Artificial Intelligence for Operation and Maintenance of PV Plants

Deliverable D3.3

Method for cost-optimized predictive maintenance

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EXECUTIVE SUMMARY

This deliverable includes the main results obtained in the task **T3.3 Method for cost-optimized predictive maintenance** from the project AI4PV. The work carried out in this task has focused on the cost optimization of the predictive maintenance in the different assets in PV plants.

As a result, a system has been designed and implemented to generate a set of recommendations based on a Markov Decision Process, which is capable of modelling the whole system and its evolution in time based on its current status. An optimisation process based on the Markov Decision Process developed is then used to find the optimal O&M policy to pursue which results in the maximum Return on Investment.

The output of these results will set the baseline for the validation phase of the tools to support the operation and maintenance tasks of the photovoltaic plants considered.

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ABBREVIATIONS AND ACRONYMS

Acronym	Meaning
MDP	Markov Decision Process
MINLP	Mixed Integer Non Linear Programming
O&M	Operation and Maintenance
RoI	Return on Investment
SCADA	Supervisory Control and Data Acquisition

GLOSSARY OF KEY TERMS

Artificial Intelligence	Artificial intelligence is a wide-ranging branch of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence.
Machine Learning	Machine learning is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention.
Deep Learning	Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behaviours of the human brain—albeit far from matching its ability—allowing it to “learn” from large amounts of data.
Fault	A fault is an unpermitted deviation of at least one characteristic property (feature) of the system from the acceptable, usual standard condition.
Failure	Permanent interruption of a system’s ability to perform a required function under specified operating conditions.
Malfunction	Intermittent irregularity in fulfilment of a systems desired function.
Fault detection	Determination of faults present in a system and time of detection.
Fault diagnosis	Determination of kind, size, location and time of detection of a fault by evaluating symptoms. Follows fault detection. Includes fault detection, isolation and identification
Markov Decision Process	A Markov decision process (MDP) is defined as a stochastic decision-making process that uses a mathematical framework to model the decision-making of a dynamic system in scenarios where the results are either random or controlled by a decision maker, which makes sequential decisions over time

1. INTRODUCTION

This document, deliverable **D3.3 Method for cost-optimized predictive maintenance**, includes a description of the recommendation engine used to indicate the problems with the highest associated energy loss, evaluated by comparing the data generated by the digital twin developed in the project with that recorded by the plant's SCADA system.

1.1 SCOPE OF REPORT

In order to face the challenges incurred by climate change, the industry has been striving to improve the overall performance of PV systems. Unsolved challenges remain concerning reliability, numerous unforeseen outages, and high operation and maintenance (O&M) costs. In this context, this report brings the developments to increase the operational performance of PV plants by improving current methodologies for O&M in PV systems. A maintenance approach was developed based in a Markov decision process model to analyse the data from PV power plants, prioritise actions, advise asset replacement, and schedule preventive maintenance tasks based on past experiences and the PV system condition. The results allow economic improvement through downtime reduction and early detection of system under performance.

The results presented here have been achieved in the development of task **T3.3 cost-optimised predictive maintenance**, included in the context of the work package **WP3 Prescriptive analysis for O&M**. These advancements, in addition to those achieved in the other tasks of the work package (T3.1 and T3.2) will allow not only the precise detection of deviations in the signals of the devices but also the identification of the root cause and O&M policy that maximise the RoI.

1.2 OUTLINE OF REPORT

This report is structures as follows,

- ***Chapter 1*** introduces the scope of the document
- ***Chapter 2*** provides background on Markov Decision Process (MDP) and on the AI4PV's recommendation system
- ***Chapter 3*** explains the methodology for the definition of the optimal policy and some validation examples
- ***Chapter 4*** presents the conclusions of the report

2. MDP-BASED TASK RECOMMENDATION ENGINE

Markov decision process has been often used to model maintenance management. Maintenance covers technical and associated administrative actions to retain an item or system in, or restore it to a state in which it can perform its required function. A Markov model is a dynamic model that allows modelling in time probabilistic evolution of a system. A Markov chain is a discrete time process governed by a discrete state space and transition matrix. A Markov decision chain is an extension of a Markov chain, steered by actions and with which optimal actions can be determined. A Markov Decision Process describes a stochastic process. It is defined by the state space, the action set in each state, the transition probabilities, and the immediate rewards in each state when a given action is chosen. The control is defined through policies and decision rules. A policy is a sequence of decision rules.

Control policies are machine-age dependent. Therefore, the dimension of the problem is large given that the machine's ages and preventive maintenance states are additional state variables and Markov chain states [1] [2] proposed the equipment modelling through modified Markov chain, describing the deterioration process, inspection, and maintenance. [3] used a semi-Markov decision process to determine whether maintenance should be performed to power equipment in each deterioration state and, if so, what type of maintenance. [4] proposed a Markov chain model to estimate an interval for the deterioration of offshore structures and discussed the use of the stochastic model in the prediction of maintenance timing. [5] presented a method to find the optimum maintenance policy for a component. Using Markov processes, they calculated the state probabilities and the optimal value of the mean time for preventive maintenance while maximising the availability of a single component.

2.1 METHODOLOGY

The problem is modelled as a Markov Decision Process as described in D3.2 [6]. The whole model consider:

- **Power electronics**: whose state can be expressed via a binary variable (0 or 1) which indicates whether the device is fault-free or not. Three possible actions can be undertaken: i) "do-nothing", ii) "minor repair", iii) replacement.
- **PV panels**: whose state can be expressed via a binary variable (0 or 1) which indicates whether the device is fault-free or not. Two possible actions can be undertaken: i) "do-nothing", ii) replacement.
- **Soiling**: whose state can assume discrete values between 0 and 1. Soiling equals to 0 means PV panel completely clean, whilst when it is equal to 1 the PV panel is assumed to be completely dirty. Two possible actions can be undertaken: i)"don't clean", ii) "clean".
- **Power transformer:** even if different faults and failures can be classified they all rely to two possible states, i)"fault-free", ii) "faulty". Even in this case, the two possible actions are: i)"do nothing", ii) "replace".

At each stage, the states are retrieved from the classification and detection algorithms developed within the project [7] [8] [9] and the transition matrices are updated according to [6].

Thus, this model considers t = 1, . . ., N the discrete-time and N the planning horizon. The decision variables are Boolean.

As explained in D3.2, for each component, for each state we can compute the reward based on the different possible actions.

The estimation of future rewards guides the decisions regarding maintenance actions. A objective function considers the reward for the irradiance, by measuring the equipment state and the maintenance action costs. The objective function is given by EQUATION 2-1.

$$\max_{a^t_{component\_i}} \sum_{t=t\_c}^{N} \sum_{i=1}^{Ncomp} (Reward_{component\_i}(s^t_{component\_i}, a^t_{component\_i}, a^{t-1}_{component\_i}, \dots a^0_{component\_i}) - Cost_{component\_i} \qquad \textbf{EQUATION 2-1}$$

The reward for each component depends on its current state and on all the actions taken in the past.

3. DEFINING THE OPTIMAL POLICY AND PRIORITISATION

In recent years, optimal maintenance policy solution techniques have been sought using only one maintenance state. It ignores the possibility that different types of maintenance can be done to correct specific problems. Including more than one maintenance state, a maintenance model can be more sufficiently applied to real-life situations.

The optimal maintenance policy is determined using Markov Decision Processes. It describes the action to be taken at each state, which yields minimal cost and ensures high equipment availability.

The system may have numerous states with different alternatives for each state. This makes the number of total possible policies very large.

The optimal policy is found by solving EQUATION 2-1, through a MINLP problem.

The definition of criticality used in this project is based on the potential energy loss of each fault or inefficiency detected in the generation elements of the plant, calculated as the difference between the energy predicted by the digital twin and the energy measured. As an example of this, an inverter fault will be more critical than a string disconnection, since the inverter usually involves a large number of strings and therefore much more energy.

Thus a priority scale that goes from 0 to N, where N is the number of components. The highest value set that action as the most important to pursue in order to maximise the RoI of the plant. Value 0 is used when "no-action" is required for that component. An example is provided in TABLE 3-1.

TABLE 3-1: EXAMPLE OF OPTIMAL POLICY AND PRIORITISATION

Date	Component	State	Action	Priority
01-02-2023	**PV panels**	0 (fault-free)	0 (do nothing)	0
01-02-2023	**Soiling**	0.5 (dirty)	1 (clean)	3
01-02-2023	**Inverter**	1 (faulty)	1 (replace)	4
01-02-2023	**Transformer**	0 (fault-free)	0 (do nothing)	0

3.1 USE CASE EXAMPLE: INVERTERS

In this section, three tests are presented, which were used to validate the proposed model and the optimal policy. All cases consider *t* in months, three maintenance actions, where:

- a_0 represents no *maintenance action*,
- a_1 a minor maintenance action,
- and a_2 the equipment replacement.

The state represent deterioration, three states were assumed:

- D_{ok} is a *working equipment*,
- D_{1k} is a *fault* and
- D_{2k} is a *failure*.

Transition among the states is given by the matrices:

$$P_{ka_0}^t = \begin{bmatrix} 0.93 & 0.06 & 0.01 \\ 0.00 & 0.85 & 0.15 \\ 0.00 & 0.00 & 1.00 \end{bmatrix} \quad P_{ka_1}^t = \begin{bmatrix} 0.98 & 0.015 & 0.005 \\ 0.75 & 0.20 & 0.05 \\ 0.45 & 0.30 & 0.25 \end{bmatrix} \quad P_{ka_2}^t = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

The irradiance rewards consider the average of daily hours of sun per month and the maintenance action a_n^t, represented by the following matrix ($s \ x \ N$):

$$R(I^t|\mathbf{a}_n) = \begin{bmatrix} 5 & 10 & 15 & 20 & 30 & 50 & 50 & 30 & 20 & 15 & 10 & 5 \\ 30 & 40 & 50 & 40 & 30 & 10 & 10 & 30 & 40 & 50 & 40 & 30 \\ 50 & 40 & 30 & 10 & 10 & 5 & 5 & 10 & 10 & 30 & 40 & 50 \end{bmatrix}$$

The maximum and minimum rewards values consider the months with the highest solar incidence. It considers not planning maintenance in months with high sun exposure, as the actions may cause system interruption, and planning the equipment replacement in months with the lowest sun exposure.

The equipment efficiency $E(d_k^t)$ is a function of the probability vector of equipment k at time t:

$$E(\mathbf{d}_k^t) = \mathbf{d}_k^t \cdot \begin{bmatrix} 100 \\ 70 \\ 20 \end{bmatrix} \quad (4)$$

An efficiency of 100% represents the equipment in the deterioration state D_0; 70% of the efficiency represents the equipment in deterioration state D_1 ; and 20% of the efficiency represents the equipment in deterioration state D_2.

The maintenance cost relates equipment efficiency reduction associated with the deterioration states and the maintenance planning actions a_n^t. This matrix is proposed to have: no reductions for the action a_0, 20% of reduction for the action a_1 , and 90% of reduction for the action a_2. Thus, this matrix is defined as follows:

$$C(a_n^t) = \begin{bmatrix} 0\%(100) & 20\% & 90\% \\ 0\%(70) & 20\% & 90\% \\ 0\%(20) & 20\% & 90\% \end{bmatrix} = \begin{bmatrix} 0 & 20 & 90 \\ 0 & 14 & 63 \\ 0 & 4 & 18 \end{bmatrix}$$

TABLE 3-2 shows the components k and its respective lifetime (TP), the number of low maintenance level actions already performed (w^{tp}), and the time when this action has been performed t_p.

TABLE 3-2: COMPONENT CHARACTERISTICS

k	TP	w_k^{tp}	t_p
1	10	1	3
2	12	1	8
3	6	1	3
4	12	0	0
5	12	1	12

3.1.1 ONE EQUIPMENT

This demonstration considers one equipment (K = 1). The equipment has been working for 10 months, and a minor maintenance action was performed in month 3.

The updated deterioration d_k^0 is calculated as in EQUATION 3-1, where λ= [1 0 0].

$$d_k^0 = \lambda[P_{a_0}]^2 \cdot [P_{a_1}] \cdot [P_{a_0}]^7 = [xx\ xy\ yy]$$ **EQUATION 3-1**

The vector d_k^0 means that this equipment has xx%, xy% and yy% of the probability of being in the deteriorating states 0, 1 and 2, respectively.

The planning horizon starts in January. The model performs strategic maintenance planning regarding irradiation while simultaneously maximising equipment efficiency.

TABLE 3-3 shows the results obtained by the algorithm.

TABLE 3-3: RESULTS FOR COMPUTATIONAL EXPERIMENT 1

k	Z	Optimal Solution (months)											
		1	2	3	4	5	6	7	8	9	10	11	12
1	1295.4	2	2	2	2	1	1	1	1	2	1	1	1

The value of the objective function Z was calculated using EQUATION 3-2, which represents the accumulated sum of the rewards and the equipment efficiency throughout the year, discounting the maintenance costs.

$$\max Z = \sum_{t \in T} R(I^t | a_n^t |) \sum_{k \in K} E(d_k^t) - C(a_n^t)$$ **EQUATION 3-2**

For the case with only one equipment and two levels of deterioration, the optimal maintenance policy indicates that no maintenance actions are performed in months 5,6,7,8,10,11, and 12. Minor performance actions are performed in months 1,2,3,4, and 9. The equipment has not been replaced. That is, the optimal solution avoid maintenance actions in months with higher irradiances levels (May, June, July, and August) and the total reward was 1295.4.

3.1.2 MULTIPLE EQUIPMENTS

This demonstration considers more than one equipment (k=1,2,3,4,5). All components presented in TABLE 3-2 are considered in the planning horizon of one year, starting in January. TABLE 3-4 shows the suggested maintenance policy for each equipment k, comprising the objective function values and the maintenance action performed each month for each equipment. The executions were split since there was no dependency on functionality among the components.

TABLE 3-4: RESULTS FOR COMPUTATIONAL EXPERIMENT 2

k	Z	Optimal Solution (months)											
		1	2	3	4	5	6	7	8	9	10	11	12
1	1295.4	2	2	2	2	1	1	1	1	2	1	1	1
2	1306.2	1	2	2	2	2	1	1	1	2	1	1	1
3	1311.7	1	2	2	2	2	1	1	1	2	1	1	1
4	1281.5	3	1	1	2	2	1	1	1	2	1	1	1
5	1330.5	1	2	2	2	1	1	1	1	2	1	1	1

3.1.3 IMPACT OF IRRADIANCE LEVELS

This demonstration considers a smaller planning horizon, of only six months. TABLE 3-5 shows the suggested maintenance policy for each equipment k for a planning horizon starting in April. TABLE 3-6 shows the suggested maintenance policy for each equipment k for a planning horizon starting in June. The irradiance rewards directly affect the results. However, it does not avoid that highly deteriorated equipment performs maintenance actions in months with higher solar exposure.

TABLE 3-5: RESULTS FOR COMPUTATIONAL EXPERIMENT 3: RESULTS STARTING IN APRIL

k	Z	Optimal Solution (months)					
		4	5	6	7	8	9
1	703.6	2	2	1	1	1	2
2	715.7	2	2	1	1	1	2
3	719.3	2	2	1	1	1	2
4	597.6	3	1	1	1	1	2
5	736.2	1	2	1	1	1	2

TABLE 3-6: RESULTS FOR COMPUTATIONAL EXPERIMENT 3: RESULTS STARTING IN JUNE

k	Z	Optimal Solution (months)					
		6	7	8	9	10	11
1	624.5	3	1	1	2	1	1
2	644.2	1	1	2	2	1	1
3	657.7	1	1	2	2	1	1
4	624.5	3	1	1	2	1	1
5	709.2	1	1	1	2	1	1

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4. CONCLUSION

The proposed Markov Decision Process model allows to replace the interval-based maintenance with a cost-efficient predictive approach to prioritise maintenance actions and equipment replacement based on past experiences and the PV system forecasted condition.

Numerical experiments simulating scenarios in PV systems were presented to validate the model. The case studies showed that the model adequately plans preventive or corrective maintenance actions once the model analyses the current state and estimates the future state. Moreover, it was evident that the larger the system and the planning horizon, the solution space increases exponentially. Therefore, an overall analysis highlights that an optimisation method or a heuristic shall be applied.

The work done here completes the **WP3 Prescriptive analysis for O&M** and the technical part of the project as a whole. Once this stage is completed, the algorithm system is ready for validation in the next work package, **WP4 Validation**. This last part will be the confirmation of the suitability of the solution proposed and the feedback necessary to make the possible adjustments.

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