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Analysis and Real-time Data of Meteorologic Impact on Home Solar Energy Harvesting

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Abstract

Solar energy production increased in the world from 0 TWh in 1965 to 724.09 TWh in 2019. Solar energy is adopted as a source for residential renewable energy sources because, besides Biomass sources, it's the only one that can be installed and maintained at home. Operating efficiency is an important consideration when evaluating the application of photovoltaic panels (PV) technology. A real-time system monitoring is required to analyse the current production and understand the impact of the weather conditions on PV production. This paper extends the literature on the residence solar energy harvesting subject, by providing a scalable architecture that can be used as starting point on data analysis on PV panels efficiency and how weather conditions impact energy production. A dataset was collected related to PV panel energy production, the residence energy consumption and that's reading weather conditions. Wind intensity and direction, temperature, precipitation, humidity, atmospheric pressure and radiation were weather conditions analysed. Moreover, this data was analysed and interpreted in order to evaluate the pros and cons of the architecture as well as how the weather impacted the energy production.

Keywords: *Solar energy harvesting, real\-time energy harvesting, meteorologic impact analysis, home solar energy production*

1. INTRODUCTION

To reduce the impact of over-reliance on fossil fuels for energy supply, and thus increase world sustainability, several countries are pushing for energy efficiency and for the use of local, renewable energy sources (RES) [1]. According to the organization "Our World in Data" the percentage of energy that came from renewable sources in the world increased from 6.04% in 1965 to 11.41% in 2019 [2]. One of sources is solar energy, that according to the same source, energy production also increased in the world from 0 TWh in 1965 to 724.09 TWh in 2019 [3]. Solar energy is being adopted as the key residential source renewable energy, besides the Biomass source, because can be installed and maintained at home [4]. Currently, wind, hydro and nuclear sources are not used as residential energy sources because they either demand infrastructures that are difficult to implement at home or lack ideal sources conditions. Solar energy, on the other hand, uses photovoltaic panels (PV) to convert the sun's energy into usable energy - electricity. These systems require less space than other sources and, as long as the sun is shining, they're producing energy. Although it demands an initial financial investment, it brings savings on the electricity bill in the long run, and, in some cases, one can even get paid for injecting electricity on the public grid [5].

Since solar energy source relies on sun's radiation, its efficiency depends from external factors such as meteorologic conditions. One can suppose that different weather conditions and different climates should affect energy production. Nowadays, the only data that someone interested in installing a photovoltaic system can rely on, is the max production capacity of that system, not taking into account if the climate/weather is appropriated. Nevertheless, operating efficiency is an important factor regarding the evaluation of the application of PV technology [6]. Standard testing of PV is normally carried out indoor, under controlled test conditions (STC) of 25 °C and solar irradiance of 1000 W/m2. However, the solar spectrum through the atmosphere presents variation depending on the location, climatic conditions as well the existing agents in the air such as water vapor, CO2 and dust particles [7].

In order to understand the impact of the weather conditions on PV production, it is important to consider a real-time monitoring system providing analysis of energy production. Internet of Things (IoT), a concept that supports communicating among the different devices by using the Internet or another different kind of network, can be used to gather data from a PV panel and, as such, the IoT technology and related big data applications are clearly on a penetrative path across the systems and domains of smart sustainable cities [8]. Big data applications are increasing and constitute a significant opportunity for the energy sector in the field of energy management, environmental protection, and energy conservation [9]. Data generated by IoT devices in the energy industry not only include the massive smart meter reading data, but also the huge amount of related data from other sources, such as weather or climate data. Therefore, working with IoT on the PV data harvesting requires new technologies to efficiently store and process a large amount of data.

This paper pretends to extend the base knowledge of this field by presenting an architecture for analysis and real-time data of meteorologic impact on residential solar energy harvesting as well as a case study of its implementation on Coimbra, Portugal.

The remainder of this paper is organized as follows. Section III outlines the methods for this research in detail, presenting insight on how the data set was generated and also presenting the architecture used. Section IV thoroughly describes the results of the case study. Section V presents the discussion regarding the implemented solution. Finally, Section VI concludes the paper.

2. RELATED WORK

RES data analysis is a field of interest for academic circles as well as in industry, consequently, there exist a large number of papers addressing the problem on this subject.

In 2014, Sanaz Ghazia and Kenneth Ip conducted a study of the weather conditions effects on PV panels in the southeast of the UK where they concluded that weather conditions, particularly rain and snow, have the most negative effect on the performance of installed PV panels in the case study area. Moreover, over a period of one year, there were instances of output close to zero because of high humidity (higher than 80%) and rainy conditions [6].

Another case study was done regarding the effects of Saharan dust transport to Portugal. The authors demonstrated the negative impact of Saharan dust events on the southern Iberian Peninsula at thousands of kilometers away from its point of origin. A significant decrease has been stated in production of photovoltaic energy due to soiling and significant economic effects on solar energy installation, especially in low rain seasons [10].

There are other similar studies at specific locations such as Doha, Qatar [11] or São Paulo, Brazil [12] addressing the impact of weather on PV production.

In the subject of data harvesting and processing, studies like [13], [14], [15] or present their framework for monitoring PV systems. [13] address the topic on efficient monitoring of PV power station and, although it is focused more on the low-level architecture, it provides some insight of the complexity on processing big data and handling large scale PV power station installations. [14] presents a distributed network architecture supported by IoT applications to harvest data and technologies like Hadoop MapReduce cloud-based for data handling. This research covers the topic of smart sustainable cities with the sensor-based big data applications of the IoT and they conclude that their approach has great potential to advance environmental sustainability. [15] covers an overview of different failure detection methods in a PV system. [16] expose an IOT-based solar panel remote monitoring system that has been proposed to collect data on parameters of solar panels using a RaspeberryPi and storing it on an IoT Cloud. It's a base architecture for faults diagnosis, data collection for forecasting, preventive maintenance.

Another frequent topic related with this topic is the PV production forecast. As such, Gabriel de Freitas Viscondi and Solange N. Alves-Souza, in 2019 published a literature review on big data for solar photovoltaic electricity generation forecasting [17]. The study concluded that despite solar electricity being the main motivation behind the papers examined, most of the publications are focused on predicting the natural resource – solar radiation – instead of using some variety of electricity-related data. Consequently, the key problem is more related to the meteorological factors of the energy conversion. [18] and [19] are examples of papers addressing prediction, where the first one proposes an architecture to nowcasts the energy generation of photovoltaic systems from ambient sensor information and the second propose a sensor network based on IoT from weather data for prediction of power output from PV panels.

Walch et. al [20] present a big data mining approach to estimate the PV potential on 9.6 million rooftops at monthly-mean-hourly temporal resolution and propose a quantification of the uncertainty on the estimated potential. By developing a methodology that combines Machine Learning algorithms, Geographic Information Systems, and physical models to estimate the technical PV potential for individual roof surfaces at the hourly temporal resolution, estimate the uncertainties related to each step of the potential assessment and combine them to quantify the uncertainty on the final PV potential, they concluded that 55% of the total Swiss roof surface is available for the installation of PV panels.

Marinakis et. al [21] proposes a data-driven Decision Support System that analyse multi-source data within a smart city context. According to the authors, a wide range of data analysis techniques (including among others optimization, forecasting, classification and clustering) can be applied using this system.

The literature review has revealed that there is no existing knowledge on a solution that can be used for a generic data analysis on the effect of weather conditions on PV panels for a small residential solar energy producer.

3. ARCHITECTURE

This section describes the implemented solution architecture in detail. The solution entails the architecture presented in Fig. 1, composed of the following elements: Data collector; Data Storage; Queue; Web Rest API and Data Visualization. Each component is isolated from the other in terms of dependencies and concerns. Also, each element can run on a self-contained environment, allowing horizontal scalability.

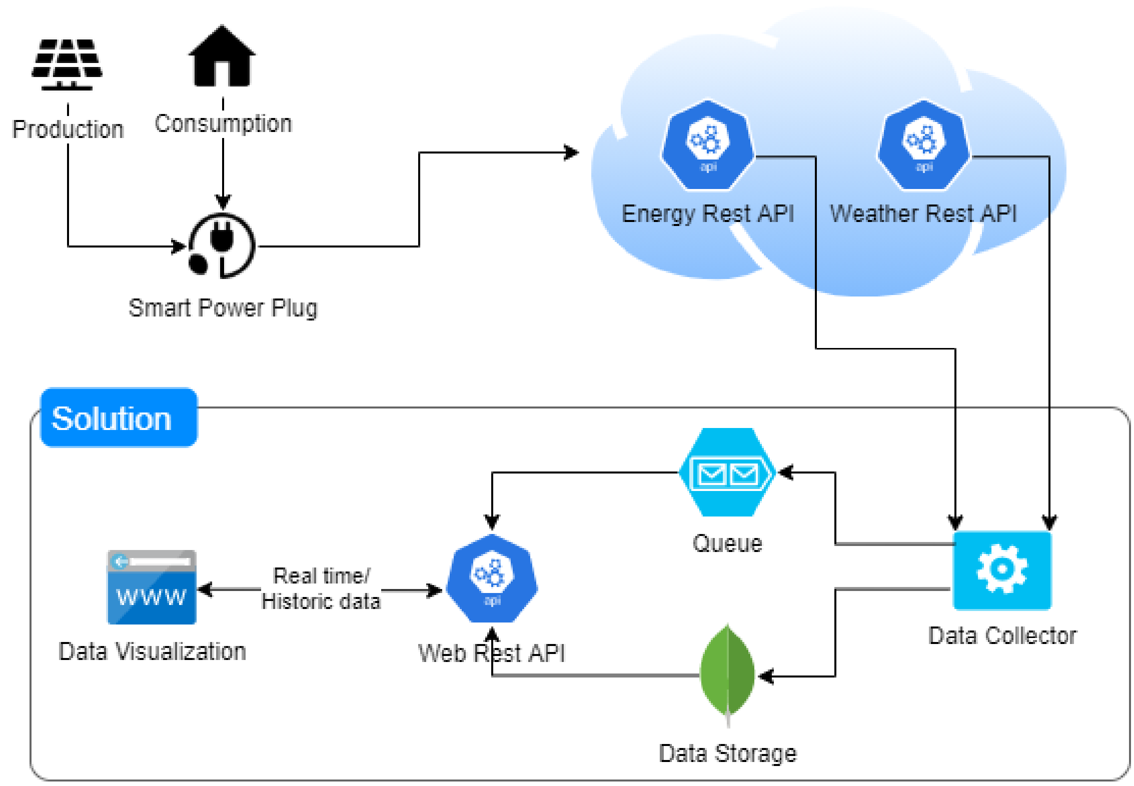

Figure 1 – Implemented Architecture

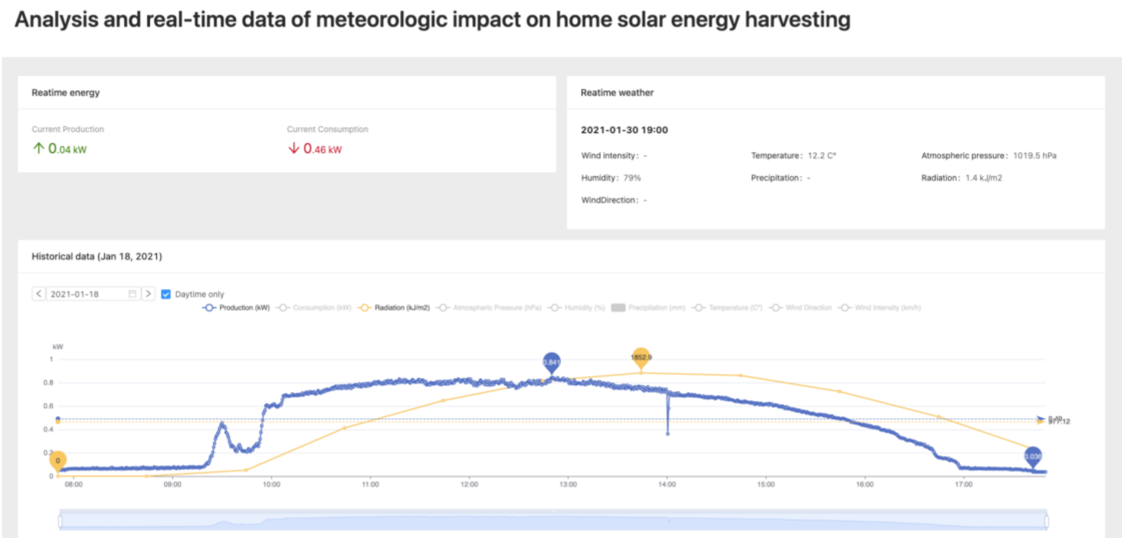

Figure 2 – Data Visualization Interface

Data Collector service is called worker in this context is responsible for data collecting. It entails two asynchronous services running independently. One of them gets the data from Energy Rest API and the other one gets data from Weather Rest API. The worker also associates the weather data with the specific energy reading. It is also responsible to publish the data into a queue, providing a real-time reading to any subscriber, and also store the data into the Data Storage for historical data.

Data Storage is the component responsible for storing the historical data of energy production/consumption reading with the associated weathers conditions. The perfect storage solution should correspond to a NoSQL database to better accommodate the data types of this use case, which is often unstructured. Moreover, the use of a NoSQL database can contribute to reducing the amount of data to be fetched as well as reducing some outliers as a result of aggregation operations.

The **Queue** component is responsible for handling the messages between a data producer and a data consumer, Data Collector and Web Rest API, respectively. By using a Queue instead of direct communicating, this architecture can expand the number of consumers and producers when scaling the use case. Also, it allows the possibility of operating the producer and consumer independently without causing downtime in the whole system.

The **Web Rest API** is the component responsible for exposing the available data to external elements. It subscribes to the Queue updates and every time a new message comes in, it handles the message and sends it through each client subscribed to real-time data notification. Also, this Web service makes available a Rest API to access historical data, by accessing Data Storage, filtered by day

Data Visualization is the component that shows to an end-user the real-time PV panel production, home consumption and the current weather condition. Also, historical data is available through interactive charts, allow the user to retrieve information regarding the weather effect on the PV production and home energy consumption on a specific day. This component also includes the processing capabilities implementing the corrective actions addressing the previously highlighted known issue affecting the real consumption reading when the production is higher than the energy consumption and correctly in the visualization data.

3.1. Implementation

The presented architecture was fully implemented in this work. The focus was put on the analysis of the relationship between energy production and weather conditions. Also, the objective was to assess the architecture, understanding the limitations and researching solutions to deal with scalability. This architecture was implemented using containerization and micro-services for the different components assigned to different roles. At the end, a solution was built able to be run from a single command.

A Data Collector component was developed in .Net Core 3.1 as a standalone service. Once up, the worker would collect energy data every 30 seconds and, the weather every 30 minutes. Despite the energy API does not provides the minimum refresh rate data, 30 seconds refresh option was adopted attending the amount of generated data and its variation in time. Apart from any type of shadow (a cloud or a human when doing some intervention), the PV energy generation would not present a significant variation in 30 seconds. Regarding the weather data, the IPMA API provides the updated data, including the summary of the data collected in the last hour. Therefore, the worker queries that data every 30 minutes to avoid any incorrect reading. This service operation was done manually by turning it up or down when needed.

The Data Storage component was developed as a MongoDB technology providing NoSql database capabilities. A collection was created, with a single index by the self-generated document Id. To have an instance of MongoDB, a container from a docker image was used besides a Mongo Express for visualization purposes. This docker container was running in a local machine to save the ongoing data being fetched in the same period the Data Collector component was also running.

A Queue component supported by RabbitMQ technology was also included as a single queue to connect and save data from the publisher (Data Collector) and notify the consumer (Web Rest API). Likewise MongoDB, also RabbitMQ queue solution was deployed as a container from a docker image providing management capabilities.

The Web Rest API component was developed using .Net Core 3.1 and ASP.Net Core. The component provides an endpoint to collect historical data, filtered by day. Real-time data communication capabilities were supported on the use of SignalR library. Once up, the Web API component connects to the Queue component and makes available a SignalR Hub for clients' connection. When the Queue notifies with a new message, that message is broadcasted to every client connected through SignalR. The API operation was manually performed by turning on or stopped when required.

The Data Visualization component was developed using Angular 8, ng-zorro design system, Javascript SignalR client and eCharts library for the chart display. Fig. 2 presents the interface of this Data Visualization component, displaying the current energy production, consumption, weather conditions and the historical data for 2021-01-08, daytime only.

Docker Compose was the tool to deploy and manage the containerized Data Storage and Queue components. The remaining components in the architecture can also be containerized and managed by the Docker Compose tool.

4. EXPERIMENT

To research the impact of the weather on photovoltaic panel energy production a dataset was collected including 25266 readings, 8.13 MB of data related to PV panel energy production, the residence energy consumption and that's reading weather conditions on Coimbra, Portugal, from 2021-01-18 to 2021-01-26. The residence photovoltaic system has the following specs and setup:

- 5 photovoltaic modules (panels) ULICA SOLAR 305 Full Black 305W with 60 monochromatic cells
- 5 microinverters Enphase M250 that allow a max power of 310W - allowing each panel to produce energy independently
- 1 PV panel facing the raising sun's direction - angle and direction manually calibrated on each season of the year
- 2 PV panel facing south - angle and direction manually calibrated on each season of the year
- 2 PV panel facing the sunset direction - angle and direction manually calibrated for each season of the year
- 1 HUB Efergy Engage connected with two sensors - one reading the house energy consumption another reading the PV panel energy production

The Efergy Hub is connected to a platform called EnergyHive [22], which has a public API that can be accessed by any owner of an Efergy device. The API provides an endpoint with the current home production and consumption [23]. There is a known issue on the Hub that affects the real consumption reading when the production is higher than the current consumption. This issue occurs when the remnant energy from production-consumption is injected into the public grid because when energy goes through the consumption sensor on the Hub (located between the house and the public grid), it is interpreted as a consumption, although the energy it is going on the "opposite direction", from the house grid to the public grid.

Regarding the weather data, "Instituto Português do Mar e da Atmosfera" (IPMA) [24], the Portuguese weather institute, provides a public API [25] with several weather related data. In this paper scope two endpoints were used:

- List of weather station identifiers
- Last 3 hours weather observation per weather station

The first endpoint was used to determine which stations were closest to the residence where the energy data was being collected. Collecting that endpoint data and using an online geojson visualizer [26], a manual selection was done to find the closest weather stations to Coimbra, Portugal. The closest was "Coimbra, Bencanta" and the second closest was "Coimbra (Aeródromo)" (see Fig. 3). All the weather data used on the dataset was collected from those two stations.

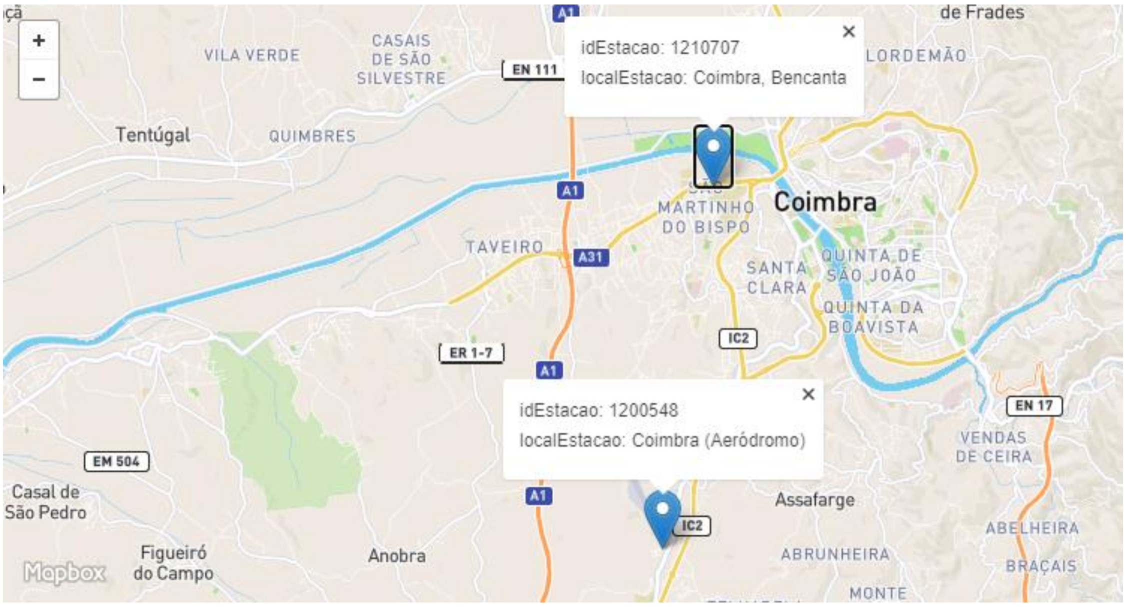

Figure 3 – Closest weather stations to Coimbra, Portugal where the PV panels were located

The second endpoint was used to get the weather condition status by hour, getting the following parameters:

- wind intensity (km/h) - at 10 meters from the ground
- temperature (Cº) - average hour temperature at 1.5 meters from the ground
- wind direction - average hour wind direction at 10 meters from the ground
- total precipitation (mm) - total hour precipitation at 1.5 meters from the ground
- humidity (%) - average hour of air relative humidity at 1.5 meters from the ground
- atmospheric pressure (hPa) - average hour atmospheric pressure, at average sea level
- radiation (kj/m2) - suns radiation

5. Results

In this section, the main results are presented. They were collected through the Data Visualization tool created for this use case. Each table represents a parameter to be used on the data analysis: energy production (Table 1), energy consumption (Table 2), radiation (Table 3), atmospheric pressure (Table 4), humidity (Table 5), precipitation (Table 6), temperature (Table 7) and wind intensity and direction (Table 8). These tables show the max reading for each parameter and what time did it occur (approximately) as well as the average value per reading. The periods include data from daytime only (7:50 to 17:50).

Date	Max	Average
2021-01-18	0.841 kW at 12:50	**0.49 kW**
2021-01-19	0.929 kW at 11:50	0.23 kW
2021-01-20	0.549 kW at 12:25	0.10 kW
2021-01-21	0.172 kW at 10:06	0.08 kW
2021-01-22	**0.982 kW at 12:30**	0.23 kW
2021-01-23	0.156 kW at 11:25	0.03 kW
2021-01-24	0.878 kW at 13:22	0.03 kW
2021-01-25	0.211 kW at 12:30	0.03 kW
2021-01-26	0.230 kW at 11:20	0.08 kW

Table 1 – Max and average energy production by day

Date	Max	Average
2021-01-18	1.434 kW at 09:03	0.45 kW
2021-01-19	2.275 kW at 08:30	0.41 kW
2021-01-20	2.213 kW at 13:05	0.42 kW
2021-01-21	2.814 kW at 13:00	0.49 kW
2021-01-22	**4.815 kW at 12:15**	**0.89 kW**
2021-01-23	2.651 kW at 14:30	0.49 kW
2021-01-24	3.395 kW at 13:15	0.59 kW
2021-01-25	3.622 kW at 12:40	0.47 kW
2021-01-26	2.556 kW at 13:00	0.50 kW

Table 2 – Max and average energy consumption by day

Date	Max	Average
2021-01-18	**1852.9 kJ/m2 at 13:45**	**977.12** kJ/m2
2021-01-19	1758.7 kJ/m2 at 13:45	577.4 kJ/m2
2021-01-20	685.8 kJ/m2 at 14:45	268.09 kJ/m2
2021-01-21	361.8 kJ/m2 at 13:40	218.69 kJ/m2
2021-01-22	1446.3 kJ/m2 at 14:40	493.97 kJ/m2
2021-01-23	462.7 kJ/m2 at 12:40	165.55 kJ/m2
2021-01-24	743 kJ/m2 at 11:40	402.3 kJ/m2
2021-01-25	325.2 kJ/m2 at 13:45	158.78 kJ/m2
2021-01-26	376.4 kJ/m2 at 12:45	177.86 kJ/m2

Table 3 – Max and average radiation by day

Date	Max	Average
2021-01-18	**1027.8 hPa at 13:45**	**1026.64 hPa**
2021-01-19	1019.2 hPa at 17:45	1022.2 hPa
2021-01-20	1007.1 hPa at 12:45	1006.6 hPa
2021-01-21	1012.9 hPa at 17:45	1013.77 hPa
2021-01-22	1018 hPa at 17:45	1015.4 hPa
2021-01-23	1012.1 hPa at 16:40	1015.42 hPa
2021-01-24	1018.5 hPa at 12:40	1017.59 hPa
2021-01-25	1017 hPa at 17:45	1015.76 hPa
2021-01-26	1025.2 hPa at 13:45	1024.08 hPa

Table 4 – Max and average atmospheric pressure by day

Date	Max	Average
2021-01-18	99 % at 09:45	53.45 %
2021-01-19	96 % at 07:50	73.36 %
2021-01-20	97 % at 11:47	87 %
2021-01-21	98 % at 15:50	94.33 %
2021-01-22	89 % at 08:40	71.36 %
2021-01-23	98 % at 14:40	94.45 %
2021-01-24	96 % at 10:40	90.18 %
2021-01-25	99 % at 07:50	98.82 %
2021-01-26	**100 % at -**	**100 %**

Table 5 – Max and average humidity by day

Date	Max	Average
2021-01-18	0 mm at -	0 mm
2021-01-19	0 mm at -	0 mm
2021-01-20	1.9 mm at 10:47	0.58 mm
2021-01-21	1.8 mm at 15:38	0.87 mm
2021-01-22	0.2 mm at 14:40	0.10 mm
2021-01-23	**3.7 mm at 14:40**	**1.63 mm**
2021-01-24	0.6 mm at 14:45	0.10 mm
2021-01-25	1.3 mm at 16:45	0.53 mm
2021-01-26	1.9 mm at 12:45	0.80 mm

Table 6 – Max and average precipitation by day

Date	Max	Average
2021-01-18	**17.6 Cº at 16:45**	9.66 Cº
2021-01-19	13.6 Cº at 13:45	8.92 Cº
2021-01-20	15 Cº at 14:45	13.23 Cº
2021-01-21	14.7 Cº at 17:50	13.82 Cº
2021-01-22	13.6 Cº at 14:40	12.27 Cº
2021-01-23	14.6 Cº at 15:40	12.88 Cº
2021-01-24	14.3 Cº at 16:45	11.93 Cº
2021-01-25	14.7 Cº at 14:45	14.25 Cº
2021-01-26	15.6 Cº at 13:45	**15.05 Cº**

Table 7 – Max and average temperature by day

Date	Max	Average
2021-01-18	10.8 km/h (NE) at 08:45	7.04 km/h (E)
2021-01-19	23 km/h (SW) at 13:45	16.63 km/h (S)
2021-01-20	**27.4 km/h (S) at 08:45**	**21.91 km/h (SW)**
2021-01-21	21.2 km/h (SW) at 14:40	18.27 km/h (SW)
2021-01-22	24.8 km/h (W) at 15:40	18.35 km/h (W)
2021-01-23	25.6 km/h (W) at 16:40	18.11 km/h (SW)
2021-01-24	13.3 km/h (W) at 14:40	7.86 km/h (SW)
2021-01-25	19.4 km/h (W) at 7:50	16.6 km/h (W)
2021-01-26	10.4 km/h (W) at 16:45	8.83 km/h (SW)

Table 8 – Max and average wind intensity and direction by day

6. DISCUSSION

This section provides the discussion about data analysis. To better understand the impact of weather conditions on energy production, Table 1 provides the support for data analysis. From the provided data as average values, it is possible to depict that, on 2021-01-18 energy production has achieved the highest value with 0.49 kW per reading, followed by days 2021-01-19 and 2021-01-22 with 0.23 kW average per reading, and the remaining days an average of 0.1 kW or less per reading.

Table 3 presents the variation for radiation. The highest radiation on average per day was also achieved on 2021-01-18 with 977.12 kJ/m2, followed by days 2021-01-19, 2021-01-22 and 2021-01-24 with 577.4 kJ/m2, 445.3 kJ/m2 and 402.3 kJ/m2, respectably. In the remaining days, the average radiation drops below 270 kJ/m2. By comparing this data with the energy production, it is possible to depict the correlation between radiation and energy production. On 2021-01-18 it is achieved the highest values for energy production and radiation. Days 2021-01-19 and 2021-01-22 present lower energy production and radiation than day 18, but visible more than the remaining days.

Atmospheric pressure, presented in Table 3, shows irrelevant variation throughout the days included in the dataset. That suggests that atmospheric pressure does not impacts energy production.

The percentage of relative humidity is an important parameter because it is related to the amount of clouds, which decreases the levels of radiation reaching the PV. Therefore, data in Table 5 depicts that on 2021-01-18 has achieved the lowest average, around 53.45%, followed by days 2021-01-19 and 2021-01-22 with relative humidity average between 71% and 73%. The remaining days had an average percentage above 87%. By comparing this data with the energy production, it is possible to depict that the lower the humidity, the higher the energy production. Therefore, the data confirms that the relationship between parameters humidity, clouds and radiation on energy production.

Similar to the relative humidity parameter, precipitation also plays a major role in energy production due to its relationship with the existence of clouds. by analysing data in Table 6, it is possible to observe that the days recording higher average radiation are the days with less average precipitation, corresponding to days 18, 19, 22 and 24 of January 2021. The opposite behaviour can also be verified, and days recording the higher values on average for precipitation are the days with less radiation. Therefore, it is possible to conclude that precipitation impacts indirectly PV energy production because even without precipitation, the humidity causing clouds formation has an impact on production of PV energy.

On the other hand, temperature, wind intensity and direction don't seem to have a direct impact on PV production. Despite data analysis reveals some variation, has not been found a direct relationship in terms of energy production.

Regarding the relationship between energy production and consumption, on 9 days of the dataset, comparing the periods of energy production - consumption only on the first day the production was higher than the consumption, showing that only in perfect scenarios the PV panels could cover the consumption.

Another relevant insight is the max energy generated is not on the same day as the max average energy production. The max energy production has four days where the production was higher than 800 kW, days 18, 19, 22 and 24 of January 2021. Those days are the ones with higher radiation, less precipitation and three of them, less humidity. By comparing the energy production behaviour on the Fig. 4, Fig. 5 and Fig. 6 one can clearly see that how different weather conditions change the energy production throughout the day. On 24 (Fig. 4) the energy production average is lower than days 22 and 18, and that's visible on the line close to the bottom of the chart. Nevertheless, there are several spikes with short duration when there is no precipitation. That suggests that the weather conditions improved on small periods, increasing energy production. However, since the data only shows the average data on weather conditions, that cannot be proven. Even though, comparing charts of days 22 (Fig. 5) and 18 (Fig. 6) it's possible to clearly visualize how with lower humidity and no precipitation the energy production is much more constant, without ups and downs, increasing the amount of kW production, visible through the average. To increase the humidity impact on PV production on day 18 at 9:45 the humidity increases from 67% to 99% decreasing the current production from 0.43 kW to 0.22 kW, having it increased once the humidity drops again. This high humidity spike can be justified by the evaporation of morning frost when exposed to the first daylight radiation, causing a small period of fog, blocking the radiation on the PV panels. This weather phenomenon in winter is common at Coimbra, Portugal.

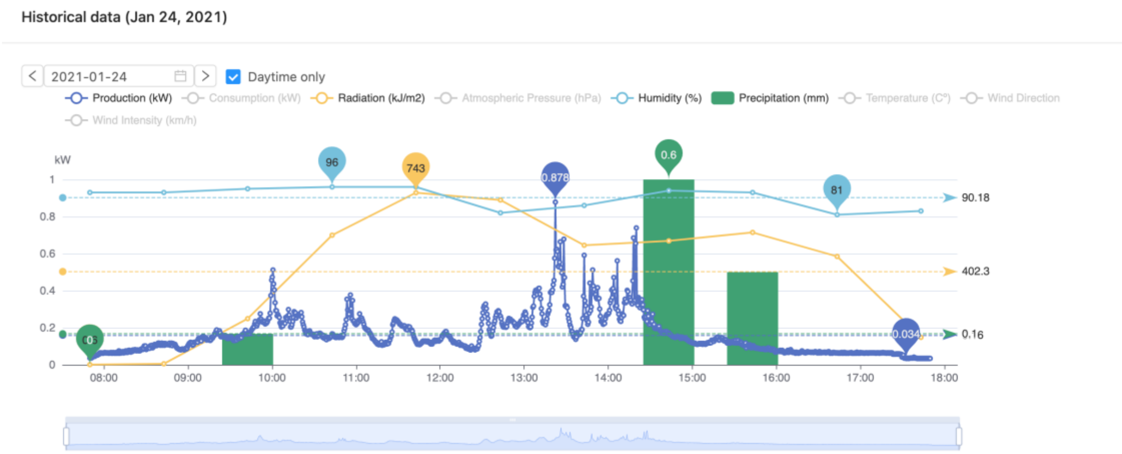

Figure 4 – Readings on 2021-01-24 of energy production, radiation, humidity and precipitation

Figure 5 – Readings on 2021-01-22 of energy production, radiation, humidity and precipitation

Figure 6 – Readings on 2021-01-18 of energy production, radiation, humidity and precipitation

7. Conclusion

This work departs from the existing literature on the subject of residence solar energy harvesting and proposes a scalable architecture to support data analysis on PV panels efficiency in order to understand how weather conditions are impacting energy production. This architecture is able to perform real-time data analysis of the meteorologic impact on residential solar energy harvesting as an important approach to understand the efficiency of PV panels. The analytic component also fixes reading errors in terms of produced and consumed energy. Its implementation was important to understand how weather impacted PV energy production. It is possible to conclude that radiation, humidity and (indirectly) precipitation are the most relevant parameters impacting the production of energy from PV. The sun radiation raises as the obvious most important factor that contributes to generating energy from PV panels. Likewise, humidity and precipitation are related to cloud presence and represent the important factors causing the reduction of the levels of radiation reaching the PV panels. In this dataset, the temperature, atmospheric pressure, wind direction and intensity don't seem to have a relevant impact on energy generation.

Regarding the limitations and improvements, this study was supported by weather data. They were synthesized by hour on stations near the home where the PV panels were located. That caused a limitation when analysing occurrences on a scale below one hour. In order to improve future analysis and provide real-time readings, the weather condition station should be installed on the same roof as the PV panel. Another limitation of this analysis was the short period of time included in the dataset. Nine days were analysed on winter, where only one day provided the perfect conditions for sun's energy harvesting, while along seven days it was raining. In the case the dataset has included all seasons, probably it would be possible to extend this analysis to different weather conditions and for instance, try to understand how high temperatures may affect the PV efficiency. Moreover, it will be possible to know how many days in a year the PV production is able to maintain a higher level of consumption in order to help to understand how sustainability can be achieved. Future work can explore and extend the proposed architecture with a machine learning model able to predict the level of energy production.

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REFERENCES

[1]G. de Oliveira e Silva and P. Hendrick, “Photovoltaic self-sufficiency of belgian households using lithium-ion batteries, and its impact on the grid,” Applied Energy, vol. 195, pp. 786 – 799, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261917303495

[2]O. W. in Data. (2019) Renewable energy generation. [Online]. Available: https://ourworldindata.org/renewable-energy#renewable-energy-generation

[3]——. (2019) Renewable energy generation. [Online]. Available: https://ourworldindata.org/renewable-energy#solar-energy

[4]S. DAO. (2017) Why solar? the advantages of pv solar energy compared to the other renewables. [Online]. Available: https://medium.com/@solar.dao/why-solar-theadvantages-of-pv-solar-energy-compared-to-the-other-renewables-1664f82ba9fe

[5]Energywise. (2020) Types of renewable energy. [Online]. Available: https://www.edfenergy.com/for-home/energywise/renewable-energy-sources

[6]S. Ghazi and K. Ip, “The effect of weather conditions on the efficiency of pv panels in the southeast of uk,” Renewable Energy, vol. 69, pp. 50 – 59, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S096014811400161X

[7]A. Ibrahim et al., “Effect of shadow and dust on the performance of silicon solar cell,” Journal of Basic and applied scientific research, vol. 1, no. 3, pp. 222–230, 2011.

[8]S. E. Bibri and J. Krogstie, “On the social shaping dimensions of smart sustainable cities: A study in science, technology, and society,” Sustainable Cities and Society, vol. 29, pp. 219 – 246, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2210670716305881

[9](2013) Sungard, big data — challenges and opportunities for the energy industry, 2013. [Online]. Available: https://www.sungard.com/media/fs/energy/resources/white-papers/Big-Data-Challenges-Opportunities-Energy-Industry.ashx

[10]R. Conceição, H. G. Silva, J. Mirão, M. Gostein, L. Fialho, L. Narvarte, and M. Collares-Pereira, “Saharan dust transport to europe and its impact on photovoltaic performance: A case study of soiling in portugal,” Solar Energy, vol. 160, pp. 94 – 102, 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0038092X17310526

[11]B. Guo, W. Javed, B. W. Figgis, and T. Mirza, “Effect of dust and weather conditions on photovoltaic performance in doha, qatar,” in 2015 First Workshop on Smart Grid and Renewable Energy (SGRE), 2015, pp. 1–6.

[12]A. C. Francisco, H. Ewbank, R. Romano, and S. Roveda, “Influência de parâmetros meteorológicos na geração de energia em painéis fotovoltaicos: um caso de estudo do smart campus facens, sp, brasil,” urbe. Revista Brasileira de Gestão Urbana, vol. 11, 01 2019.

[13]T. Hu, M. Zheng, J. Tan, L. Zhu, and W. Miao, “Intelligent photovoltaic monitoring based on sola irradiance big data and wireless sensor networks,” Ad Hoc Networks, vol. 35, pp. 127–136, Dec. 2015. [Online]. Available: https://doi.org/10.1016/j.adhoc.2015.07.004

[14]S. E. Bibri, “The IoT for smart sustainable cities of the future: An analytical framework for sensor-based big data applications for environmental sustainability,” Sustainable Cities and Society, vol. 38, pp. 230–253, Apr. 2018. [Online]. Available: https://doi.org/10.1016/j.scs.2017.12.034

[15]A. Triki-Lahiani, A. B.-B. Abdelghani, and I. Slama-Belkhodja, “Fault detection and monitoring systems for photovoltaic installations: A review,” Renewable and Sustainable Energy Reviews, vol. 82, pp. 2680–2692, Feb. 2018. [Online]. Available: https://doi.org/10.1016/j.rser.2017.09.101

[16]C. Zedak, A. Lekbich, A. Belfqih, J. Boukherouaa, T. Haidi, and F. E. Mariami, “A proposed secure remote data acquisition architecture of photovoltaic systems based on the internet of things,” in 2018 6th International Conference on Multimedia Computing and Systems (ICMCS). IEEE, May 2018. [Online]. Available: https://doi.org/10.1109/icmcs.2018.8525902

[17]G. de Freitas Viscondi and S. N. Alves-Souza, “A systematic literature review on big data for solar photovoltaic electricity generation forecasting,” Sustainable Energy Technologies and Assessments, vol. 31, pp. 54–63, Feb. 2019. [Online]. Available: https://doi.org/10.1016/j.seta.2018.11.008

[18]G. Almonacid-Olleros, G. Almonacid, J. I. Fernandez-Carrasco, M. Espinilla- Estevez, and J. Medina-Quero, “A new architecture based on IoT and machine learning

paradigms in photovoltaic systems to nowcast output energy," Sensors, vol. 20, no. 15, p. 4224, Jul. 2020. [Online]. Available: https://doi.org/10.3390/s20154224

[19]M. Vestenicky, S. Matuska, R. Hudec, and P. Kamencay, "Sensor network proposal based on IoT for a prediction system of the power output from photovoltaic panels," in 2018 28th International Conference Radioelektronika (RADIOELEKTRONIKA). IEEE, Apr. 2018. [Online]. Available: https://doi.org/10.1109/radioelek.2018.8376390

[20]A. Walch, R. Castello, N. Mohajeri, and J.-L. Scartezzini, "Big data mining for the estimation of hourly rooftop photovoltaic potential and its uncertainty," Applied Energy, vol. 262, p. 114404, Mar. 2020. [Online]. Available: https://doi.org/10.1016/j.apenergy.2019.114404

[21]V. Marinakis, H. Doukas, J. Tsapelas, S. Mouzakitis, Á. Sicilia, L. Madrazo, and S. Sgouridis, "From big data to smart energy services: An application for intelligent energy management," Future Generation Computer Systems, vol. 110, pp. 572–586, Sep. 2020. [Online]. Available: https://doi.org/10.1016/j.future.2018.04.062

[22]Energy hive. [Online]. Available: http://www.energyhive.com/

[23]Energy hive api. [Online]. Available: https://energyhiveapi.docs.apiary.io

[24]Instituto português do mar e da atmosfera. [Online]. Available: http://www.ipma.pt/pt/index.html

[25]Instituto português do mar e da atmosfera api. [Online]. Available: https://api.ipma.pt/

[26]Geojson viewer & validator. [Online]. Available: https://geojsonlint.com/