Artificial Intelligence for Operation and Maintenance of PV Plants

Deliverable D3.2

Method for return-on-investment prediction

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EXECUTIVE SUMMARY

The present deliverable D3.2 has been developed in the framework of WP3 activities related to the "Prescriptive analytics for O&M" of AI4PV project results and it is the outcome of T3.2 "Return-on-investment (ROI) prediction".

This deliverable presents the methodology developed and designed to evaluate a given O&M policy so as to estimate its ROI. This module, developed in collaboration by all the project partners, is necessary to assess the impact of a given policy and fault on the ROI and thus it allows to prioritize actions whose impact is higher.

The document explains the ROI prediction model and its module quite extensively and together with D3.3 "Method for cost-optimized predictive maintenance" constitute the basis of the O&M recommendation key solution within AI4PV project.

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ABBREVIATIONS AND ACRONYMS

Acronym	Meaning
DNI	Direct Normal Irradiance
MDP	Markov Decision Process
MTBF	Mean Time Between Failure
PD	Price Data
PR	Performance Ratio
PV	Photovoltaic
RAM	Reliability, Availability and Maintainability
RE	Rain Event
REN	Redes Energéticas Nacionais
ROI	Return on Investment
SR	Soiling Rate

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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.
Reinforcement Learning	Reinforcement learning, a subset of deep learning, relies on a model's agent learning how to determine accurate solutions from its own actions and the results they produce in different states within a contained environment. This self-interpreting model is trained on a system of rewards and punishments learned through trial and error, seeking the outcome that results in the highest possible reward.
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.

1. INTRODUCTION

This document, deliverable D3.2 "Method for return-on-investment prediction", includes a description of the main modules of this tool, whose objective is to estimate the ROI of a given policy and thus prioritise actions which would have the highest impact.

1.1 SCOPE OF REPORT

The purpose of this document is to describe quite extensively the ROI prediction model which is a key part of the Cost-optimised O&M predictive maintenance.

This tool, developed within Task 3.2 "Return-on-investment (ROI) prediction", is a decision-aid layer built on top of the digital twins from WP2 and AI algorithms from T3.1 in order to perform a prediction of the ROI of a single PV power plant considering parameters such as: O&M costs, assets lifetime, PV resource.

AI is employed here, to simulate the operation of the PV power plant during its maximum lifetime by using Markov models as described in the following sections.

1.2 OUTLINE OF REPORT

This report is structured as follows:

- ***Chapter 1*** introduces the scope of the document;
- ***Chapter 2*** provides an overview of the MDP which is the basis and key representation of the whole ROI prediction model.
- ***Chapter 3*** presents the MDP built for the PV panels;
- ***Chapter 3*** digs into the cleaning module explaining the algorithms and methodology used;
- ***Chapter 5*** presents the MDP tailored for the inverter;
- ***Chapter 6*** goes over the MDP for the transformer;
- ***Chapter 7*** presents the conclusions of the report

2. MARKOV DECISION PROCESS

Markov decision processes (MDPs) are a powerful mathematical framework for modeling decision processes in situations where the outcome of an action depends on the current state of the system, but is also affected by some degree of randomness or uncertainty. MDPs are widely used in various fields, including operations research, economics, artificial intelligence, and control engineering, to name a few. In this section, we provide a comprehensive overview of MDPs, including their mathematical foundations, key concepts and terminology, algorithms to solve them, and applications in various fields.

An MDP can be defined as a tuple *(**S, A, T, R, γ**)*, where:

- ***S*** is a set of states,
- ***A*** is a set of actions,
- ***T*** is a transition function describing the probability of moving from one state to another after performing a certain action,
- ***R*** is a reward function assigning a scalar value to each state-action pair,
- ***γ*** is a discount factor controlling the trade-off between immediate and future rewards.

In other words, an MDP specifies the rules in which the player (**agent**) can choose from a set of available actions, each of which can lead to a different state with a certain probability, and receive a reward based on the current state and action. The agent's goal is to maximize the total expected reward over a sequence of actions.

Furthermore, MDPs are based on the *Markov property*, which states that *the future state of a system depends only on the current state and action and is independent of the past history of the system*. This property allows us to represent the system as a directed graph, where each node corresponds to a state and each edge corresponds to an action, and the probability of moving from one node to another is given by the transition function. The reward function assigns a scalar value to each state-action pair that reflects the desirability or cost of being in that state and performing that action. The discount factor γ controls the relative importance of immediate and future rewards and typically takes a value between 0 and 1, where 0 means that only immediate rewards are important and 1 means that all future rewards are equally important.

Figure 2-1 shows a graphical representation of a general MDP.

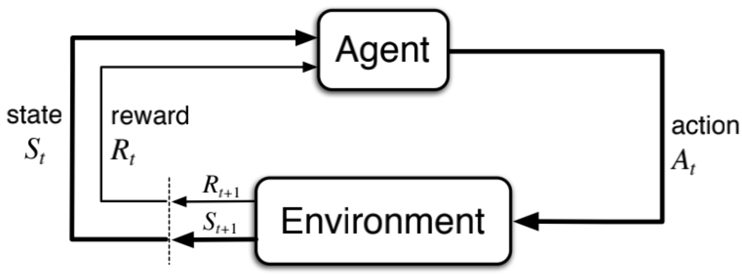

FIGURE 2-1: GRAPHICAL REPRESENTATION OF AN MDP

In fact, analysing Figure 2-1 it is possible to observe that, given a certain environment (world where the agent takes actions), the agent will take certain actions and receive rewards based on them, transitioning into a future state. Diving deeper in terms of MDPs concepts and terminologies there are a few that should be highlighted[1]:

- **States:** The states represent all the possible configurations of the problem.
- **Actions:** The actions are the collection of all possible motions an agent can take;
- **Transition function:** The transition function holds the uncertainty of an MDP. Given a certain state and action, this function governs the probability of the next state that will follow.
- **Reward function:** This function determines how much reward is gained by choosing a certain action in a certain state.
- **Policy:** A policy is a function that maps any state to an action. It defines the agent's behavior or strategy in the game and can be deterministic or stochastic.
- **Value function:** the value function *V(s)* of a state *s* is the expected discounted total reward that the agent can receive starting from that state and following a given strategy. It measures the desirability of being in that state under the given policy.
- **Q-function:** the Q-function *Q(s, a)* of a state-action pair *(s, a)* is the expected discounted total reward that the agent can receive if it performs action *a* in state *s* and then follows a given strategy. It measures the desirability of performing that action in that state under the given policy.
- **Bellman equation:** the Bellman equation is a recursive equation that expresses the value function or Q-function of a state or state-action pair in terms of the value function or Q-function of its successor states or state-action pairs. It is an important tool for solving MDPs because it allows us to derive a set of equations that can be solved iteratively to find the optimal strategy.
- **Optimal strategy:** an optimal strategy is one that maximizes the expected discounted total reward across all possible strategies. It is the best possible strategy that the agent can pursue in the game given its current knowledge of the system.
- **Optimal value function:** The optimal value function $V^*(s)$ of a state *s* is the maximum expected discounted total reward.

Additionally, to solve MDPs there are several algorithms that can be used, including[2]:

- *Value Iteration:* in this algorithm, the value function is iteratively updated until it converges to the optimal value function for the MDP.
- *Policy Iteration:* In this algorithm, a strategy is alternately evaluated and improved until an optimal strategy is found.
- *Q-learning:* This is a model-free reinforcement learning algorithm that estimates the optimal action value function using temporal difference learning.

[1] Kallenberg, Lodewijk. "Markov decision processes." Lecture Notes. University of Leiden 428 (2011).
[2] Martijn van Otterlo, Marco Wiering, "Markov Decision Processes: Concepts and Algorithms", (2012)

- *SARSA:* This is another model-free reinforcement learning algorithm that estimates the action value function, but uses an on-policy approach that learns the value of an action in the current state and following the current policy thereafter.
- *Monte Carlo methods:* These methods use experience gained through interaction with the MDP to estimate the value function or optimal policy.
- *Dynamic programming:* This is a family of algorithms that includes both value iteration and policy iteration, as well as other approaches such as modified policy iteration and linear programming.

Each of these algorithms has its own strengths and weaknesses, and the choice of algorithm depends on the specific characteristics of the MDP and the goals of the agent.

3. PV PANEL

In this section the module of the ROI prediction model related to the PV panels is described. As for all the other components composing the ROI prediction model, the PV panels were modelled as an MDP. In this case the MDP is modelled at string level. Hereafter, the description will focus on a single string.

3.1 MARKOV DECISION PROCESS

As described in Section 2, an MDP is made of different parameters:

- **State:** describes the condition of the PV panels, in particular it represents the degradation of the efficiency/performance ratio of the PV panels. In this case a discrete approach is used where the degradation (d) is distributed in 0.05 intervals, between 0 and 1.
- **Action:** is the set of possible actions that the agent can take. In this case two possible actions are applicable:
  - Action=0, "do nothing". The string is kept as it is without any intervention.
  - Action=1, "replace". The string should be replaced with a new one.
- **Transition matrix**: it describes in a probabilistic way how the string can move from one condition to another.
- **Reward:** it is the reward that the agent receives when taking a certain action A_t at time t, under the current state S_t.

Each of the abovementioned parameters is extensively described in the following sections.

3.1.1 STATE AND ACTION

AI4PV string's faults detection algorithms can detect different fault and failures (excluding soiling for which a dedicated model has been implemented). All these faults result in a decrease of the efficiency of the PV panels up until their shutdown. The degradation was discretized into 0.05 range intervals between 0 and 1, which gives us a total of 20 states:

- $State\ 0: 0 < d \leq 0.05$
- $State\ 1: 0.05 < d \leq 0.10$
- $State\ 2: 0.10 < d \leq 0.15$
- $State\ 3: 0.15 < d \leq 0.20$
- $State\ 4: 0.20 < d \leq 0.25$
- $State\ 5: 0.25 < d \leq 0.30$
- $State\ 6: 0.30 < d \leq 0.35$
- $State\ 7: 0.35 < d \leq 0.40$
- $State\ 8: 0.40 < d \leq 0.45$
- $State\ 9: 0.45 < d \leq 0.50$
- $State\ 10: 0.50 < d \leq 0.55$
- $State\ 11: 0.55 < d \leq 0.60$
- $State\ 12: 0.60 < d \leq 0.65$
- $State\ 13: 0.65 < d \leq 0.70$

- $State$ 14: $0.70 < d \leq 0.75$
- $State$ 15: $0.75 < d \leq 0.80$
- $State$ 16: $0.80 < d \leq 0.85$
- $State$ 17: $0.85 < d \leq 0.90$
- $State$ 18: $0.90 < d \leq 0.95$
- $State$ 19: $0.95 < d \leq 1$

Even though, different faults have different impact on the power output of the string and need dedicated algorithms for their detection, in case these faults occur the only possible intervention is to replace the device, depending on their impact on the power output.

3.1.2 TRANSITION PROBABILITIES

PV panels undergo different degradation processes (i.e., micro-cracks and hot spots, light induced degradation, etc) that lead to underperformance of the PV cells. Thus, it is essential to quantify such degradation in order to evaluate possible economic benefits that may arise from the replacement of PV panels. The probabilistic approach used to model the degradation of PV panels is described in this section.

3.1.2.1 DEGRADATION

The degradation process of the PV panels was modelled using the gamma process, a commonly used distribution to describe degradation processes. The Gamma degradation process is characterized by a shape parameter (α), and a scale parameter (β), which determine the shape of the degradation curve and the rate at which the degradation occurs, respectively. The shape parameter reflects the degree of heterogeneity in the degradation of the system or component, while the scale parameter determines the overall rate of degradation. A higher shape parameter indicates that the degradation rate varies more widely across the population of systems or components, while a higher scale parameter indicates a faster overall degradation rate.

To estimate the shape and scale parameters for the degradation of PV panels, information provided by the supplier related to underperformance of the PV panels during their lifetime are considered. Generally, PV panels degrade around 0.5% every year, generating around 12-15% less power at the end of their 25-30 lifespan. The probability density function of the gamma distribution is given by:

$$\boldsymbol{f}(\boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \mathbf{t}) = \frac{\boldsymbol{\beta}^{\boldsymbol{\alpha}\mathbf{t}} \boldsymbol{x}^{\boldsymbol{\alpha}\mathbf{t}-\mathbf{1}} \boldsymbol{e}^{-\boldsymbol{\beta}\mathbf{x}}}{\boldsymbol{\Gamma}(\boldsymbol{\alpha}\mathbf{t})}$$

EQUATION 3-1

The gamma process is varying on time (*t*) and allows to compute the probability of a given degradation *x*, given the shape and scale parameters.

3.1.2.2 TRANSITION MATRIX

The transition matrix has dimension $s \times s \times a$, where s is the number of states and a is the number of possible actions.

The transition probabilities of degradation (d) in the absence of replacement is given by the gamma distribution, whilst in the case of replacement, the d is set to its minimum value. The transition probabilities of performance ratio when the action is to replace are given by:

$$\boldsymbol{p_k}(\boldsymbol{d}|\boldsymbol{d_i},\boldsymbol{a}=1)=\begin{cases}1 & \boldsymbol{d_j}=0\\ 0 & \boldsymbol{dj}\neq 0\end{cases}$$

EQUATION 3-1

3.1.3 REWARD

The reward is what the agent receives when taking a certain action A_t at time t, under the current state S_t. In the case of PV panels the reward depends on the revenue that results from selling the energy produced and on the cost of replacing the power transformer. In the case of not replacing, the reward depends only on the status of the PV panels and on the current PR.

The revenue associated with each state at each time t is related not only with the PR of that state but also with the irradiance and energy price at the time considered. So, to determine the increase of revenue it is necessary to determine the Direct Normal Irradiance (DNI) and energy price at the current and future time steps. For this, historical data were used to compute an average for each day of the year considering the values of the 15 previous and 15 following days, and the values over the years. The meteorological data were collected from Copernicus [1] and the historical electricity price data (PD) from REN [2].

$$\boldsymbol{E}\big(\boldsymbol{DNI}(\boldsymbol{t_k}),\boldsymbol{price}(\boldsymbol{t_k})\big)=\frac{\boldsymbol{1}}{\boldsymbol{31Y}}\sum_{y=1}^{Y}\sum_{i=-15}^{15}\boldsymbol{DNI}_{\,y,d(tk)+i}\cdot\boldsymbol{PD}_{y,d(tk)+i}$$

EQUATION 3-2

Having that information, the rewards for moving from state s_i to state s_j taking the actions of not replacing ($a=0$) and replacing ($a=1$) are given by:

$$\boldsymbol{r_k}(\boldsymbol{d_j}|\boldsymbol{d_i},\boldsymbol{a}=\boldsymbol{0})=\boldsymbol{Area_{cell}}\cdot\boldsymbol{Efficiency}\cdot(\boldsymbol{PR_{max}}-\boldsymbol{d_i})\cdot\boldsymbol{N}\cdot\boldsymbol{E}(\boldsymbol{DNI}(\boldsymbol{t_k}),\boldsymbol{price}(\boldsymbol{t_k})))$$
$$\boldsymbol{r_k}(\boldsymbol{d_j}|\boldsymbol{d_i},\boldsymbol{a}=\boldsymbol{1})=\boldsymbol{Area_{cell}}\cdot\boldsymbol{Efficiency}\cdot\boldsymbol{PR_{max}}\cdot\boldsymbol{N}\cdot\boldsymbol{E}\big(\boldsymbol{DNI}(\boldsymbol{t_k}),\boldsymbol{price}(\boldsymbol{t_k})\big)-\boldsymbol{Cost_{PV\_panels}}$$

EQUATION 3-3

Where:

- $Area_{cell}$ is the area of 1 PV panel;
- $Efficiency$ is the efficiency of the PV panels stated by the manufacturer;
- PR_{max} is the maximum PR;
- d_i is the degradation of the state i;
- N is the number of PV panels in the park;
- $E\big(DNI(t_k),price(t_k)\big)$ is the expected value of Irradiation*Price for $t=t_k$ based on historical values.
- $Cost_{PV\_panels}$ is the cost encountered to replace the PV panels.

4. CLEANING MODULE

In this section we will describe the component of the ROI model that is related to the soiling of the PV Panels. Soiling of photovoltaic (PV) panels can significantly reduce their efficiency, making soiling a critical issue in PV parks. Regular cleaning is essential to ensure optimal performance, increase power production, and prevent permanent damage to the panels. To maximize energy output and thus the profit, optimizing the cleaning schedule based on local weather patterns, dust levels, and the time of year is crucial. In this section we will describe how to evaluate the cleaning policy that will result in the highest ROI having into account soiling, seasonal variations in weather (irradiance and precipitation) and variations in electricity prices.

4.1 MARKOV-DECISION PROCESS

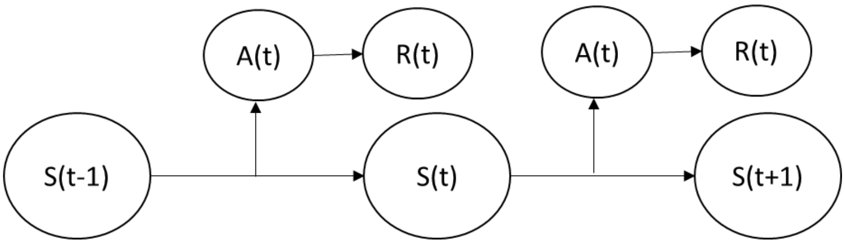

FIGURE 4-1: REPRESENTATION OF FINITE HORIZON NON-STATIONARY MDP

The problem of soiling was formulated as a Finite Horizon Non-Stationary Markov Decision Process (MDP) with the goal of minimizing cleaning costs and lost revenue due to soiling. Figure 4-1 describes the model, where:

- **State S(t):** describe the condition of the Soiling Rate (SR). In this case a discrete approach is used where the SR is distributed in 0.05 intervals, between 0 and 1.
- **Action A(t):** is the set of possible actions that the agent can take. In the case of the PV Panels cleaning two possible actions are applicable:
  - Action=0, "do nothing". The PV panels are kept as they are without any intervention.
  - Action=1, "clean". The PV panels are cleaned, and the performance ratio returns to its maximum value.
- **Transition matrix**: it describes in a probabilistic way how the performance ratio can move from one condition to another depending on the soiling, probability of rain and action taken.
- **Reward R(t):** it is the reward that the agent receives when taking a certain action A_t at time t, under the current state S_t. It depends on the historic data of irradiance and prices at the current day.

Each of the above-mentioned parameters is described in the following sections.

4.1.1 STATE AND ACTION

AI4PV representation of the state of PV panels is based on the SR of the panels, which can take continuous values from 0 to 1. In the MDP representation the continuous values of the SR were discretized into 0.05 range intervals between 0 and 1, which gives us a total of 20 states:

- $State\ 0: 0 < SR \leq 0.05$
- $State\ 1: 0.05 < SR \leq 0.10$
- $State\ 2: 0.10 < SR \leq 0.15$
- $State\ 3: 0.15 < SR \leq 0.20$
- $State\ 4: 0.20 < SR \leq 0.25$
- $State\ 5: 0.25 < SR \leq 0.30$
- $State\ 6: 0.30 < SR \leq 0.35$
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- $State\ 14: 0.70 < SR \leq 0.75$
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- $State\ 16: 0.80 < SR \leq 0.85$
- $State\ 17: 0.85 < SR \leq 0.90$
- $State\ 18: 0.90 < SR \leq 0.95$
- $State\ 19: 0.95 < SR \leq 1$

As mentioned above, the 2 possible actions are to "do nothing" or to "clean". In the next section it is explained how these actions influence the transition probabilities and the rewards.

4.1.2 TRANSITION PROBABILITIES

The Transition Probabilities were computed based on the soiling process, rain probability, the days since the previous cleaning and the action taken.

4.1.2.1 SOILING PROCESS

To characterize the soiling process the first step was to determine the evolution in time of the SR in Evora, by analysing historic data of the Monte das Flores PV Park. The SR expresses the rate of change of the soiling loss per day. A thorough analysis of the Performance Ratio (which is monitored by a sensor of the panel in the park) of the panels over the course of 4 years was performed. Within the historical data, time periods where it didn't rain for more than 10 days were selected, so that the most probable cause for the change of Performance Ratio of the panels was soiling. The SR was determined by fitting a linear regression to the evolution of the performance ratio with time, see Figure 4-2.

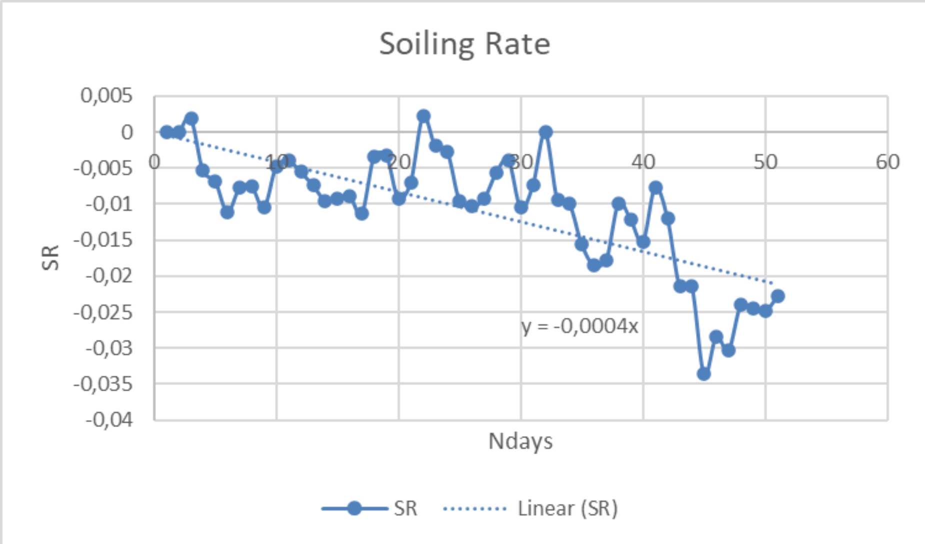

FIGURE 4-2: LINEAR REGRESSION OF THE SR

Subsequently, the soiling process was modelled using the gamma process, a commonly used distribution to describe degradation processes. The Gamma degradation process is characterized by a shape parameter (α), and a scale parameter (β), which determine the shape of the degradation curve and the rate at which the degradation occurs, respectively. The shape parameter reflects the degree of heterogeneity in the degradation of the system or component, while the scale parameter determines the overall rate of degradation. A higher shape parameter indicates that the degradation rate varies more widely across the population of systems or components, while a higher scale parameter indicates a faster overall degradation rate.

To estimate the shape and scale parameters for the soiling process, the degradation data from historical SCADA data were fitted to a Gamma degradation distribution [3]. The probability density function of the gamma distribution is given by:

$$f(x, \alpha, \beta, t) = \frac{\beta^{\alpha t} x^{\alpha t - 1} e^{-\beta x}}{\Gamma(\alpha t)}$$

EQUATION 4-1

The gamma process is varying on time (*t*) and allows to compute the probability of a given degradation *x*, given the shape and scale parameters.

4.1.2.2 RAIN PROBABILITY

The rain probability was computed based on [4] and a more detailed description can be found in the article. A rain event (RE) was defined as a day where the daily precipitation was above 5 mm, which is in agreement with the range described in the literature. The arrival rate of rain, λ, during day *d* of any year was estimated as the combination of the moving average of 7 days and the average of the same day over *Y* years:

$$\lambda(d) = \frac{1}{7Y}\sum_{i=-3}^{3}\sum_{y=1}^{Y} RE_{y,d+i}$$ **EQUATION 4-2**

The rain occurrence is then modelled as a non-homogeneous Poisson process with arrival rate $\lambda(d)$:

$$p_R(t_k) = 1 - e^{\lambda(d)\cdot\Delta t}$$ **EQUATION 4-3**

This estimation of rain probabilities assumes that the time-varying statistics of rain events are repeated periodically each year and that the statistics of rain vary slowly enough to be considered stationary over a week timeframe. The probability distribution of RE of the PV park at stake is shown in Figure 4-3.

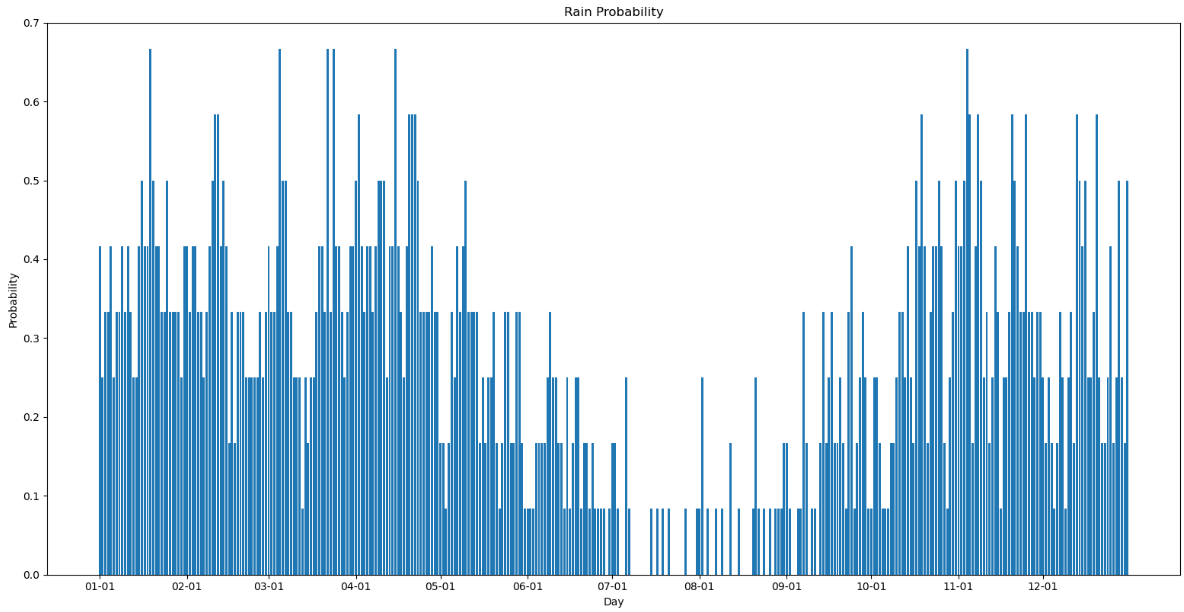

FIGURE 4-3: RAIN PROBABILITY THROUGHOUT THE YEAR

The cleaning effect of rain events depend on many factors, especially on the amount of rainfall. Long and heavy rain may clean the panels nearly perfectly while short and light rain events may increase the soiling. The probability of a state going into another state after a rain event was computed analysing historic transitions of rain events for each state, which can be written as:

$$p_S(s_j|s_i, rain) = \frac{N\,(s_j|s_i)}{N(s_i)}$$ **EQUATION 4-4**

Where $N(s_j|s_i)$ is the number of times that there was a transition from state s_i to state s_j after a rain event and $N(s_i)$ is the total number of times that $s = s_i$ before a rain event.

4.1.2.3 TRANSITION MATRIX

The transition matrix has dimension $s \times s \times a$, where s is the number of states and a is the number of possible actions.

The transition probabilities of performance ratio in the absence of cleaning are given by:

$$p_k(SR_j|SR_i, a = 0) = p_R(t_k)p_{SR}(SR_j|SR_i, rain) + [1 - p_R(t_k)]p_{SR}(SR_j|SR_i, no\ rain)$$

EQUATION 4-5

Where:

- $p_R(t_k)$ is the probability of rain when $t = t_k$;
- $p_{SR}(SR_j|SR_i, rain)$ is the probability of SR_i going into SR_j in the case where it rains;
- $p_{SR}(s_j|s_i, no\ rain)$ is the probability of SR_i going into SR_j in the case where it does not rain.

In the case of cleaning, we assume a perfect cleaning that results in the SR being set to zero. The transition probabilities of SR when the action is to clean are given by:

$$p_k(SR_j|SR_i, a = 1) = \begin{cases} 1 & SR_j = 0 \\ 0 & SR_j \neq 0 \end{cases}$$ **EQUATION 4-6**

4.1.3 REWARD

As described above, the reward is what the agent receives when taking a certain action A_t at time t, under the current state S_t. In the case of cleaning PV panels, the reward depends on the increase of revenue that results from cleaning since the PR increases, but also on the cost of cleaning. In the case of not cleaning the PV panels, the reward depends only on the current PR and the revenue associated with that.

In the case of not cleaning, the reward represents the revenue losses due to soiling, whilst in the case of cleaning it is the cost of that intervention.

Having that information, the rewards for moving from state s_i to state s_j taking the actions of not cleaning ($a = 0$) and cleaning ($a = 1$) are given by:

$$r_k(SR_j|SR_i, a = 0) = -Area_{cell} \cdot Efficiency \cdot SR_i \cdot N \cdot E(DNI(t_k), price(t_k)))$$
$$r_k(SR_j|SR_i, a = 1) = -cost_{cleaning}$$

EQUATION 4-7

Where:

- $Area_{cell}$ is the area of 1 PV panel;
- $Efficiency$ is the efficiency of the PV panels stated by the manufacturer;
- SR_i is the SR of state *i*;
- N is the number of PV panels in the park;
- $E(DNI(t_k), price(t_k))$ is the expected value of Irradiation*Price for $t = t_k$ based on historical values.
- $Cost_{cleaning}$ is the cost encountered to clean the whole plant.

5. INVERTER MODEL

In this section the module of the ROI prediction model related to the inverters is described. As for all the other components composing the ROI prediction model, the inverters were modelled as an MDP.

5.1 MARKOV DECISION PROCESS

As described in Section 2, an MDP is made of different parameters:

- **State:** describes the conditions of the inverter.
- **Action:** is the set of possible actions that the agent can take based on the state of the inverter.
- **Transition matrix**: it describes in a probabilistic way how the inverter can move from one condition to another.
- **Reward:** it is the reward that the agent receives when taking a certain action A_t at time t, under the current state S_t.

Each of the abovementioned parameters is extensively described in the following sections.

5.1.1 STATE AND ACTION

AI4PV inverter's faults detection algorithms are capable of detecting different fault and failures which are represented by three possible states:

- **State 0**: *Fault-free condition:* the equipment is trouble-free and in optimal working condition.
- **State 1:** *Degraded equipment*: the equipment is still operational, but its performance has degraded below the optimal levels.
- **State 2:** *Equipment failure:* the equipment has experienced a failure, compromising the production.

All these states can be represented by a variable $d_{inverter}$ which assumes values between 0 and 1. When $d_{inverter}$ is equal to 0 the component is in State 0, whilst where $d_{inverter}$ is equal to 1 the component failed. When $d_{inverter}$ assumes values between 0 and 1, this implies degradation in the component performance and thus on the energy injected by the PV plant.

There is a total of *N* maintenance actions that can be taken to transition between states. These actions are represented by the variable a, where a_o indicates no maintenance action and a_σ represents corrective maintenance of level σ . Three possible actions were identified:

- **Action 0**: "*do nothing*". No intervention is envisioned.
- **Action 1**: *"minor repair"*. Minor repairs are envisioned such as replacement of minor components such as cables, connectors, etc.
- **Action 2:** *"major repair".* the equipment has experienced a failure and it requires major repair such as replacement of the whole converter.

5.1.2 TRANSITION PROBABILITIES

The Transition Probabilities were computed based on the degradation process.

The degradation process was modelled using the gamma process, a commonly used distribution to describe degradation processes. The Gamma degradation process is characterized by a shape parameter (α), and a scale parameter (β), which determine the shape of the degradation curve and the rate at which the degradation occurs, respectively. The shape parameter reflects the degree of heterogeneity in the degradation of the system or component, while the scale parameter determines the overall rate of degradation. A higher shape parameter indicates that the degradation rate varies more widely across the population of systems or components, while a higher scale parameter indicates a faster overall degradation rate.

5.1.2.1 FAILURE PROBABILITY

The failure probability was computed considering the mean time between failures (MTBF):

$$MTBF = \frac{\sum total\ operational\ time}{number\ of\ failures} \quad \text{EQUATION 5-1}$$

The failure rate $\lambda(d)$, during day d of any year was estimated as the:

$$\lambda(d) = \frac{1}{MTBF} \quad \text{EQUATION 5-2}$$

The failure occurrence is then modelled as a non-homogeneous Poisson process with arrival rate $\lambda(d)$:

$$p_F(t_k) = 1 - e^{-\lambda(d)\cdot\Delta t} \quad \text{EQUATION 5-3}$$

Where $R(t_k) = e^{-\lambda(d)\cdot\Delta t}$ is the reliability, that is the probability of the equipment working in perfect condition in the following t_k days. This estimation of failure probabilities assumes that the time-varying statistics of events are repeated periodically each year and that the statistics of failure events vary slowly enough to be considered stationary over a week timeframe.

5.1.2.2 TRANSITION MATRIX

The transition matrix has shape $s \times s \times a$ where s is the number of states and a is the number of possible actions.

The transition probabilities of performance ratio in the absence of maintenance are given by:

$$p_k\left(d_{inverter_j} | d_{inverter_i}, a = 0\right) = p_F(t_k) \quad \text{EQUATION 5-4}$$

The transition probabilities of performance ratio when the action is maintenance level σ are given by:

$$p_k\left(d_{inverter_j} | d_{inverter_i}, a = 1\ or\ 2\right) = \begin{cases} 1 & d_{inverter_j} = 0 \\ 0 & d_{inverter_j} \neq 0 \end{cases} \quad \text{EQUATION 5-5}$$

5.1.3 REWARD

It is necessary to estimate the future rewards that can be expected to make informed decisions about maintenance actions. It requires considering various factors, such as the efficiency of the equipment and the costs associated with performing maintenance actions.

Having that information, the rewards for moving from state s_i to state s_j taking the actions of "do nothing" ($a = 0$) correspond to the revenue losses due to the current level of degradation ($d_{inverter_i}$) whilst for "minor repair" ($a = 1$) and major repair ($a = 2$) the reward is associated to the cost of the action. The rewards can be computed as follows:

$$r_k(d_{inverter_j}|d_{inverter_i}, a = 0) = -(Reward_{PV_{panels}} + Reward_{cleaning}) * d_{inverter_i}$$

$$\boldsymbol{r_k(d_{inverter_j}|d_{inverter_i}, a = 1) = -\,Cost_{minor\_repair}}$$

$$r_k(d_{inverter_j}|d_{inverter_i}, a = 2) = -\,Cost_{major\_repair}$$

EQUATION 5-6

Where:

- $Reward_{PV_{panels}}$ is the reward computed by the PV panels module, as described in Section 3.1.3;
- $Reward_{cleaning}$ is the reward computed by the Cleaning module as described in Section 4.1.3;
- $d_{inverter_i}$ is the degradation at state i.
- $Cost_{minor\_repair}$ and $Cost_{major\_repair}$ are the costs for minor and major repair.

6. TRANSFORMER MODEL

In this section the module of the ROI prediction model related to the transformer is described. As for all the other components composing the ROI prediction model, the transformer was modelled as an MDP too.

6.1 MARKOV DECISION PROCESS

As described in Section 2, an MDP is made of different parameters:

- **State:** describe the condition of the transformer. In this case a binary approach is used where:
  - *State=0*, means fault-free condition. The transformer is operating in normal conditions.
  - *State=1*, means faulty condition. There is the presence of a fault in the transformer (short-circuit or open-circuit condition).
- **Action:** is the set of possible actions that the agent can take. In the case of the transformer two possible actions are applicable:
  - Action=0, "do nothing". The transformer is kept as it is without any intervention.
  - Aciton=1, "replace". The transformer should be replaced with a new one.
- **Transition matrix**: it describes in a probabilistic way how the transformer can move from one condition to another.
- **Reward:** it is the reward that the agent receives when taking a certain action A_t at time t, under the current state S_t.

Each of the abovementioned parameters is extensively described in the following sections.

6.1.1 STATE AND ACTION

AI4PV transformer's faults detection algorithm (explained in D3.1 [5]) is based on a Digital Twin representation, and can detect three types of conditions:

- *Fault-free condition;*
- *Turn-to-turn short circuits;*
- *Open-circuit conditions.*

In the MDP representation just two states have been identified: "no faulty" or "faulty" state. The first type of condition (fault-free) belongs to the first state (state=0 "no faulty") whilst the other two belong to the "faulty" state.

Even though, short circuit and open circuit faults have different impact on the power output of the transformer and need dedicated algorithms for their detection, in case these faults occur the only possible intervention is to replace the device, this is the reason why both faults are represented through the same state.

6.1.2 TRANSITION PROBABILITIES

Reliability, Availability and Maintainability (RAM) for power transformers provides insights for the prediction of their performance and for the evaluation of the economic impact of their outages. Moreover, RAM can be used to improve reliability planning and enhance maintenance and monitoring practises [6].

A product goes through three different phases during its life cycle [7] [8]:

- **Infant mortality phase:** it is an interval with a decreasing failure rate. Failures within this phase are usually driven by manufacturing defects, design flaws or installation issues.
- **Useful life phase:** within this phase the product shows a relatively constant failure rate, where failures are mainly due to random events. Nevertheless, with an increased use of the asset, failure events become less random and more predictable leading towards the wear out phase.
- **Wear out phase:** in this phase the failure rate increases over time due to the ageing of the product.

In reliability assessment, these three phases are commonly represented by what is called bathtub curve (see Figure 6-1).

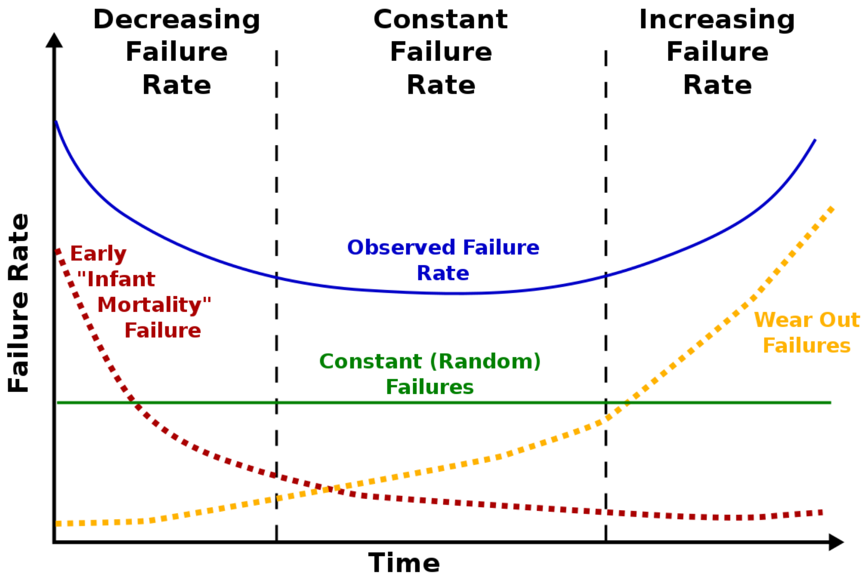

FIGURE 6-1: BATHTUB CURVE

The Weibull distribution is a model that is commonly used to characterise failure distributions in all three phases of the bathtub curve [9]. Equation 6-1 shows the Weibull Reliability Probability distribution, where:

- θ is the scale parameter also known as the characteristic failure time: it indicates when in time a given population will fail. It is the inverse of the failure rate over a certain time.
- β is the shape parameter of the distribution and it enables the application of the distribution to any phase of the bathtub curve. A $\beta < 1$ models a failure rate that decreases over time (infant mortality phase), a $\beta = 1$ models a constant failure rate (useful life phase) and a $\beta > 1$ models a failure rate increasing over time (wear out phase).

$$R(t) = e^{-\left(\frac{t}{\theta}\right)^{\beta}}$$

EQUATION 6-1

[10] and [11] have analysed historical data on a given population of power transformers in order to determine the failure rate of such component. In average 110 kV power transformers present a failure rate of 0.31%, 220 kV units have a failure rate of 0.62% while for 380 kV units it stands at 0.61%. Within this project the first value is considered as the power transformers installed in the demo site is a MV one.

6.1.3 REWARD

As described above, the reward is what the agent receives when taking a certain action A_t at time t, under the current state S_t. In the case of power transformers, since the device is either working or not, the reward depends on the revenue that results selling the energy produced and on the cost of replacing the power transformer. In the case of not replacing, the reward depends only on the status of the transformer and on the current PR.

In this case, the reward takes into account the state of all the other components and thus can be seen as the total reward that the agent wants to maximise. It is thus the reward of the whole MDP obtained by the combination of all the single MDPs representing the different components.

Having that information, the rewards for moving from state s_i to state s_j taking the actions of not replacing ($a = 0$) and replacing ($a = 1$) are given by:

$$\boldsymbol{r_k(s_j|s_i, a = 0) = (Reward_{PV_{panels}} + Reward_{cleaning} + Reward_{inverter}) * (1 - s_i)}$$
$$r_k(s_j|s_i, a = 1) = (Reward_{PV_{panels}} + Reward_{cleaning} + Reward_{inverter}) - Cost_{transformer}$$

EQUATION 6-2

Where:

- $Reward_{PV_{panels}}$ is the reward computed by the PV panels module, as described in Section 3.1.3;
- $Reward_{cleaning}$ is the reward computed by the Cleaning module as described in Section 4.1.3;
- $Reward_{inverter}$ is the reward computed by the Inverter module as described in Section 5.1.3
- $Cost_{transformer}$ is the cost necessary to replace the power transformer.

7. CONCLUSIONS

This deliverable detailed the ROI prediction model developed within AI4PV which will be employed to estimate the ROI of a given policy and prioritise the actions which have the highest impact.

As discussed within this document, the MDP represents the backbone of this tool as it is employed to simulate the lifetime of all the components. Even tough, in this document each component has been described individually, it is clear that the status of one component will impact on all the others. For this reason, the ROI prediction model is built as a unique MDP whose parameters (states, actions, transition matrix and rewards) are given by the combination of all the single MDPs.

Figure 7-1 depicts the operation of this tool. It receives as input a certain policy which the user wants to evaluate, as well as the current status of all the components. Given these inputs, it provides the ROI of that given policy as well as the order of the actions that should be taken, thus prioritising the actions with highest impact.

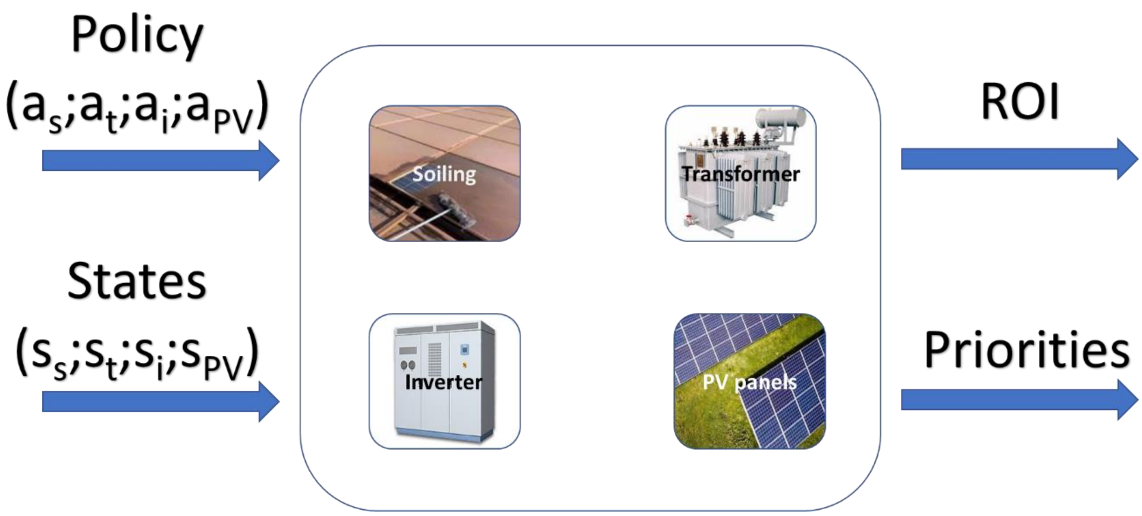

FIGURE 7-1: REPRESENTATION OF THE ROI MODEL

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