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PV panel monitoring system for cell temperature analysis and comparison by embedded models

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Abstract

In recent decades, the use of renewable energy sources and the development of related technologies have been boosted due to the energy and environmental paradigm, with photovoltaic (PV) panels being one of the most implemented and optimised to date. The behaviour of panel operation is dependent on multiple parameters such as irradiance, wind speed or operating temperature. This paper presents a monitoring system based on IoT software focused on the study of the cell temperature (CT) of PV panels, highlighting the importance of this variable in the current generation and the equipment overall performance. For this purpose, a dashboard is implemented in Grafana to visualise the evolution of the CT and the associated variables. The implemented dashboard includes embedded models for the simulation of CT, in order to compare real and simulation data. This comparison determines the most suitable model to the real dynamics and could facilitate the development of intelligent control strategies for the panel.

Keywords: Renewable energy, Photovoltaic, Grafana, IoT, Monitoring system.

1. Introduction

In recent years, the worsening of the environmental scenario due to the increase in pollutant emissions has encouraged the development and implementation of technologies for the use of renewable energy sources (RES) (Sayed et al., 2021; Tsilingiridis et al., 2011; Shakya et al., 2022). Some of these, such as solar, wind and hydro, have become fully integrated into the socio-economic fabric, forming part of the compendium of energy sources used on a daily basis to satisfy the population's energy demand. In particular, the technologies associated with photovoltaic (PV) energy have prospered notably, serving as a key part of the energy generation system in a multitude of contexts, such as industrial (Catalbas et al., 2021) or residential (Panagiotidou et al., 2021).

PV panels are made up of a set of interconnected cells with the capacity to generate electricity by means of the photoelectric effect of the materials of which they are composed. These devices are widely studied and integrated in applications together with other secondary generation systems based on RES, such as hydrogen generators (Gutiérrez-Martín et al., 2021), or applied for energy storage by means of batteries (Mulleriyawage and Shen, 2020). To optimise the operation of these devices, detailed control of the parameters that condition their behaviour, such as voltage, generated current or irradiance, is required. One of these key parameters is cell temperature (CT), whose relationship with the power dissipation affects the performance of the cells. Due to its importance, there are models in the literature for estimating this variable based on conditions indicated by the panel manufacturer (Alonso García and Balenzategui, 2004; Migan, 2013), practical models (Araneo et al., 2014; Kamuyu et al., 2018; Ross, 1976) as well as models based on energy balance equations (Appelbaum and Maor, 2020).

To carry out the study of these models, a series of sensors and a system to manage the operation of the physical device and data acquisition are required. The current paradigm of IoT technologies provides users with highly versatile tools, such as Grafana. This software is used in many areas as a monitoring system (Gimeno-Sales et al., 2020; González et al., 2022).

This work describes a Grafana-based monitoring system for PV panels. This system is dedicated to the study of the real temperature of the cells and its comparison with a set of models selected from the literature. The goal is to understand the effects associated with this parameter and to select the most suitable model for the operation of the installed panels.

The structure of the rest of the manuscript is as follows. The second section describes the operation of the PV panel and the selected CT models for the monitoring system. Section 3 deals with Grafana and the implementation of the system. Finally, a series of conclusions about the work carried out are detailed.

2. PV panels operation and cell temperature models

The operation of PV panels can be explained as an interaction of two processes. Firstly, the electrical generation is due to the photoelectric effect of the cell materials. On the other hand, there is an energy dissipation effect in the form of heat due to this generation process. This energy loss is greater the higher the temperature of the cell.

Equivalent Circuit Models (ECM) are based on an electrical diagram whose components are associated with physical effects of device operation. For the case of PV panels, these models are widely used, such as in (Amiry et al., 2018; Sarikh et al., 2020; González et al., 2021). More specifically, the single diode model is commonly used to estimate the electrical generation of a PV cell. Figure 1 shows the diagram of the single diode ECM for a PV cell.

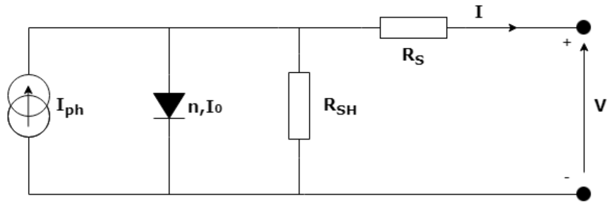

Figure 1: Electrical Circuit Model of a PV cell.

The circuit consists of a single diode connected in parallel with a photo-generated current source I_{ph}, a series resistance R_S to represent voltage drops and internal losses, and a shunt resistance R_{SH} to consider the leakage currents. The relationship between these electrical components defines Eq.(1) for the current generation I for a PV module of N_s cells in series.

$$I = I_{ph} - I_0 \left[exp\left(\frac{V + IR_S}{nN_sV_{TH}}\right) - 1\right] - \frac{V + IR_S}{R_{SH}} \quad (1)$$

Where I_0 is the saturation current of the diode, V is the output voltage, n the diode ideality factor and V_{TH} is the thermal equivalent voltage. The last parameter is described in Eq.(2) and depends on the electric charge q, the Boltzmann constant K and the cell temperature T_c.

$$V_{TH} = KT_c/q \quad (2)$$

As shown in Eq.(1) and Eq.(2), the single diode model is dependent on the operating CT, whose variations have a direct impact on the current generation and overall panel efficiency. Therefore, it is critical to monitor the evolution of this variable through models that predict its value in order to optimise the operation of the PV panels.

The models for determining the operating temperature T_c included in the monitoring system consider environmental parameters such as ambient temperature T_a, irradiance G or wind speed V_w.

In (Alonso García and Balenzategui, 2004; Migan, 2013) the Eq.(3) called Nominal Operating Cell Temperature (NOCT) is used, where the nominal conditions indicated by the manufacturer (T = 25 ºC, G = 800 W/m^2) are applied as a reference to determine the CT.

$$T_c = (T_a + NOCT) \times \frac{G}{800} \quad (3)$$

The work described in (Ross, 1976) expresses the operating temperature by Eq.(4), where the irradiance is varied by a constant.

$$T_c = T_a + 0.035G \quad (4)$$

The model developed in (Migan, 2013) defines Eq.(5), where the effect associated with temperature dissipation due to wind is included by implementing the wind speed parameter.

$$T_c = T_a + \frac{0.32}{8.91 + 2V_w}G \quad (5)$$

The models listed above have been selected for their simplicity and ease of implementation. Moreover, they have been widely applied and validated in previous literature These characteristics make them ideal for integration into the monitoring system.

3. Grafana and implementation

Grafana is an IoT software dedicated to the monitoring of information through a graphical interface based on dashboards composed of visual elements such as graphs, historical data or numerical indicators. Derived from its IoT nature, Grafana offers an extensive catalogue of add-ons and plug-ins, providing the platform with versatility and customisation to undertake the design of interfaces that meet the user's needs.

The performance of Grafana is based on its interaction with one or more data sources, allowing both real-time operation and the representation of data over a specific time range. Figure 2 illustrates this principle of operation.

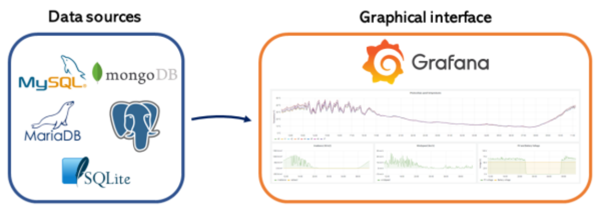

Figure 2: Interaction between data sources and Grafana.

For the case of the system described in this work, a data acquisition system (DAQ) is used to gather measurements associated with the sensors installed close to the PV panels. The DAQ system then sends the information to a Raspberry Pi which stores it in a database and displays it on a dashboard in Grafana. The monitoring system and all the components involved are represented in Figure 3, as well as the interactions between each of them.

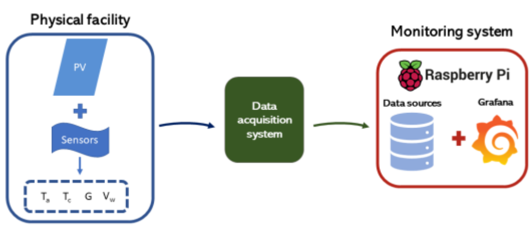

Figure 3: Monitoring system and components involved.

Within Grafana, a dashboard is designed to represent the time evolution of the parameters acquired from the physical system and to simulate the CT models described in section 2. For this purpose, the interface hosts three graphs which are programmed by means of Search Query Language (SQL) to visualise the information stored in the data source. In the case of the models, these are embedded in the interface through SQL code in one of the graphs. In this way, Grafana performs the simulation process of the models from the data stored in data sources. Figure 4 depicts the process carried out by the monitoring system to implement the model expressions.

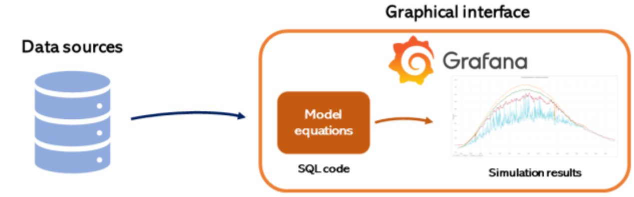

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Figure 4: Model simulation process.

To show the potential of the designed monitoring system, Figure 5 represents the data evolution of the stored parameters and the resulting model values for a time range of 15 hours.

This figure shows the graphical aspect of the interface, consisting of a total of three graphs, each with a specific purpose. First, there is a comparative graph of the values associated with the models described in section 2 and the measurement obtained from the sensor placed in the panels. Next, an independent graph for irradiance and another for wind speed are presented. These last two panels allow us to understand the nature of the variations in the models.

Looking more closely at the first of these graphs, four curves can be distinguished: the green curve refers to the model based on NOCT used in (Alonso García and Balenzategui, 2004; Migan, 2013). The orange curve represents the results obtained by the model of (Ross, 1976). The cyan curve represents the behaviour described in (Migan, 2013). Finally, the red line describes the evolution of the actual temperature measured on the panels by the sensors. Figure 6 shows in detail the development of these curves over time.

The information presented by the dashboard plots allows to determine the behaviour of the models in comparison with the real dynamics shown by the panel cells. The results obtained by the model based on NOCT and (Ross, 1976) coincide with relative accuracy with the experimental values. Peculiarly, the model described in (Ross, 1976) presents fluctuations associated with point variations in irradiance, as can be seen in Figure 5. These sudden changes in irradiance are due to slight shading caused by to clouds. On the other hand, it is worth noting the behaviour of the model of (Migan, 2013), whose constant and pronounced fluctuations are due to the continuous variations in wind speed, as can be seen in the graph of this parameter in Figure 5.

These abrupt variations are caused by the fact that the selected models allow estimating the instantaneous value of the CT, without considering the time factor or previous values. Therefore, although their approximations are close to the real cell dynamics, a sudden variation of their input parameters results in an instantaneous fluctuation of the model.

As a counterpart to this behaviour, experimental measurements show a temperature evolution without abrupt variations. This effect is due to the actual dynamics of the cells, whose operating temperature evolves more smoothly due to thermodynamic parameters such as resistivity or thermal conductivity. These parameters limit the rate at which the cell transports heat, thus limiting the rate of fluctuation of the operating temperature.

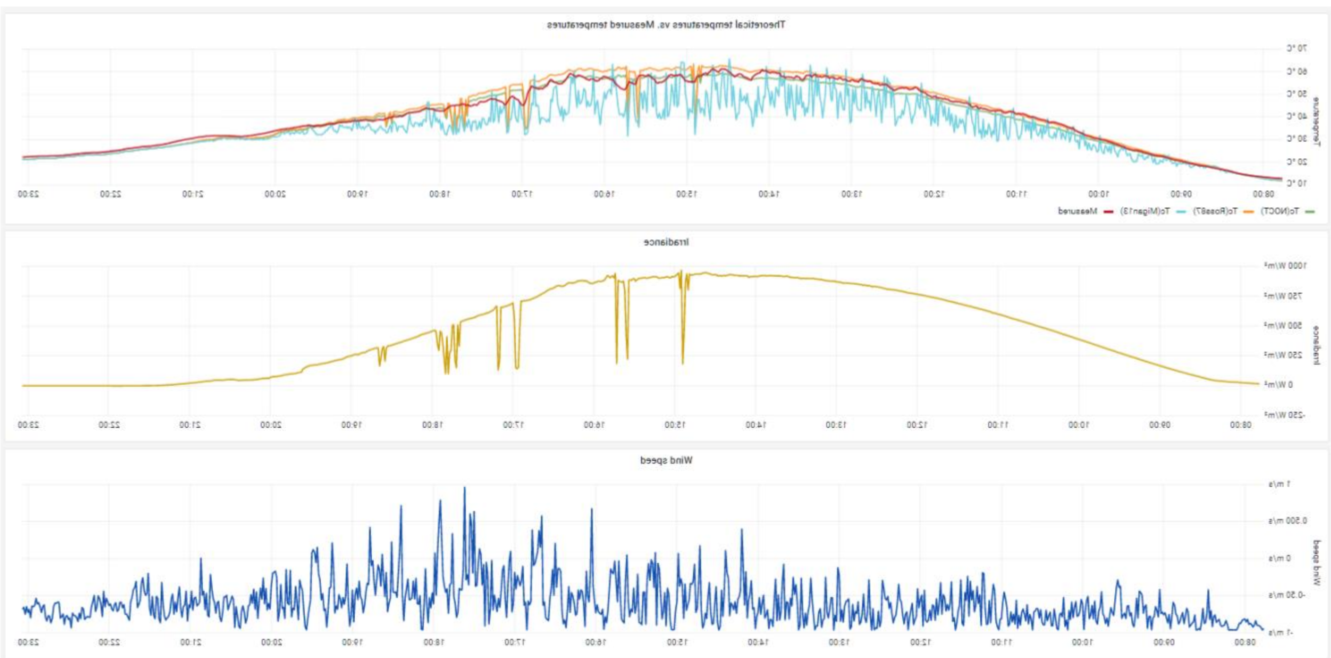

Figure 5: Monitoring system in operation.

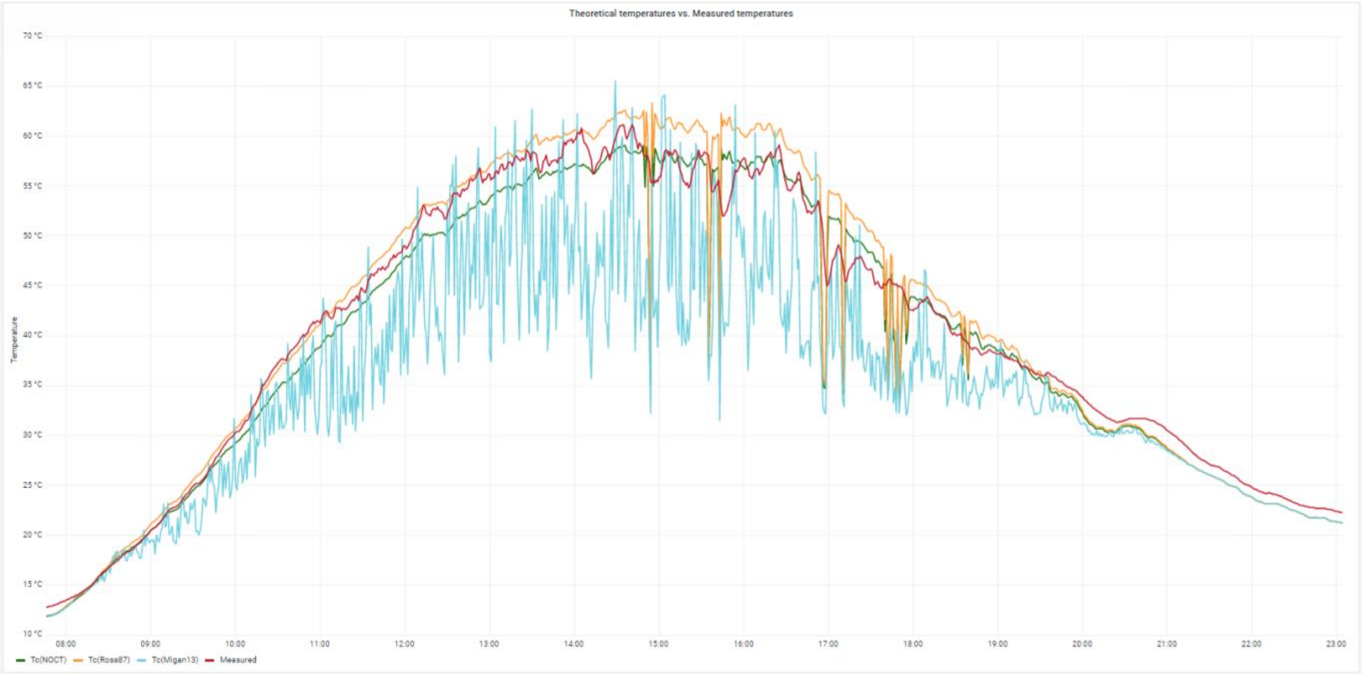

Figure 6: Comparative temperature graph.

4. Conclusions

This paper has presented a Grafana-based monitoring system for PV panels, focusing on the study of the operating CT. For this purpose, the system has embedded models in the dashboard for analysis and comparison of experimental values and simulation results. Grafana provides a graphical environment for the management of the information acquired from the panels while providing versatility due to its customisation and ease of use. The most accurate CT model could be used to apply intelligent control strategies.

Future work will address the implementation of new graphic elements that facilitate the interpretation of the data represented on the dashboard. At the same time, new models will be included to enrich the study derived from the comparison between experimental data and model simulations.

Acknowledgments

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