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*RESEARCH ARTICLE*

# USING DYNAMIC BAYESIAN NETWORKS TO EVALUATE THE PHOTOVOLTAIC MODULES DEGRADATION PROCESS WITH ARTIFICIAL INTELLIGENCE

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## Abstract

The performance of PV systems is highly dependent on climatic hazards (wind, dust, low sunshine, etc.). Some of these hazards can even accelerate its degradation process during its life cycle if nothing is done in terms of maintenance policy. This paper aims to model the degradation process of PV systems under environmental conditions. To do this, a system study is first performed to analyze the experimental data of the PV system in question according to the location of the site and simulated under the PVsyst software to extract the parameters of the study. In a second step, taking into account the Markovian approach, passing rules are established to design our dynamic Bayesian model. To this model, we have integrated a maintenance policy decision node and performance indicators in order to reproduce the degradation process in the real context and under stress. We have associated the decision node to enable AI integration through reinforcement learning on this node.The simulation results effectively reproduce the behavior of the PV system under environmental stress according to several scenarios (with or without IA). Furthermore, simulation allows us (a) to observe and validate the experimental values taken during the tests on the PV, (b) to see their availability increase with reinforcement learning compared to the case without learning. At the same time, we note that the increase in this availability leads to a relative decrease in income. The model allows to evaluate the performance of the system and propose the bestmaintenance policy configurations according to the input parameters (transition parameters, maintenance cost).



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## Introduction:-

PV systems are exposed to weather hazards (low sunshine due to clouds, dust, etc.), mechanical and electrical stress during operation (falling of solid particles on PV, forces of disturbance and vibration due to wind, short circuits due to mechanical vibrations of the wind, lightning, etc.), etc.

Indeed, the impact of these phenomena on PV modules decreases the performance of the system over time. This decrease means that a degradation process occurs in the PV system and can lead to its partial or total failure (for example, low power relative to rated power) if nothing is done to mitigate it.

Then, it is necessary to follow the degradation process, quantify it over time to evaluate the performance of the system and decide on the optimal choice of maintenance policy to achieve a desired level of performance.

The objective of this paper is to propose a method for evaluating the performance of PV modules under meteorological and mechanical stress.

Indeed, it is about analyzing the degradation process of PV modules by building a model of the system degradation process capable of better understanding the performance of the PV system and making decisions based on the degradation parameters and the associated maintenance. This model of the degradation process transformed into a so-called Bayesian model, obeys the Bayes principle and is subject to intelligence techniques in particular reinforcement learning in order to have a decision support system for performance evaluation and choice of PV system maintenance policy.

However, although there are other modeling tools in the literature, Bayesian networks are preferably a very powerful tool in decision support systems, in knowledge engineering and modeling with integration of uncertainty in probabilistic form, etc.

The rest of this paper is described as follows: Section 2 deals with the state of the art on system performance evaluation and associated modeling, Section3 sets out the methodology of our paper, Section4 gives the results of the simulation and their discussions, and Section 5 provides the conclusion and perspectives to this paper.

## Literature Review:-

Much work has been carried out in various fields with the application of Bayesian networks. This work can be classified into three points:

The first point concerns the maintenance of industrial systems, including work on the analysis of machine failures and the choice of maintenance policy to ensure their availability or reliability
( [1]; [2]; [3] [4] ), modeling and simulation of complex systems [5]; [6] , prognosis [7] and decision support for the maintenance of complex or multi-state systems [8]; [9].

The second point deals with health optimization, in particular (a) medical diagnosis and modeling of influencing parameters in medical treatments ( [10]; [11]) (b) data uncertainty classification and quantification [12], genetic predisposition disease analysis [13].

The third relates to AI in particular on climate data [14], prediction or risk assessment models [15], object recognition [16] and dynamic regulation [17].

Indeed, the Bayesian network is widely used in several areas to evaluate the prediction, diagnosis, reliability and performance of systems related to industry, health, agriculture, etc.

However, in relation to the energy system in particular, PV on modeling, performance study and failure analysis under environmental stress remain very little or poorly treated in the literature. Here in this work, we will use dynamic Bayesian networks to evaluate the degradation process of PV modules over time and propose a decision aid for maintenance based on the integration of artificial intelligence(learning by reinforcement).

## Methodology:-

To develop our model, we will use the meteorological data of the study site (humidity, solar radiation, temperature, wind speed, dust, etc...) detailed by month, by year in PVsys software and calculate their probability of occurrence.

From these variables related to meteorological data, mechanical and electrical shocks, we will build a Bayesian model where each of the variables is considered as a node. Indeed, this Bayesian model represents the degradation process of PV modules subjected to these meteorological, mechanical and electrical constraints. The implementation of the model is done in the environment of the Bayesialab software.

The model thus constructed is studied and simulated according to four (4) scenarios in order to follow the evolution of the degradation process of the modules over time and to decide on the optimal choice of maintenance policy via artificial intelligence(reinforcement learning method).

**Modeling the degradation process of photovoltaic modules:-**
All systems whose future state of operation depends only on the present state can be described by a Markov process, those for which the probabilities of transitions between any states are not affected by time.
The photovoltaic module is a model of multi-state systems, whose electrical production leaves an initial (normal) operating state to occupy in time more and more degraded production states until its major degradation.
This degradation process is equivalent to a Markovian system which we will model by considering the different states of transitions occupied over time and the parameters of the transition rates of the system.

**Bayesian model of the PV degradation process:-**
We will model a dynamic Bayesian network of multi-state system (SME) type from the Markovian SME model by adopting passage rules.

The rules for moving from the Markovian model to the dynamic Bayesian model are:
1. Transformation of the transition rate parameters into nodes and simultaneously integrating a decision node for maintenance policy but also performance indicators.
2. Transformation of the states occupied by the system over time.

In the PV degradation process, we identified environmental and electrical variables that may affect the state of the PV. These variables can be degradation modes (corrosion, fading, delamination, crack and hot spot) that will determine the state of the PV at a given time. Environmental variables include: humidity, temperature, solar radiation, dust, mechanical variable refers to mechanical shocks. For the electrical variables, we take overvoltage and overcurrent.

These variables were transformed into nodes to form a dynamic Bayesian network (RBD).

At a certain time, we will observe that the system degrades from a state (t) to a state (t+1) under the control of the decision node which will decide the maintenance policy to adopt.

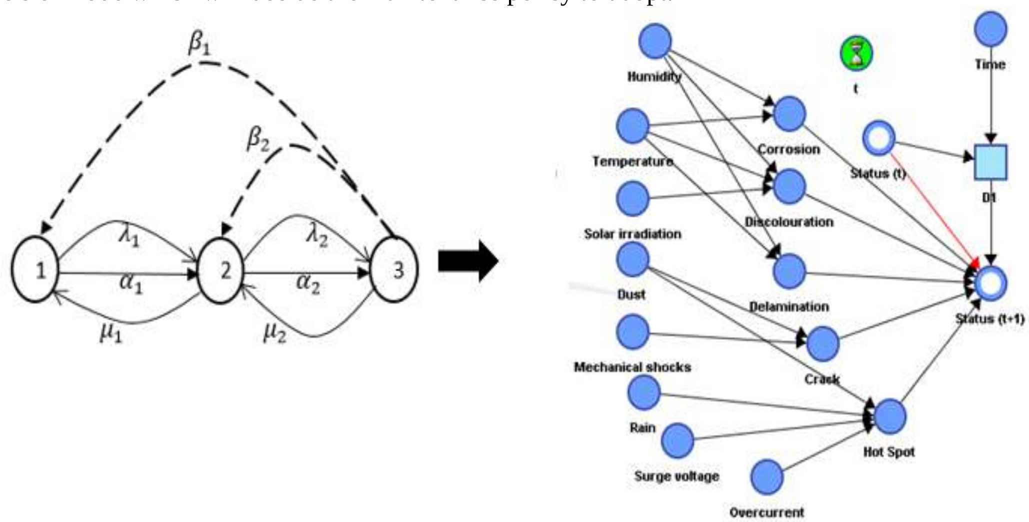


**Figure 1:-**Transition graph from the Markov model to the dynamic Bayesian model of the PV modules degradation
The different states of the system and the transition rates between them are such that:
State 1: corresponding to the normal state of the PV modules or there is no degradation;
State 2: corresponds to the state of minimal degradation;
State 3: corresponds to the state of major degradation;
$\alpha_1$ : Rate of degradation from normal to minimal degraded state;
$\lambda_1$ : Failure rate from normal to minimal degraded state;

$\mu_1$ : Repair rate from minimal degraded to normal condition;

$\alpha_2$ : Rate of degradation from a minimal degraded state to a maximum degraded state;

$\lambda_2$ : Failure rate from a less degraded state to a more degraded state;

$\mu_2$ : Repair rate from a more degraded state to a less degraded state;

$\beta_1$ : Rate of passage, by the maximum preventive maintenance action from major degradation (state 3) to normal (state 1);

$\beta_2$ : Rate of passage, by the minimum preventive maintenance action, from the state of major degradation (state 3) to the minimal degradation (state 2);

In our dynamic Bayesian model of the multi-state system E(t) and E(t+1) respectively denote the state of the system at time t and t+1. The other nodes represent the probability ratios of the different variables and the transition rates between system states.

**Decision support for PV maintenance:-**

In the decision node, we have planned different maintenance policies:

1. No preventive maintenance (No_PM),
2. Minimum Planned Maintenance (Min_PM)
3. Maximum preventive maintenance (Max_PM).

We have defined three modalities for the state of degradation of the PV module:

1. No degradation ($E_0$),
2. Minimum degradation ($E_1$)
3. Major degradation ($E_2$).

We will study the model under different scenarios with or without learning on the photovoltaic module maintenance policy decision node using the influence diagram including utility nodes, decision nodes, probabilistic and deterministic nodes.

We will observe how the photovoltaic module will behave in a state (t+1) time span under the influence of environmental and electrical parameters.

Finally, a proposal for the choice of maintenance policy is made by simulation according to the different configurations of transition rates between states occupied by the system over time.

**Study of maintenance costs and downgrading of the PV system:-**

For the evaluation of the photovoltaic (PV) modules maintenance policy, we integrate performance indicators such as:

1. System availability;
2. The cost of repair curative maintenance on multi-state system (Repair_Cost);
3. The minimum cost of preventive maintenance (Min_Cost_PM);
4. The maximum cost of preventive maintenance (Max_Cost_PM);
5. Income.

We can calculate the maintenance cost by

$$\mathbf{C_{system} = C_{unavailability} + C_{degradedstate} + C_{failure}} \quad \mathbf{(1)}$$

$C_{system}$ : System maintenance cost

$C_{unavailability}$ : Cost of system unavailability

$C_{degraded\ state}$ : Cost associated with degraded states

$C_{failure}$ : Cost associated with failed states

$$\mathbf{C_{failure} = \sum_{j=2}^{d} x_D . P_{2j-1}} \quad \mathbf{(2)}$$

$$\mathbf{C_{unavailability} = \sum_{i}^{2d+m} productionpenality \times P(E(t) = i)} \quad \mathbf{(3)}$$

To track the evolution of a given system, we consider a preventive maintenance policy decision variable called

$$x_D = \begin{cases} 1 & Preventivemaintenance \\ 0 & NoPreventivemaintenance \end{cases}$$

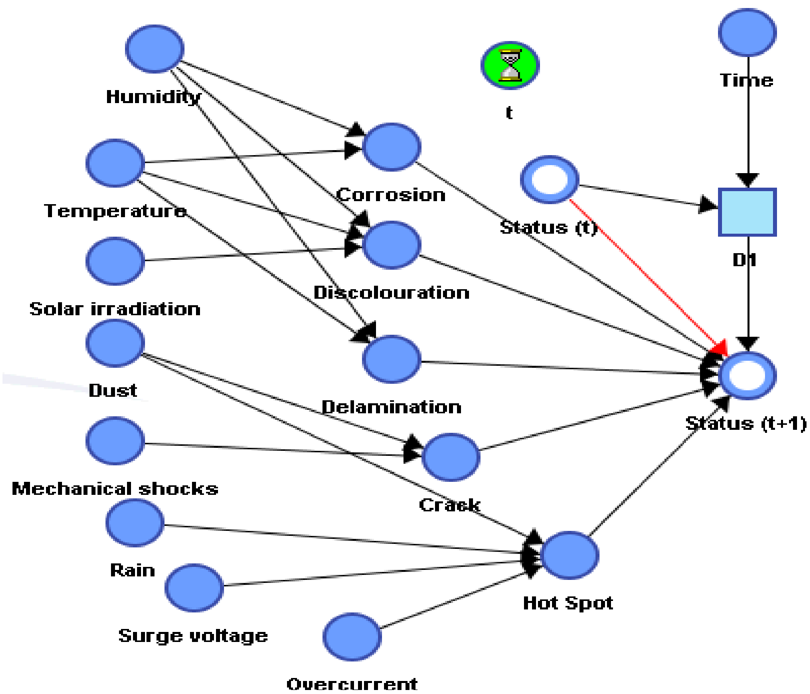


**Figure 2:-** Influence diagram with decision support.

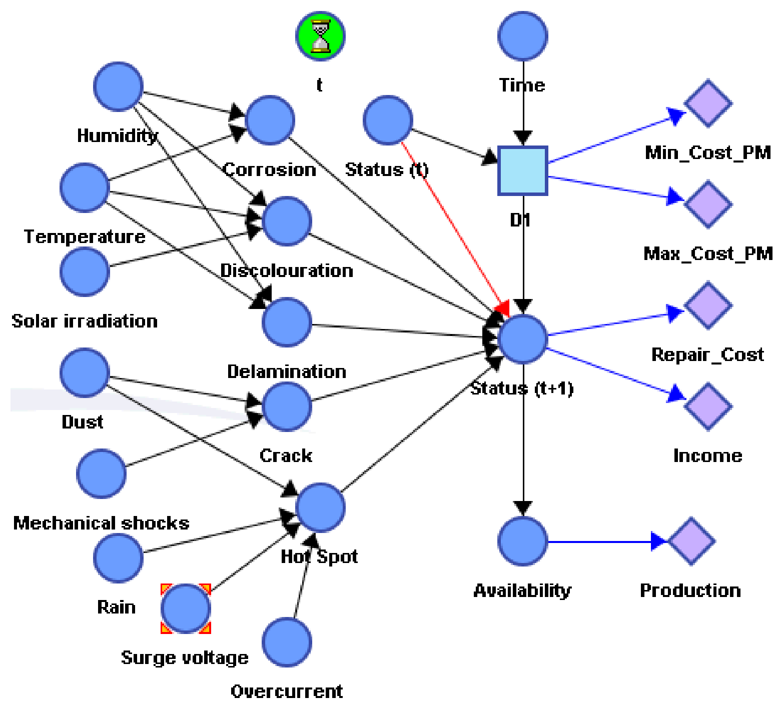


**Figure 3:-** Dynamic Bayesian model of the PV system with integration of maintenance costs.

**Simulation of the Bayesian model:-**

The simulation study is done over an operating time of 17000. It is considered necessary to simulate over a long period of time in order to be in intensive use of the system under study[8].

We will perform a simulation study to examine and determine the correct configurations of maintenance actions on a production system.

In our simulation study, we will use the parameters of learning algorithms by reinforcing the following values: discount factor: 0.99; Learning rate 0.25 and initial exploration rate 0.50 for all cases of learning maintenance actions. We start with three modalities to be able to analyze the optimal level of preventive maintenance:

1. No preventive maintenance;
2. Minimum preventive maintenance;
3. Maximum preventive maintenance.

The level “zero preventive maintenance” means that no preventive maintenance action is taken, Minimum preventive maintenance is to return the system to a degraded but better operational state and maximum preventive maintenance is to return the system to its perfect initial state[8].

The decision node D imposes one of the maintenance levels mentioned above and a learning algorithm allows to decide the right decision among the modalities at each iteration

The Chapman-Kolmogorov equation for our model is:

$\sum_i^3 P_j^k = 1$ ; $0 \leq t \leq T$

It is noted that:

$P_j^k$ is the probability that the system will be in state j at time t;

$P_j^{k+1}$ is the probability of transition to state j.

$$\lim_{\Delta t \to t} \frac{P_j(t+\Delta t) - P_j(t)}{\Delta t} = \frac{dP_j(t)}{dt} = P_j^{k+1} \quad \textbf{(4)}$$

Then, based on this table 1 and the Chapman-Kolmogorov equations, the probability distributions of the different nodes in our RBD model are calculated and put into their probability tables (TPC).

**Table 1:-** Distribution of probabilities of states.

Sélection du noeud : Status (t+1)

Type du noeud: Label

Mode de visualisation: Déterministe | Equation

| Valeurs |
|---|
| E0 |
| E1 |
| E2 |

| Status (t) | D1 | Corrosion | Discolouration | Delamination | Crack | Hot Spot | E0 | E1 | E2 |
|---|---|---|---|---|---|---|---|---|---|
| | D1 par de | True | True | True | True | True | 99,965 | 0,005 | 0,030 |
| | | | | | | False | 99,965 | 0,005 | 0,030 |
| | | | | | False | True | 99,965 | 0,005 | 0,030 |
| | | | | | | False | 99,965 | 0,005 | 0,030 |
| | | | | False | True | True | 99,965 | 0,005 | 0,030 |
| | | | | | | False | 99,965 | 0,005 | 0,030 |
| | | | | | False | True | 99,965 | 0,005 | 0,030 |
| | | | | | | False | 99,965 | 0,005 | 0,030 |
| | | | False | True | True | True | 99,965 | 0,005 | 0,030 |
| | | | | | | False | 99,965 | 0,005 | 0,030 |
| | | | | | False | True | 99,965 | 0,005 | 0,030 |
| | | | | | | False | 99,965 | 0,005 | 0,030 |
| | | | | False | True | True | 99,965 | 0,005 | 0,030 |
| | | | | | | False | 99,965 | 0,005 | 0,030 |
| | | | | | False | True | 99,965 | 0,005 | 0,030 |
| | | | | | | False | 99,965 | 0,005 | 0,030 |

Ajout avant | Ajout après | Supprimer | Générer les noms | Générer les modalités | Compléter | Normaliser | Aléatoire

## Results and Discussions:-

We will analyze the evolution of degradation of PV modules through our basic model with the consideration of all possible levels of preventive maintenance policy.

The environmental and electrical parameters between the different degradation states of the modules to be studied are considered. The basic model of the system to be studied must indeed reproduce the different states of degradation over time as that of a Markov graph.

We do a simulation of the degradation process of these modules which gives us the set of joined probabilities of the system's degradation states over a time step of 17000. This choice of high value time steps allows to observe the degradation of modules over a long operating life.

The figure below (Figure 4) shows the joint probabilities of different degraded states of operation of the modules after a time step of 17000.

- 1.40% of the photovoltaic modules operate normally, which corresponds to the perfect state of operation of the $E_0$ modules.
- 4.70% of photovoltaic modules operate with minimal degradation. $E_1$.
- 93.90% of the photovoltaic modules show major degradation $E_2$.

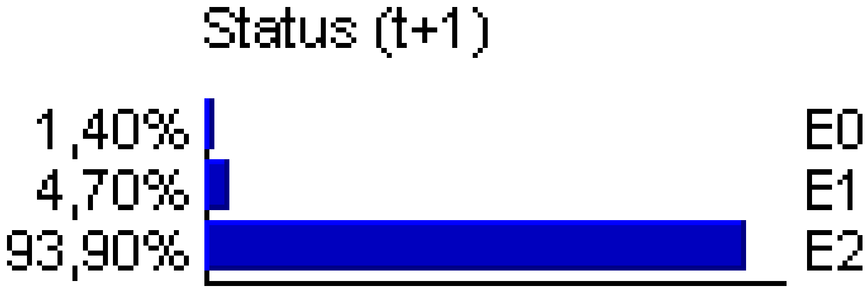


**Figure 4:-** Joint probabilities of system states.

Furthermore, the progression of the photovoltaic (PV) module degradation process for a designated state $E_0$, which corresponds to the PV system's standard operating condition, is hereby presented. The degradation process exhibits a decline over time, contingent upon the adopted maintenance strategy, income, and production costs (see Figure 5).

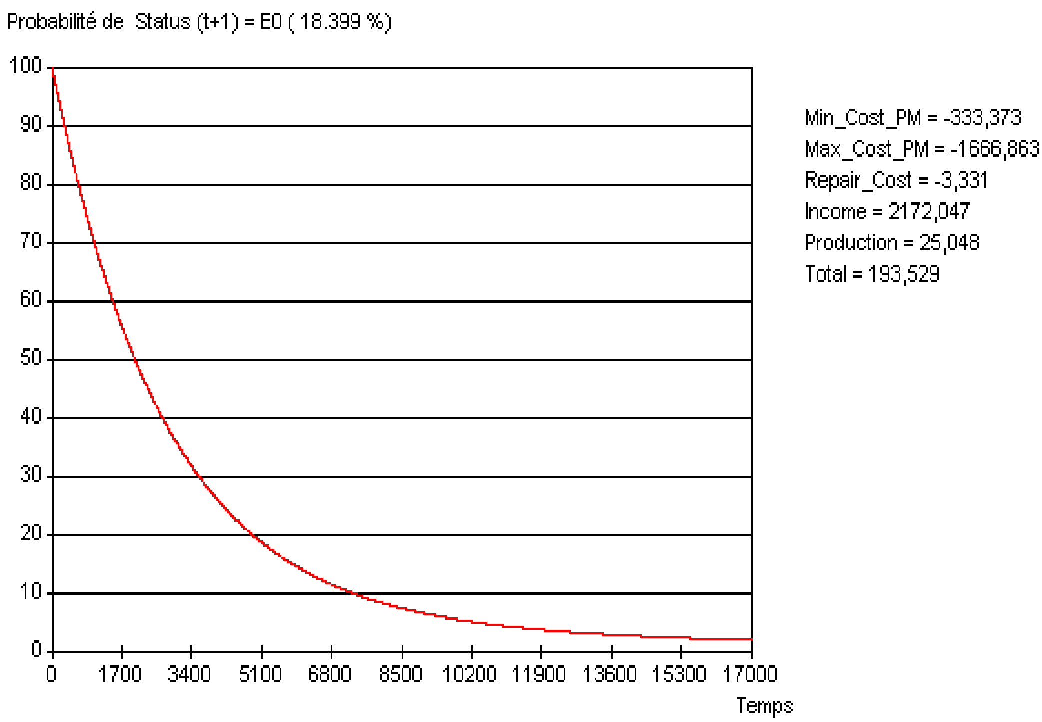


**Figure 5:-** Evolution of the $\boldsymbol{E_0}$ degradation process.

Figure 6 illustrates the progression of the degradation process, commencing from state $\boldsymbol{E_1}$ (minimal PV module degradation) and culminating at a production threshold of less than 10%, whereupon it undergoes a subsequent decline.

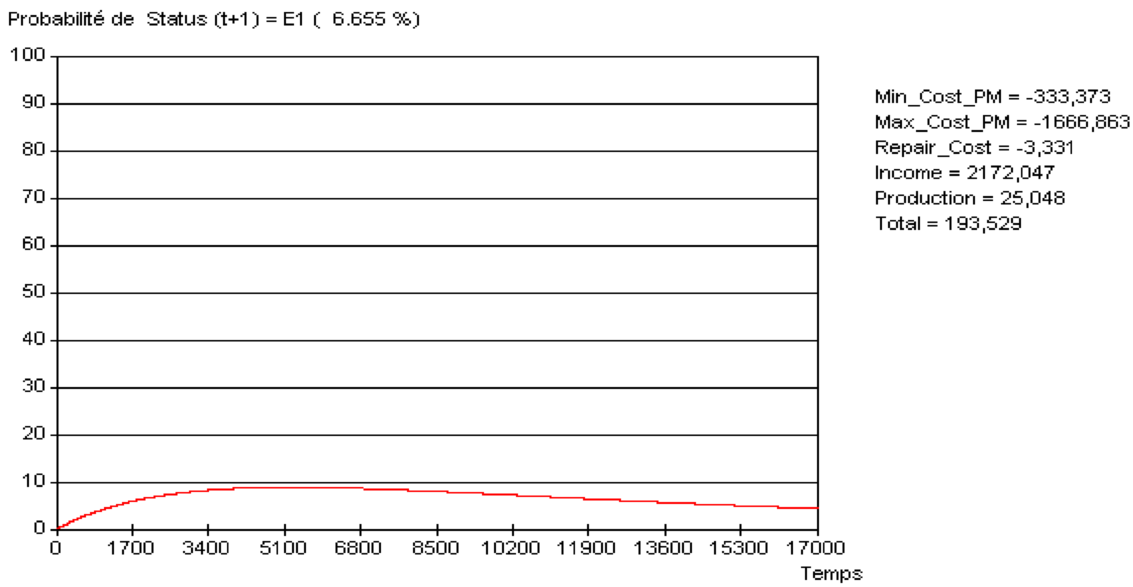


**Figure 6:-** Evolution of the $E_1$ degradation process.

Furthermore, Figure 7 demonstrates an escalating degradation process in state $E_2$ (the state of maximum degradation) in comparison to state 1.

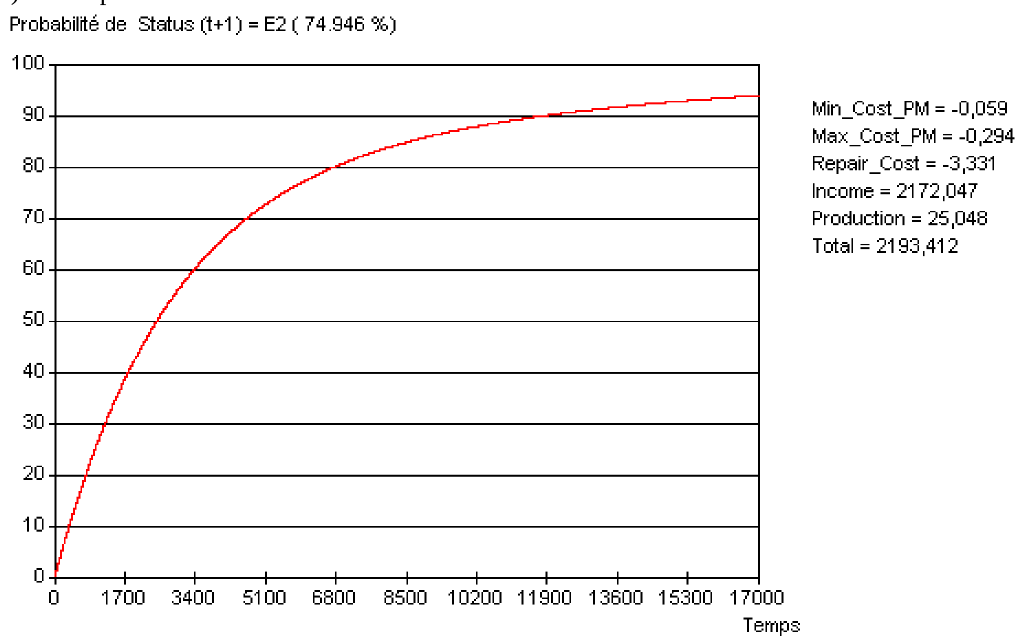


**Figure 7:-** The evolution of the degradation process of $E_2$

We note in this monitoring that at the initial instant State E(t) while considering $E_0$ ( No_degr), the system follows a degradation process up to a time step of 1700, we obtain at instant (t+1), 93,90% of $E_2$ ( Maj_degr) ; 4.70% of $E_1$ (Min_degr) and 1.40% of $E_0$ against 0% of $E_1$ (t) and $E_2$ (t) at the initial instant E(t).

Furthermore, at time E(t) the probability of certain variables responsible for degradation such as:corrosion (6.45%); discoloration (18.74%) and delamination (8.30%) saw their values increased by (7.60); (19.30% and (9.10%) at time E(t+1) respectively.
On the other hand, the probability of the other variables (crack and hot spot) was reduced.

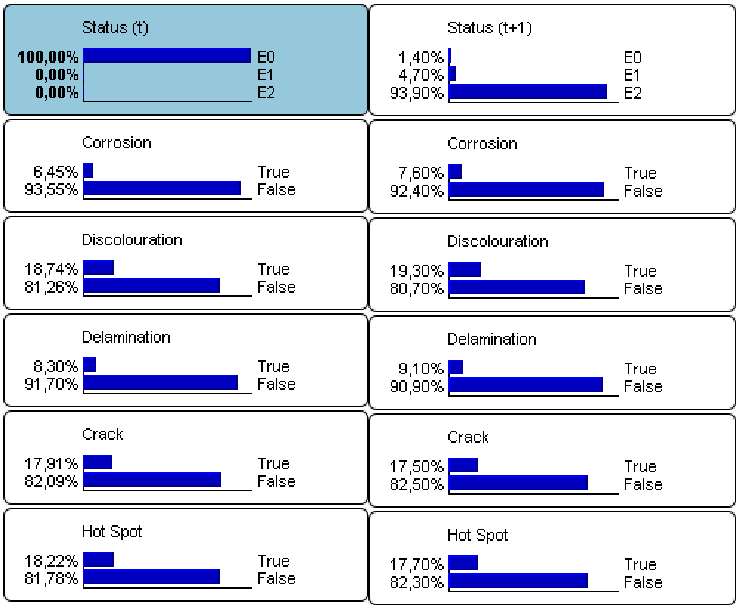


**Figure 8:-** Evolution of different degradation modes.

**Learning the model**

We will carry out simulation tests to study the maintenance policy as a function of performance indicators.To do this, we choose four cases with or without reinforcement learning, depending on two parameters: system availability and income. Income is the average gain obtained in an operating state of the modules over a time step of 17,000 in the operating phase.

**Case 1: Simulation without learning based on income**

Simulation studies give us around 24% availability with an average hourly income of around 2102 euros over a time step of 17000 (Figure 10).

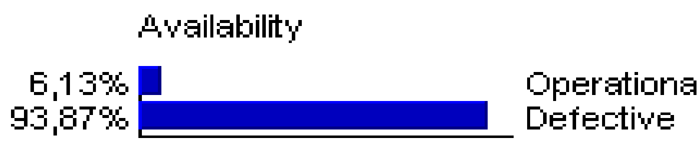


**Figure 9:-** Probability of system availability without learning based on income.

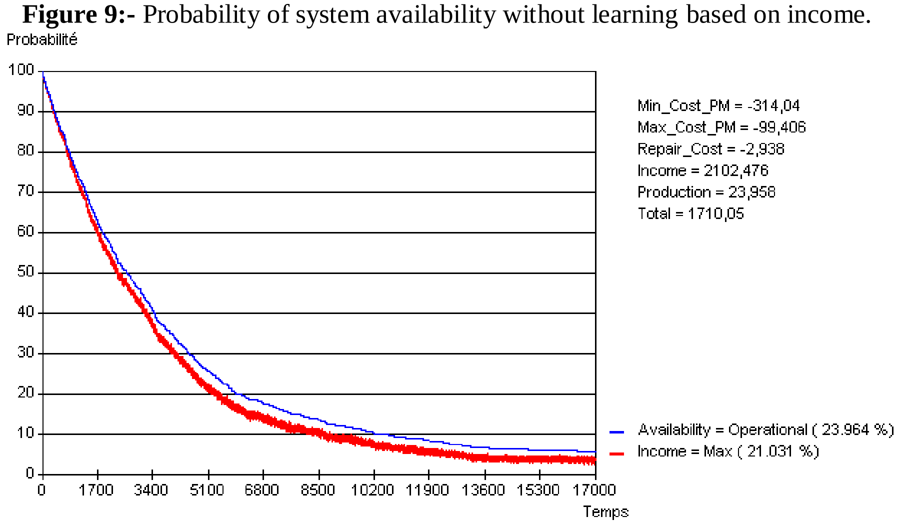


**Figure 10:-** Simulation curve: without learning on node D based on income.

We can see from figure 10 that availability decreases over time, and this decrease has an impact on income, as they decrease together. We also observe that system availability drops to around 6% at a time step of 17,000. This loss of availability should prompt us to review the maintenance policy at the income level, which is a function of availability.

**Case 2: Simulation with income-based learning:-**
Analysis of the simulation with learning as a function of income, we obtain the following figure:

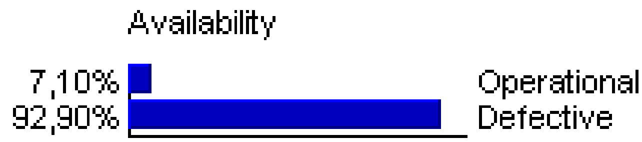


**Figure 11:-** Probability of system availability with learning as a function of income.

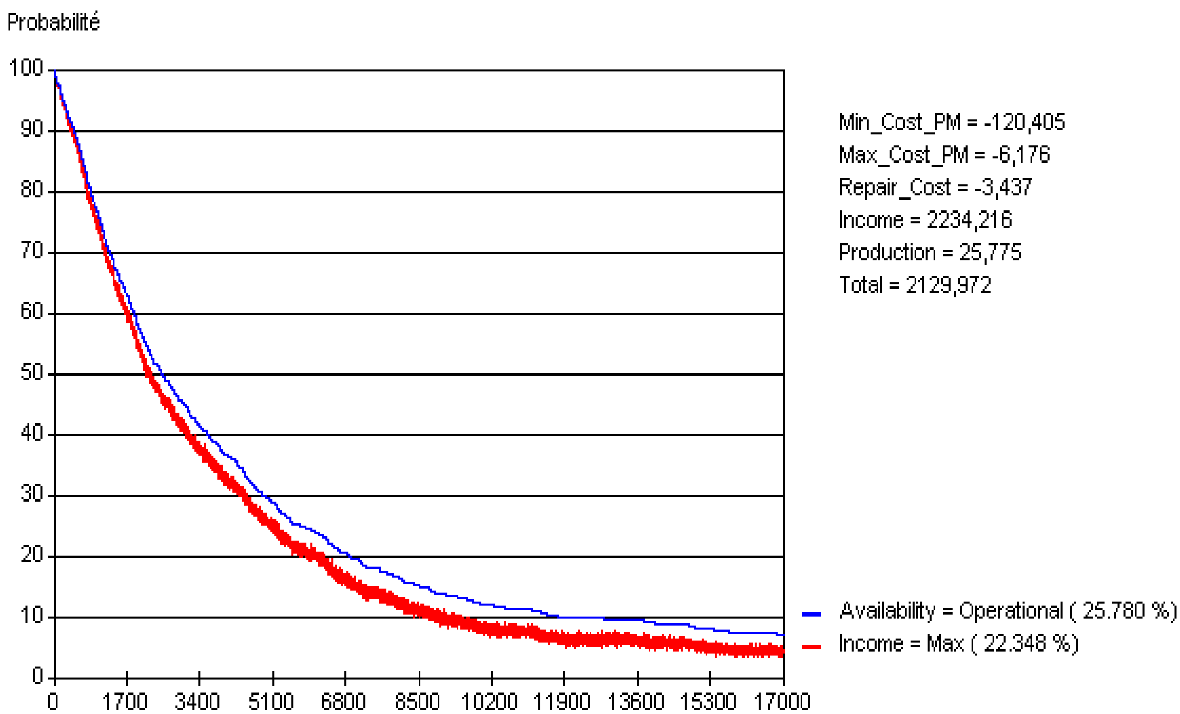


**Figure 12:-** Simulation curve: learning on node D with income.

This simulation curve shows us a significant drop in availability of around 7%, compared with 6% in the first case above, at a time step of 17000. This fall in the availability curve has a negative effect on the income curve, as shown in the figure, but its value remains only slightly higher than in the first case.

By learning about preventive maintenance, we can see that the modules studied have:
1. an availability of around 26%, compared with 24% in the case without learning (Case 1)
2. an average hourly income of 22%, compared with 21% in the same simulation (Case 1).

We therefore observe a 2% increase in availability compared with the simulation without learning. We also note that maintenance costs have risen compared to the (1st case), to reach a gain of 1% more than the gain in availability.

**Case 3: Simulation without *learning* based on availability:-**
Our aim is to determine a preventive maintenance policy that does not require learning, and optimizes system availability as a function of transition parameters and maintenance costs.

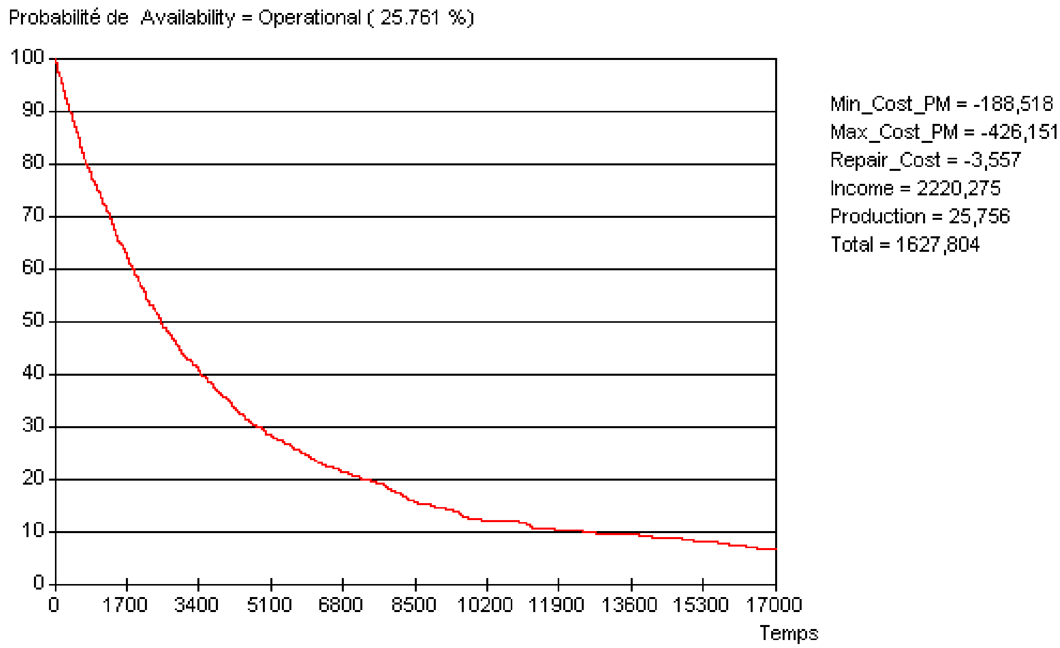


**Figure 13:-**Simulation curve without learning based on availability.

We can see from the unlearned results that the modules studied have anincome of around 2220 euros per time step and an availability of around 26%.

**Case 4: Simulationwith learning on the preventive maintenance decision based on availability:-**
This simulation with learning gives us an availability of around 31% and an income of 2143 euros.

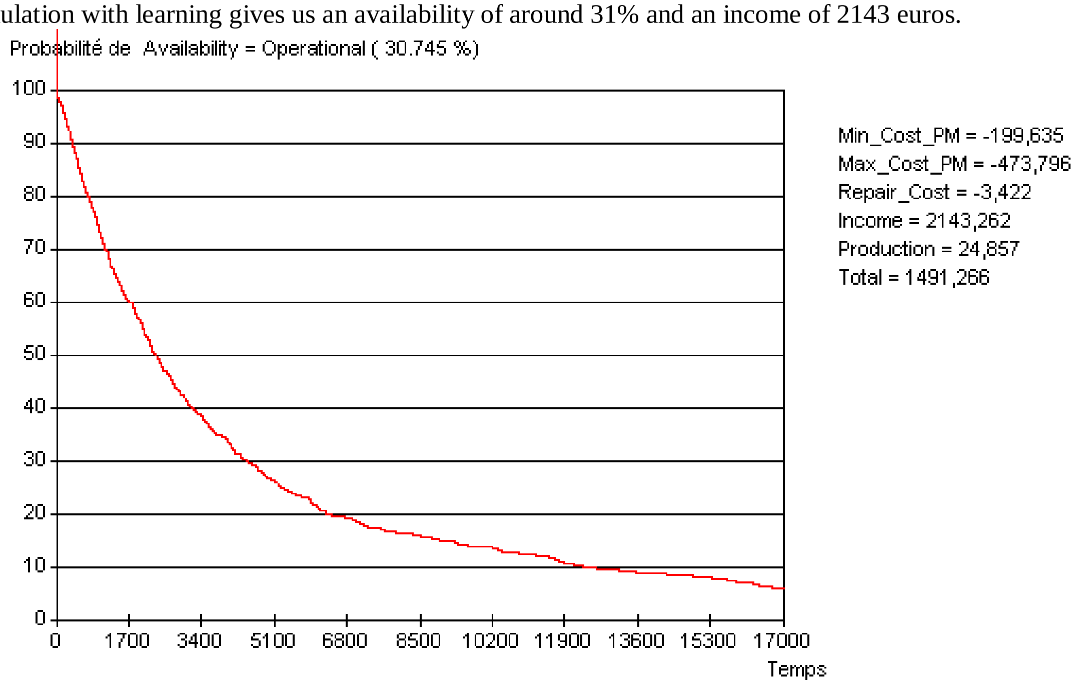


**Figure 13:-** Simulation curve: learning about preventive maintenance based on availability.

By learning about preventive maintenance, we can see that:
- The system studied has an availability of around 31%, compared with 26% in the previous case without learning (3rd case).
- With an hourly income of 2143 euros versus 2220 euros in the same case (3rd case).

So a 5% increase in availability compared with the simulation without learning of the (3rd case).

The results of the different simulation cases are summarized in the table below.

**Table 2:-** The results of the different simulation cases.

| Simulation case | Case 1 | Case 2 | Case 3 | Case 4 |
|---|---|---|---|---|
| **Income** | 2102 | 2234 | 2220 | 2143 |
| **Availability** | 24 | 26 | 26 | 31 |

## Conclusion:-

In this paper, we have proposed a methodology for assessing the performance of PV systems under environmental constraints. A dynamic Bayesian model of the degradation process was built using experimental data and simulated under several scenarios with or without reinforcement learning, in order to propose maintenance policy configuration choices. Indicators such as availability, income, cost and production were integrated into the model to assess system performance and the cost associated with the choice of preventive maintenance policy adopted.

The simulation study of our dynamic multi-state model of the PV system shows the evolution of the PV module degradation process, as well as the Markov graph, according to the choice of preventive maintenance policy adopted.

In addition, the simulation with reinforcement learning on preventive maintenance allowed us to observe that availability increases with income compared to the simulation without learning. A fairly substantial decrease in income was also observed, this is due to the increase in the availability of the system and may allow decision-makers not to exceed a certain threshold of availability at the expense of income.

The results obtained prove that AI associated with our dynamic model contributes to decision support for decision makers in particular maintenance managers in choosing the appropriate maintenance policy for the PV system.

The results obtained demonstrate that the AI associated with our dynamic model contributes to decision support for decision-makers, in particular maintenance managers, in choosing the appropriate maintenance policy for the PV system.

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