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Fault Prediction in a Smart Building Lighting System

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With the advances in many areas such as sensing technologies, new connectivity options and improved IoT architectures, predictive maintenance is considered as a promising solution for the maintenance of Smart Buildings (SBs). However, because of the lack of failure data for these systems, the approaches in the literature, which are mostly data-based approaches, are not always applicable. Moreover, a SB is a system of systems where failures in one system can propagate and impact other systems, making maintenance decisions difficult. In this paper, we propose a fault prediction model for the smart building lighting system. This model is based on a Bayesian Network that is scalable according to the operating conditions of the system components. We solely rely on manufacturer's data that characterize each component to build the failure probability distributions. We show that we are able to characterize and generate statistics of the impacts of a maintenance operation on the system and its components for different intervention scenarios.

Keywords: Smart Building, Predictive Maintenance, Bayesian Network, Weibull distribution, Reliability, Failure rate

1. Introduction

With advances in many fields such as sensing technologies, new connectivity options and improved IoT architectures, predictive maintenance (PdM) is proposed as a new type of paradigm in the field of operational safety, allowing maintenance operations to be performed based on the prediction of certain failures or degradations. Several models of failure prediction have been proposed for general use cases, such as in Muthumani (2010). According to Zonta et al. (2020), three types of approaches can be distinguished to PdM, namely: Physical model based approaches, knowledge-based approaches and data-driven approaches. Currently, data-driven approaches are most often used for PdM. When considering a Smart Building (SB), most of PdM approaches are data-based, mainly through the development of machine learning algorithms such as in Susto et al. (2015) and Bouabdallaoui et al. (2021). However, these approaches are not always applicable because they require a large amount of failure data which is generally not available in the case of SB as these buildings are newly constructed. Moreover, a SB can be seen as a system of systems where failures in one system can propagate and impact other systems, making maintenance decisions difficult. Designing a process that optimizes operating costs through maintenance is therefore a very complex task. Such a decision-making process requires the development of a predictive model that can integrate the various interactions of each SB subsystem including the interactions between them and predict their failure. Such failure prediction model must be able to evolve according to maintenance actions performed over time. Thus, modelling the smart building in its entirety is a very complex task. Studies conducted by Cauchi et al. (2018) present a framework for modeling a single system and perform a predictive maintenance approach using Fault Maintenance Trees using Continuous Time Markov Chains.

In this paper, we propose a fault prediction model for a smart building lighting system. It is based on a Bayesian Network that is scalable according to the lighting system component's operating conditions. With the lack of failure data of this system, we solely rely on manufacturer's data – the Mean Time to Failure (MTTF) metric– that characterizes each component of this system to build their failure probability distribution. We assume that the component failure distribution is a Weibull Distribution, since it is one of the most widespread models used to describe failure time in component reliability analysis of complex systems (Hossain et al. (2003)). By modifying the value of the shape coefficient, it accurately describes the model of faults that can occur in the different phases of the life-cycle of a component and allows them to be related to the bath curve (Hisada (2002)). The proposed approach allows modeling the maintenance operation impact as an update of the Weibull distribution parameters and then the Bayesian Network. The proposed model can then be integrated into a decision support process for maintenance decision-making optimization.

Structure of the paper: Section 2 introduces the Smart Building Lighting System. This is followed by the developed methodology for modeling the SB Lighting System in Section 3. The numerical results are presented in Section 4, and a conclusion is given in Section 5.

2. The Tesla Room Lighting System

The Smart Building of Nanterre 3 (NR3) is a two-storey building belonging to CESI-Nanterre, an Engineering School in Paris suburb area, France. This SB is composed of the following 7 rooms: 5 multipurpose rooms, an *electrical room* (resp. *server room*) where the electrical (resp. computer) system is centralized.

Each room contains a lighting system and a HVAC (Heating, Ventilation, and Air Conditioning) system. Each system is composed of a physical part and a logical part with several sensors that can interact with each other, and communicate with the sensors of the other rooms. In this paper, we are interested in the lighting system of one specific room: the Tesla room. This room general architecture with the different interactions is given in Figure 1. The Tesla room lighting system is composed of:

- **Light fixtures**: There are 6 of them, each representing a block composed of 12 bulbs, a temperature sensor (°C), an infrared sensor (IR) and a Lux meter sensor.
- **Internal switch (Cisco Catalyst 3650CX)**: It communicates with all the sensors in the room and supplies the lighting fixtures with Power Over Ethernet energy.
- **Floor switch (Cisco Catalyst 2950X)**: It communicates with the room internal switch, the server and the electrical system.

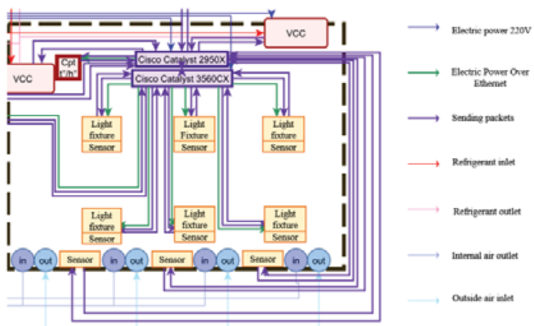

Fig. 1. Architecture of the Tesla room

3. Fault Prediction Methodology

Based on the architecture presented in Figure 1, the lighting system includes a logical part and a physical part. The logical part is defined by all the data from the sensors as well as the transmission of these data to the server, while the physical part is defined by all the hardware components of the room. To achieve predictive maintenance of the room's lighting system, it is necessary to know:

- The operating status of each component of the room's lighting system.
- The impact of each component on the operation of the room.
- The room operating status after a maintenance operation has occurred.

In order to meet the above requirements, we follow the methodology summarized in Figure 2

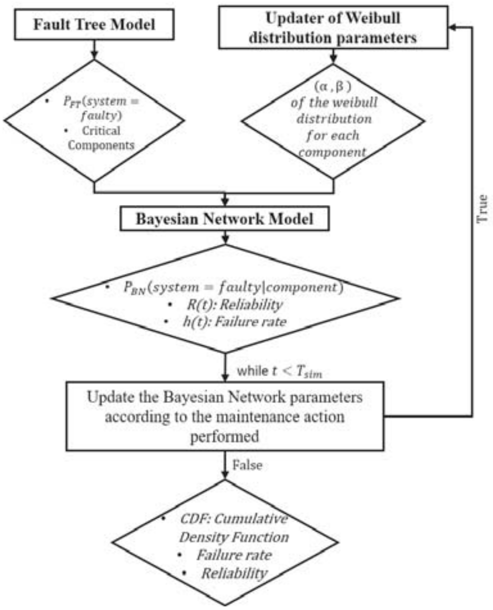

Fig. 2. Fault Prediction Methodology

- **Step 1:** Using fault trees, we are able to calculate the probability of failure of the room's lighting system P_{FT}, considering the logical combinations between its components.
  The fault tree model also allows us to identify the critical components of this system, i.e., the set of components which individual failure induce directly the system's global failure.
- **Step 2:** Determine the Weibull's distribution parameters (α, β) according to the $MTTF$ values provided by the manufacturer. We can obtain by simulation the values of α and β by using the Weibull distribution mean formula.
- **Step 3:** The fault tree model defined in Step 1 is used as the basis for building the knowledge representation. By adding the component probability distributions obtained in Step 2, we are able to build the Bayesian network. Using Bayesian inference, we compute the conditional system's failure probability.

Depending on the maintenance action performed, the Weibull distribution parameters for each component in Step 2 may change. Therefore, a Bayesian inference is performed again to obtain the new system failure probability.

We present the details of each step in the following subsections.

3.1. *Lighting System Fault Tree Model*

The Fault Tree Analysis (FTA) is a method which uses a tree structure to represent the elementary events (causes of failures) and their combinations leading to the occurrence of a dreaded event, namely the failure of the whole system. The combinations of the elementary events are realized using logic gates. The interest of this method is that it makes it possible to quantify the occurrence probability of the undesirable event, in our case the lighting system failure. Moreover, it allows us to identify the critical paths (shortest ways) leading to the occurrence of this event. The fault tree of the Tesla room lighting system is shown in Figure 3. The events ***in bold*** represent the failures which directly induce the failure of the whole lighting system of the room and are obtained by applying the Minimum Cut Set (MCS) method (Kumar et al. (2018)). In this fault tree, the critical event is: *the lighting system does not work (the bulbs do not light up)* and it can be due to one of the following failures:

- The failure of all the bulbs in the room.
- The failure of all the IR and Lux sensors.
- The failure related to the HT and LT MicroGrid.
- The failure of the floor and internal switches.

3.2. *Characterization process of maintenance operations*

The Weibull distribution is a continuous distribution in the exponential distribution family. It has been used extensively for life or failure analysis. Various studies in operational safety describe the life cycle of a component (Xie (1996)). This cycle is decomposed in three phases, described in Figure 4. The parameter β of the Weibull distribution (α, β) can be used to distinguish between these three phases. Thereby, when an intervention is carried out on a component, its operating status improves. This improvement can be modeled as a decrease of the β value. We then assume, in our case study, that the failure of each component

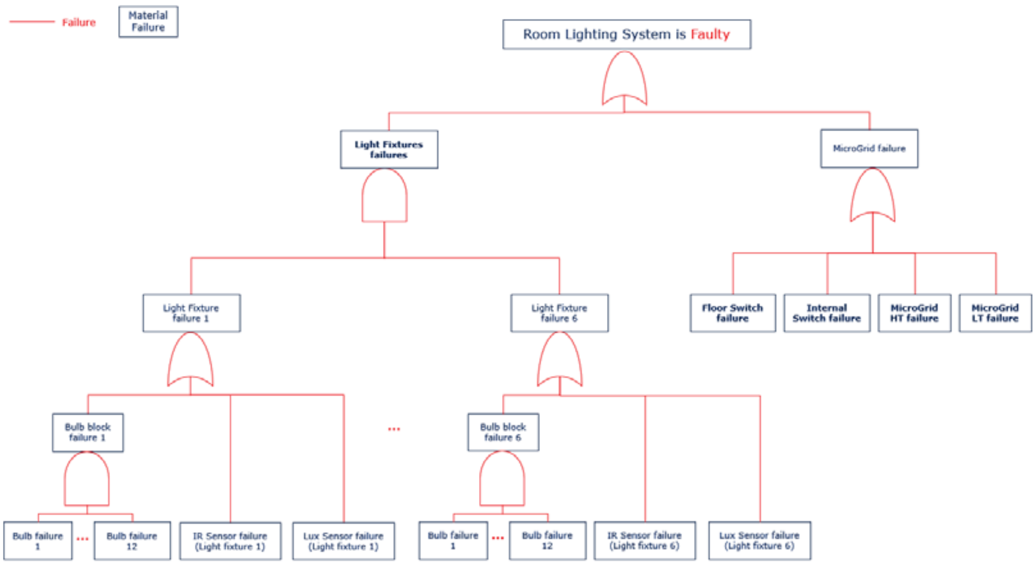

Fig. 3. Fault tree of the Tesla room lighting system.

of the system is given by the Weibull distribution (α, β). Table 1 summarizes the different mathematical formulas of this distribution.

Table 1. Equations related to the Weibull distribution (α, β).

Description	Equation
Hazard Rate	$h(t) = \frac{\beta}{\alpha}(\frac{t}{\alpha})^{\beta-1}$
Probability Density Function	$f(t) = \frac{\beta}{\alpha}(\frac{t}{\alpha})^{\beta-1}e^{-(\frac{t}{\alpha})^{\beta}}$
Cumulative Density Function	$F(t) = 1 - e^{-(\frac{t}{\alpha})^{\beta}}$
Reliability Function	$R(t) = e^{-(\frac{t}{\alpha})^{\beta}}$

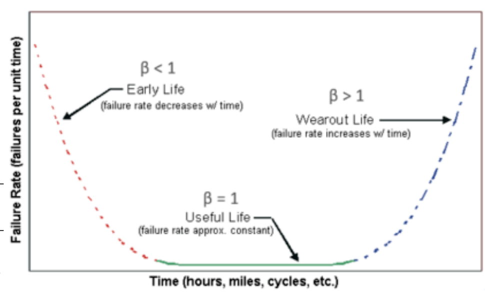

Fig. 4. Component life cycle

3.3. *Bayesian Network Model*

A Bayesian network is a probabilistic graphical model representing a set of random variables in the form of a directed acyclic graph. Cause and effect relationships between variables are not deterministic, but probabilistic. Thus, the observation of a cause or several causes does not systematically lead to the effects which depend on it, but only modifies the probability of observing them.

- **Bayesian Network structure**: It is a directed acyclic graph $G(V, E)$ where V is the set of vertices called nodes, and E the set of edges. Each node $v \in V$ corresponds to a vertex in the Fault Tree, and each edge that connects two nodes of the Bayesian network represents the logical link in the fault tree. Since Bayesian networks satisfy the Markov property (Fox et al. (2008)), a node of the Bayesian network depends only on its direct parents. This property allows us to simplify the joint distribution $P(v_1, v_2, ..., v_{|V|})$ such as $v_i \in V$, for all $i \in$

$\{1, ..., |V|\}$. After simplification (Spiegelhalter et al. (1993)), the joint distribution is equal to:

$$P(v_1, v_2, ..., v_{|V|}) = \prod_{i=1}^{|V|} P(v_i|Parents(v_i)) \quad (1)$$

The set V is thus a discrete set of random variables. In the case considered in this paper, each $v \in V$ represents a binary variable $(Faulty(0), Functional(1))$.

- **Bayesian Network parameters**: These are the conditional probabilities of each variable (node in the Bayesian Network graph) and are usually computed from experimental data.
  The conditional probabilities of each variable with respect to its direct parents are represented as tables on the edges of the graph $G(V, E)$, called conditional probability tables (CPT).

In the following a Bayesian Network Construction from Fault Tree Algorithm is presented in (Algorithm 1), we denote by:

- $N_s(v)$: possible states of the event $v \in V$.
- $Pred(v)$: the predecessor set of the event $v \in V$.
- $typeArc(v, Pred(v))$: the type of logic gate (OR, AND) linking the event $v \in V$ and its predecessor.
- S_v: the state of the event $v \in V$ such as $0 \leq S_v \leq N_s(v)$.
- $P_F(v)$: the failure probability of the event $v \in V$.

Using the equations that describe the Weibull distribution shown in Table 1, we are able to define the component's failure probability. The failure probabilities of the intermediate events and the system are computed by Bayesian inference, and thus, if the Weibull parameters α and β change, the Bayesian network is automatically updated, and the new probabilities are computed. In the following, we present three illustrative maintenance policies to demonstrate how the proposed method can predict the impact of a policy on the system.

4. Policy Maintenance Analysis

In this section, statistical results are produced by simulation to analyze the impact of a maintenance policy using the proposed fault prediction model. Those results are provided for three kinds of maintenance policies.

Algorithm 1 Fault Tree transformation to a Bayesian Network

```
Input: FT(V, N_s(v) for v ∈ V), P_F(v)
Output: Bayesian Network (BN)
BN ← {}
FOR EACH v ∈ V by DFS (Depth-First Search):
  Add v to the BN
  IF Pred(v) = ∅ :
    CPT(v)← [P_F(v),1-P_F(v)])
  ELSE:
    A ← ∏_{k∈Pred(v)} N_s(k)
    FOR EACH i in A:
      IF typeArc(v, Pred(v)) = "OR":
        IF ∑_{k∈Pred(v)} S_k = |Pred(v)|:
          CPT(v)[-1] ← [0,1]
        ELSE:
          CPT(v)[i] ← [1,0]
      IF typeArc(v, Pred(v)) = "AND":
        IF ∑_{k∈Pred(v)} S_k = 0:
          CPT(v)[0] ← [1,0]
        ELSE:
          CPT(v)[i] ← [0,1]
```

4.1. *Maintenance Policies*

Policy 1: No maintenance operation

We assume that in this case, **no maintenance operation is performed** in a simulation interval $[0, T]$, where T is any fixed duration. To determine how the parameters evolve over time, we proceed as follows:

(i) At $t = 0$, we use the relation that links Weibull distribution parameters (α_0, β_0) to the MTTF (Lai et al. (2006)) :

$$MTTF_0 = \int_0^{\infty} sf(s)ds = \alpha_0 \Gamma(1 + \frac{1}{\beta_0}) \quad (2)$$

Γ is the Gamma function defined as :

$$\Gamma(x) = \int_0^{\infty} s^{x-1} e^{-s} ds \quad (3)$$

By solving Eq. (2) we obtain the parameters (α_0, β_0) for each component of the system.

(ii) At $0 < t < T$, we assume that the β^i value for each component i increases and α^i is constant $\alpha^i = \alpha_0^i$, such that:

$$\beta_{t+1}^i = \beta_t^i + \delta^i \quad (4)$$

δ^i is the value at which β_t^i increases at each time step t. This assumption is based on the fact that the component ages over time, which leads it to the wear out phase, which is characterized by a $\beta_t^i > 1$. By solving Eq. (4), we obtain the δ^i value.

$$\delta^i = \frac{\beta_{MTTF_0^i} - \beta_0^i}{MTTF_0^i} \quad (5)$$

4.1.1. *Policy 2: Maintaining all the components*

In the following, **an intervention occurs** every time interval T_{int}. We determine how the parameters evolve over time.

(i) At $0 < t < T_{int}$, we use the same approach seen in Policy 1.

(ii) At $t = k.T_{int}$, the k^{th} intervention is performed on all components. This action implies an improvement of the state of each component i. The health status is improved such as the component is in his Useful Life, which means $\beta_{k.T_{int}}^i = 1$, but the component i is not new. This means that at each intervention, the component ages over time. This aging is modeled in our case by a linear decrease of the MTTF, such as:

$$MTTF_k^i = \frac{MTTF_0^i}{k+1} \quad (6)$$

Using Eq. (2) we obtain α_k^i such as:

$$\alpha_k^i = \frac{MTTF_k^i}{\Gamma(1 + \frac{1}{\beta_{k.T_{int}}^i})} \quad (7)$$

(iii) At $k.T_{int} < t < (k+1).T_{int}$, as in Policy 1, the β_t^i value of the Weibull distribution for each component i increases as follows:

$$\beta_{t+1}^i = \beta_t^i + \delta^{i'} \quad (8)$$

where:

$$\delta^{i'} = \frac{\beta_{MTTF_k^i} - \beta_{k.T_{int}}^i}{MTTF_k^i} \quad (9)$$

Policy 3: Maintaining only a MCS components

In this case, we start by ranking the MCSs by maintenance priority. This ranking is based on two main criteria: the **MCS sizes** and the **MCS failure probability**. Then, similar to Policy 2, maintenance is only applied to the highest priority MCS components. So we just update their respective distributions before the Bayesian network.

4.2. *Numerical Results*

For each maintenance scenario described previously, the metrics calculated are: the Tesla Room Lighting System (TESLA-LS) and all its component's failure probability, and their failure rates. For our experiments, we assume that:

- The probability density distributions of similar components follow the same Weibull distribution.
- At time $t = MTTF^i$, each component i is in the wear out phase and its probability density distribution, follows a Normal distribution. Taking a $\beta_{MTTF^i}^i$ value equal to 3.6 allows us to approximate the Weibull distribution to the Normal distribution. Thus, $\beta_{t=MTTF^i} = 3.6$

Table 2 shows the manufacturer's data, and its corresponding Weibull parameters after simulation Eq. (2). First, we determine which MCS compo-

Table 2. (α_0, β_0) using $MTTF_0$ manufacturer value.

Component	MTTF_0 (days)	α_0	β_0
Bulb	3650	1825	0.5
IR Sensor	1825	912.5	0.5
Lux Sensor	730	365	0.5
Floor Switch	10 950	5475	0.5
Internal Switch	10 950	5475	0.5
MicroGrid LT	7300	3650	0.5
MicroGrid HT	7665	3832.5	0.5

nents are selected in Policy 3. The system's smallest MCS are of **size 1** ({Internal Switch}, {Floor Switch}, {MicroGrid LT}, {MicroGrid HT}) and **size 6**, which include all conceivable arrangements of Lux sensors and IR sensors. The MCS made up of 6 Lux Sensors has the highest failure probability out of all size 1 and size 6 MCSs. As a result, Policy 3 is applied in this case, to the MCS (Lux Sensors). Figures 5,6 and 7 show the fault prediction model simulation results for each maintenance policy. Thanks to this model, we are able to measure the impact of a maintenance policy on the system. For example, when no maintenance operation is performed, the failure rate shows that the system evolves over the 3 phases of its life cycle, until it fails at the same time as the Lux sensors. However, when a maintenance operation occurs (Figure 6 and 7), the failure rate decreases at each T_{int} and aged over time. For each maintenance operation type performed (on all components (Figure 6) or on the MCS (Figure 7)), the system fails at the same time in both cases. However, the probability evolution between the first intervention and the failure time is different. Note that a maintenance policy may change depending on the evolution of other MCS's failure probability, as well as other constraints (financial, logistical and others). This model, then, offers a first decision support tool for the choice of the maintenance policy to adopt (either with the help of an expert, or by integrating it in an optimization model).

5. Conclusion

In this paper, a methodology for fault prediction of a lighting system in a smart building has been proposed. The components of this system and their interactions are modeled by a fault tree model. We then transform it into a Bayesian network such that the structure is determined using the fault tree and the parameters of the network using a Weibull distribution. The results show that using this distribution and relying only on the $MTTF$ manufacturer's data, since failure data are generally very few and insufficient, we are able to characterize and generate statistics of the impact of a maintenance operation on the system and its components by updating the couple $(\beta, MTTF)$ for different intervention scenarios. The whole model can be used as a decision support tool for maintenance operation decision-making, and can be integrated to a global optimization approach.

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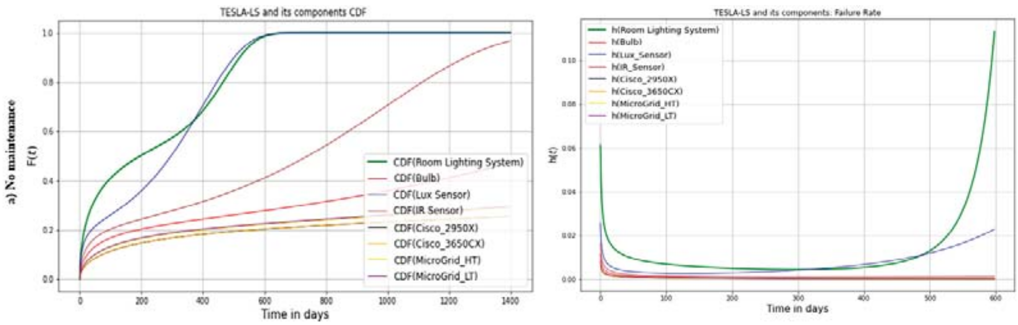

Fig. 5. CDF and Failure Rate for policy maintenance 1.

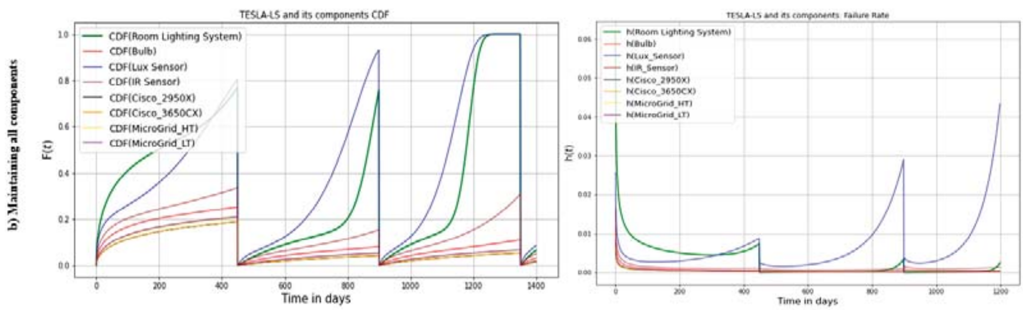

Fig. 6. CDF and Failure Rate for policy maintenance 2.

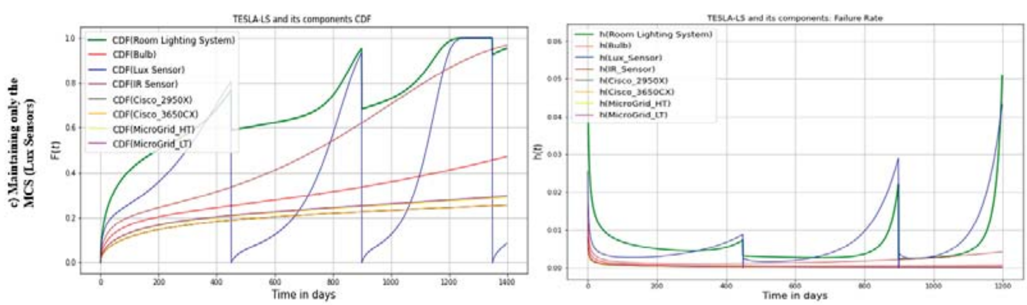

Fig. 7. CDF and Failure Rate for policy maintenance 3.