Maximum Power Point Estimate through Computational Intelligence Technique

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Abstract

The Maximum Power Point (MPP) is the working state of a solar panel which maximizes its energy production and can depend on several factors. In the present paper prediction of the MPP value of a panel is modeled using mainly on the temperature of the panel, the voltage, the current and used Feed-forward Neural Networks for this task. Finally, the result of the model has been studied and discussed the prediction error.

Contents

1. Introduction

As we know every day utilization of electricity growing exponentially. The energy production from the renewable source and its use are considered strategic to reduce the emission. In the last twenty years, the growth of renewable energy industries is impressive. Nowadays in major countries electricity produced by green technology is addressed in grid parity. In last few years, the problems in the production of electricity are becoming so important and an effect on the national power distribution system of the countries where the energy particularly produced by photovoltaic systems are must be mixed with the energy produced by conventional fossil fuel sources. This makes the reliable and accurate PV characterization is so important.

One hour of Sunlight (Energy) received on Earth surface is enough whole world for a year. This well convinces to industry for PV systems energy production, especially in countries where sunny days and high level of radiation are frequent. This technology allows us to develop small production plants and which can be easily connected to the national grid to obtain a network of distributed generation [1], or, finally, used combined with traditional energy generation plants the achieve a higher efficiency (local production of thermal and electrical energy from solar plants) [2]. in this case, essential to handle the energy source mix [3,4] and can maintain the plant with inexpensive tools [5,6].

The power produced by a PV panel, given the environmental conditions such as irradiance and temperature, depends also on its electrical load. The highest power is produced by the VP panel is called Maximum Power Point (MPP). Hence, the MPP prediction is of paramount importance [7, 8, 9, 10, 11] to improve panel efficiency. Moreover, the ability to predict the MPP value using indirect measurements allows cost-effective monitoring of the plant efficiency, which can be useful for maintenance. In this paper, a methodology to predict the MPP from a simple measurement of a few features of the working conditions of a PV panel will be presented and discussed. In a panel, a sensor is installed to get the features [12].

2. PV Panels and Systems

PV panel(s) and power converter(s) are the two main components in the PV system. The solar cells (PV cells) are devices which produce a voltage difference when illuminated by a source light [13]. If PV cell is connected to an external circuit then current start flowing through the connection, so energy is produced. PV cells are produced by different materials and technologies so can have different performances. Typical silicon PV cells produce less than 3W at 0.5 V DC and several cells are combined in solar panels to obtain higher power. This module is arranged in serial and parallel, form a complex structure called PV arrays. This array produces enormous power ranges from hundreds to thousands of Watts. PV array feeds to power converter which gives the interface between PV model and the load, PV panels have forced work in a particular point of voltage-current (V-I) to generate maximum power for given environmental conditions. This main task of the power electronics converter is to control the voltage of the string according to a reference value, which is provided by the Maximum Power Point Tracking (MPPT) algorithm.

Perturb and Observe (P&O) and Incremental Conductance methods are the most famous MPPT techniques [15,16,17,18]. Each PV model can have its own power converter, controlled by proper MPPT, the main advantage of this architecture is high efficiency compared to usual string converter, particularly when some of the modules in the string are shaded Prediction Model.

3. Feed-forward Neural Networks

The Feed-forward Neural Networks (FNNs) [17, 18, 19] are composed of processing units (called neurons) organized in layers. Each neuron computes its output as a function of a linear combination of the output of the neurons of the previous layer (often called transfer or activation function). The information flows only from the input layer to the output one, through the layers in between (hidden layers). Single hidden layer networks enjoy the universal approximation property [17]. An FNN is characterized by the number of neurons of the hidden layer, Multi-layered Network of neurons is composed of many sigmoid neurons. MLNs are capable of handling the non-linearly separable data. The layers present between the input and output layers are called hidden layers. The hidden layers are used to handle the complex non-linearly separable relations between input and the output [19]).

4. Experimental Activity

The experiments performed on the solar panel produced the following parameters:

- The Maximum power, PMAX = 5 W
- The maximum voltage produced, VMP = 17.5 V
- Maximum current produced, IMP = 0.285 A

The dataset has all the possible working condition of the panel and used it to estimate the MPP through the prediction module. Based on the electric load, the panel produces a current.

For the experiment, I have used the latest 3.1 GHz Intel Core i5 processor and 8GB DDR3 RAM. MATLAB 2017B is used for the simulation.

5. Dataset Pre-processing

Data we have is here is huge and it has more than 82 million samples. The data is collected in 2013 from May to June. Dataset samples have both voltage-current characteristic curves. MPP value is estimated from the corresponding I-V curve.

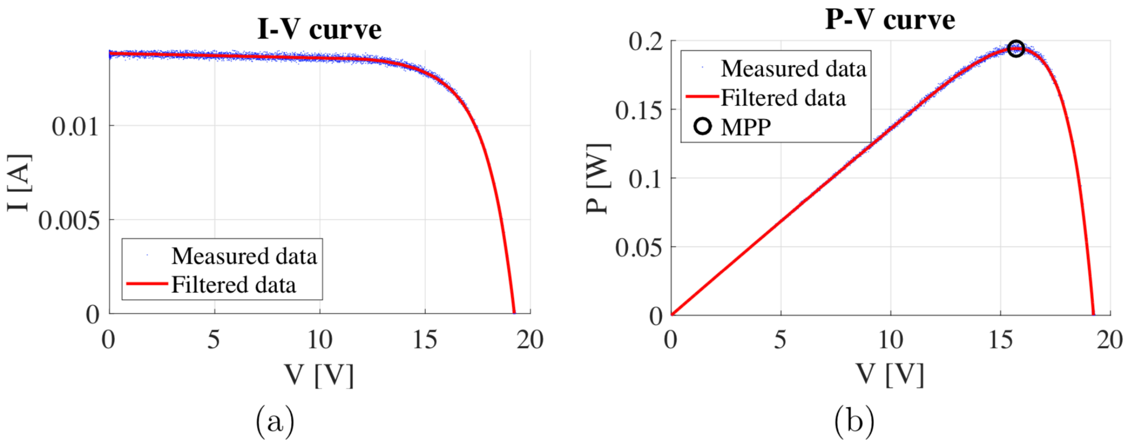

Figure 3: (a) A typical solar panel Current vs Voltage curve (solid line). (b) A typical Power vs Voltage curve. The electrical load applied to the panel affects the power output of the solar panel. The circle represents the Maximum Power Point.

Fig. 3a shows a typical I-V curve and blue points represent sampled data. Electrical load varied on the panel to measure the V and I. Before computing, the Gaussian filter has applied because to reduce the effect of the measurement noise in the maximum power point computation (Fig. 3b). The dataset used for the experiments has been composed by joining the filtered I-V data with the temperature of the panel and the MPP of the corresponding curve.

Since the dataset size is very large, we simulated different levels of knowledge of the problem by subsampling the data. S_{train}= {1M, 2M, 5M, 10M,20M,30M,40M,50M}

All the remaining data in the set has been assigned to S_{test}. The Mean Absolute error (MAE) achieved on S_{test}.

$$MAE(f) = E(|y - f(x)|)$$

where f(x) is the model's output for the sample (x, y), whereas x is a point in the $(I \times V \times T)$space, and y is the corresponding measured value of MPP.

We trained the network with many different numbers of the unit in the hidden layer for this experiment, L = { 10, 15, 20, 30, 50 }. The simulation has been run in MATLAB 2017B.

6. Results and Discussion

Number of Neurons

Sample Size	10	15	20	30	50
1M	0.01676959	0.01632315	0.01508214	0.01517911	**0.01483546**
2M	0.01627259	**0.01502612**	0.01546295	0.01555036	0.01512167
5M	0.01594151	0.01568553	0.01528276	0.01588953	**0.01480544**
10M	0.01610061	0.01528769	0.0152922	0.01579929	**0.01513588**
20M	0.01908181	0.01568367	0.01582469	0.01482878	**0.01468658**
30M	0.01609512	0.01548797	0.0159432	**0.01468449**	0.01477668
40M	0.01901966	0.01497493	0.01531258	0.01634728	**0.01489073**
50M	0.01629459	**0.01515795**	0.01556314	0.01565681	0.01534242

The table shows the performance of the model and MAE has been used to compare the performance of the challenged model. In the table, rows represent a number of neurons used for experimentation, columns represent the number of the data sample (in millions) used to train the model and rest used for the test.

Since the data set is very large, results are not getting any better after some time. So, I have stopped the training model at 50 neurons and best results are highlighted in green.

7. Conclusions

The Maximum PowerPoint is an important Factor for the efficiency of a PV panel and hence for the effective utilization of a solar plant. Implementation of the panel and its electrical load are two major factors to estimate Maximum Power Point, data on the possible states of the panel could be used to build a model of its electrical behavior. This dataset can be collected by measuring the most important quantities for the description of this phenomenon, i.e., the temperature of the panel, and the operating voltage and current at different working conditions. In this paper, we used FNN to estimate the MPP from its working condition and achieved the lowest error. Since this research direction has been proven effective, future works will focus on a more flexible architecture including a growing number of experts strategy, and a better choice of the size of each expert depending on both the availability of data and the local prediction error.

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