# Comparison of knowledge based feature vector extraction and geometrical parameters of Photovoltaic I-V Curves

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**Abstract.** Current methods for evaluating the performance of PV modules and systems in the field are exposed to weather conditions during system evaluation. The experimental measurement of performance naturally requires a corresponding amount of solar radiation, which is not available at all times of the year. The aim of this work is the development of a method for the weather-independent PV plant evaluation using the so-called dark I-V curve and an artificial neural network (ANN). The dark I-V curve can be measured at any time of the year and in any weather condition. In combination with the performance measurements from conventional methods an extensive database is already available, which was used as the ground truth for the development of the proposed model. The results show that with the proposed method a prediction of the power output for illumination levels above $800W/m^2$ a maximum prediction error below 10% is achieved. Thus, the dark I-V curve can be used for a weather-independent evaluation of PV systems in order to show first indications of performance losses and further analysis.

**Keywords:** Machine Learning · Artificial Neural Network · I-V Curve

## 1 Introduction

The in-field evaluation and fault diagnosis is crucial for a high-yield operation of photovoltaic plants. Analyzing the light I-V curve (current-voltage curve) of a PV array is the commonly used method for in-field evaluation and characterisation [2,3,4,5,9,12]. The I-V curve (see Figure 1) describes the energy conversion capacity under given conditions of irradiation and temperature. Only the experimental measurement of the I-V curve is able to specify with precision the electrical parameters of a photovoltaic cell, module or array.

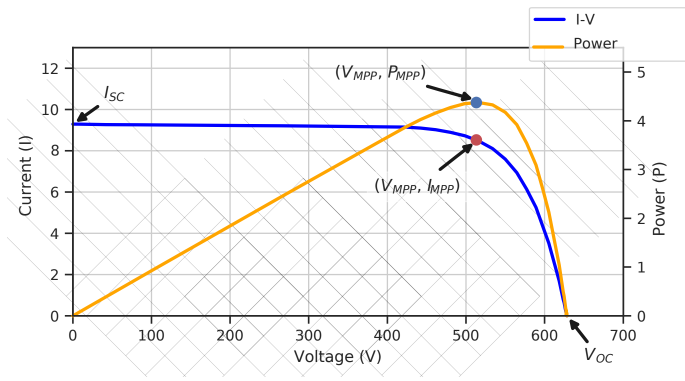



Fig. 1: I-V curve of a solar cell

The I-V curve starts at the short-circuit condition, $I_{SC}$, where the voltage is zero. The current decreases slightly as the voltage is increased, until the curve nears the open-circuit condition where the current rapidly drops off. The curve ends at the open-circuit condition, $V_{OC}$, with the current at zero. At some point on the I-V curve, the power of the cell is at its maximum. This point is known as the maximum power point (MPP), and solar cells are the most efficient at converting light energy into electrical energy at this point.

The in-field experimental measurement of the I-V curve is highly dependent on the weather conditions during the evaluation of the system. Passing clouds or shadows from other objects at certain times of the day result in a not negligible loss of time. Furthermore, the measurement requires sufficient light irradiation which is not available in all seasons of the year. To address these issues, this study proposes a novel method by predicting the light I-V curve using the so called dark I-V curve and an ANN. The dark I-V curve is measured without illumination by using an external power supply as reverse current source and is commonly used in the manufacturing process of solar modules [1,6,8]. Thus makes the dark I-V curve independent of weather conditions while maintaining many of the previously described electric characteristics.

## 2 Related Work

There are already several approaches which can identify faults using dark I-V curves for diagnostic purposes. For example, the method proposed by Mertens, K. et al. [10] is able to detect potential induced degradation (PID) and diode errors using numerical analysis of the dark I-V curve.

Besides the diagnostic value of the dark I-V curves, there are only a few methods which focus on predicting the light conversion performance under different illumination levels. King et al. [8] uses the two diode model (see Equation 1) with some experience based parameter assumptions to extract the remaining parameters of the model. Mertens et al. [11] uses also the two diode model and module parameters from the manufacturer data-sheet to solve remaining parameters of the model. Both methods extract the two diode model parameters using the dark I-V curve and use these parameters to calculate the light I-V curve. In this work, one approach also use the two diode model to extract the model parameters of both, the dark and light I-V curve, and uses this knowledge to learn the relationship between them.

## 3 Method

In cooperation with our research partners, a database with 3424 light and 1656 dark I-V curves from field and laboratory measurements of 131 different module types has been collected. Each I-V curve consists of 200 current-voltage pairs and additional metadata like irradiance level and temperature. To build the ground truth for the proposed method, the dark I-V curves of each module type are combined with all light I-V curves of the same module type, which results in 37686 training and validation data sets for the neural network. Three different feature extraction approaches for the I-V curve are considered. Each approach generates a feature set of the dark and light I-V curve. The feature set of the dark I-V curve is used as the input vector and the light I-V curve as the output vector for the neural network.

The first approach (E1) uses the the electrical two diode model [7] and performs the levenberg-marquardt curve fitting algorithm to fit the following function to the measured data points.

$$I = I_{PH} - I_{S_1} \cdot (e^{\frac{U+I \cdot R_S}{\eta_1 \cdot U_T}} - 1) - I_{S_2} \cdot (e^{\frac{U+I \cdot R_S}{\eta_2 \cdot U_T}} - 1) - \frac{U + I \cdot R_S}{R_P} \tag{1}$$

The extracted series resistance ($R_S$), parallel shunt resistance ($R_P$), saturation currents ($I_{S_{1,2}}$), diode ideality factors ($\eta_{1,2}$) and temperature coefficient ($U_T$) of the dark and light I-V curves, are used as an input and respectively output vector for the neural network.

The second approach (E2) for feature extraction performs a principal component analysis of the I-V curves while retaining 95% of its variance. This approach generates 64 components for the dark I-V curve and 76 components for the light I-V curve.

The last approach (E3) uses a barycentric lagrange interpolation to extract 20 equidistant points for each I-V curve. Since the points are equidistant, the values on the x-axis (voltage) are removed and only implied by its position in the vector.

The architecture of the neural network for all approaches consists of the input, output and a single hidden layer. The number of nodes in the hidden layer equals half the average of the input and output layers. The output of the nodes in the hidden layer are controlled by the tangens hyperbolicus (tanh) activation function and the network is optimized using the RMSE error function with RMSprop optimization algorithm. Finally the dense networks are trained with 75% of the combined data sets, using 80% of it for the training and 20% for the optimizer validation to avoid over fitting.

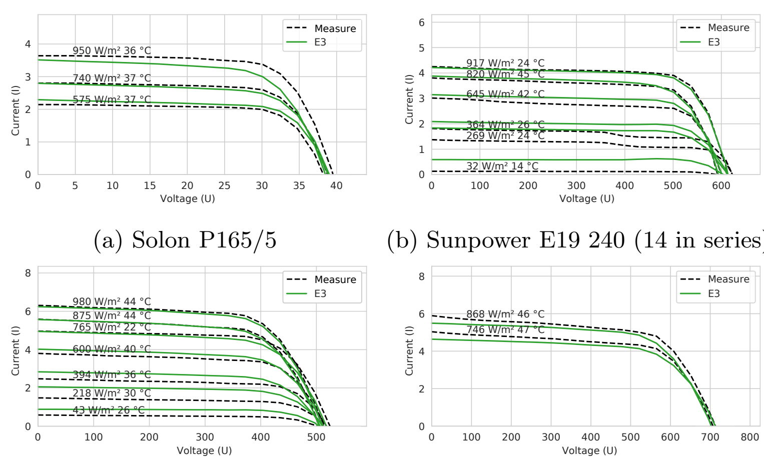
# 4 Experimental Results

For the final validation of the different approaches, 25% of the combined data sets are used. Table 1 shows the mean percentage error (MPE) using min/max and percentiles for the error distribution. For this purpose the light I-V curves are reconstructed from the features described and compared to the measured I-V curves. Overall, the third approach (E3) using the equidistant interpolation of

| | Mean | SD ($\sigma$) | Min. | 25% | 50% | 75% | Max. |
|---|---|---|---|---|---|---|---|
| E1 | 6.08 | 4.82 | 0.86 | 2.89 | 4.80 | 8.30 | 25.28 |
| E2 | 9.12 | 6.41 | 1.45 | 4.53 | 8.67 | 12.58 | 32.94 |
| E3 | 4.12 | 3.44 | 0.39 | 1.66 | 3.28 | 5.58 | 21.19 |

Table 1: Mean percentage error (MPE) and percentiles using the different preprocessing methods

the I-V curve yields the smallest prediction error. Figure 2 shows the predicted I-V curve (green) and the measured I-V curve (dashed black) for the third approach (E3). With some exceptions, the prediction becomes more accurate with




(a) Solon P165/5

(b) Sunpower E19 240 (14 in series)

(c) Kyocera KC180 (20 in series)

(d) Winaico WST-250P6 (22 in series)

Fig. 2: Prediction examples for different string configurations of the 3. approach

increasing irradiation. Above 800 $W/m^2$ the maximum prediction error is below 10%, which is in the range of peak performance prediction of commercially available light I-V curve measurement devices [13].

## 5 Conclusion and Future Work

In summary we tested different pre-processing approaches in order to predict the light I-V curve using the dark I-V curve and an ANN. The experimental results shows that using interpolated points of the I-V curve yields better results than using a PCA or the electrical two diode model for feature extraction. We plan to further investigate recurrent neural networks with an increased number of I-V curve points to further improve the prediction accuracy.

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