# Power Optimization by Cooling Photovoltaic Plants as a Dynamic Self-adaptive Regulation Problem

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Abstract: This paper shows an approach to control cooling devices for photovoltaic plants in order to optimize the energy production thanks to a limited reserve of harvested rainwater. This is a complex problem, considering the dynamic environment and the interdependence of the parameters, such as the weather data and the state of the photovoltaic panels. Our claim is to design a system composed of autonomous components cooperating in order to obtain an emergent efficient control.

## 1 COOLING PHOTOVOLTAIC PANELS

Solar energy is a very promising solution for energy production since the sun provides an unlimited source of energy. Many studies have been performed to improve the technology for converting the solar energy into electrical energy (Lewis, 2016). A photovoltaic (PV) plant consists in a large number of photovoltaic panels connected in series, producing energy according to the power received from the sun or irradiance. Studies (Akbarzadeh and Wadowski, 1996) (Skoplaki and Palyvos, 2009) showed that the ability of a PV panel depends strongly of its temperature, with a voltage decreasing by one volt per half degree (Shan et al., 2014). So, when the perceived irradiation is very high, the photovoltaic panel heats and produces less energy than with a lower irradiation.

In order to increase the panels efficiency and ensure them a longer life, researchers converge toward cooling and cleaning solutions (Sargunanathan et al., 2016). (Alami, 2014), (Chandrasekar and Senthilkumar, 2015), (Ebrahimi et al., 2015), (Bahaidarah et al., 2016), (Nižetić et al., 2016), (Sargunanathan et al., 2016). These solutions involve an intelligent use of water reserves in order to be efficient. Adopting an automatic regulation reinforces the importance of a right balance between using water supplies to improve current energy production and saving the water reserves in order to not miss them later. This equilibrium depends on several interdependent data: current water level and current energy production, but also current meteorological conditions, weather forecasts, statistics about past meteorological conditions, etc. Consequently the regulation process for cleaning and cooling panels must answer several questions: What amount of water reserve has to be used for the current day? How to distribute it during the day? How the estimation of water reserve during the next days is influenced by the weather forecast?

Considering the non-linearity of this regulation problem, the imprecision of the forecast, the possible changes (addition or removal of sensors), or the degradation of the photovoltaic panels, these choices become a complex problem. Using a system able to perform a learning process for changing its own behaviour at runtime becomes therefore inevitable.

The objective of the work described in this paper is to propose such an intelligent strategy. A multi-agent system, named *AmaSun*, is designed for optimizing the energy production of a photovoltaic plant considering a limited amount of water. The paper is structured as follows: sections 2 and 3 present the context of this work, section 4 describes the system designed to regulate the cooling of PV panels, and section 5 evaluates some aspects of this system before concluding on prospects in section 6.

## 2 LIMITATIONS OF STANDARD CONTROL PROCESSES

Controlling systems is a generic problem that can be expressed as finding which modifications are needed



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to be applied on the inputs in order to obtain the desired effects on the ouputs. The most well-known types of control are perfomed by PID, adaptive or intelligent controllers.

The widely used Proportional-Integral-Derivative (PID) controller computes three terms related to the error between the current and the desired state of the controlled system, from which it deduces the next action to apply (Åström and Hägglund, 2001). PID controllers are not efficient with complex systems, due to their difficulties to handle several inputs and outputs and to deal with non-linearity.

Model-based approaches like Model Predictive Control (MPC) (Nikolaou, 2001) use a model able to forecast the behaviour of the system in order to find the optimal control scheme. These approaches handle several inputs but are limited by the mathematical models they use. The Dual Control Theory uses two types of commands: the actual controls that drive the system to the desired state, and probes to observe the system reactions and refine the controllers knowledge (Feldbaum, 1961). The concepts behind this approach are interesting but a heavy instantiation work is still required for a system such as a PV plant.

Intelligent control regroups approaches that use Artificial Intelligence methods to enhance existing controllers among which neural networks (Hamm et al., 2002), fuzzy logic (Lee, 1990), expert systems (Stengel and Ryan, 1991) and Bayesian controllers (Del Castillo, 2007). These methods can be easily combined but they unfortunately require a fine grain description of the system to control, which is inappropriate for the photovoltaic plant because it evolves during time.

## 3 ADAPTIVE MULTI-AGENT SYSTEMS

Considering the dynamics to take into account during the regulation: inaccuracy of the weather forecasts, possible changes in sensors (addition/removal), or degradation of the PV panels, a system able to perform a learning process in order to change its own behaviour at runtime is then required. Some heuristic learning algorithms, as the genetic algorithms, allow to take account of these constraints but require a large number of iterations to obtain a relevant behaviour. Therefore they are not relevant for our objective of a quick learning. On the other hand, because of the evolution of the environment, a dynamic learning is required, making the offline learning process not relevant.

Multi-agent systems represent an appropriate technology to deal with the dynamic and complex nature of such a problem (Jennings and Bussmann, 2003), and considering the fact that self-adaptation is a key to solve it, we focused our study on Adaptive Multi-Agent Systems (AMAS) (Gleizes, 2011). The AMAS approach enables to design a system to solve a complex problem through a bottom-up approach: local functions of the agents composing the system are first defined – bearing in mind that each agent tries to reach its own objective – and then the cooperative interactions between these agents allow to collectively produce a global emerging functionality. According to the AMAS approach, each agent must maintain – from its local point of view – cooperative interactions with the agents it knows and with the environment of the system (Georgé et al., 2011). If an agent encounters a Non Cooperative Situation (NCS), it has to solve it to come back into a cooperative state. The criticality measure – the distance between the current state of an agent and the state where its goal is reached – helps also an agent to remain in a cooperative state. The behaviour of an agent in an AMAS consists to continuously act for decreasing both its own criticality and the criticality of its neighborhood. The AMAS technology has been, for instance, used to solve problems of real-time control such as heat engine (Boes et al., 2013) or game parameters control (Pons and Bernon, 2013).

Considering the ability of AMAS to take into account environmental dynamics, we consider this approach relevant for designing a system able to optimize the energy production of a photovoltaic plant by using environmental conditions and weather forecasts to determine when to activate cooling devices.

## 4 A SELF-ADAPTIVE CONTROLLER FOR OPTIMIZING PV PRODUCTION

This section first defines the general architecture of *AmaSun*, a self-adaptive multi-agent system which aims at maximizing energy production by controlling when to cool photovoltaic panels while using water reserves in an effective way, as only harvested rainwater can be used. The behaviours of the agents involved in this control system are then described.

Figure 1 represents the global architecture of *AmaSun* and its environment. The *AmaSun* control system collects data from external modules such as the database in which the historical meteorological data of previous years are recorded, as well as the weather forecasts. It also collects data from local sensors through the *DataManager* module, including environmental data (temperature, wind power, solar irradiance) and internal data about the photovoltaic plant (panel temperatures, water level in the tank, current energy produced). All these data are collected thanks to sensors at the level of the photovoltaic panels. The system is also connected to the cooling devices to which it can send activation commands.

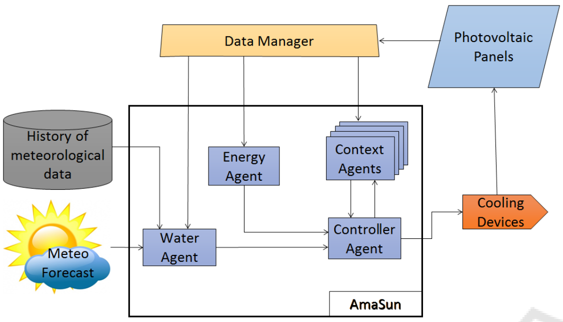


Figure 1: General architecture of *AmaSun*.

Four types of agents are used in *AmaSun* to control the cooling: the *Energy* agent determines if the current energy production is satisfactory or not, the *Water* agent determines the amount of water usable by the system, and the *Controller* agent, thanks to a set of *Context* agents, determines when to activate the cooling devices. Every minute (i.e. every cycle), the system receives a data update from the DataManager, and each agent acts depending on these values.

## 4.1 Energy Agent

The objective of the *Energy* agent is to maximize the Energy Production (*EP*) i.e. to minimize the loss of efficiency by reducing the gap between the optimum energy production and the current energy production. As we do not consider the optimum energy production as a theoretical value but as an empirical evaluation depending on the additions or removals of sensors, the decay of the panels, and so on, we prefer to consider the Real Optimum Energy Production (*ROEP*).

If we consider a PV panel with a constant low temperature, the energy production depends only on solar irradiance. Therefore, *ROEP*, the highest energy value that can be produced with this irradiance, is computed by the linear function $F_{ROEP}$ which applies a ratio $R$ to the value of irradiance $Ir$:

$$F_{ROEP}(Ir) = R * Ir$$

Even if the *Energy* agent cannot directly decide when to activate the cooling devices, it can express its criticality level to drive the *Controller* agent to spray water when it is necessary. Because the goal of the *Energy* agent is to minimize the difference between $EP$ and $ROEP$, we consider the criticality $C$ of the *Energy* agent as this difference : $C = ROEP - EP$.

The good behaviour of the system depends on the ability of the *Energy* agent to correctly estimate $ROEP$. If $C$ is globally too low, the system will not perform enough cooling activations and the *Energy* agent will not be able to reach its goal. If $C$ is globally too high, too many activations will be performed to try to decrease it, to the detriment of the other agents. These two problems occur when the ratio $R$ used to convert the irradiance into $ROEP$ is too high or too low. Therefore, the *Energy* agent has to detect these situations and consequently to adapt the value of $R$ to solve them.

When the value of $EP$ is higher than $ROEP$, since this situation is theoretically not possible, this means that $R$ is too low, so the *Energy* agent increases $R$ until $EP$ becomes lower or equal to $ROEP$. When $ROEP$ is higher than 100%, another situation theoretically not possible, this means that $R$ is too high, so the *Energy* agent decreases $R$ until $ROEP$ becomes lower than 100.

This cooperative mechanism allows the *Energy* agent to learn at runtime how to convert the irradiance value into $ROEP$.

## 4.2 Water Agent

The goal of the *Water* agent is to make an efficient use of the harvested rainwater; it is satisfied when it is able to supply the water requested by the *Controller* agent to cool panels. Two obvious situations could prevent it to perform in the best way: the tank is empty when water is required, which means too much water was previously used, or the tank is full while it is raining, which means more water could have been used previously. However, it is not reasonable to wait until these situations happen to decide too much or too little water was used.

The decisions about when to efficiently use water are then performed by cooperation of both the *Water* and *Controller* agents: the *Water* agent determines how much water the system has to use for a given amount of time, and the *Controller* agent determines which policy as to be applied during this same period of time in order to use as precisely as possible this amount of water. On average, a constant loss of water is used each time a cooling device is activated, the *Water* agent therefore expresses the amount of water the *Controller* agent is allowed to use as a number of activations of the cooling devices.

Actually, the *Water* agent is not completely implemented yet in the current *AmaSun* version, and an empirical number of activations of the cooling devices per day is considered. In the future, the *Water* agent will decide the value of the activation number based on the weather forecast and the amount of water.

### 4.3 Controller Agent

The aim of the *Controller* agent is to determine the behaviour of the cooling devices, for a given period of time (e.g., a day), in order to meet both the *Water* and *Energy* agents' requirements. At the beginning of the day, the *Controller* agent determines an activation threshold value, $AT$. During the day, for meeting the constraints of the *Energy* agent, each time the criticality $C$ of this *Energy* agent exceeds $AT$, cooling devices are activated. To fulfil also the constraints of the *Water* agent, the value of $AT$ takes into account the required number of cooling devices activations it requested.

However, this policy of activation depends strongly on the context in which the photovoltaic panels are, in particular the temperature, the solar irradiance and, more generally, the weather conditions.

The $AT$ value is determined thanks to the weather forecast for the next day. As a matter of fact, if we consider the number of activations for a period of one hundred cycles, i.e. the percentage of activations *Pa* for a period of time, this value depends, on the one hand, on the $AT$ value, a higher value for $AT$ involving a lower value of *Pa*, and on the other hand, on the weather of the next day, a bright day involving a higher value for *Pa* than a rainy or a dark day. To determine which value of $AT$ will involve the correct *Pa* value for the next day, the *Controller* agent is associated with a set of *Context* agents. Each *Context* agent represents a specific weather, and owns a function $\tau(AT)$ that takes an $AT$ value chosen by the *Controller* agent, as input, and sends back an estimation of the *Pa* value with this value of $AT$, as output.

Thanks to the set of *Context* agents representing the weather forecasts – each *Context* agent being involved depending on the duration its associated weather is forecasted – the *Controller* agent can establish the value of *Pa* for the next day depending on a given value of $AT$ by interacting with the *Context* agent, as explained in the next section. So, at the beginning of each day, it estimates by dichotomy the correct value of $AT$ to obtain the *Pa* that corresponds to the required number of cooling device activations.

### 4.4 Context Agents

There are typically several hundred of *Context* agents in the controller system since a *Context* agent represents information about a specific weather condition. The goal of such an agent is to be able to evaluate the percentage of activations of the cooling devices for its associated weather depending on the activation threshold $AT$ given by the *Controller* agent.

A *Context* agent owns a values range per each weather piece of data associated with its weather condition: temperature, solar irradiance and wind speed. When the current weather values are included in the values ranges of a *Context* agent, it considers itself as *valid*, and *invalid* otherwise. In a similar way, when it becomes valid for a weather forecast, this means that it will probably be *valid* the next day, so it signals this information to the *Controller* agent which will take it into account when computing $AT$.

A *Context* agent observes the state of the cooling devices, it counts the total number of cycles where it is *valid* and the specific number of cycles where the cooling devices are also activated. A *Context* agent records a map to associate these values, in other words, the ratio of the number of cycles with activated cooling devices $NB_{activated}[AT]$ to the total of cycles $NB_{total}[AT]$, depending on the $AT$ value. This ratio not only depends on $AT$ but also on the weather associated with the *Context* agent, some weather involving more cooling devices activations, so each *Context* agent has its own map.

When the *Controller* agent tries to estimate the percentage of activations *Pa* with a given threshold $AT$ at the beginning of the day, each *Context* agent has to be able to generalize its estimation thanks to its previous observations. So, it uses its function $\tau(AT)$, which is a linear regression weighted by the total number of cycles for each value of $AT$. With every functioning day, the *Context* agent increases the precision of the $\tau(AT)$ function. To perform the learning process, a *Context* agent makes evolving its knowledge, such as its $\tau(AT)$ function, in order to represent more correctly its associated weather. Then, the evolution of the number and knowledge of the *Context* agents allows to improve the knowledge of the *Controller* agent.

## 5 RESULTS

The goal of the Adaptive Multi-Agent System *AmaSun* is to estimate the amount of rainwater which has to be used each day, and then to determine each day when to activate the cooling devices to maximize the energy production by using this rainwater amount. However, the *Water* agent behaviour is still under study and then we focus here on evaluating the ability of *AmaSun* to learn how to maximize the energy production with a given amount of rainwater.

The learning process performed by *AmaSun* is an on-line learning, that means it requires a retro-action loop with its environment: it makes actions and observes the feedback from this environment. To perform the next evaluations, simulated photovoltaic panels are used for testing several months of *AmaSun* operation in a few minutes. They are based on real data recorded from an actual PV panel plant and coupled with historical weather data, to generate a model of the photovoltaic panels using a neural network system, thanks to the Weka tool (Holmes et al., 1994). This model takes into account the environmental conditions (solar irradiance, temperature and wind power), state of the cooling devices (activated or not) and the previous temperature of the PV panels, for generating the new temperature of the panels.

In this evaluation, the *Water* agent decides how many cooling devices activations have to be performed each day, depending only on the solar irradiance forecast. This simple computing is sufficient enough to evaluate the *AmaSun* ability to perform the number of actions we tell it to perform, independently from the pertinence of this number. Once the *Water* agent will also be able to decide what is the best number of activations to do, *AmaSun* will be able to find the best cooling control.

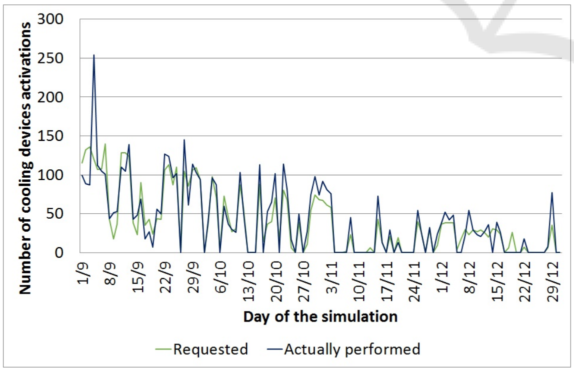


Figure 2: Requested and actually performed number of cooling devices activations.

Figure 2 shows the number of cooling devices activations that *AmaSun* has to perform during the day (i.e. requested, light curve), as determined by the *Water* agent at the beginning of the day, and the number of activations actually performed at the end of each day (dark curve). The decreasing number of requested actions is only the result of the decreasing irradiance between the beginning of September and the end of December. The important thing is the low difference between the two curves, represented in figure 3. While still high the very first days of the learning, this difference rapidly decreases.

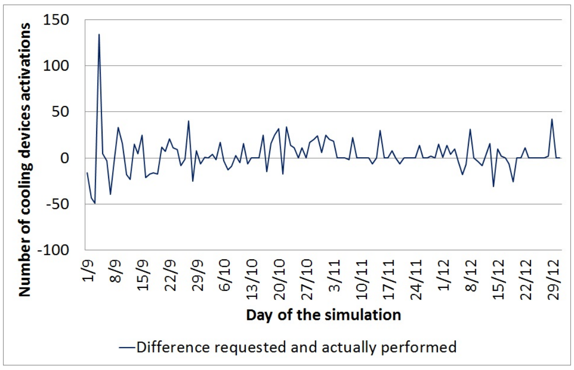


Figure 3: Difference between requested and actually performed number of cooling devices activations.

We performed the same simulation with data coming from three different real power plants. For each place, we observed the difference between the number of requested and actually performed actions, and we obtained an average deviation of 18%. This value can be considered good because it is obtained without any previous knowledge. At the end of the simulations, we have an average number of 154 *Context* agents to represent the encountered weathers. Since *AmaSun* starts without any *Context* agents, the ability of the agents to evaluate the correct value of threshold *AT* in order to obtain the right number of activations depends only on the observations made by the system at runtime over the days. Moreover, the data used as input to *AmaSun* are subject to a lot of disturbances: the data perceived by the sensors are heavily noisy, weather forecasts are partially inaccurate, and given hourly whereas the system works with a cycle per minute.

# 6 CONCLUSION

This paper introduced the problem of using a Multi-Agent System-based controller to increase the energy production of a photovoltaic plant thanks to the use of cooling devices connected to a limited reserve of rainwater. Due to the interdependence of several parameters, we cannot define a classical control function to optimize the energy production.

To answer this problem, we designed *AmaSun*, an Adaptive Multi-Agent System able to learn, depending on environmental conditions and weather forecasts, the amount of water to use during a period, the optimal energy production depending on the perceived solar irradiance value and which gap, between the current energy production and the estimated optimal energy production, is permitted before activating the cooling devices in order to use the allowed water in the most efficient manner.

Preliminary results were given on this latter point and to complete *AmaSun*, our ongoing work will study how, depending on weather forecasts, the optimal number of activations is to be estimated, and, considering the amount of water the system possesses, how many activations it has to perform each day. Moreover, in order to more efficiently evaluate the impact of *AmaSun*, we plan to equip half of the photovoltaic panels of a real plant with this control system, while the other half of the panels will work without any cooling device.

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