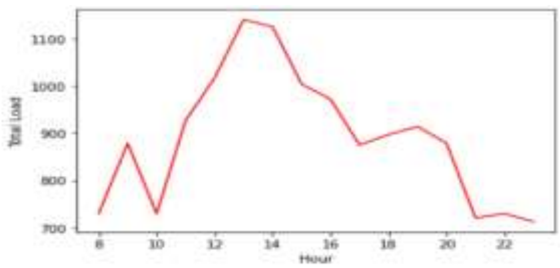


Fig: Hourly load demand of 03/03/2022

Again from the plot of weekly load variation of the first week of March 2022, we can clearly observe the periodic nature of load data due to weather change and human nature.

In 2015, a lot of data were missing. An hourly normal distribution of load gives a similar weekly load variation curve like the previous.

MODEL TRAINING AND TESTING:

For training the load forecasting model, the training was done for 20 epochs. Which means the output of the trained model was compared to the given output and was again sent to the input side of the cycle repeatedly until we reached a minimal error in the output with respect to the truth value. And this process was done through 20 iterations (or epochs). At first, in order to train the data, we passed the subsidiary data (such as weather data, Holidays, Weekday) through a Feed Forward Network and then a parallel CNN and LSTM layer respectively for prediction. Meanwhile the Load data were passed through 2 Layer LSTM and later was concatenated with the subsidiary data.

But unfortunately, after some iterations the value of the error started to repeat, and more iterations were pointless. This state is known as the Vanishing Gradient Problem. In this state error does not reduce anymore regardless how many iterations are done, so the model is not trained. This can be seen in the following curves:

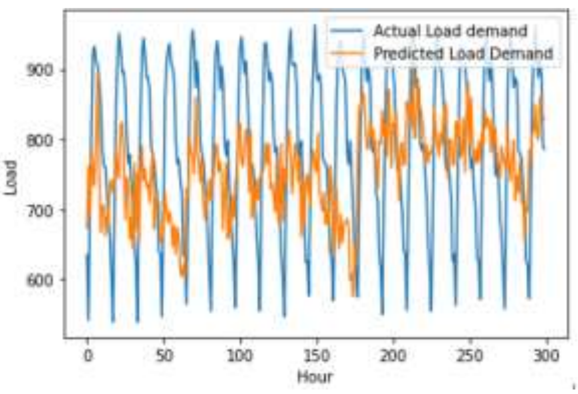


Fig: Ineffectiveness of the first model

## III. RESULTS AND ANALYSIS

First, P controlled simulation is tested. So, Required P is a step function and required Q is zero in Figure-4. In Figure-5, the simulation result is shown. The first plot indicates grid voltage magnitude which is constant with power change. The first plot of the 2nd row shows the referance required P, Q values which are a step function for P and Q is zero. P is tuned to 10kW for 1 second and 20kW for next 1 second. 1st plot of the 3rd row shows frequency of the system which is stable at 50Hz. 2nd plot of the 1st row is indicating three phase current which is increased with reference power increase. 2nd plot of the 2nd row is showing the Id_ref which is increased with P increase to ensure extra power supply. 2nd plot of the 3rd row is showing Iq_ref which is not changing much as Q is here zero. 3rd plot of 1st row and 3rd plot of 2nd row are showing Id, Iq, Vd, Vq with time. 3rd plot of 3rd row indicates instantaneous grid voltage which is stable. 4th plot of 2nd row and 4th plot of 3rd row are indicating PV generator voltage and current respectively. Here voltage is decreasing and current is increasing to shift the power point to maximize power delivered from the PV generator.

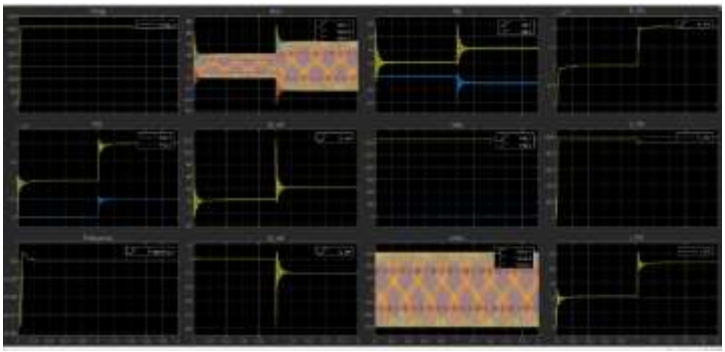

Figure -5

This model had the following validation loss curve:

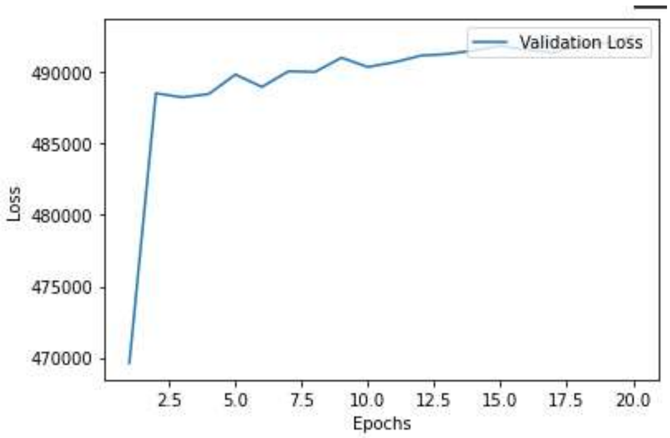


Fig: Validation loss curve of the previous model

We can clearly see that the validation loss is increasing, which is
not at all desirable for any machine learning model.

Also, we see here that the MAE and MAPE is:

| MAE (Mean Average Error) | MAPE (Mean Average Percentage Error) |
|---|---|
| 150.4337 | 21.07% |

So, we decided to approach it in a slightly different way.
As the first method failed, we then decided to remove the CNNs from the training portion and use only LSTM and the feed forward networks. So, we passed all the data we have (load data & subsidiary data) through an increased 128-layer LSTM and did the training again. This time we achieved a very accurate result and the error was below threshold value.

This model gave the following output:

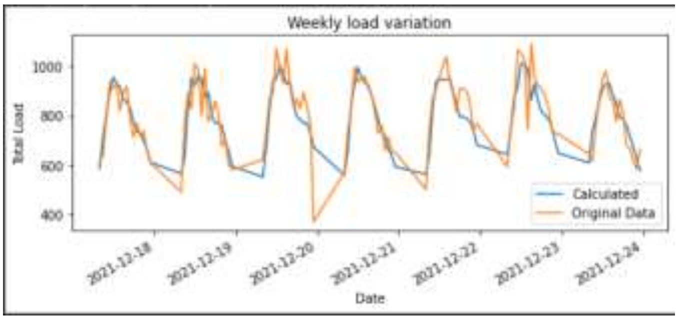


Fig: Prediction & test curve we got in the second process

As our prediction curve and test curve look a lot similar, now we can use this curve or the load forecasting data for predicting the load demand of BUET during any week of several upcoming years.

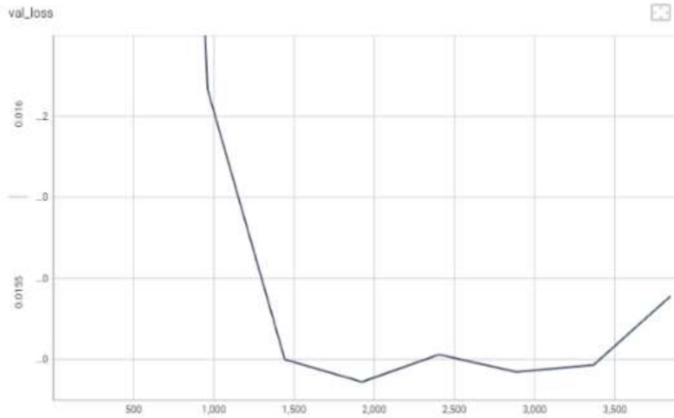


Fig: Validation Loss of the new model

And now measuring the new model's MAE and MAPE:

| MAE (Mean Average Error) | MAPE (Mean Average Percentage Error) |
|---|---|
| 81.59 | 10.92% |

This indicates the new model is substantially better.

## IV. ACKONWLEDGEMENT

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## V. CONCLUSION

Modern power grid companies use load forecasting techniques widely for efficient and economic operation of the power systems. Although in our country, it is not used that much. In our project, we tried to develop a model that can perform forecasting of loads which can be an asset for the power grid companies. We got pretty good results from the sparse time series data. Improvement of this model can be done by using more dataset which will reduce the MAE and MAPE errors. Eventually from the predicted load, we designed a system where base loads are fed by the main generators and the fluctuating loads will get power from the solar arrays using P-Q control based on load following mode.

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