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## A USE OF ARTIFICIAL INTELLIGENCE FOR IMPROVING PV ARRAY PERFORMANCE (EMPIRICAL APPROACH)

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**ABSTRACT:** This paper reflects research to design an Artificial Intelligence (AI) platform for controlling the cooling of Si-based PV modules in commercial solar arrays. The AI technology used for this purpose is based on Adaptive Multi-Agent Systems (AMAS). The information fed to the control platform combines locally-collected and exogenous sources, such as grid data and weather forecasts. Elaborating on an existing PV modules cooling equipment driven by traditional industrial algorithms, the AI control platform substantially improves the use of information to make or recommend operational decisions. Thanks to AMAS techniques, the platform can anticipate events by analysing a broader range of information, thereby improving the economics of PV modules cooling. Introducing Artificial Intelligence in this and related areas of solar plant operations has the potential of further improving resource utilization and maintenance efficiency.

**Keywords:** Artificial Intelligence, Multi-agent systems, Photovoltaics, PV Cooling

### 1 INTRODUCTION

This work derives from year-long software development efforts to precisely control cooling/cleaning equipment fitted to regular commercial Si-based PV arrays situated in temperate and tropical climates [1,2]. The software controls the equipment with the aim to maximise the power output of entire PV systems based on a possibly very limited water resource. In this paper, we examine the cooling of the PV arrays based exclusively on rainwater collected at site.

Using Artificial Intelligence techniques for taking optimal decisions about when to automatically cool PV modules avoids creating *ad hoc* models depending on PV types or their geographical location. Learning abilities have then to be integrated in such a decision support tool, in order to identify optimal production conditions for these panels.

Interesting results were already possible with classical industrial controller algorithms, but the addition of AI to the software aims to attain the most efficient and cost-effective cooling approach.

### 2 MEASUREMENTS / SOFTWARE APPROACHES

Both traditional algorithms and Artificial Intelligence may be used to control industrial processes. The aim of this research is to compare the performance of the two approaches, in terms of cooling effect and/or addition power output from a PV array. Cooling PV panels produces a significant increase in power (primarily in voltage), almost directly proportional to the cooling intensity [3]. This increase is the translation into practice of the PV modules thermal coefficient, as specified in manufacturer datasheets.

To measure the performance of cooling software, we compare the power output differential of the two PV fields and the quantity of water, expressed in % [1]. The PV Performance Ratio (PR) was not used here, because the effectiveness of a rainwater-based cooling system relates to weather variables other than solar irradiation (seasonal precipitations, humidity, wind characteristics).



**Figure 1:** The demonstrator is located on the farm in Saint- Marcel . The photovoltaic plant has a power of 777 kWp for a surface of 7000 m<sup>2</sup> .

In order to be able to representatively make these calculations and to statistically analyze the determinants of any output gain, it is necessary to use twin solar (Fig.1) generators instrumented with relevant measurement instruments (separate electric meters at the grid injection point, multiple sensors for PV temperature, wetting, irradiance, weather parameters, etc.).

The initial research uses a twin solar system (specially built in 2011 to offer the possibility of real-time comparison). The installation consists of a steel roof with mounting systems and PV modules with two identical solar generators of which one only is equipped with rainwater-cooling. In 2015 a second twin generator of 250 kWh was equipped in a region benefitting from different weather patterns (Figure 2).



**Figure 2:** Twin generator of 250 kWh.

The same industrial control software was used on all comparators [1]. This software was based on imperative programming and traditional optimization models.

We compare the outcome of this software with an alternative optimisation approach offered by an Artificial Intelligence technique (Fig.3): called Adaptive Multi-Agent Systems (AMAS). The AMAS approach has been successfully used in many domains of applications for controlling, in a real-time manner, systems such as car heat engines [4], bioprocesses [5], videogames [6], robots [7] or ambient systems [8].



**Figure 3:** The development industrial control software with an optimisation approach offered by AMAS.

### 3 INDUSTRIAL ALGORITHMS vs. ARTIFICIAL INTELLIGENCE

#### 3.1 Industrial Algorithms

The algorithmic approach showed an ability to calculate the cooling opportunities, i.e. the moments when it is economically useful to cool the solar field. This was based on static models that are predetermined by engineers.

The static rules are based on logical deductions and previous man-made observation of a prototype system, which are then implemented in imperative programming within a fixed core program. This is generally efficient but this kind of solution is unable to evolve by itself. If an unpredicted situation appears, algorithmic systems will end up with a cooling configuration as appropriate as it can, according to the logic insufflated initially (i.e. not necessarily an optimum configuration).

There are two areas where the algorithms, in spite of 5 years of R&D, failed to produce excellence:

1. The first area is related to errors in assessing data: a traditional industrial algorithm is fixed, it cannot be adjusted frequently (and by definition it does not adjust by itself). It will assess data based on hard-coded formula calculations. On the contrary, the AI software adjusts to find optimal ways to use the data.

2. The second area is related to cooling strategies: testing and choosing among different cooling approaches (for example continuous water sprinkling) vs. a traditional industrial algorithm is fixed, it cannot be adjusted frequently (and by definition it does not adjust itself).

#### 3.2 Artificial Intelligence

The AI technology used for this control platform is based on Multi-Agent Systems (MAS) and more specifically Adaptive ones (AMAS). A Multi-Agent System is a system composed of a set of interacting agents [9]. An agent is an autonomous entity which evolves in an environment from which it has only a local and incomplete perception. An agent possesses skills that enable it to carry on a behaviour which is generally dictated by a local objective [12].

MAS are a recognized paradigm to deal with complex problems and the AMAS approach, used here, is focused on the cooperative behaviour of the agents

composing a MAS. The functional adequacy theorem ensures that the global function performed by any kind of system is the expected one if all its parts interact in a cooperative way [10]. Cooperation, as intended in AMAS, is not only a mere resource or task sharing, but truly a behavioural guideline. This cooperation is considered in a proscriptive way, implying that agents have to avoid or solve any Non Cooperative Situation (or NCS) encountered. Therefore, an agent is considered as being cooperative if it understands perceived signals without ambiguity, if received information is useful for its reasoning and if its reasoning leads to useful actions toward other agents. Once an agent detects a NCS it takes actions for coming back to a cooperative state by changing its internal state (tuning) or its relationships with others (reorganization) or by creating new agents or removing itself (evolution). These changes therefore make the structure of the global system self-organize and the global function performed by this system emerges from the interactions between agents. This AMAS is thus able to react to changes coming from the environment and therefore becomes (self-) adaptive.

The AMAS involved in the control platform performs a contextual learning by identifying all the specific environmental conditions (temperature, light, sunshine, wind direction, hygrometry...) which may influence the functioning of the panels. These environmental conditions are embedded into specific agents, called context agents, which are dynamically created and self-adapt on-the-fly. A context agent is composed of three parts: a context, an action and an appreciation. The context is a set of validity ranges – one per percent – that is used by the agent to determine if the context it represents is valid (when all the ranges are valid). The action is the modification of the environment proposed by the agent when it considers itself valid. The appreciation represents the estimation the agent has about the effects of the action on the environment; this appreciation is constantly adjusted by the agent depending on what it perceives in its environment [11].

### 4 RESULTS AND DISCUSSION

Traditional industrial algorithms operating the cooling equipment over long periods were able to increase by around 6 percent the power output of the PV array. Power output gains on each of the twin solar generators (full-year 2013 on Comparator 1 and 6 months in 2015H2 on Comparator 2) were respectively 6.24% and 5.5%. However, operation of the cooling system was less than perfect, as shown by our statistics on the first 6 months of the second twin comparator:

- Days in the analysis period: 184
- Days when cooling system was operated: 106
- Equivalent full days of non-performance due to errors: 27
- Days when cooling system was not or sub-optimally operated: 78

It is estimated that AI techniques will enable to gain more than 20% additional productivity over the cooling equipment's performance using traditional industrial algorithms.

Difficulty when designing models to control systems resides in the fact that these models depend on the situation. Using an AMAS enables to ignore these situations, a learning phase during a period of some months enables to calibrate this control system before

actually using it in production phase. The learning is automatically done, in real-time, customized and able to adapt to situations that were not previously encountered by the control system.

#### 4.1 Principle and Architecture of the AI System

The core of the AI system is based on learning the maximum power of photovoltaic panels. For this, a multi-agent of context agents has to find the maximum power produced by a set of panels (Fig.4) (typically one or more strings of PV panels, but to simplify things we will call each of these agents a "panel agent"). This optimality depends on environmental conditions (temperature, wind, irradiance...) and endogenous conditions (when internal temperature and cleanliness of panels are optimal). Feedbacks are required to make the system learn and the variation in photovoltaic production plays this role: when it increases, the decision is considered as good; otherwise, context agents reconsider their decision by modifying their validity range.

Each set of panel is "agentified" in the AI system and these panel agents use the multi-agent context system in order to know the maximum power they are able to obtain under the current environmental conditions. Thus the criticality of an agent panel corresponds to the difference between this maximum power value and the actual power.

The second important software component is the scheduler whose role is to decide which action to perform. This scheduler receives the criticality of the available water (actual rainwater collected and the rain expected by the meteorological forecast) and all the criticalities of the panel agents. According to these criticalities, the scheduler decides or not to cool (or clean up) a given set of panels.

The initial MAS calibration is obtained from two data sets: firstly, the system learns the behavior of the currently used industrial tool, and secondly, this behavior is tuned using real historical data obtained on the target site. When installed on the site, the AI system learns from real time data.

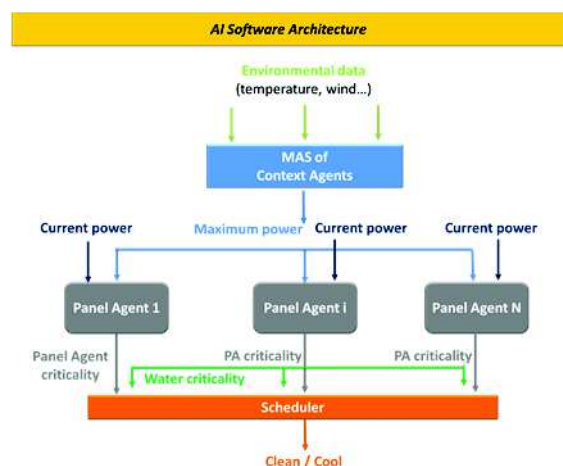


Figure 4: AI software architecture

The standard MAS context is currently used in several applications (singularity detections in a Building Management System [11], heat engine calibration [4], robotic learning from demonstration [8], ambient systems [7], bioprocess control [5]) and is currently in the integration phase for large-scale agricultural project.



Figure 5: AI compared to traditional algorithms.

The figure above (Fig.5) shows that substantial improvements are possible using AI compared to traditional algorithms. The gain of power output using traditional algorithms is shown in red. Additional gains from AI are expected from reducing errors and improving the cooling strategies.

#### 5 FUTURE WORK AND CONCLUSIONS

This work derives from year-long software development efforts to precisely control cooling/cleaning equipment fitted to regular commercial Si-based PV arrays situated in temperate and tropical climates. Interesting results were already possible with classical industrial controller algorithms based on logical deductions. It is expected that a control system based on an AMAS (multi-agent system with adaptive abilities) will enable to cool and clean panels in a more effective manner than more classical approach.

The AMAS approach will be applied to additional areas of PV O&M. Once this control system is deployed on test sites, it is also expected that this AMAS will enable to be used for signaling problems that may occur during the functioning of the set of panels such as failures.

A new test bench is being built (2016H1) on the premises of the University Paul Sabatier in Toulouse, France, as part of the University's neOCampus project.

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