

# Evaluation of the PV energy production determined by measurements, simulation and analytical calculations

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**Abstract.** The study provides a comparative analysis of the energy production of a 3 kW peak PV array connected in an islanded microgrid, in correlation with solar radiation and ambient temperature measurements. The experimental system is located in Cluj-Napoca Romania and was monitored during the year 2017, based on a graphical user interface. It was also evaluated the capability to predict the PV energy production by using the PV\*SOL simulation software and an analytical model, developed at the Technical University of Cluj-Napoca. As input data in the analytical model was used the measured solar radiation and ambient temperature while in the simulations was used alternatively measured data and average meteorological data available in the software database. Besides energy production it was compared the solar radiation on the tilted plane of the PV panels, the PV panel's temperature and the system efficiency. For the predictions accuracy evaluation it was used the weighted mean absolute error based on total energy production, which was found to be lower than 1%, in good agreement with the values reported in literature. The outcomes of this study are valuable for expanding the PV installations in this area and for predictive energy management developments.

## 1 Introduction

The islanded microgrids brace the power generation challenges for isolated/small communities or the new emerging energy demands for EV charging stations. According to [1] the world energy consumptions are estimated to be 30 TW per year. Different configurations of microgrids that use wind or solar power as primary or secondary renewable energy sources are presented in literature [2-7]. The PV system analysed in this study is included in a microgrid that uses three renewable energy sources: geothermal water, solar energy, and biogas. By using solar energy combined with other resources [8-12], the start and shutdown costs of the other generating units can be reduced [13]. The use of different resources reduces the unstable behaviour of islanded power grids when solar energy fluctuations occur as stated in [14]. As mentioned in [15] one should consider that solar energy usage requires a large space for the PV array and storage system installation.

As stated in [13-14] there is a growing need for solar power forecasting in microgrids, where the solar energy produces a significant amount of the total electrical energy, due to meteorological influences on PV arrays energy production. Machine learning routines are used to predict the solar irradiance but many of the algorithms still use ground data measurements and are prone to the accuracy of the measurements [16].

Studies for energy production were made as in [17], where hourly global irradiance values are used.

The models and parameterizations used for weather predictions are accurate only in some conditions as indicated by [14].

The output power of the PV system depends on both direct and diffuse components of the solar radiation [18]. In most works Kipp&Zonen pyranometers are used and the measurement data are filtered by removing negative, night data and erroneous readings [18]. These equipment have a high cost of acquisition and operation and due to this a small amount of ground data is available and only for limited and small areas. Nevertheless, data provided by pyranometers can be used to create long-term meteorological forecast and this data is of great importance for the development of efficient solar energy-based devices [19]. In [20], ground based solar radiation using pyranometers is recorded and presented for two complete years as monthly mean values for a northern region in India. In [21] the ground data measurements from the pyranometers are completed by Meteosat second generation images for the south of Algeria. In [22] besides the solar irradiance the monthly average daily temperature and relative humidity are used for better predictions results.

For sizing the energy storage systems it is better to use hourly based solar radiation data than daily or monthly based data [23].

The 10-min and hourly data, measured by Kipp&Zonen pyranometers, are used in [23, 24] for the gulf of Ajaccio and respectively for Hong Kong. Some quality test are made to eliminate the erroneous values as

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in [25-26]. An argument for solar irradiation measurements can be found in [27] as many city administrations have or are creating solar maps to inform their citizens about the potential and benefits of solar power energy usage in their area. An example of this approach is presented in [28] for Basel Switzerland where the citizens were encouraged to install PV arrays on the roofs that showed a high solar energy potential after the analysis of the data provided by the city. Beside the orientation, the decision of installing a PV array can be influenced by a performance ratio as mentioned in [29] where a relationship between the actual produced energy and the estimated value can be found considering the meteorological data, PV panel's temperature, line losses and inverter efficiency. Based on information about solar radiation and operation temperature, the AC power output can be estimated together with the cost and payback time [30].

The goal of the study is to present the PV energy production obtained by the experimental installation and to analyse the capability to predict the energy production, of the PV\* SOL simulation tool and of an analytic model, by comparing the results of predictions with the real ones. The study is continuing previous concerns on the PV conversion of the solar energy, at the Technical University of Cluj-Napoca [31, 32].

## 2 Material and method

In order to study the conversion efficiency of different renewable energy sources into electricity, at the Technical University of Cluj-Napoca, was developed a microgrid based on a forming inverter and a grid follower one, with the scheme presented in figure 1, including photos of the main components.

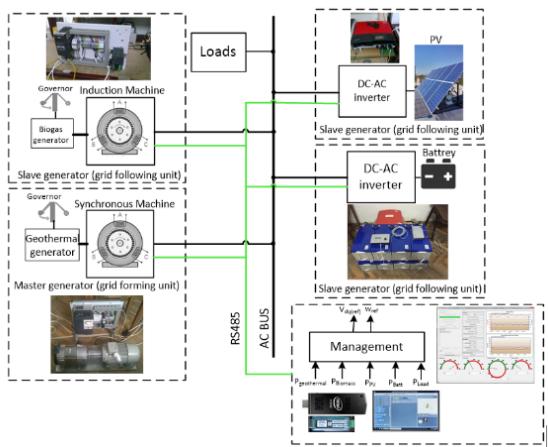


Fig. 1. Hybrid renewable energies microgrid.

The grid forming inverter is connected to a storage system of 8 200Ah VRLA batteries and the follower inverter to 19 square meters of 12 ET-P660250WW PV panels with a peak power of 3000 W. The Sunny boy 3600TL-21 solar inverter provided by the company SMA Solar Technologies, has an MPPT algorithm implemented to deliver the maximum available power to the grid. The MPPT algorithm does not consider partial shading thus unpredictable power losses may occur on the inverter side. This issue is of low relevance for this particular

application because the PV array, tilted at 42° and oriented at 32° counted from South through East, is placed on the highest building in the area with no shading obstacles.

An image of the PV array is presented in figure 2.



Fig. 2. Image of the PV array on the building.

The solar irradiation is measured using a SMP-3 Kipp&Zonnen pyranometer installed at 46°46'22" longitude and 23°35'7" latitude on the horizontal axis. The data from the pyranometer and the solar inverter is gathered through an RS-485 communication network using a Raspberry Pi device. A data base is created and the information is used for analysis purposes in a C# program with Graphical User Interface (GUI). Data is displayed in Grafana as suggested in figure 3.



Fig. 3. Grafana interface for the real-time measurements.

Ambient temperature is measured and recorded in the same database with the same Kipp&Zonnen pyranometer.

All measured data are recorded hourly and are also used as input data in the predictions of the PV energy production. Equally as implicit input data in the PV\* SOL simulation software were used the meteorological data from the Meteonorm database for Cluj-Napoca, containing averaged values for 20 years, from 1986 to 2005. Figure 4 presents the total monthly global solar radiation on horizontal plane, measured and from the database.

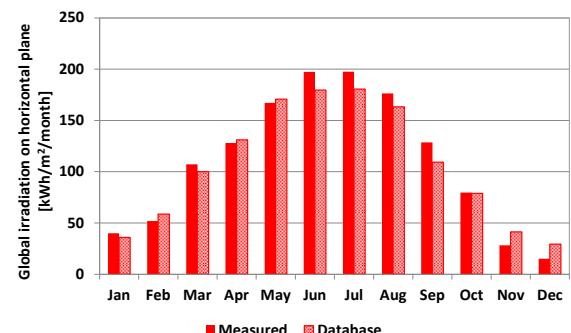


Fig. 4. Monthly global solar radiation on horizontal plane.

The total yearly global solar radiation on the horizontal plane, measured during the year 2017 is of 1799.4 kWh/m<sup>2</sup> while the similar value of the database is of 1277.6 kWh/m<sup>2</sup>.

Figure 5 presents the average monthly ambient temperatures, measured and from the database.

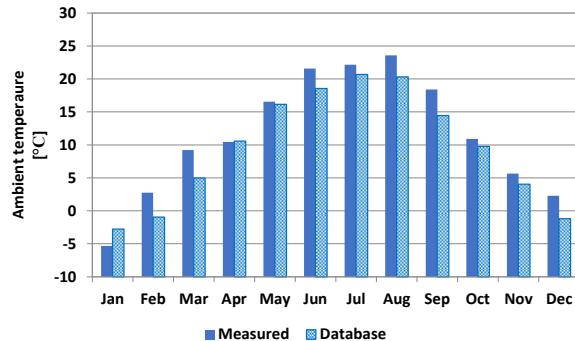


Fig. 5. Monthly average ambient temperatures.

The measured yearly average ambient temperature is of 11.5 °C while the similar value of the database is of 9.6 °C.

The prediction of the PV energy production was realised both by simulation with the PV\*SOL software and by the use of an analytical model. With the simulation tool were used both the measured solar radiation and ambient temperature, while with the analytical model was used only the same measured data.

The PV panels were modelled in PV\*SOL as a 3D model of the real system as presented in fig. 6.



Fig. 6. PV\*SOL model of the PV array.

The PV\*SOL electrical scheme of the whole system including the PV array and the PV inverter with MPPT is presented in figure 7.



Fig. 7. PV\*SOL electrical scheme of the PV system.

The scheme of the PV system considered in the mathematical model, including the solar radiation, the PV array, the inverter and the electricity consumer, is presented in figure 8.



Fig. 8. Scheme of the PV system in the mathematical model.

The model of the solar position and geometry was already presented in [33, 34] and successfully used in [32].

The electric efficiency of the PV collectors ( $\eta_{PV}$  [%]) can be calculated by [35]:

$$\eta_{PV} = N_{Tref}(1 - \beta_{ref} \cdot A) \quad (1)$$

$$A = \left[ T_a - T_{ref} + (T_{NOCT} - T_{aNOCT}) \frac{I_{gt}}{I_{gNOCT}} \right] \quad (2)$$

where:  $\eta_{Tref} = 15.37\%$  is the nominal efficiency of the PV panels in reference conditions, at the reference solar radiation and at the reference temperature ( $T_{ref} = 298\text{ K}$ );  $\beta_{ref} = 0.004\text{ }^{\circ}\text{C}^{-1}$  is a coefficient of correction available in the technical leaflet of the PV panel;  $T_a [\text{K}]$  is the ambient temperature;  $T_{NOCT} = 318\text{ K}$  is the normal operating collector temperature determined in test conditions (ambient temperature  $T_{aNOCT} = 293\text{ K}$ ; global solar radiation  $I_{gNOCT} = 800\text{ W/m}^2$ ; wind speed  $w = 1\text{ m/s}$ );  $I_{gt} [\text{W/m}^2]$  is the global radiation normal at the tilted surface of the PV collector.

In order to evaluate the global radiation normal at the tilted surface of the PV collector ( $I_{gt}$ ) the direct and diffuse solar radiation on the horizontal plane had to be determined, because only the global solar radiation in horizontal plane was measured.

By analyzing the solar radiation data from the available Typical Meteorological Year (TMY), it were determined the rules to split the global horizontal radiation into direct horizontal radiation and diffuse horizontal radiation, as shares of global horizontal radiation, presented in Table 1.

Table 1. Rules to split the global horizontal radiation into its components, as shares of global horizontal radiation.

Global radiation [ $\text{W/m}^2$ ]	Direct radiation [ $\text{W/m}^2$ ]	Diffuse radiation [ $\text{W/m}^2$ ]
0-99	0%	100%
100-299	10%	90%
300-399	40%	60%
400-799	70%	30%
800-1000	80%	20%

The PV modules temperature ( $T_c [\text{K}]$ ) can be calculated from the relation between the electric efficiency of the PV collectors and their temperature [37] as:

$$T_c = T_{ref} + \frac{\eta_{Tref} - \eta_{PV}}{\eta_{Tref} \cdot \beta_{ref}} \quad (3)$$

with the significance of all notations, already presented.

As parameter to evaluate the accuracy of PV energy production by simulations and by using the analytical model, was used the weighted mean absolute error based on total energy production (WMAE) was determined as:

$$\text{WMAE} = \frac{\sum |E_m - E_e|}{\sum E_m} \cdot 100 [\%] \quad (4)$$

where:  $E_m$  is the measured monthly PV energy production and  $E_e$  is the estimated monthly PV energy production. The PV system efficiency ( $\eta_{sys}$  [%]) was determined as:

$$\eta_{sys} = \frac{E_{PV}}{E_{sol}} \quad (5)$$

This performance parameter was determined for the measured data but also for both simulation and analytical model.

### 3 Results and discussions

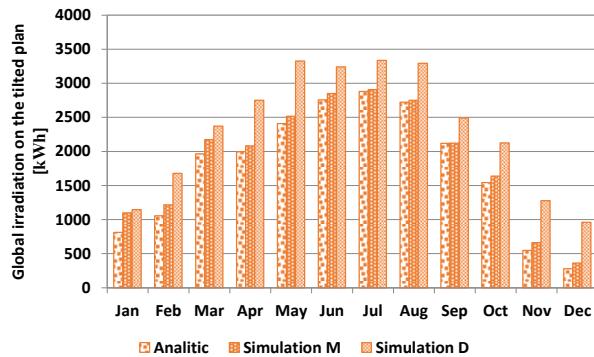
The following notations were used to label the different types of results: Measured – for results obtained by direct measurement; Analytic – for results obtained by the analytical model; Simulation M – for results obtained by simulation with measured input data and Simulation D – for results obtained by simulation with database input data.

The developed **GUI** provides access to the recorded data and reports can be generated for a year, month or day regarding the solar radiation, PV modules temperatures, inverter power and the PV system efficiency.

The information gathered is of high economical interest because one can compare the available data from different meteorological registers with the one measured in situ and can consider the tolerance for future designs.

Despite that all the results are determined on hourly basis, in this study only monthly results are presented.

The total monthly global solar radiation on the tilted PV array is presented in figure 9.



**Fig. 9.** Monthly global solar radiation on the tilted PV array

It can be observed that values determined by the analytical model are close to those determined by Simulation M. This relative similarity confirms the correctness of the proposed rules to split the global horizontal radiation into direct and diffuse components of solar horizontal radiation.

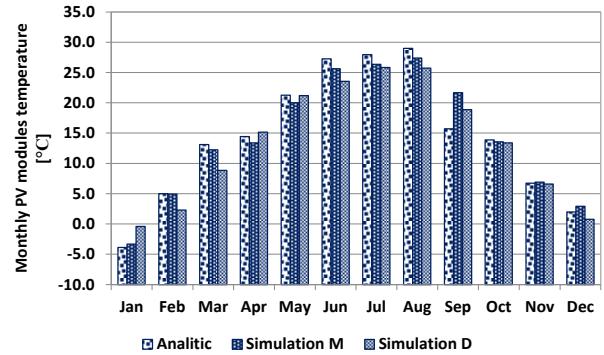
The average monthly PV modules temperatures are presented in figure 10.

This parameter was not determined by measurements, but almost similar values were obtained by all the prediction methods.

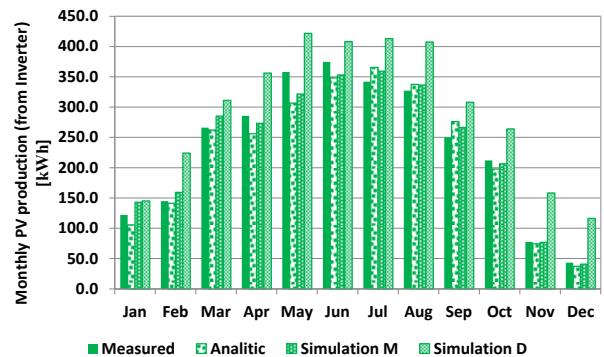
The total monthly PV energy production AC electricity at the output of the inverter is presented in figure 11.

Relative similar values were obtained for measured, analytic and simulation M methods. The total yearly amounts of PV electric energy production for the considered methods are: 2802.9 kWh by direct measurement, 2604.3 kWh by analytic model, 2823.5 kWh by the simulation M and 3536.5 kWh by simulation

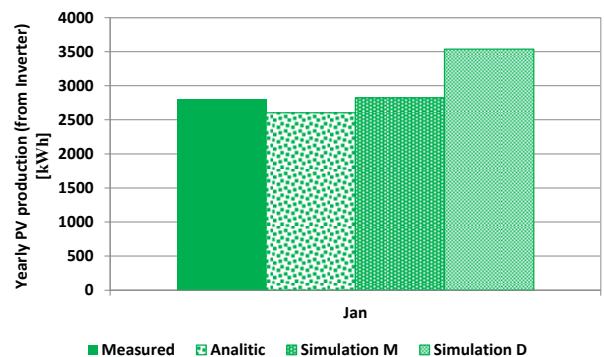
D. The yearly values of the produced PV electricity are presented for comparison on figure 12.



**Fig. 10.** Average monthly PV modules temperatures.



**Fig. 11.** Monthly PV energy production.



**Fig. 12.** Yearly PV energy production.

The slight underestimation of the PV electricity production with -7.1% of the measured value, can be explained because the analytical model provides known unrealistic results for low solar altitude corresponding to the period immediately after sunrise and just before the sunset [33, 34]. Due to this fact, in the analytical model all the electricity production corresponding to these periods is neglected. The yearly PV energy production is overestimated with only 0.7 % by the simulation M and with 26.2 % with the simulation D. This differences obtained with the same method is highlighting the importance of the input data for the accuracy of any prediction method.

The values of the monthly system efficiencies determined with the different methods, are presented in figure 13.

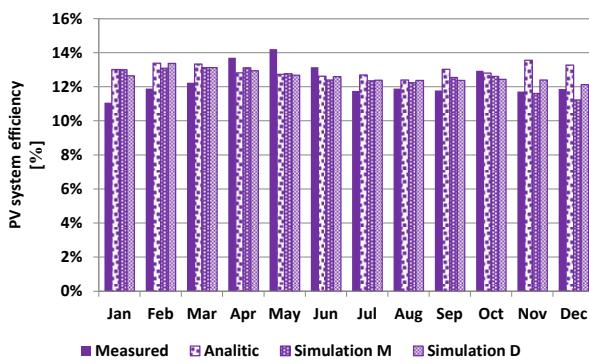


Fig. 13. Monthly PV system efficiency.

Values of this parameter range between (11.1-14.2) % for measurements, between (12.4-13.6) % for the analytical model, between (11.2-13.1) % for the simulation M and between (12.2-13.4) % for the simulation D.

**WMAE**, the parameter that evaluates the accuracy prediction of PV energy production was determined as 0.57 % for the analytical model, 0.76 % for the simulation M and 0.84 % for the simulation D. These values are similar or lower than other reported values: (1.7-10) % in [37]; (5.0-6.3) % in [38] or (0.62-1.75) % in [39], proving that all the considered methods is capable of correct predictions for the PV energy production.

The gathered data from the database is used by the developed **GUI** to build graphs for results analysis after a small refining by eliminating the erroneous readings is made. Erroneous data are considered negative values and readings greater than the atmospheric irradiance. When computing mean values, the days without readings due to different causes are not taken into account and the value corresponds to the days where data is present.

As one can see in fig. 14 and fig. 15 in January even though the irradiance level is lower than in August the energy produced in correlation with the irradiance is greater. This is due to the azimuth and temperature difference between the two months.

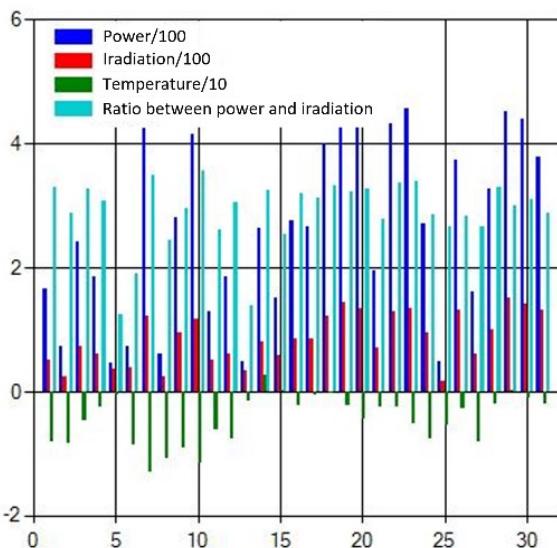


Fig. 14. Recorded data for January 2017.

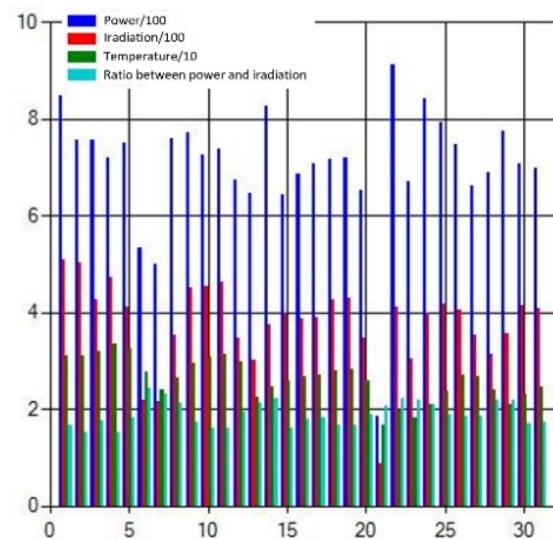


Fig. 15. Recorded data for August 2017.

The data for the whole year 2017 is presented in fig. 16. Comparing the results with the estimated energy production from PV\*SOL fig. 10 one can see that a slight difference is present for July. This is due to some data loss during tests and maintenance of the microgrid. Despite this difference the energy delivered by the solar inverter in the microgrid is in concordance with the estimation. Besides the energy and irradiance data, the ambient temperature and the ratio between the produced power and irradiance is also presented in fig. 14. This data can be later used to build predictive management algorithms and a real time load scheduler. Because of the MPPT algorithm implemented in the solar inverter and partial shadings small discrepancies can occur in the estimated energy production and the one produced by the microgrid. These differences do not affect the analysis due to their small values and short time effect.

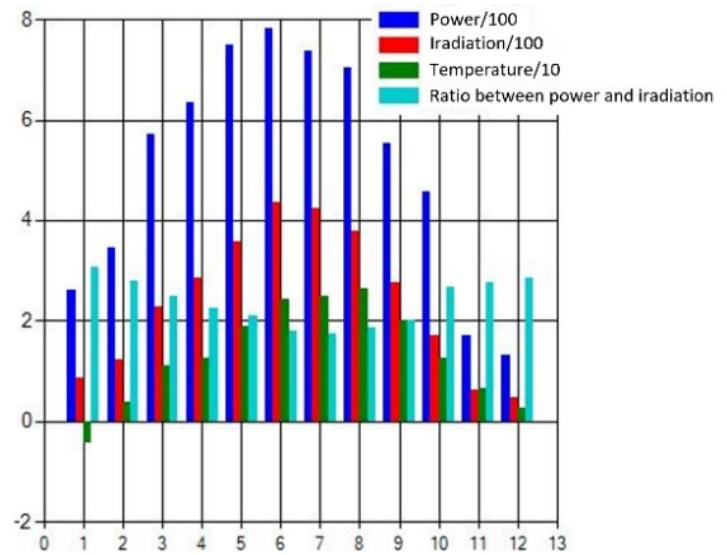
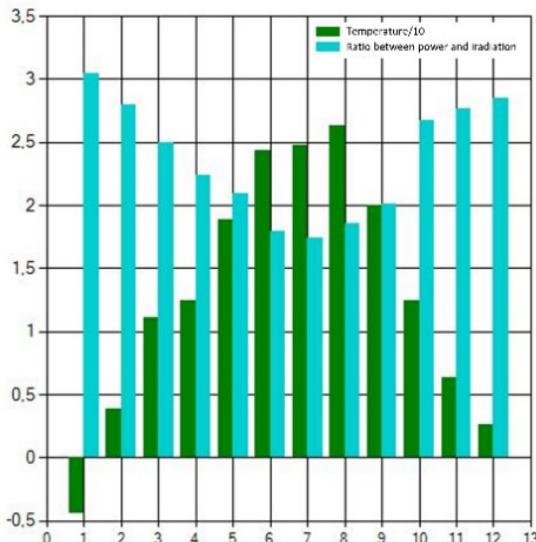


Fig. 16. Recorded data for year 2017 with monthly mean values.

In fig. 17 is presented the efficiency dependency on temperature.



**Fig. 17.** Monthly mean values for 2017 for the ratio between produced power and irradiance and temperature.

The efficiency value will consider all the losses due to the solar inverter, the power cables, temperature and season. Because only the global irradiance is measured, the PV panels efficiency must be computed separately using values of the direct irradiance. Even if the efficiency is greater during the cold seasons comparing the date with fig. 15 one can conclude that the high irradiance value and the daylight length in the summer compensate for the dependency of temperature, the system reaching the maximum energy production in June-July.

## 4 Conclusions

A study on the PV energy production was performed base on an islanded microgrid developed to convert different forms of renewable energy in electricity. Together with an experiment conducted for the whole year 2017, simulations based on PV\*SOL software and an analytical model were used to predict the energy production for the same PV system. With the simulation software, as input data was used both measured solar radiation and data available in the software database for the same location.

Based on WMAE, it was proved that all the considered prediction methods are capable of correct evaluation of the PV energy production, since this parameter is lower than 1% for all the estimation methods, lower or at less in the range with other values reported in literature.

Both the analytic model and the simulation based on measured input data, are capable to correct evaluate the global solar radiation on the tilted plan of the PV array.

All the calculation methods provided almost similar values for the PV modules temperature, leading to similar confidence, from this point of view, in all the considered methods.

The PV energy production was slightly underestimated by the analytical model due to the known calculation limits immediately after sunrise and just before sunset. The simulation based on measured input data provided almost similar results with the

measurements, while the simulation based on database input data provided overestimated results. This aspect is highlighting the importance of the quality of input data for solar radiation and ambient temperature, for this type of calculations.

A database containing information of irradiance and temperature might be of great importance for the PV energy production and can contribute to the increasing of the PV market in the region. This study can be further used to create a solar map for the region of Cluj-Napoca. Users can predict the contribution of integrating distributed PV power production units in the city to balance the overall energy usage.

In most cases the problems in a microgrid arise when due to clouds, for short periods of time the PV production decreases significantly in high load demand periods followed by short periods of high energy production. Future work can be done by integrating the data collected by the acquisition system for developing predictive energy management algorithms. This data correlated with satellite data or image recognition systems can be used also for small time laps operation of the microgrid.

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