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Degradation modelling and maintenance optimisation of PV panels affected by dust accumulation

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Résumé—L'objectif de cet article est d'étudier la modélisation et l'optimisation de la politique de maintenance d'un système panneau photovoltaïque se dégradant dans le temps. Dans cet article, nous modélisons le processus d'accumulation de poussière comme principale cause de dégradation des panneaux PV en considérant le comportement du vent comme covariables. Le processus d'accumulation de poussière est modélisé par un processus de Poisson composé non homogène (NHCPP). Le processus des covariables est modélisé par une chaîne de Markov homogène en temps à espace d'état fini. Un modèle similaire au modèle des risques proportionnels est utilisé pour montrer l'influence des covariables sur le processus de dégradation. Dans le cadre du système considéré, nous proposons une politique de maintenance qui minimise le coût moyen à long terme et qui maximise les profits moyens à long terme. Des essais numériques sont présentés pour illustrer la performance de la politique proposée.

Abstract—The objective of this paper is to discuss the problem of maintenance modelling and optimisation for a deteriorating Photovoltaic panel system. In this paper, we model the dust accumulation process as PV panels' as the main degradation cause considering the wind conditions as covariates. The dust accumulation process is modeled by a non-homogeneous compound Poisson process (NHCPP). The covariates process is assumed to be a time-homogenous Markov chain with finite state space. A model similar to the proportional hazards model is used to show the influence of covariates on the degradation process. In the framework of the system under consideration, an appropriate maintenance policy which minimises the long run average maintenance cost and maximises the long run average profits is derived. Numerical implementations are presented to illustrate the performance of the proposed model.

Keywords—Solar system, Dust accumulation, Degradation model, Maintenance optimization, NHCPP, Covariates

I. OBJECTIVES

The implementation of photovoltaic (PV) systems plays an important role in future electricity generation [1]. It is particularly important to improve the reliability of PV systems and to investigate the degradation performance of PV panels.

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However, the degradation of PV systems is a complex process, which is affected by various environmental conditions. One factor that affects is the dust deposition over the surface of PV modules, which may cause problems that lead to a poor efficiency of the PV system [2, 3]. Especially in desert areas, a deficiency of self-cleaning due to various extended rainless periods makes situation worse. Authors in [3] review the effect of dust on the PV performance. In order to avoid losses due to reduced efficiency of PV panels, timely maintenance operations such as cleaning should be implemented. Previous studies on PV system are usually based on experimental tests [4, 5], which are time-consuming and labor-intensive. Considering this problem, we use the simulation study tools to investigate the degradation process, providing a reference for the decision-making when developing maintenance policies of solar farm.

In order to propose an appropriate maintenance policy, the most important thing to consider is the environmental conditions under which the system is operating. Most of the attention has been focused on systems with static environment and increasing degradation. Such assumption is often unrealistic. Hence in the framework of the proposed maintenance policy, the changes of environment are taken into account.

II. INTRODUCTION AND OVERVIEW

Solar photovoltaic (PV) panels use sunlight as a source of energy to generate direct current electricity. A collection of PV modules is called a PV panel. A PV panel has an average life expectancy of 25 years. A PV module's power output efficiency is an essential indicator when assessing the reliability of the PV module. However, dirt and dust accumulation may cause an loss in the energy production and power output [6]. Previous studies ([7, 8]) have shown that a layer of hardened dust with stains can reduce the power output of a PV panel as much as 30%. Setting up a proper

maintenance (cleaning) policy for deteriorating PV panel is an important issue. In this paper, we work on modelling the degradation of the PV panels and based on this we propose a maintenance policy.

Many degradation models [9] were developed to capture the deterioration process of the system and provide support for decision making. The commonly used degradation models include general path models [10] and stochastic process models [11]. The stochastic nature of stochastic processes is capable of modelling the randomness of the degradation over time because of unobserved environmental factors, or the unknown effects of the environmental factors on the degradation process. For degradation modelling, the most commonly used stochastic processes include Wiener process [12], Gamma process [13], Poisson process [14] and IG process [15].

A number of different maintenance policies have been proposed in the literature. [16, 17] gave a survey of maintenance and replacement models for the maintainability and reliability of multi-component systems. According to the state of the component when it is maintained, the maintenance actions can be divided into two major classes: corrective maintenance [18] and preventive maintenance [19]. Corrective maintenance is applied to a failed system, and preventive maintenance is performed before the failure. According to the efficiency of maintenance actions on the maintained component, maintenance actions can also be classified into three categories: perfect maintenance [20], minimal maintenance [21] and imperfect maintenance [22]. After a perfect maintenance operation, the system is as good as new. A minimal maintenance restores the system to the state it had just before the failure. After an imperfect maintenance action, the system is not as good as new.

In this paper, the degradation model is based on a non-decreasing stochastic process with covariates. Environmental conditions are considered as covariates in the degradation model. To precisely represent the effect of covariates on PV panels' degradation, we combine proportional hazard models (PHM) [23] and time-continuous Markov chain (TCMC) into our degradation model. The system is monitored through perfect inspections. Upon inspections, we implement two types of maintenance policies. One is a maintenance policy that combines preventive maintenance with corrective maintenance. We refer to this policy as policy A. The other is only based on corrective maintenance. We refer to this policy as policy B. The long run average maintenance cost and profits from power generation is derived and we validate these theoretical calculations by simulations. Numerical implementations are given to illustrate the applicability of the proposed model. The impact to covariates and model parameters are analyzed. The optimal inspection interval value is determined when the objective function achieves the minimum cost and maximum profits.

The remainder of this paper is organized as follows. In Section 2, the solar panel degradation process is modelled by a non-homogeneous compound Poisson process where the influence of the covariate is taken into account. In section

3, a maintenance policy combining preventive and corrective maintenance is proposed. The maintenance policy is evaluated by using the optimal expected maintenance cost and profits on a renewal cycle. On the other side, by comparing the cost and profit rate of this strategy to the case of corrective maintenance only we can get the effectiveness of the policy A. In section 4, we give the numerical implementations based on the degradation and maintenance model. Finally, in Section 5, conclusions are drawn from the work.

III. DEGRADATION MODEL

A. System description

We consider one panel as a multi-component system (as shown in Figure 1). A PV panel is an assembly in parallel of M PV modules. A PV module, as a component of the system, is composed of a series-connected set of solar cells. The components are subjected to a continuous degradation in terms of power production efficiency in time. The degradation of the system satisfies the following assumptions:

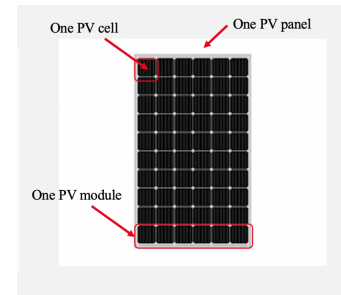


Figure 1. One PV panel

- PV modules suffer from dust accumulation, which leads to a reduction in their power production efficiency. As dust accumulates, the power production efficiency of the PV module continues to decrease until the efficiency drops to a level where we say the module is in a state of 'failure'. Based on this fact, the dust accumulation process also stands for the PV module degradation process.
- The accumulation of dust is a dynamic and complex process, influenced by the surrounding environment, especially wind conditions [2]. We consider the wind condition, as a covariate. It has an influence on the dust accumulation process.
- Considering the above practical situation, we propose a non-homogeneous compound Poisson process (NHCPP) to describe the degradation process. The dust accumulation process is described by the non-homogeneous Poisson process (NHPP) with the arrival rate function $\lambda(t)$. The jump sizes in NHCPP corresponds to the amount of dust at one arrival time, which follows an exponential distribution with parameter μ .
- Let $\{X_i(t), t \geq 0, 1 \leq i \leq M\}$ be the dust accumulation process (degradation process) of i th PV module. It starts from zero at $t = 0$ ($X_i(0) = 0$). Its increments in a time

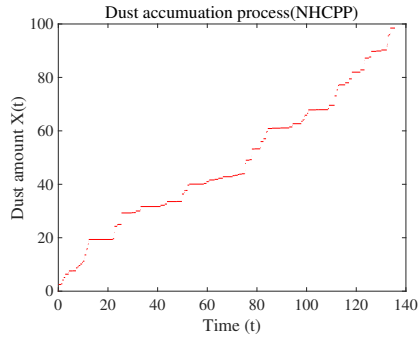


Figure 2. degradation process of i_{th} PV module

interval are non-negative, stationary, and stochastically independent. (see Figure 2)

- Let $Y_i(t)$ be the efficiency reduction of the i th PV module power generation. The relationship between the reduction of PV module power generation $Y_i(t)$ and the amount of dust accumulation $X_i(t)$ is proposed by [24] as:

$$Y_i(t) = \frac{-0.521}{1 + \left(\frac{X_i(t)}{12.653}\right)^{1.74}} + 0.532 \quad (1)$$

- The greater the amount of dust, the more sunlight is blocked and the higher is the reduction of efficiency of PV module power generation. When the efficiency of a PV module is too low, it can not be put into service. We say it is in a state of failure. We assume this state of failure is described by a threshold L : when $Y_i(t) \geq L$, the PV module is said to be in the ‘failed’ state (see Figure 3).
- The state of the PV panel is based on the states of the PV modules. Let $n(t)$ be the number of failed PV modules at time t . It can be expressed as:

$$n(t) = \sum_{i=1}^M \mathbb{I}_{Y_i(t) > L} \quad (2)$$

where $\mathbb{I}_A = 1$ if A is true, 0 otherwise. When the number of failed modules on a PV panel exceeds a certain integer value denoted as F_c , with $1 \leq F_c \leq M$, the panel won’t work efficiently. We assume the system enters a ‘‘failure’’ state. The time of failure t_f is such that:

$$t_f = \inf\{t \mid n(t) \geq F_c\}. \quad (3)$$

B. NHCPP Model

As explained previously, the dust accumulation process on PV module i is described by NHCPP with the arrival rate function $\lambda(t)$ and jump sizes obeying exponential distribution with parameter μ . The non-homogeneous compound Poisson process (NHCPP) can be defined as in [25] with:

$$X_i(t) = \sum_{j=1}^{N_i(t)} J_{ij}, t \geq 0 \quad (4)$$

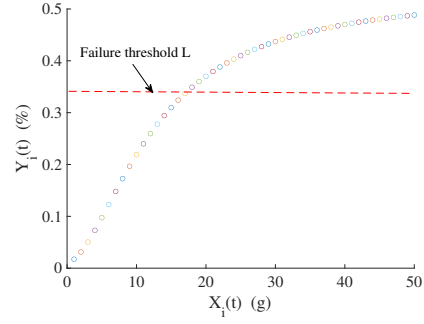


Figure 3. The correlation between $Y_i(t)$ and $X_i(t)$

where $N_i(t)$ represents the number of events on i -th PV module in a time interval $[0, t]$. J_{ij} represents the j -th jump size for module i .

$$\{N_i(t), t \geq 0\} \sim \text{NHPP}(\lambda_i(t)) \quad (5)$$

$$J_{ij} \sim \exp(\mu) \quad (6)$$

C. Wind speed

The failure of modules is caused by dust layers due to the environment. The wind condition, as a covariate $Z(t)$ with s possible states, is thought to have an effect on the dust accumulation process. A model similar to the proportional hazards model proposed by [23] is used to show the influence of the covariate on the dust accumulation process. Each arrival rate of NHPP $\lambda_i(t)$ is related to a covariate state. The model is as follows:

$$\lambda_i(t) = \alpha e^{-\sum_{j=1}^s \beta_{ij} \mathbb{I}_{z_i(t)=j}} \quad (7)$$

$$\beta_{ij} = (\beta_{i1}, \beta_{i2}, \dots, \beta_{is}) \quad (8)$$

where α is the so-called baseline hazard rate. β_{ij} is the vector of regression coefficients. j is the number of covariate states. $z_i(t)$ is the state of covariate for the i th module at time t .

Considering that the environmental conditions of the system are time related sequential data, we use the time-continuous Markov chain (TCMC) to model the covariates. The covariate process $\{Z_i(t), 1 \leq i \leq M\}$ is assumed to be a time-homogeneous Markov chain with state space $S = \{1, 2, \dots, s\}$ describing the states of the wind condition. The transition rate q_{ij} as a matrix is:

$$Q = \begin{pmatrix} q_{11} & q_{12} & \cdots & q_{1s} \\ q_{21} & q_{22} & \cdots & q_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ q_{s1} & q_{s2} & \cdots & q_{ss} \end{pmatrix} \quad (9)$$

where the diagonal elements are

$$q_{ii} = - \sum_{j=1, j \neq i}^s q_{ij} \quad (10)$$

Let t_{ij} be the time the process spends in state i before entering into state j . The time t_{ij} is exponentially distributed with rate q_{ij} .

We assume that the system is in a constant environment, i.e. there are no changes in covariates. Each arrival rate of NHPP $\lambda_i(t)$ is related to a fixed covariate state in formula 7. For β_{ij} in formula 8.

$$\beta_{i1} = \beta_{i2} = \dots = \beta_{is} \quad (11)$$

IV. MAINTENANCE OPTIMIZATION POLICY

A. Maintenance assumption

If dust is neglected for a long enough time, it will significantly influence the performance of the PV panel and it may cause permanent stains. In addition to the risk of permanent stain, dust accumulation is a major factor in minimizing the efficiency of a solar panel. In this paper, this effect is simplified and only the amount of accumulated dust is considered. The maintenance policy A can be summarized in Figure 4, based on the following assumptions:

- The system is periodically inspected at time $k\tau, k \in \mathbb{N}_+, \tau > 0$. Inspections are perfect in the sense that we can know the number of failed modules. The cost incurred by any inspection is C_i . In policy A, at each inspection time, there are three decisions: no maintenance, preventive or corrective replacement. In policy B, there are two decisions: no maintenance or corrective replacement.
- When the number of failed PV modules crosses the failure threshold F_c , the whole panel is at "failure" state and a corrective replacement with C_c is carried out.
- When the number of failed PV modules is greater than the over-degraded threshold F_p and less than the failure threshold F_c , the system is at "worn-out" state and a preventive replacement with cost C_p is performed.
- Since a corrective maintenance operation is performed on a more deteriorated system, it can be more complex and consequently more expensive than a preventive one, hence it is supposed that $C_p \leq C_c$. The corrective cost C_c includes all the possible costs related to the failure of the system, but not the unavailability cost.
- The period from the time point when the system come into "failure" state at time $t_f \in [(k-1)\tau, k\tau]$ till the maintenance point $k\tau$ is the "unavailability time". In the period of unavailability of the system, an additional cost per time unit C_d is incurred. The cost for such period is $(k\tau - t_f) \times C_d$.
- Maintenance actions are only implemented at each inspection times. After each replacement, the panel is said to be in the 'new' state. The system inspection times and the replacement times are negligible. The maintenance actions have no influence on the covariates.
- Let P_0 be the power generation of a new panel in a clean condition. $P_i(t)$ is the power generation of i -th PV module at time t . $P(t)$ is the power generation of whole

panel. $Y_i(t)$ is the efficiency reduction of i -th PV module at time t . Consequently:

$$P_i(t) = P_0(1 - Y_i(t)), 0 < Y_i(t) \leq 1 \quad (12)$$

$$P(t) = \sum_{i=1}^M P_i(t) \quad (13)$$

- Per unit of power, gains of G_0 can be obtained. We define as $G_i(t)$ the gains associated with the energy production of i th PV module. For the whole panel the generated gain $G(t)$ is the sum of all the panel PV modules gains. As a consequence:

$$G(t) = G_0 P(t) \quad (14)$$

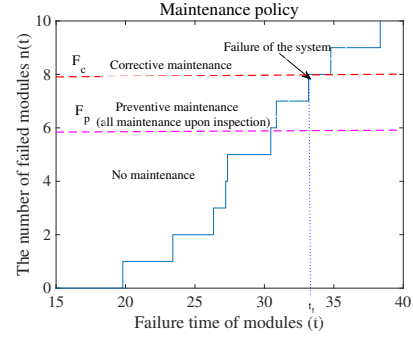


Figure 4. The maintenance policy

B. Evaluation of the maintenance policy A

1) *Cost analysis of policy A:* The maintenance cost is considered as a function of two parameters: the inspection periods τ and preventive threshold F_p . The maintenance cost increases at each inspection time and it includes three parts.

- When $n(k\tau) \geq F_c$, and the failure time occurs at time t_f between $(k-1)\tau$ and $k\tau$, corrective maintenance is implemented with replacement cost C_c , inspection cost C_i and unavailability cost.

$$C_{\text{corrective}}(t_f) = C_c + C_i + (k\tau - t_f)C_d \quad (15)$$

- When $F_p \leq n(k\tau) < F_c$, preventive maintenance is implemented with replacement cost C_p and inspection cost C_i .

$$C_{\text{preventive}} = C_p + C_i \quad (16)$$

- When $0 < n(k\tau) < F_p$, no maintenance action is implemented and only inspection cost C_i is incurred.

$$C_{\text{no}} = C_i \quad (17)$$

Let $C(t)$ denote the accumulated cost of the system in the period $[0, t]$ due to maintenance.

$$C(t) = \sum_{k=1}^{\lceil t/\tau \rceil} \{C_{\text{no}} \mathbb{I}_{(n(k\tau) < F_p)} + C_{\text{preventive}} \mathbb{I}_{(F_p \leq n(k\tau) < F_c)} + C_{\text{corrective}}(t_{f_k}) \mathbb{I}_{(n(k\tau) \geq F_c)}\} \quad (18)$$

where t_{f_k} is the failure time when a failure occurs between times $(k-1)\tau$ and $k\tau$ during the considered time horizon t .

The expected average cost rate per time unit on infinite horizon is defined as

$$EC_\infty = \lim_{t \rightarrow \infty} \frac{E(C(t))}{t} \quad (19)$$

Applying classical renewal theorems [26], the expected cost per time unit on an infinite horizon can be computed as the ratio of the expected cost $E(C(T))$ on a renewal cycle (i.e. period between two as-good-as-new replacements) over the expected length of a cycle $E(T)$. T is the first replacement time. The ratio of the expected costs on a renewal cycle T is

$$EC_\infty = \frac{E(C(T))}{E(T)} \quad (20)$$

According to the formula (18), the costs on a renewal cycle T is

$$C(T) = (\lceil T/\tau \rceil - 1)C_{no}\mathbb{I}_{(n(k\tau) < F_p)} + C_{preventive} \mathbb{I}_{(F_p \leq n(T) < F_c)} + C_{corrective}(t_f)\mathbb{I}_{(n(T) \geq F_c)} \quad (21)$$

where t_f is the failure time during the period T .

2) *Gain analysis*: We suppose that P_0 is the power generation of a new panel in a clean condition. $Y_i(t)$ is the efficiency reduction of i -th PV module power generation because of the dust accumulation according to equation (1).

The expected average gain per time unit on infinite horizon is defined as

$$EG_\infty = \lim_{t \rightarrow \infty} \frac{E(G(t))}{t} \quad (22)$$

where $G(t)$ is given by equation (14).

Applying classical renewal theorems, the expected gain per time unit on an infinite horizon can be computed as the ratio of the expected gain $E(G(T))$ on a renewal cycle $E(T)$. The ratio of the expected gains on a renewal cycle T is

$$EG_\infty = \frac{E(G(T))}{E(T)} \quad (23)$$

The expectation gains on a renewal cycle $E(G(T))$ is

$$E(G(T)) = G_0 P_0 \sum_{i=1}^M (1 - \mathbb{E}(Y_i(T))) \quad (24)$$

3) *Profit analysis*: The expected average profits per time unit on infinite horizon is defined as

$$EP_\infty = \lim_{t \rightarrow \infty} \frac{E(P(t))}{t} \quad (25)$$

Applying classical renewal theorems, the expected profits per time unit on an infinite horizon can be computed as the ratio of the expected profits $E(P(T))$ on a renewal cycle $E(T)$. We can obtain the expected cost and gain from formula (20) and (33). The ratio of the expected profits on a renewal cycle T is

$$\begin{aligned} EP_\infty &= \frac{E(P(T))}{E(T)} \\ &= \frac{E(G(T)) - E(C(T))}{E(T)} \end{aligned} \quad (26)$$

C. Evaluation of the maintenance policy B

1) *Cost analysis of policy B*: If we don't consider the preventive maintenance, the system can only be maintained correctively. The cost on a renewal cycle T is

$$C(T) = (\lceil T/\tau \rceil - 1)C_{no}\mathbb{I}_{(n(k\tau) < F_c)} + C_{corrective}(t_f)\mathbb{I}_{(n(T) \geq F_c)} \quad (27)$$

where t_f is the failure time during the period T .

2) *Gain analysis and Profit analysis*: There are no difference analysis of Gain analysis and Profit analysis between policy A and policy B.

V. NUMERICAL EXPERIMENTS

A. Parameters influence

A numerical implementation is presented to illustrate the performance of the proposed model. To begin, the main goal is to examine the impact of unit cost of the different maintenance operations on the optimal inspection interval τ^* selection. Typically, a common home distributed PV system consists of 20 panels, each containing 10 solar modules. Each module contains 6 cells. In the simulation program, the initial parameters setting are as follows: $M = 10, F_c = 8, F_p = 4, L = 0.35, \mu = 1, \alpha = 6, \beta_{ij} = [0.2, 1, 2], P_0 = 10KW/month, G_0 = 0.17\text{€}/KW$. The covariate space has initial state $Z_i(0) = 1$ with state space $S = \{1, 2, 3\}$. The different values of the covariate represents different state of the wind. When the covariate is in state 1, it means that the wind condition is at weak level. Higher value of the covariate indicates a higher wind speed. The transition rate matrix is set as

$$Q = \begin{pmatrix} -1/10 & 9/100 & 1/100 \\ 95/100 & -1 & 5/100 \\ 9/10 & 1/10 & -1 \end{pmatrix} \quad (28)$$

For the case without covariate changing, we assume that $\beta_{ij} = [0.2, 0.2, 0.2]$. The covariate space has initial state $Z_i(0) = 1$ with state space $S = \{1, 1, 1\}$. It means that the system is operating at constant low wind speed.

In order to have sensible results the maintenance cost optimisation is implemented with the simulation of 200 life-cycles. By using Monte Carlo simulation method, we can get the mean time to failure as expectation of $E(t_f)$ (month).

B. Influence of unit maintenance costs

Four different cases of unit maintenance costs are considered:

- case I (value of reference for costs): $C_i = 20, C_p = 30, C_c = 60, C_d = 100$.
- case II (expensive preventive actions): $C_i = 20, C_p = 60, C_c = 60, C_d = 100$.
- case III (expensive inspections cost): $C_i = 100, C_p = 30, C_c = 60, C_d = 100$.
- case IV (cheap unavailability): $C_i = 20, C_p = 30, C_c = 60, C_d = 20$

According to the simulation results, the optimal τ^* (month) in the presence of covariates and maintenance policy A are

summarized in the table I. In both CASE II and CASE III, the average cost is higher than in CASE I and CASE IV because of the expensive preventive actions and expensive inspections cost and the corresponding profit is lower. Case II has the expensive preventive actions and case III has the highest inspection costs, aiming at maximum profit, the inspection intervals under these two cases are longer than case I and case IV, as shown in the Figure 5.

The results of the case without covariate are shown in the table II and the Figure 6. We can know that the optimal average cost and profits are influenced by the covariates. In the case where the PV panels are in a constant low wind speed environment, dust accumulation on the PV panels takes less time to reach the failure threshold than in the case of covariates, and therefore τ^* is shorter.

The results of τ^* based on policy B are shown in the table III. Aiming at maximum profit, as case III has the highest inspection costs and case IV has the lowest unavailability cost, the inspection intervals under these two cases are longer than case I and case II. The comparison of two policies are presented in Figure 7. We can see that under the case of corrective maintenance only, the profits are much lower than the proposed policy that combines preventive maintenance.

Table I
DIFFERENT UNIT MAINTENANCE COST

Case	(τ^*, EC_{∞}^*)	(τ^*, EG_{∞}^*)	(τ^*, EP_{∞}^*)
I	(5.3, 12.7321)	(0.1, 49.0635)	(5.3, 29.7796)
II	(5.8, 17.2115)	(0.1, 48.9424)	(5.6, 24.1091)
III	(6.1, 27.3854)	(0.3, 49.6676)	(5.7, 13.6108)
IV	(5.4, 10.7441)	(0.2, 50.2867)	(4.9, 31.9248)

Table II
WITHOUT COVARIATE, DIFFERENT UNIT MAINTENANCE COST

Case	(τ^*, EC_{∞}^*)	(τ^*, EG_{∞}^*)	(τ^*, EP_{∞}^*)
I	(4.2, 15.8393)	(0.2, 64.2672)	(4.2, 40.5925)
II	(4.3, 21.9087)	(0.2, 64.2474)	(4.2, 34.5077)
III	(4.4, 34.2084)	(0.1, 64.6275)	(4.4, 20.7569)
IV	(4.4, 14.1739)	(0.1, 64.099)	(4.4, 40.932)

Table III
ONLY CORRECTIVE, DIFFERENT UNIT MAINTENANCE COST
($\alpha = 6, \beta_1, \mu = 1$)

Case	(τ^*, EC_{∞}^*)	(τ^*, EG_{∞}^*)	(τ^*, EP_{∞}^*)
I	(3.2, 31.1845)	(0.2, 38.011)	(1.7, 3.0472)
II	(1.8, 30.6699)	(0.1, 38.0435)	(1.5, 3.0826)
III	(7.4, 45.4999)	(0.2, 38.2719)	(7.4, -15.6201)
IV	(8.6, 14.4841)	(0.1, 38.674)	(8.2, 15.1164)

VI. CONCLUSION

In this paper, we studied a degradation model for the degradation process of solar panels as a multi-component system and proposed a combined preventive and corrective maintenance policy. The degradation of the system has been

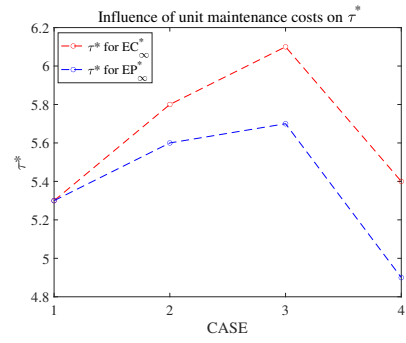


Figure 5. Influence of unit maintenance cost on τ^*

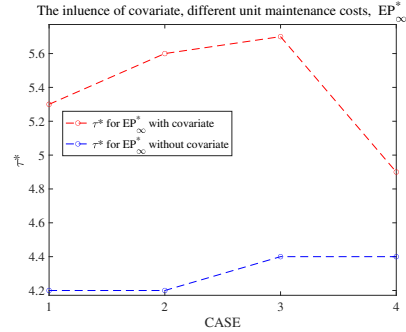


Figure 6. Influence of covariate, different unit maintenance cost

described by a NHCPP. The degradation is influenced by wind conditions as a covariate and the covariate process has been defined by a TCMC with finite state. Based on the degradation model, we propose a maintenance policy. The system is periodically inspected. Upon the inspection, we know the number of failed components and we can make maintenance decisions. The maintenance cost and power generation gains are derived to assess the proposed maintenance policy. Monte-Carlo simulations are implemented to illustrate the theoretical results. It was noticed that the proposed policy saves at least twice the cost (and increases at least twice the benefit) than the policy of only corrective maintenance. The research results can provide a reference for decision-making for PV system owners.

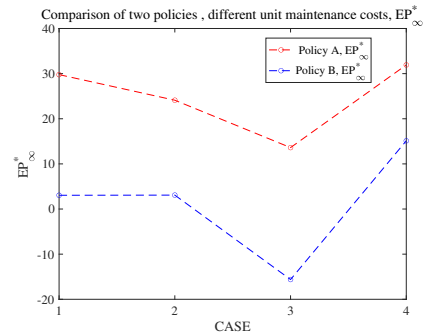


Figure 7. Comparison of two policies, different unit maintenance cost

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