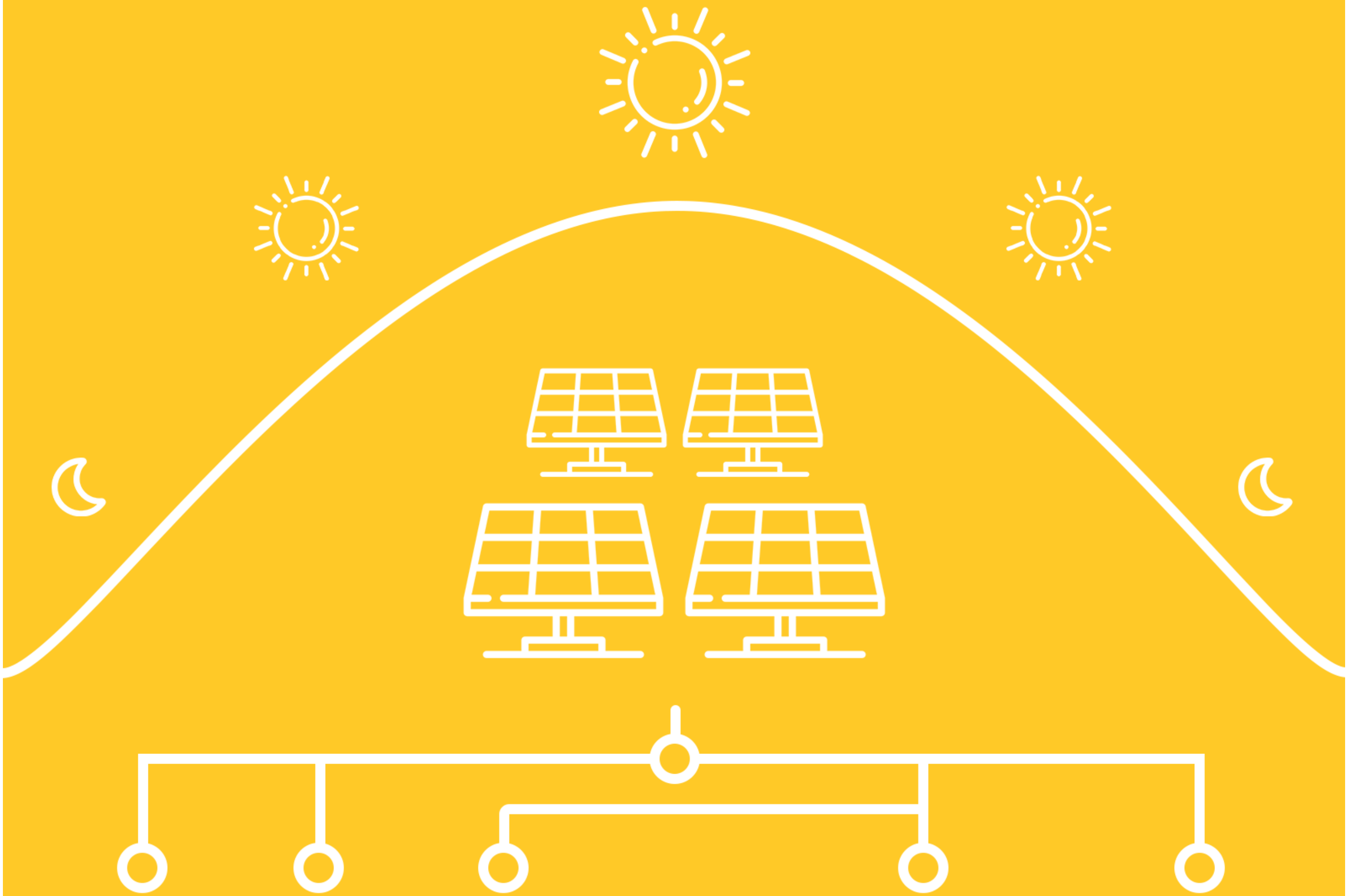

Artificial Intelligence for the green transition: predictive maintenance applied to photovoltaic plants

A success case developed with SAIDEA Srl and Eurac Research

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Sum-up

Client: SAIDEA Srl
Application field: renewable energy, predictive maintenance
Expertise: Artificial Intelligence / Machine Learning

Client company: SAIDEA

The client company of the current case study is **SAIDEA Srl**, a business that offers software development and ICT-outsourcing services. SAIDEA is a partner of the project "*EU FESR1128 PV 4.0 - Use of Industry 4.0 and Internet of Things logic in the photovoltaic sector*", coordinated by the Institute for Renewable Energy at Eurac Research, whose aim is optimizing maintenance activities on plants and photovoltaic parks.

As part of the project, SAIDEA needed to appoint an external supplier for the development and integration of predictive maintenance models based on Artificial Intelligence; **U-Hopper was chosen thanks to its recognized excellence in the field of predictive modeling.**

Challenge

The photovoltaic sector is playing a main role in the current **energy transition path,** which is occurring at national, European and global level. One of the main aspects that has triggered the adoption of large-scale solar energy plants is undoubtedly the **cost reduction of initial investments** (costs of cell panels and inverters, above all).

At the same time, though, **increased competition** has led to a **drop in revenue margins for operations and maintenance (O&M) engineers.** Indeed, maintenance activities in a photovoltaic plant **involve high costs and require time:** the higher the number of failures or breakdowns, the more challenging become maintenance routine operations.

Being able to **prevent failures and breakdowns,** such as an unexpected drop of energy production for an extended period of time, allows **prompt intervention.** As a result, technical **downtimes can be reduced,** while associated **costs** (i.e. loss of earnings) **can be minimized.**

This *modus operandi* is called **predictive maintenance** and it is today a fundamental pillar of the Industry 4.0 paradigm; it is based on Internet-of-Things technologies for gathering data generated by high-tech devices, and Artificial Intelligence algorithms for processing that data and distilling valuable insights. The global predictive maintenance **market** is expected to **grow up to $12.3** billion by 2025 (source: Capgemini).

Given the high level of competitiveness in the O&M sector, the opportunity of relying on predictive maintenance tools and services makes the difference between growing on the market and fighting for survival. Being aware of the advantages that can be gained thanks to these tools, **SAIDEA has appointed U-Hopper to create a series of methods and models** - based on Artificial Intelligence - **aimed at autonomously predicting anomalies in photovoltaic plants,** and communicate them promptly to the maintenance team in order to avoid breakdowns.

"To enhance the Decision Support System of our Enterprise Management System (EMS) Antares, we wanted to create an algorithm for predictive analysis of the plant. Following our needs and specifications, U-Hopper developed an effective model for predictive maintenance, which can be integrated into Antares and makes our EMS more comprehensive."

Filippo Segata

Project Manager

Solution

The solution developed by our team consists of a **platform,** integrable with SAIDEA's Enterprise Management System (EMS) called ***Antares***, **collecting and analyzing data generated by IoT sensors installed on photovoltaic plants** with the aim of monitoring their operation and notifying any anomaly.

The **algorithm at the heart** of the platform is **based on a Machine Learning model,** whose training has been run on a rich dataset, provided by Eurac Research, containing more than four years of historical data: a total of 2.5 million measurements taken at 10-minute intervals, from 2014 to 2018.

The process for developing the solution was divided into **five phases:**

1. Dataset analysis

by making use of statistics and data representations, we identified a few dozen examples of both atypical and normal behaviors; to allow the ML algorithm to differentiate between these two status categories, it was also necessary to identify the relevant and functional information to feed the algorithm with;

2. Data annotation

given that initial data was not associated with *labels* distinguishing the case of "*atypical*" from the case of "*normal behavior*", this second phase consisted in a manual annotation of the dataset; the aim was to identify the rules for classifying the two cases on the basis of statistical analysis;

3. Development of the AI model and its training

we created a Machine Learning (ML) model that could autonomously detect possible failures by following the rules defined in Phase 2;

4. Software engineering

we engineered the ML model and built the necessary APIs to facilitate its integration with the existing platform;

5. Integrations and implementation

we finally integrated the solution with the SAIDEA platform as well as the software for data acquisition from the plants, and we implemented it on the cloud.

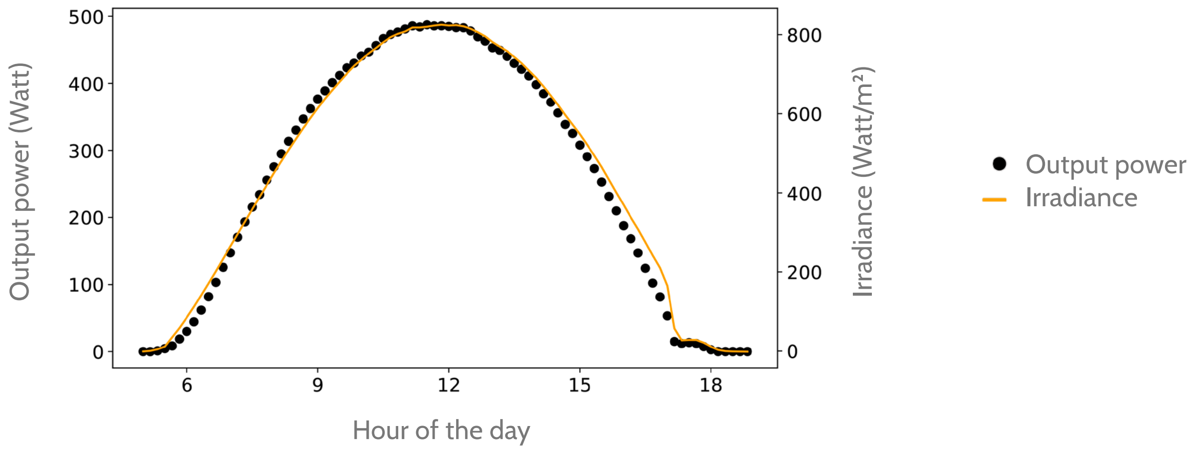
We will now focus on the first three phases, characterized by a strong **data science component.**

Phase 1. Dataset analysis

The dataset at disposal consisted of an enormous amount of **data referring to the health status of several inverters**, i.e. devices on photovoltaic panels that convert solar energy from direct into alternating current.

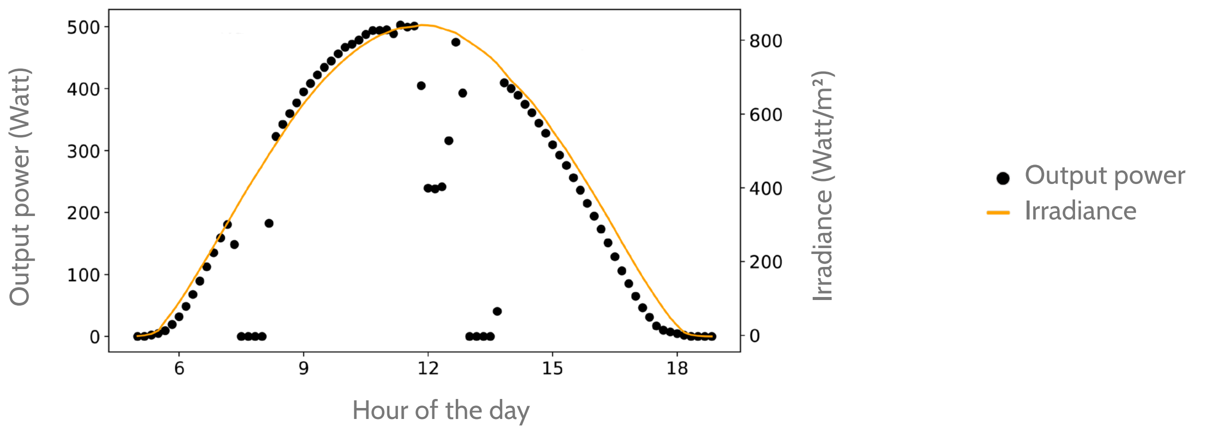
However, since the dataset was not annotated[2], the initial analysis needed to be based on the observation of graphs such as the one shown below which represents an ideal environment for a photovoltaic plant: a sunny day with no clouds.

In principle, the greater the radiation solar panels receive from the Sun, the greater the energy they should produce. In this case, we can observe that the current produced by the inverter (represented by black dots) faithfully follows the orange curve (which instead refers to the irradiance, i.e. the energy that solar panels receive from the Sun), therefore indicating the correct functioning of the plant.



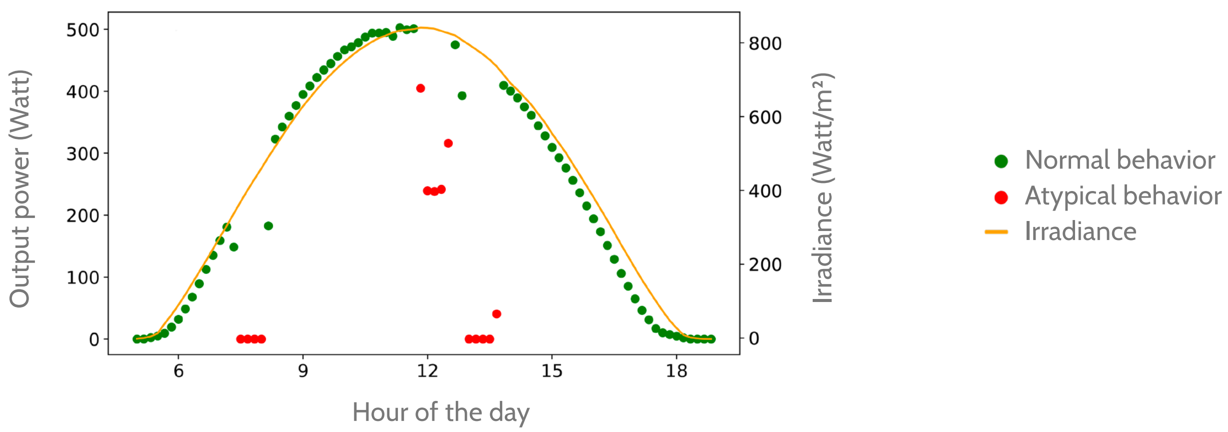
[2] data does not entail information about its meaning - i.e. data does not provide any hints whether it refers to a normal or atypical situation. Learn more by reading this article on our blog.

The graph below represents yet another example of a sunny day without clouds - and one would expect the same results in terms of plant functioning. However, we can observe a few anomalies, i.e. a dozen of measurements referring to the power generated by the inverters (black dots) differ significantly from the irradiance curve.



Phase 2. Data annotation

Taking into account the analysis and considerations gathered during Phase 1, the team created a series of **heuristics** which, if combined with each other, **could shed light on the health status of each inverter contained in the dataset.** The result of this operation is shown in the next figure.
In this way, we obtained an annotated dataset and laid the groundwork for creating a Machine Learning model that could autonomously classify the health rating status of each inverter.



Why should we train a ML model to recognize the health status of an inverter, while we have been able to do it manually by creating a set of ad-hoc rules?

The creation of heuristics is the result of a "combined analysis" **that compares data generated by an inverter with data generated by other inverters,** in order to identify any atypical behavior. In addition, it is based on a **historical series** of observations which allows, for example, to identify downtimes.

A Machine Learning model, instead, is designed to analyze **continuous flows of data relating to the health status of an inverter;** in other words, once the ML model learns from the heuristics how to classify certain situations, it is able to analyse **autonomously** and in **real-time each single inverter,** without requiring a comparison with the others or waiting for some time to ensure that a certain measurement actually refers to a real downtime; in fact, a ML model is able to detect straightaway any sign of upcoming atypical behaviors.

On the one hand, this makes a ML model a quite **flexible tool**, since it can be used in systems relying on just one single inverter (i.e. where it is impossible to compare its performance against that one of other inverters). On the other hand, it allows **timely maintenance activities,** since there is no need to take multiple and consecutive measurements to establish whether a given data represents an atypical behaviour or not.

Phase 3. Development of the AI model and its training

In principle, a Machine Learning model is a tool which, upon receiving an *input*, returns an *output* with predefined characteristics. In this specific case, the *input* is composed by a list of features **regarding the weather conditions and the inverter situation at a given time,** while the *output* is the **probability that this inverter is not working correctly:** if this probability exceeds a certain threshold, the inverter's behavior is classified as atypical (and therefore the inverter will require inspection / maintenance).

The internal structure of the ML model depends on the type of the chosen algorithm. For SAIDEA, we decided to use the so-called **Neural Networks,** which are currently considered the state of the art in the field of Machine Learning.

In order to accurately calculate this probability, it was necessary to properly **configure and calibrate** the structure of the Neural Network; in other words we proceeded to **train the model,** whereby each record of the annotated dataset was processed to obtain the corresponding probability that the system was facing an atypical behaviour.

To achieve this **all labels of the annotated dataset (normal / atypical behavior) were converted into a numerical format, i.e. a probability,** so that they could be processed by the Neural Network: when the behavior of an inverter was labelled as *normal*, a probability of 0 was assigned, while those corresponding to *atypical behaviors* were assigned with a probability of 1. These probabilities represent the *ground truth*, i.e. the correct probability that each inverter is facing a malfunction at a precise moment in time.

As a second step, **records deprived of the *ground truth*** - i.e. containing just the *weather conditions* and *electrical variables* - **were given as inputs to the Neural Network.** At this point, the ground truth was compared to the model output probability. On the basis of the correctness (or incorrectness) of predicted results, the Neural Network parameters were "smartly" updated, with the aim of replicating them as close as possible to the probabilities obtained through the heuristics.

This procedure is repeated a few hundreds of times, for each record in the dataset, until **predictions stabilize.** The final result is a **trained ML model,** which we can describe as a tool that, based on the experience gained during the training process, is **able to recognize the occurrence of atypical behaviours in the system with a high degree of reliability.** This model was finally integrated into the existing Antares platform, to allow O&M operators to arrange timely maintenance interventions on the plant.

Conclusion

Starting from 2020, in conjunction with the outbreak of the Covid-19 pandemic, the **energy transition already well-underway started showing signs of acceleration.** This happened partly as a consequence of political strategy changes in some countries, as in the U.S.A., and partly due to several constraints imposed by the European Commission on the Next Generation EU: **at least 37% of total funds addressed to each European country will have to be allocated to energy transition projects.**

According to the International Energy Agency, **renewable sources should cover the global energy demand for at least 90% by 2050.** Moreover, short- and medium-term objectives have been set by the European Commission, and are required to be met by 2030; Italy, for example, is planning to install around 70 GW of renewable energy capacity by 2030 in order to reach its objective of producing 32% of total energy from renewable sources by the end of that year. Furthermore, the ambition is to **increase energy efficiency: predictive maintenance could contribute to the achievement of this objective,** since it allows acting promptly in case of anomalies and eventually replacing components whose energy efficiency has fallen below a certain threshold.

The system developed by U-Hopper allowed SAIDEA to detect atypical behavior of inverters, and to suggest maintenance activities before a major breakdown occurs. From the acquisition of data generated by IoT-sensors to the prediction of the health status for each single inverter, the solution is a **360° automated tool,** which **can be easily implemented in other photovoltaic plants,** even including domestic systems, and therefore helping foster the energy transition at a more widespread level.

This solution has been developed in the context of the project "EU FESR1128 PV 4.0 - Use of Industry 4.0 and Internet of Things logic in the photovoltaic sector", *which has received funding from the* Fondo Europeo di Sviluppo Regionale (FESR) *under grant agreement* Asse 1 "Ricerca e Innovazione".

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