*Revue des Energies Renouvelables Vol. 19 N°2 (2016) 277 - 290*
**DOI:** https://doi.org/10.54966/jreen.v19i2.567

# Estimation and monitoring of grid connected PV system generation

Salim Bouchakour [1*], Ahmed Tahour [2], Kamel Abdeladim [1],
Houari Sayah [3†] and Amar Hadj Arab [1]

[1] Centre de Développement des Energies Renouvelables, CDER
B.P. 62, Route de l'Observatoire, Bouzaréah, 16340, Algiers, Algeria
[2] University of Mascara, 29000, Algeria
[3] Electrical Department, Djillali Liabes University, Sidi Bel Abbes, 22000, Algeria

(reçu le 12 Juin 2016 - accepté le 28 Juin 2016)

**Abstract** - *This paper presents a new method to identify the operating performance parameters of a photovoltaic (PV) generator and a grid connected inverter. This method has been applied to the behavior modeling and simulation of the grid connected PV system at the Centre de Developpement des Energies Renouvelables (CDER) in Algeria. The PV module (PVM) parameters has been identified in static with outdoor measurements of I-V curves in order to model the PV array generation. Using the Linear Reoriented Coordinates Method (LRCM), the prediction of maximum power point (MPP) of the PV array has been performed without using complicate approximations or Taylor series. In order to estimate the ac output power, a PV inverter performance model based on empirical relationship was used. However, an accurate identification of the inverter performance parameters is performed using an optimization algorithm, named Levenberg-Marquardt (LM) algorithm, and a moutput current and voltage. The simulation results were achieved through MATLAB/Simulink environment, for the setting and the testing of the models. The results show a good agreement between the measured and estimated results based on the identified parameters. The integration of the proposed method and the presented model present a simple way to estimate the expected system performance with a high degree of accuracy. This solution allows a development of automatic supervision, energy generation prediction and fault detection procedure.*

**Résumé** - *Le présent article présente une nouvelle méthode d'identification des paramètres de performances opérationnelles d'un générateur photovoltaique (PV) et d'un onduleur connecté au réseau. Cette méthode a été appliquée à la modélisation et la simulation du comportement du système PV connecté au réseau du Centre de développement des énergies renouvelables (CDER) en Algérie. Les paramètres des modules PV (MPV) ont été identifiés en mode statique avec mesures en extérieur des courbes I-V dans le but de modéliser la génération des surfaces PV. En utilisant la méthode des coordonnées linéaires réorientées (Linear reoriented coordinates method LRCM), la prédiction du point de puissance maximale (maximum power point MPP) des panneaux PV a été effectuée sans avoir recours à des approximation complexes ou des séries de Taylor. Dans le but d'estimer la puissance AC de sortie, un modèle de performance d'un onduleur PV basé sur des relations empirique a été utilisé. Les paramètres de performances de l'onduleur ont toutefois été déterminés avec une plus grande précision en utilisant l'algorithme d'optimisation de Levenberg-Maquardt (LM). Les résultats des simulations des modèles ont été obtenues en utilisant l'environnement Matlab/Simulink. Les résultats mesurés sont en accord avec ceux qui ont été estimés à partir des paramètres identifiés. L'intégration de la méthode et du modèle proposés présente une manière simple d'estimer les performances d'un système avec une précision élevée. Cette solution permettrait le développement de mesures de supervision automatisées, de procédures de prédiction de l'énergie qui sera générée et de la détection de pannes.*

**Keywords**: Photovoltaic systems - Parameter identification - Modelling - Simulation.

---

[*] salim.bouchakour@gmail.com ; tahourahmed@yahoo.fr
[†] housayah@yahoo.fr , k_abdeladim@cder.dz ; a.hadjarab@cder.dz

## 1. INTRODUCTION

Algeria has created a green momentum by launching an ambitious program with an aim of developing renewable energies. This strategic choice is motivated by the huge availability potential of solar irradiation in our country, the decrease of the photovoltaic (PV) module price and environmental considerations. The use of renewable energy should reach 30 % of national electricity production by 2030, essentially PV solar energy (60 %) according to the latest updated National Renewable Energy Program (2015-2030).

The amount of small PV systems (< 5 kWp) in the distribution network and in the urban context is expected to grow rapidly. The reduction of PV generation costs and the integration of grid connected PV systems are main reasons of this trend [1-5].

However, the performance of PV modules (PVMs) do not reach the desired levels as expected because of some obstacles (e.g. chimneys, antennas, trees, and snows) or because the modules are not optimally oriented toward the sunlight. Therefore, these circumstances may cause partial shading on different subsections of PVMs, so that they operate under mismatching conditions [6].

Although there is a high growth in PV industry, this development has not been implemented in diagnosis, supervision and fault detection of PV systems, especially in small PV plants having output power levels below than 25 kWp [7].

For this reason, the system behavior should be observed, hence the important issue of the monitoring of the PV systems. Furthermore, the most fault detection algorithms reported in the literature follow the idea of comparing monitored data from the PV system with model prediction results to identify faults when significant differences are observed between the two sets of data [8-11]. Furthermore, the accuracy and versatility of the prediction models depends on the exactitude of the parameters used by these.

In this work, we report a simple way to identify the operating performance parameters of a photovoltaic (PV) generator and a grid connected inverter. The behavior modeling and simulation is performed for the grid connected PV system at the Centre de Developpement des Energies Renouvelables (CDER) in Algeria. It is the first installed PV grid connected system for experimentation and performance evaluation purpose.

The PVM forming part of the whole PV array is modeled by behavioral model using the electrical characteristics usually provided by the manufacturer. They are never the same, their evaluation in real operating condition is essential for a good estimation of PV array output. In fact, we conducted parameters identification based on outdoor characterisation of selected PVMs. The estimated I-V characteristics based using identified parameters are confronted with measured values under Matlab environment.

For the dynamic behaviour of the PV array, a maximum power point tracking (MPPT) algorithm is required. There are different algorithms that need the use of long and tedious iterations. The use of Linear Reoriented Coordinates Method (LRCM) as MPPT algorithm is very simple and powerful to continuously predict the maximum power point (MPP), particularly during shading effect and sudden variations in solar irradiance. The assessment of measured and estimated values is discussed.

The PV power conversion (dc/ac) is modeled by an inverter performance model developed by Sandia National Laboratories, applicable to all commercial inverters used in PV power systems. It is an empirical model that simply but accurately replicates the power delivery characteristics of the dc- to ac-inversion process.

The accuracy depends on available data for determining the performance parameters used in the model. Therefore an identification of these parameters is performed using an optimization algorithm and a measured electrical data.

The pursued steps to develop a behaviour al model based on several techniques of extraction parameters, allows a more realistic simulation of the PV systems in real operating conditions. This method it is a simple and powerful way to perform an automatic supervision, a prediction of PV generation and a fault detection procedure.

## 2. PV SYSTEM DESCRIPTION

The grid-connected PV system plan, currently in service, was achieved in cooperation with the Spanish Agency for International Development Cooperation (AECID). The installation is located at 'Centre de Développement des Energies Renouvelables', (CDER) in Bouzaréah, Algiers (latitude 36.8 °N, longitude 3 °E and 345 m of altitude). It started operating on June 2004, the installation operate without storage system. The electricity produced by the PV array feeds our laboratory loads, meanwhile in case of good weather conditions the extra PV generation is injected into the grid, otherwise, the backup is assured by the grid.

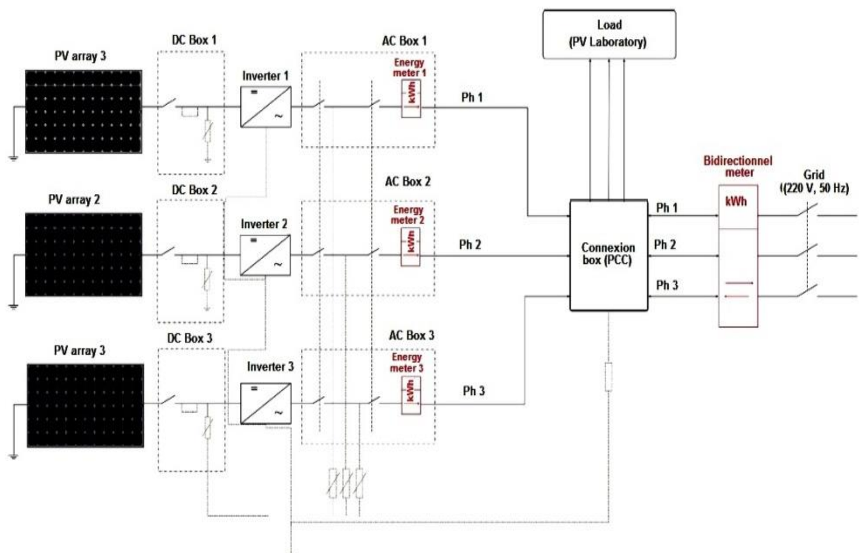


Fig. 1: Grid-connected PV-system of CDER

Figure 1 shows a diagram of the CDER grid-connected PV system. The electrical energy is calculated through single-phase and tree-phase energy meters. Unidirectional meters for the PV energy and bidirectional meters for the imported and exported energy to the grid.

The grid-connected PV system includes 90 modules covering a total area of 76 m$^2$ with an installed capacity of 9.45 kWp. The PV generator was designed in three equal PV arrays, of 30 modules for rated power around 3.15 kWp; each one was built interconnecting 15 modules in series and 2 in parallel.

Three single-phase inverters, of 2.5 kWp nominal power, were used to inject PV generation to the grid. The specification of PVM (ISOFOTON I -106/12) and inverter (FRONIUS IG 30) are summarized in **Tables 1** and **2**.

**Table 1**: ISOFOTON PV module specifications at STC

| Symbol | Parameter | Value | Units |
|---|---|---|---|
| NOCT | Nominal Operating Cell Temperature | 47 | °C |
| V | Nominal voltage | 12 | V |
| $P_{max}$ | Max power | 106 ±5% | Wp |
| $I_{sc\_ref}$ | Short-circuit current | 6,54 | A |
| $V_{oc\_ref}$ | Open-circuit voltage | 21,6 | V |
| $I_{mpp\_ref}$ | MPP current | 6,1 | A |
| $V_{mpp\_ref}$ | MPP voltage | 17,4 | V |

**Table 2**: FRONIUS inverter specifications at rated conditions

| Symbol | Parameter | Value | Units |
|---|---|---|---|
| $V_{mpp}$ | MPP-voltage range | 150 - 400 | V |
| $P_n$ | ac-nominal power | 2500 | W |
| Cos φ | Power factor | 1 | |
| F | Frequency range | 49,8 - 50,2 | Hz |
| $V_{Grid}$ | Grid voltage range | 195 – 253 | V |
| H | Efficiency | 92,7 - 94,3 | % |

## 3. PV MODEL

### 3.1 PVM performance model

The following equations define the model used for modeling the PV array. This equations describe the electrical performance for individual PVM, and can be scaled for any series or parallel combination of PVMs.

The modeling of PVM performance in the real conditions is complicated by the influences of a variety of interactive factors related to the environment and solar cell physics. In general, the usual proposed models required additional parameters not specified in manufacturer data sheets.

At the same time, these models can be impractical and too complex for common tasks in power systems such as power flow, harmonic analysis, sensitivity analysis and load matching for maximum power transferred from the source to the load [12-14]. Therefore, we use the analytical performance model of PVM for the distribution power generation study.

The PV array performance model is empirically based and takes into consideration the nominal values, provided by the manufacturer data sheet under Standard Test Conditions (STC), and the changes and effects of the temperature and the effective irradiance over the PVM [15, 16]. The $I-V$ relationship for one PVM is given by:

$$I(V) = \frac{I_{sc\_x}}{1 - e^{(1/b)}} \left( 1 - e^{\left( \frac{V}{b \times V_{oc\_x}} - \frac{1}{b} \right)} \right) \quad (1)$$

with $I_{sc\_x}$ and $V_{oc\_x}$ the short circuit current and the open circuit voltage at any solar irradiance level including temperature condition respectively. b is the $I-V$ characteristic constant

$I_{sc\_x}$ and $V_{oc\_x}$ can be obtained using equations:

$$V_{oc\_x} = s \times \frac{E_i}{E_{in}} \times TC_v \times (T_{cell} - T_n) + s \times V_{oc-max} - s \times V_{oc\_max} \times e^{\left(\frac{E_i}{E_{in}} \times \ln\left(\frac{V_{oc\_max} - V_{oc\_ref}}{V_{oc\_max}}\right)\right)} \quad (2)$$

$$I_{sc\_x} = p \times \frac{E_i}{E_{in}} \times \left(I_{sc\_ref} + TC_i \times (T_{cell} - T_n)\right) \quad (3)$$

$I_{sc\_ref}$ and $V_{oc\_ref}$ are the short circuit current and open circuit voltage at STC respectively. $V_{oc\_max}$ is the open-circuit voltage at 25°C and more than 1200 W/m$^2$ (slightly superior to $V_{oc\_ref}$). $T_{cell}$ is the solar cell temperature in °C with nominal temperature $T_n$ = 25°C. $E_i$ is the effective solar irradiation in W/m$^2$ with nominal effective solar irradiance $E_{in}$ = 1000 W/m$^2$. $TV_c$ is the temperature coefficient of $V_{oc}$ = -0.074 V/°C. $TV_i$ is the temperature coefficient of $I_{sc}$ = 0.0023 A/°C. The variable $s$ is the number of PV panels with the same electrical characteristics connected in series and $p$ is the number of PVMs with the same electrical characteristics connected in parallel.

The characteristic constant $b$ can be calculated using the Fixed Point Theorem (4). The constant $b$ is defined between 0.01 and 0.18, where smaller is the $b$, greater is the produced power. The variable $\varepsilon$ is the maximum allowed error to stop the iteration.

While, $\left| b_{n+1} - b_n \right| \rangle \ \varepsilon$

$$b_{n+1} = \frac{V_{mpp\_ref} - V_{oc\_ref}}{V_{oc\_ref} \times l_n \left(1 - \frac{I_{mpp\_ref}}{I_{sc\_ref}} \times \left(1 - \exp(-1/b_n)\right)\right)} \quad (4)$$

The PVM model was tested using manufacturer data sheet parameters (**Table 1**) and a fixed-point theorem algorithm (4) for characteristic constant calculation, $b = 0.07205$

Figure 2 shows the simulation results of PVM model with the operating temperature at 25 °C and the effective irradiance changing level: 200 W/m$^2$, 400 W/m$^2$, 600 W/m$^2$, 800 W/m$^2$ and 1000 W/m$^2$. The simulated $I-V$ curves are similar to those $I-V$ characteristics curves provided by the ISOFOTON manufacturer.

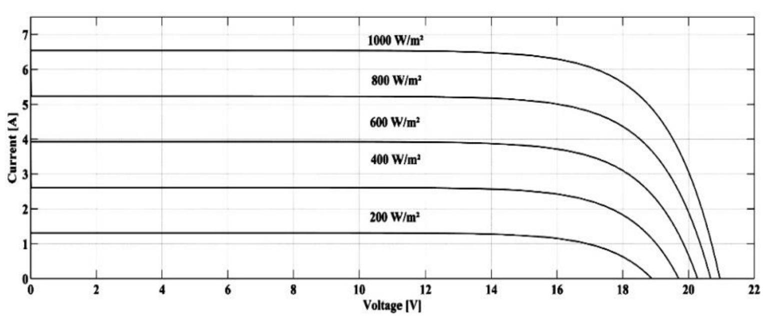


Fig. 2: $I-V$ curves of PVM (ISOFOTON I-106 W) under different irradiance levels

Figure 3 shows simulation results of PVM model under different temperatures of operation: 0 °C, 25 °C, 50 °C and 75 °C, with the irradiation level at 1000 W/m$^2$.

The effects of changing the irradiance level are more visible than the effects of changing temperature over the PVM. At the same time other plots, not provided by the manufacturer, can be calculated using this PVM model.

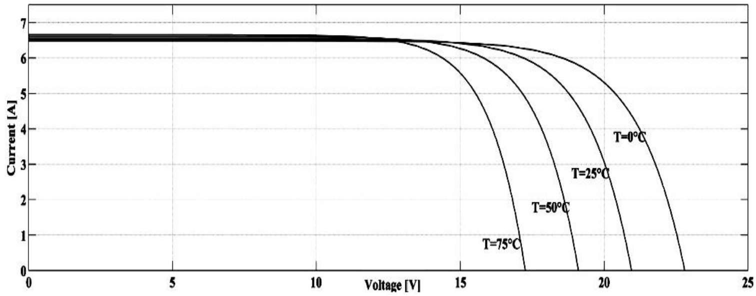


Fig. 3: $I-V$ curves of PVM (ISOFOTON I-106) under different temperatures

### 3.2 PVM parameters at real condition of work

The manufacture parameters induce a significant error in the estimation, because the PVMs are already in operation since 2004 and the accuracy of used empirical model depends on precision of the required parameters. Therefore, we conducted parameters identification for the PVMs based on the outdoor test field.

The voltage and the current experimental measurements, for the commercial mono-crystalline solar panels from ISOFOTON I-106/12, were performed at CDER (Algiers) at maximum intensity light.

A Peak Power Measuring Device and Curve Tracer for PV Modules (PVPM2540C) was used in order to perform measurement of experimental $I-V$ curves, 100 operating points were stored for each measure. Through the PVPM 2540C device we were able to automatically measure the $I-V$ characteristic of the generator at a capacitive load. From the measured data, it calculates the effective solar cell characteristic, Peak Power and Internal Series Resistance, [17]. After measurement, the data are stored automatically in a non-volatile storage. The device internally stores data of more than 100 measurements.

A several outdoor measurements were performed in situ. The average value of each identified parameter is used in the PVM model, as summarized in **Table 3**. $I_{mpp\_ref}$ and $V_{mpp\_ref}$ are the MPP current and voltage at STC respectively.

The characteristic constant $b$ was re-evaluated using real conditions parameters specified in **Table 3**, $b$ equal to 0.098. This indicates the decrease over time of the PVM performances.

**Table 3**: Parameters at reference and real conditions

| STC parameters | Parameters at reference conditions | Parameters at real conditions | Units |
|---|---|---|---|
| $I_{sc\_ref}$ | 6.54 | 6.473 | A |
| $V_{oc\_ref}$ | 21.6 | 20.07 | V |
| $I_{mpp\_ref}$ | 6.1 | 5.964 | A |
| $V_{mpp\_ref}$ | 17.4 | 15.788 | V |

### 3.3 Model validation

The data confrontation between the PVM model using extracted parameters and experimental measures was conducted under Matlab environment. The results at different irradiance and temperature conditions are shown in Figures 4 and 5. We observe how accurate the PVM model estimation compared to the measured data. However, it's observed that the open-circuit voltage ( $V_{oc}$ ) is under estimated. This seems to be principally due to the accuracy of $TC_v$ value, not reviewed in this study.

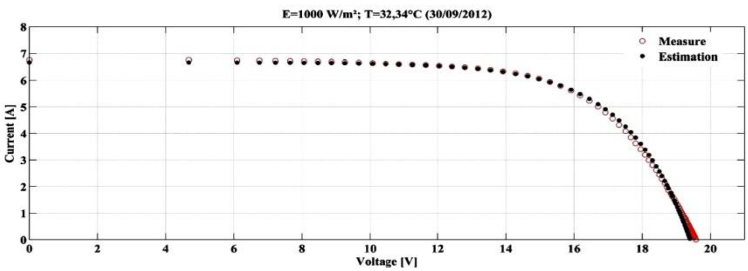


Fig. 4: Estimated and measured $I-V$ characteristic ( $E_i$ =1000 W/m$^2$, $T_{cell}$ = 32, 34 °C)

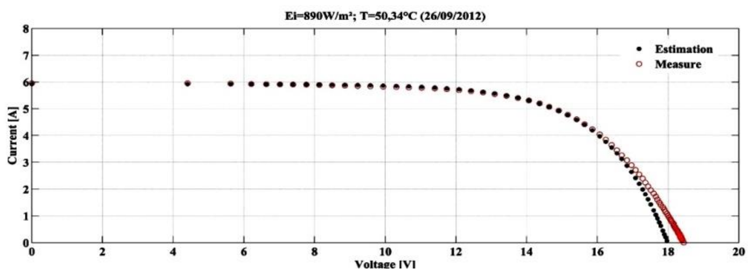


Fig. 5: Estimated and measured $I-V$ characteristic ( $E_i$ =890 W/m$^2$, $T_{cell}$ = 50, 34°C)

## 4. PV ARRAY

### 4.1 Dynamic behaviour of PV array

The MPPT algorithms are different versions of numerical iterations, long and tedious, that relate the derivative of the current with respect to the voltage equaled to the negative of the current divided by the voltage [12]. Unlike the use of The Linear Reoriented Coordinates Method (LRCM) as MPPT algorithm can be a very powerful and simple way to approximate the maximum power.

For the assessment of the PV array dynamic behaviour, the MPPT algorithm (LRCM) was combined with PV array performance model using the identified parameters as described previously.

LRCM uses the PV array model (1) to obtain a close approximation of the $I-V$ curve knee point. The $I-V$ curve knee point is the MPP defined by maximum current $I_{mpp}$ and the maximum voltage $V_{mpp}$, as shown in figure 6, [18, 19].

Using the initial and final values of the $I-V$ Curve, a linear current equation $I_L$ (V) can be determined as given in (5). Then the current equation (1) and the linear current equation (5) are differentiated and set equal to each other to solve V, as given by (6).

The slope of the $I-V$ Curve at the MPP can be approximated to the slope of the linear current equation, hence the approximate solution $V_{mpp}$.

$$I_L(V) = I_{sc\_x} - I_{sc\_x} \times \frac{V}{V_{oc\_x}} \tag{5}$$

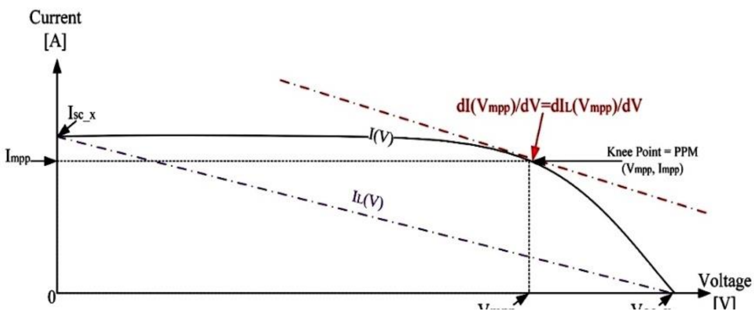


Fig. 6: $I-V$ curve and LRCM, [10]

$$\frac{\partial I_L(V)}{\partial V} \approx \frac{\partial I(V)}{\partial V} \Rightarrow -\frac{I_{sc\_x}}{V_{oc\_x}} \approx \frac{-I_{sc\_x} \times \exp\left(\frac{V}{b \times V_{oc\_x}} - \frac{1}{b}\right)}{b \times V_{oc\_x} - b \times V_{oc\_x} \times \exp(-1/b)} \tag{6}$$

Using Linear Reoriented Coordinates Method (LRCM) [18, 19], the current and voltage equations at the MPP are expressed as follows:

$$I_{mpp} = I_{sc\_x} \times \frac{1 - b + b \times \exp(-1/b)}{1 - \exp(-1/b)} \tag{7}$$

$$V_{mpp} = V_{oc\_x} + b \times V_{oc\_x} \times \ln\big(b - b \times \exp(-1/b)\big) \tag{8}$$

Figure 7 shows the simulation of the MPP curve and the $P-V$ curves for different effective irradiance levels: 200 W/m$^2$, 400 W/m$^2$, 600 W/m$^2$, 800 W/m$^2$ and 1000 W/m$^2$ with temperature at 25 °C. The proposed algorithm (LRCM) proves a good performance for the tracking of the MPP.

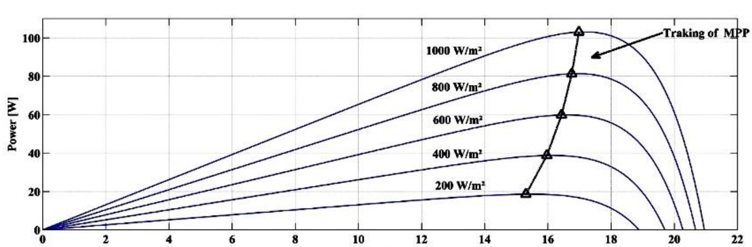


Fig. 7: Simulated $P-V$ curves with MPP under different effective irradiance levels

### 4.2 Model validation

This assessment has been carried out for a PV array of 3.15 kWp, built by two parallel connected strings; each one is formed of 15 series connected modules. The solar irradiance and cell temperature can be measured and directly used in the developed PV array performance model. For measurement of cell temperature, a temperature sensor (thermocouples) was attached to the back surface of the PVM in field. Also, for the measurement of solar radiation a pyranometer on an inclined surface of PV array has been installed.

Figure 8 shows the monitored solar irradiance and cell temperature profiles. The data were recorded every 1 minute for two representative days, clear and cloudy days. These days were chosen because they represent different weather conditions.

Figure 9 shows the measured and estimated array voltage at MPP, the result was good for a large part of the day. Nonetheless, we can observe a mismatch between the estimates and the measured values of MPP voltage during sunrise and sunset of each day. It was neglected due to the no impact on the estimated electrical parameters ( $I_{mpp}$ and $P_{mpp}$ ).

Figure 10 shows the measured and the estimated PV array output power. We observe a good agreement between measured and estimated PV array power output. Moreover, the mismatch at the sunset of the first day, between 880 and 940 minutes, is due to the shading effect, not visible in the second day due to the clouds. The presented result in this section, give an experimental validation of the PV array performance model, as well the LRCM as a MPPT algorithm.

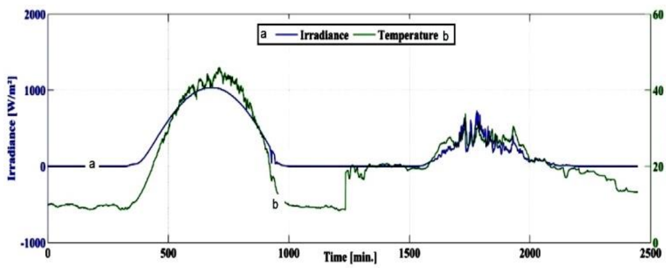


Fig. 8: Monitored irradiance and temperature

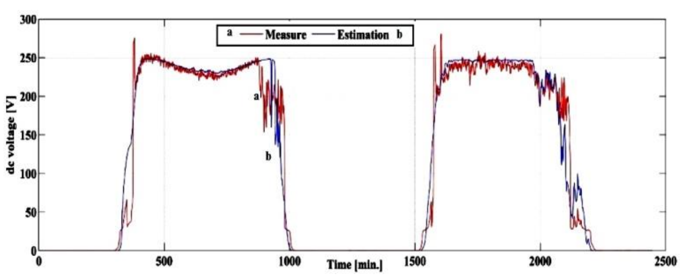


Fig. 9: Comparison between estimated and measured dc voltage at MPP

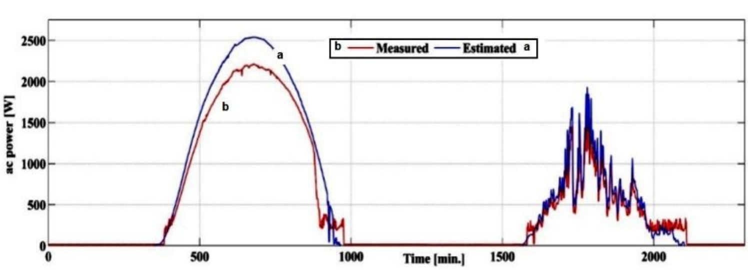


Fig. 10: Comparison between estimated and measured dc power at MPP

## 5. INVERTER MODEL

In this section, we present an empirical or phenomenological inverter model developed at SANDIA National Laboratories.

It's simple and can accurately relate the inverter ac-power output to the dc-power and the dc-voltage. The model of SANDIA is used for the dynamic behavior of our single-phase grid-connected PV inverter, FORNIUS IG30. The inverter model requires a setting of its performance parameters (coefficients) under real conditions.

We note that the inverter's MPPT effectiveness was not explicitly included in SANDIA inverter performance model, because the MPPT effectiveness of most inverters manufactured today is quite high, providing 98 to nearly 100% of the energy available from the PV array [20].

The following equations outline the behavioral inverter model developed by SANDIA National Laboratories [20]. As independent variables, the both dc power and dc voltage are used to calculate the inverter ac power. The parameters with the "o" subscript are constant values that define a reference or nominal operating condition. The $C_0$, $C_1$, $C_2$ and $C_3$ are the constant ( of inverter model. The relationship of the inverter power output according to dc power and dc voltage is given by:

$$P_{ac} = \left(\left(P_{aco} \,/\, (A-B)\right) - C \times (A-B)\right) \times (P_{dc} - B) + C \times (P_{dc} - B)^2 \qquad (9)$$

Where,

$$A = P_{dco} \times \left(1 + C_1 \times (V_{dc} - V_{dco})\right) \qquad (10)$$

$$B = P_{so} \times \left(1 + C_2 \times (V_{dc} - V_{dco})\right) \qquad (11)$$

$$C = C_0 \times \left(1 + C_3 \times (V_{dc} - V_{dco})\right) \qquad (12)$$

### 5.1 Determination of inverter performance parameters

The accuracy of the inverter estimated model, defined in equations (9) through (12), depends on the precision of the used performance parameters.

The used default or initial parameters are obtained from the manufacturer data sheets and the measurements conducted at SANDIA National Laboratories and at laboratories supporting the solar programs of the California Energy Commission (SANDIA, CEC, Spec…).

The instantaneous measurements were recorded as true root mean square (TRMS) of ac voltage/ current and dc voltage/ current under two days period including both clear and cloudy weather conditions.

The performance parameters are identified using optimization algorithm, called Levenberg-Marquardt (LM) algorithm. It is the reference algorithm for the Nonlinear Least Squares Minimization and the most widely used optimization algorithm [20, 21].

The LM algorithm is available via the Optimization Toolbox of Matlab. The toolbox includes routines for many types of optimization.

The optimization method allows us to build accurate model of our inverter based on measured data, this by adjusting the performances parameters within a model until its output coincides as well as possible with the measured output.

**Table 4** shows the default and the identified inverter performance parameters using LM algorithm under optimization toolbox of Matlab.

### 5.2 Model validation

The following results show the comparison between the estimated and measured inverter output power under different weather conditions. In figures 11 and 12, the inverter performance parameters were defined using SANDIA database and LM algorithm identification respectively.

The assessment of these results finds a significant error in output power estimation using defaults performance parameters (SANDIA). In addition we observe that the error was more important when the inverter was operating at its peak dc power limit (figure 11). However, the LM identification of the performance parameters allowed us to reduce the error of estimated output power and to improve more accuracy of the inverter performance model. Also, we can clearly diagnose the shading effect around the 900 minutes.

**Table 4**: Default and identified inverter parameters values

| Inverter performance parameters | Default (Sandia data base) | LM algorithm identification | Units |
|---|---|---|---|
| $P_{aco}$ | 2700 | 2500 | W |
| $P_{dco}$ | 2879 | 2879.9 | W |
| $P_{so}$ | 27.9 | 25 | W |
| $V_{dco}$ | 277 | 280 | V |
| $C_0$ | -1.009e-5 | 4.8429e-5 | $W^{-1}$ |
| $C_1$ | -1.367e-5 | -1.7541e-3 | $V^{-1}$ |
| $C_2$ | -3.587e-5 | 4.4922e-3 | $V^{-1}$ |
| $C_3$ | -3.421e-3 | 0.037699 | $V^{-1}$ |

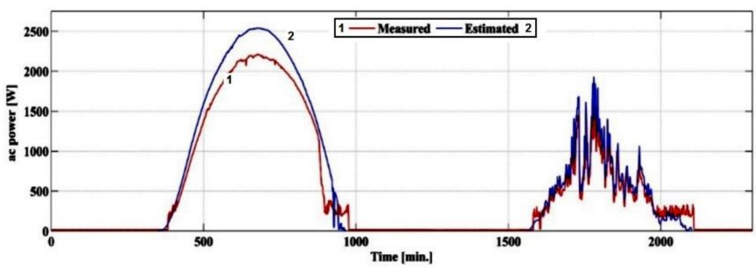


Fig. 11: Comparison between estimated and measured ac power, using the default performance parameters

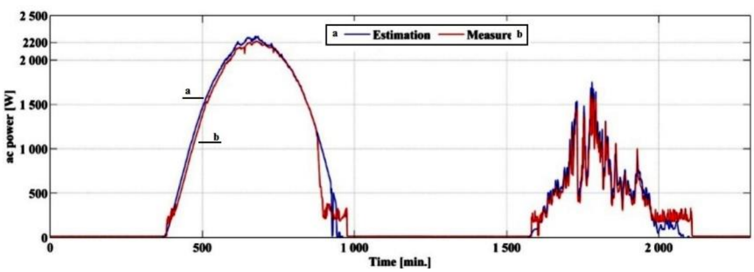


Fig. 12: Comparison between estimated and measured ac power, using the identified performance parameters

## 6. PHOTOVOLTAIC SYSTEM PERFORMANCE MODEL

The both adapted models of the PV array and inverter were combined in a global model in order to give the real time dynamic behavior of our grid-connected PV system. Furthermore, using a forecast weather conditions we can predict the PV system generation.

Figure 13 shows the monitored and estimated PV system output power for different days of the year. The selected days are: June 15th, July 23rd & 26th, August 10th and September 03rd to 05th.

Except the July days, we observed a good agreement between estimated and measured generated PV power within tolerated error limits. These essentially caused by the measurement and the unidentified PV system parameters ( $TC_v$ , $TC_i$ , etc...).

During the days of July, we can clearly diagnose the simulated fault, where the one branch of the PV array was disconnected inducing the loss of half of the generated power. It's clearly distinguished at peak solar radiation time of July 23rd, the expected power is slightly higher to 2 kW and the measured power is less than half (i. e. slightly higher to 1 kW)

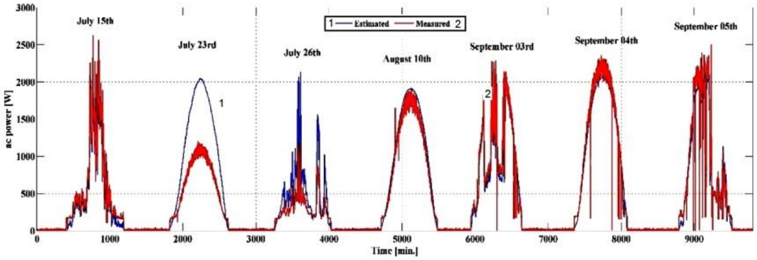


Fig. 13: Monitored and estimated grid connected PV system output power

The presented results have shown the capability of developed grid-connected PV system model to evaluate the efficiency, the potential and the diagnostic of some faults such as the shading and abnormally decrease of the generated power.

## 7. CONCLUSION

In this work, we have presented a new method to identify the operating performance parameters of the main part of the PV system.

However, the identified PVM parameter of the presented model, based on outdoor measurement of the $I-V$ curve, offers a good degree of accuracy.

Using LRCM as MPPT algorithm allows a robust and simple technique to evaluate the dynamic behavior of the PV array and the inverter MPPT. Especially, during shading and sudden variation of solar irradiation.

The inverter model has been validated, using both the input/ output measurements and the optimization Toolbox of Matlab to identify the performance parameters.

Finally, the simulation of the whole system provides a significant improvement in the ability to analyze the PV system performance, monitoring of commercial inverters and PV generators, and diagnose causes of system performance degradation.

**Acknowledgements-** The Agency for Thematic Research in Science and Technology (ATRST) is acknowledged for the help provided in this work. ATRST partially funded the presented research work in the frame of the project PRO THEME 29/2015

## REFERENCES

[1] P. Lund, '*Large-Scale Urban Renewable Electricity Schemes – Integration and Interfacing Aspects*', Energy Conversion and Management, Vol. 63, pp. 162 - 172, 2012.

[2] M. Díez-Mediavilla, C. Alonso-Tristán, M.C Rodríguez-Amigo, T. García-Calderón, and M.I. Dieste-Velasco, '*Performance Analysis of PV Plants: Optimization for Improving Profitability*', Energy Conversion and Management, Vol. 54, pp. 17 - 23, 2012.

[3] J. Urbanetz, P. Braun and R. Rüther, '*Power Quality Analysis of Grid-Connected Solar Photovoltaic Generators in Brazil*', Energy Conversion and Management, Vol. 64, pp. 8 - 14, 2012.

[4] M. Alahmad, M.A. Chaaban, S.K. Lau, J. Shi and J. Neal, '*An Adaptive Utility Interactive Photovoltaic System Based on a Flexible Switch Matrix to Optimize Performance in Real-Time*', Solar Energy, Vol. 86, N°3, pp. 951 - 963, 2012.

[5] L.M. Ayompe, A. Duffy, S.J. McCormack and M. Conlon, '*Measured Performance of a 1.72 kW Rooftop Grid Connected Photovoltaic System in Ireland*', Energy Conversion and Management, Vol. 52, N°2, pp. 816 - 825, 2011.

[6] E. Karatepe, T. Hiyama, M. Boztepe and M. Çolak, '*Voltage Based Power Compensation System for Photovoltaic Generation System Under Partially Shaded Insolation Conditions*', Energy Conversion and Management, Vol. 49, N°8, pp. 2307 - 2316, 2008.

[7] A. Chouder and S. Silvestre, '*Automatic Supervision and Fault Detection of PV Systems Based on Power Losses Analysis*', Energy Conversion and Management, Vol. 51, N°10, pp. 1929 - 1937, 2010.

[8] Y. Yagi, H. Kishi, R. Hagihara, T. Tanaka, S. Kozuma, T. Ishida, '*Diagnostic Technology and an Expert System for Photovoltaic Systems Using the Learning Method*', Solar Energy Material and Solar Cells, Vol. 75, N°3, pp. 687 - 695, 2003.

[9] K.-H. Chao, S.-H. Hob, M.-H. Wang, 'Modeling and Fault Diagnosis of a Photovoltaic System', Electric Power Systems Research, Vol. 78, pp. 97 - 105, 2008.

[10] N. Gokmen, E. Karatepe, B. Celik and S. Silvestre, '*Simple Diagnostic Approach for Determining of Faulted PV Modules in String Based PV Arrays*', Solar Energy, Vol. 86, N°11, pp. 3364 - 3377, 2012.

[11] E. Ortiz-Rivera, '*Modelling and Analysis of Solar Distributed Generation*', PhD, East Lansing, MI, USA, 2006.

[12] E. Ortiz-Rivera and F. Peng, '*Analytical Model for a Photovoltaic Module Using the Electrical Characteristics Provided by the Manufacturer Data Sheet*', Presented in $36^{th}$ Power Electronics Specialists Conference, IEEE, pp. 2087 – 2091, 2005.

[13] D.L. King, W.E. Boyson and J.A. Kratochvill, '*Photovoltaic Array Performance Model*', SAND2004-3535, Sandia National Laboratories, Albuquerque, NM, 2004.

[14] N. Srisaen and A. Sangswang, '*Effects of PV Grid-Connected System Location on a Distribution System*', presented in Asia Pacific Conference on Circuits and Systems, APCCAS, IEEE, pp. 852 - 855, 2006.

[15] The Institute of Electrical and Electronics Engineers, IEEE Recommended practice for utility Interface of photovoltaic (PV) systems, IEEE Std. 929-2000, NY, 2000.

[16] PV-Engineering GmbH, '*Peak Power Measuring Device for PV-Modules PVPM 2540C*', User Manual, 2009.

[17] E. Ortiz-Rivera and F. Peng, '*A Novel Method to Estimate the Maximum Power for a Photovoltaic Inverter System*', In Proc. 2004 IEEE Power Electronics Specialists Conference, pp. 2065 - 2069, 2004.

[18] E.I Ortiz Rivera and F.Z. Peng, '*Linear Reoriented Coordinates Method*', IEEE International Conference on Electro/information Technology, pp. 459 - 464, 2006.

[19] D.L. King, S. Gonzalez, G.M. Galbraith and W.E. Boyson, '*Performance Model for Grid-Connected Photovoltaic Inverters*', SAND2007-5036, Sandia National Laboratories, Albuquerque, NM, 2007.