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# Transformer Population Failure Rate State Distribution, Maintenance Cost and Preventive Frequency Study Based on Markov Model

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## ABSTRACT

This work investigates the state distributions of failure rate, performance curve, maintenance cost and preventive frequency of the transformer population through the Markov Model (MM). The condition parameters data of the oil samples known as Oil Quality Analysis (OQA), Dissolved Gas Analysis (DGA), Furanic Compounds Analysis (FCA) and age were analyzed from 370 distribution transformers. This work utilized the computed failure rate prediction model of the transformer population based on MM using the nonlinear minimization technique. First, the transition probabilities for each state were adjusted based on pre-determined maintenance repair rates of 10%, 20%, and 30%. Next, the failure rate state distributions and performance curves at various states were analyzed. Finally, the maintenance costs and preventive maintenance frequency were estimated utilizing the proposed maintenance policy models and the failure

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rate state probabilities. The result reveals that the transition from state 2 to state 1 with a 30% pre-determined maintenance repair rate can provide an average reduction of failure rate up to 11%. Based on the failure rate state probability, an average increment of maintenance cost from RM 18.32 million to RM 251.87 million will be incurred over 30 years. In total, 85% of the transformer population must undergo maintenance every nine months to avoid reaching very poor conditions.

*Keywords*: Failure rate, health index, maintenance cost, maintenance policy model, Markov model, preventive maintenance frequency, state distribution, transformer

## INTRODUCTION

Transformers are critical components of power systems whereby their failure can significantly impact end users and utilities, such as high replacement costs, revenue losses and customer inconvenience. Maintenance is one of the key approaches to ensuring the reliable operation of transformers (Islam et al., 2017; Tenbohlen et al., 2011). Time-based maintenance is among the common approach that utilities have utilized. Nowadays, several utilities have started to adopt condition-based maintenance to optimize the overall investments and, at the same time, maintain the safe and reliable operation of transformers (Shariffuddin et al., 2021a).

Condition-based management can improve the efficiency of asset maintenance practices, hence lowering associated costs through comprehensive analysis that acts as a preventive strategy against underlying faults (Jahromi et al., 2009). Health Index (HI) is a condition-based management concept that has been adopted as an effective tool to evaluate transformer conditions. HI considers multiple condition parameter data and employs a variety of criteria to determine the condition of transformers that may be inaccessible via individual measurement techniques. The HI is calculated using a scoring method whereby the condition parameter data is classified using weighting and ranking approaches. In accordance with HI, the condition is classified into several categories as defined by Naderian et al. (2008).

Aside from HI, the failure rate is another key factor in examining transformers' reliability, which can also be used to determine the optimized maintenance strategies (Jürgensen et al., 2016a). However, since transformers have a long lifespan, obtaining data for in-service failures is challenging (Ghazali et al., 2015; Jürgensen, 2018). Several studies have implemented techniques such as the proportional hazard model, Bayesian updating scheme and linear interpolation between different inspection outcomes to estimate the failures data based on the available information (Brown et al., 2018; Jürgensen et al., 2016a; Lindquist et al., 2005). One of the biggest challenges in failure rate modeling is the lack of historical failure records (Jurgensen et al., 2018; Lindquist et al., 2005). One unique approach to determining the failure rate can be carried out based on the condition of the assets (Jürgensen, 2016). Currently, the study to predict the failure rate of transformers is still limited. Some studies mainly focus on single-time condition parameter data and employ statistical data-driven approaches to model the failure rate (Jürgensen, 2016; Jürgensen et al., 2016b). The Markov model (MM) is identified as one of the approaches for predicting the failure rate of transformers. MM has been widely implemented in civil engineering to forecast the states of bridges, pavements, stormwater piping components and steel hydraulic structures (Riveros & Arredondo, 2010; Camahan et al., 1987; Micevski et al., 2002; Stevens et al., 2020). Additionally, it is also used in electrical equipment such as switchgear and transformers (Hamoud & Yiu, 2020; Hoskins et al., 1999). Recently, several studies have been conducted to determine the transformer population's transition probabilities for condition state prediction using the MM (Selva et al., 2018; Yahaya et al., 2017). MM can also be used to analyze the effect of asset maintenance, repair, and replacement on asset state distribution (Camahan et al., 1987; Cesare & Al, 1992; Li et al., 2016). A number of studies have examined the ideal maintenance strategy for healthcare centers using the MM (Carnero & Gómez, 2017; González-Domínguez et al., 2020). Other studies conducted by Yahaya et al. (2018a, 2018b) have employed the updated MM with designated maintenance policy to determine the maintenance and maintenance cost analysis based on the condition state distribution of the transformer population. Currently, the utilization of failure rate based on HI to estimate the maintenance cost and preventive frequency of the transformer population is yet to be explored.

This study examined the effect of pre-determined maintenance policy on the state distributions of failure rate, performance curve, maintenance cost and preventive frequency of the transformer population based on MM. The previous 370 distribution transformers rated at 33/11 kV and 30 MVA with condition parameters data of the oil samples known as Oil Quality Analysis (OQA), Dissolved Gas Analysis (DGA), Furanic Compounds Analysis (FCA) and age are utilized (Shariffuddin et al., 2021b). It is a continuation of a previous work by Shariffuddin et al. (2021b), in which the failure rate state distribution and failure rate performance curve with and without pre-determined maintenance repair rates are compared and analyzed. Finally, the maintenance cost analysis and preventive maintenance frequency based on a pre-determined maintenance policy model are conducted.

## METHODS

### Markov Model Overview

A Markov process is a memoryless process that predicts future states based on the current state. A Markov process can be modeled as a Markov chain composed of elements $P_{ij}$, where $P_{ij}$ denotes the probability of a condition transitioning from state i to state j (Borovkov, 2003; McDonald, 2004). This study interpreted the Pij as a probability of equipment decaying from state i to j at a specific time interval. Two assumptions were taken to simplify the model in this study. First, the future failure rate model was evaluated using natural and monotonic distributions, where the states of transformer failure rate either stayed the same state or changed to the next state. Second, in each row of the MM transition matrix, the probability summation was set to one. In total, five $P_{ij}$ terms were required to construct the transition matrix of MM, as per Equation 1:

$$P = \begin{bmatrix} P_{11} & 1-P_{11} & 0 & 0 & 0 \\ 0 & P_{22} & 1-P_{22} & 0 & 0 \\ 0 & 0 & P_{33} & 1-P_{33} & 0 \\ 0 & 0 & 0 & P_{44} & 1-P_{44} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad [1]$$

The final state, $P_{55}$, was set to 1, which indicated that all transformers reached and remained in the last state. This final state is known as the absorbing state because once entered, and there is no way to exit without intervention activities such as component repair or replacement. Finally, the transition probabilities matrix was determined using a nonlinear optimization technique to determine the values of four parameters, $P_{11}$, $P_{22}$, $P_{33}$, and $P_{44}$, by minimizing the sum of the absolute differences between computed and predicted failure rate data as described in Equation 2.

$$min \sum_{t=1}^{N} |A(t) - B(t, P)| \quad [2]$$

where N denotes the number of years in each zone, P denotes the transition probabilities ($P_{11}$, $P_{22}$, $P_{33}$, $P_{44}$), A(t) denotes the computed failure rate at time t, and B(t, P) denotes the MM-predicted failure rate at time t. After generating the transition matrix, the prediction of the future failure rate state in year t can be determined based on Equation 3:

$$F_t = F_0 \times P^t \quad [3]$$

where t denotes the interval number, $F_0$ denotes the initial state, and P denotes the transition probability matrix.

### Updating Markov Model

Apart from forecasting purposes, MM can also be used to aid utilities in planning and implementing maintenance strategies. A pre-determined maintenance repair rate is considered one of the maintenance strategies that can be accomplished by updating the MM. Through the application of maintenance policy in the form of a matrix, the updated transition matrix, $P_R$, with a pre-determined repair rate was determined; thus, Equation

1 becomes Equation 4. The $P_{repair\ rate}$ can be introduced at any state of the failure rate, depending on the maintenance policy. Equation 4 shows an example of an updated MM transition matrix with a pre-determined maintenance repair rate at state 2.

$$P_R = \begin{bmatrix} P_{11} & 1-P_{11} & 0 & 0 & 0 \\ P_{repair\ rate} & \left(1-P_{repair\ rate}\right)*P_{22} & \left(1-P_{repair\ rate}\right)*1-P_{22} & 0 & 0 \\ 0 & 0 & P_{33} & 1-P_{33} & 0 \\ 0 & 0 & 0 & P_{44} & 1-P_{44} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad [4]$$

Next, the transformer population's distribution and failure rate trends were evaluated once the transition matrix was updated. The transformer population distribution can be calculated using Equation 5:

$$S_{(t+1)} = S_{(t)} \times P_R \quad [5]$$

$S_{(t+1)}$ represents the next failure rate at the specified interval, $S_{(t)}$ represents the current failure rate, and $P_R$ represents the updated transition matrix.

Next, the failure rate trend was modeled based on Equation 6:

$$FR_{(t+1)} = FR_{(t)} \times P_R \times M^T \quad [6]$$

Where $FR_{(t+1)}$ and $FR_{(t)}$ represent the next failure rate at the specified interval and current failure rate, $P_R$ represents the updated transition matrix, and $M^T$ represents the matrix transform of the failure rate state scales where R = [1.59 1.99 2.69 3.59 5.60] as defined by Shariffuddin et al. (2021b).

## Maintenance Policy and Cost

Maintenance is one of the most essential tasks in an electrical power system to ensure the transformers are safe to operate and reduce unscheduled interruptions. The maintenance policy for the transformer can be determined by the MM based on the future state probability of the transformer, and it is represented in the matrix form. The restoration process can be modeled by permitting transformer current states to revert to the previous states through suitable maintenance techniques such as Condition Assessment (CA), minor work that involves Corrective Maintenance (CM) and major work, which consists of refurbishment and replacement. This study determined the maintenance cost based on several assumptions related to the maintenance policy model. First, the CA was performed for transformers in all states and was carried out annually to monitor the transformer. Second, CM was performed on all transformers in state 4 to enhance the failure rate in states 3, 2 and 1, while major work was performed on all transformers in state 5 to enhance the failure rate in states 4, 3, 2 and 1. Finally, the 10% pre-determined maintenance policy was assigned to each state to simulate the impact of the maintenance cost of the transformer. In this study, the maintenance actions, activities, and estimated cost breakdowns were obtained based on Yahaya et al. (2018b).

An example of a 10% pre-determined maintenance policy model, **M** at state 4, can be seen in Equation 7:

$$M = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0.1 & 0 & 0 & 0.9 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad [7]$$

The maintenance policy model was combined with the normal deterioration, and it is known as **PM**. This combination was used to determine the future state probability at a specific year, t, based on MM iteration formulation as shown in Equation 8:

$$F_t = F_0 \times (PM)^t \qquad [8]$$

Next, the estimated maintenance cost, **C**, of each future state in each year, t, was calculated based on Equation 9:

$$Expected\ Cost = F_0 \times (PM)^t \times C_t \qquad [9]$$

### Maintenance Policy and Preventive Maintenance Frequency

Preventive maintenance is a programmed maintenance activity, such as routine inspections, oil filtration and replacement of transformer components to reduce the probability of failure (Carnero & Gómez, 2017). Therefore, the frequency of maintenance was established considering the asset reliability requirements. The maintenance frequency was determined in this study by providing several assumptions on the maintenance policy model. In order to prevent the failure rate from reaching state 5, preventive maintenance activities were conducted to improve the failure rate to state 2 after the maintenance, and the maximum permissible state of degradation was state 4. All transformers were set as high importance in the electrical power system network. Since there was a limitation on the maintenance record of the transformer under study, the maintenance frequency matrix and transformer frequency of maintenance tests were carried out based on NETA MTS-2011 (White & Widup, 2014). The intervention states, conditions, and the frequency of maintenance tests for the transformer can be seen in Table 1.

Table 1
*Intervention state, condition, and frequency of maintenance test*

| Intervention State | Condition | Frequency of maintenance test (in Months) |
|---|---|---|
| 1, 2 | Good | 9 |
| 3 | Average | 6 |
| 4 | Poor | 3 |

The corresponding maintenance policy model matrix assumed that preventative maintenance prevented the failure rate from reaching state 5 and subsequently restored the failure rate to state 2 after the maintenance work was carried out. Therefore, Equation 10 was expressed as follows:

$$S = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \quad [10]$$

The combination of the maintenance policy model with the normal deterioration is known as **PS**. Based on MM iteration formulation, this combination was utilized to determine the future state probability at a specific year, t, as indicated in Equation 11:

$$F_t = F_0 \times (PS)^t \quad [11]$$

Next, the model was evaluated to assess the relative maintenance frequency of the transformers. Since each state j is associated with the maintenance frequency, thus the expected maintenance frequency of each future state for each year, t was based on the intervention state and frequency of the maintenance test, as shown in Table 1.

## RESULTS AND DISCUSSION

### Updated Markov Model

The distribution of future state probability for the transformer population in each state based on MM for 30 years is shown in Figure 1. It was plotted using the transition matrices for zones 1 and 2, which were calculated based on Equations 12 and 13.

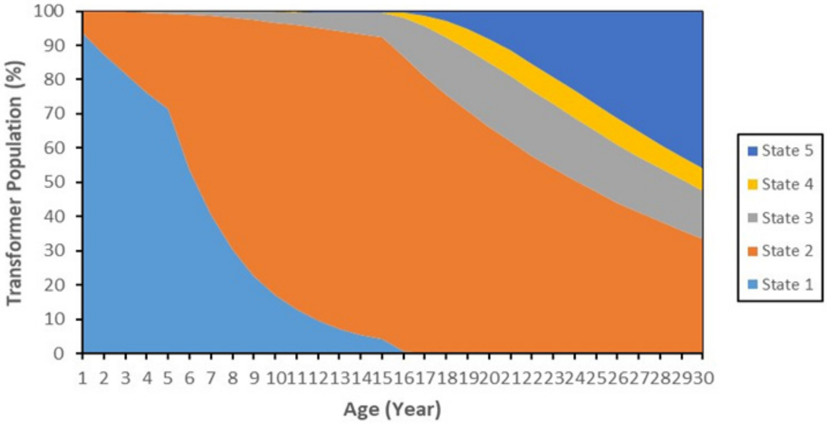



*Figure 1.* Transformer population distribution in each of the states

$$P = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0 & 0 & 0 & 0.9900 & 0.0100 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad [12]$$

$$P = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0 & 0 & 0 & 0.5003 & 0.4997 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad [13]$$

The transformer populations in state 1, state 2, state 3, state 4 and state 5 are 82.07%, 17.69%, 0.18%, 0.07% and 0% during the first five years as shown in Figure 1. At age of 30 years, the transformer populations in state 1, state 2, state 3, state 4 and state 5 change to 0.00%, 33.63%, 13.94%, 6.52% and 45.92%.

The effect of 10%, 20%, and 30% pre-determined maintenance repair rates on the transformer population by updated transition matrices in Equations 12 and 13 were also carried out. For example, the updated transition matrices with 10% pre-determined maintenance repair rates for zone 1 and zone 2, $P_R$, are shown in Equations 14 and 15:

$$P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0.1 & 0.8910 & 0.0090 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0 & 0 & 0 & 0.9900 & 0.0100 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad [14]$$

$$P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0.1 & 0.8910 & 0.0090 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0 & 0 & 0 & 0.5003 & 0.4997 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad [15]$$

Based on Equations 5 and 6, the transformer population distribution in each state and the failure rate performance curve were re-plotted using the MM algorithm. Figure 2 depicts the transformer population distribution in each state with a 10% pre-determined maintenance repair rate performed in state 2. During the first 5 years, the transformer populations in state 1, state 2, state 3, state 4 and state 5 are 84.24%, 15.55%, 0.14%, 0.06% and 0%. The transformer populations in state 1, state 2, state 3, state 4 and state 5 change to 4.73%, 37.97%, 13.14%, 5.98% and 38.18% at age of 30 years.

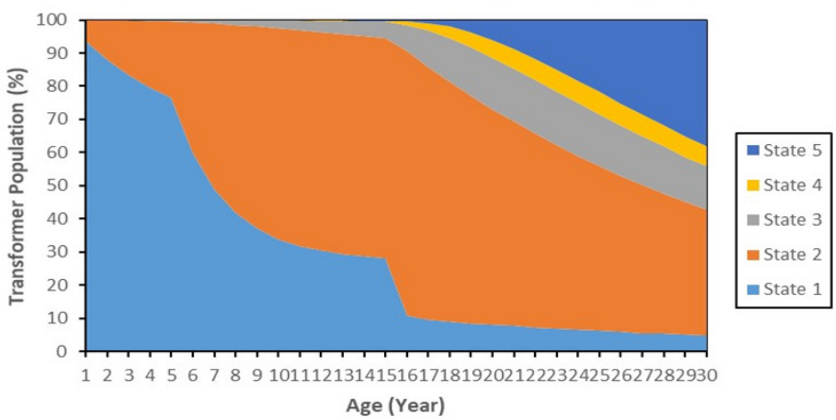



*Figure 2.* Transformer population distribution in each of the states with a 10% pre-determined maintenance repair rate performed at state 2

The failure rate performance curve with a 10% pre-determined maintenance repair rate performed at state 2 can be seen in Figure 3. It is observed that both actual and predicted failure rate increases with the increment of age. MM's predicted failure rate performance curve closely follows the actual failure rate performance curve. It is found that the failure rate performance curve decreases by 4.77% once a 10% pre-determined maintenance repair rate is implemented for the transition from state 2 to state 1.

A sensitivity study on various state transitions was carried out to examine the effect of updating transition matrices on the failure rate reduction. The updated transition matrices for each state with a 10% pre-determined maintenance repair rate are shown in Table 2.

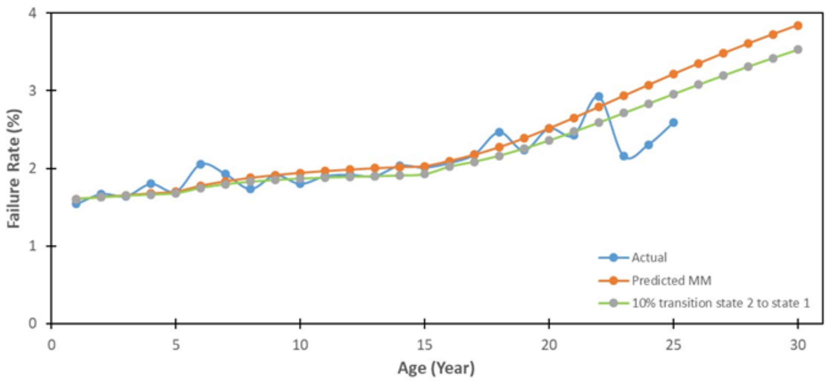



*Figure 3.* Failure rate performance curves with a 10% pre-determined maintenance repair rate performed at state 2

Table 2

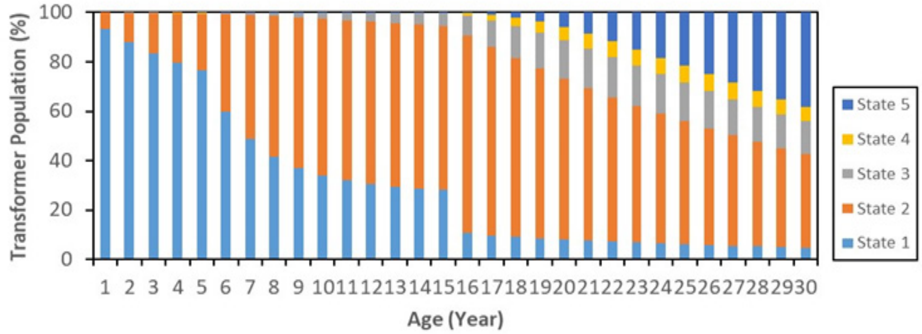
*Updated transition matrices with a 10% pre-determined maintenance repair rate for each state*

| Transition State | Updated Transition Matrices for Zone 1 | Updated Transition Matrices for Zone 2 |
|---|---|---|
| **2 to 1** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0.1 & 0.8910 & 0.0090 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0 & 0 & 0 & 0.9900 & 0.0100 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0.1 & 0.8910 & 0.0090 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0 & 0 & 0 & 0.5003 & 0.4997 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ |
| **3 to 2** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0.1 & 0.4944 & 0.4056 & 0 \\ 0 & 0 & 0 & 0.9900 & 0.0100 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0.1 & 0.8910 & 0.0090 & 0 \\ 0 & 0 & 0 & 0.5003 & 0.4997 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ |
| **3 to 1** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0.1 & 0 & 0.4944 & 0.4056 & 0 \\ 0 & 0 & 0 & 0.9900 & 0.0100 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0.1 & 0 & 0.8910 & 0.0090 & 0 \\ 0 & 0 & 0 & 0.5003 & 0.4997 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ |
| **4 to 3** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0 & 0 & 0.1 & 0.8910 & 0.0090 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0 & 0 & 0.1 & 0.4503 & 0.4500 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ |
| **4 to 2** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0 & 0.1 & 0 & 0.8910 & 0.0090 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0 & 0.1 & 0 & 0.4503 & 0.4500 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ |

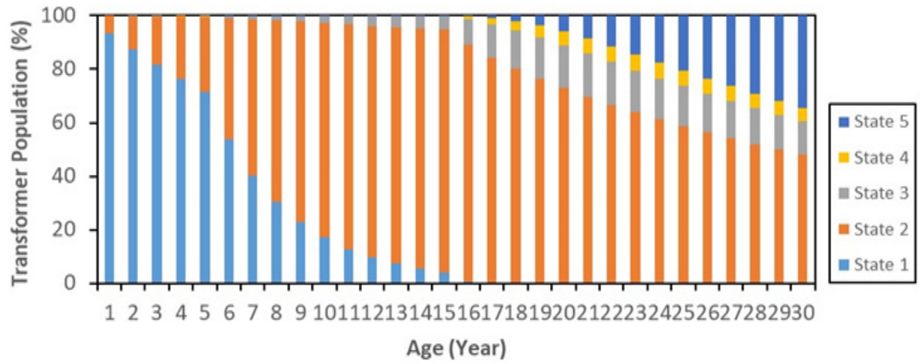
Table 2 *(Continue)*

| Transition State | Updated Transition Matrices for Zone 1 | Updated Transition Matrices for Zone 2 |
|---|---|---|
| **4 to 1** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0.1 & 0 & 0 & 0.8910 & 0.0090 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0.1 & 0 & 0 & 0.4503 & 0.4500 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ |
| **5 to 4** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0 & 0 & 0 & 0.9900 & 0.0100 \\ 0 & 0 & 0 & 0.1 & 0.9 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0 & 0 & 0 & 0.5003 & 0.4997 \\ 0 & 0 & 0 & 0.1 & 0.9 \end{bmatrix}$ |
| **5 to 3** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0 & 0 & 0 & 0.9900 & 0.0100 \\ 0 & 0 & 0.1 & 0 & 0.9 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0 & 0 & 0 & 0.5003 & 0.4997 \\ 0 & 0 & 0.1 & 0 & 0.9 \end{bmatrix}$ |
| **5 to 2** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0 & 0 & 0 & 0.9900 & 0.0100 \\ 0 & 0.1 & 0 & 0 & 0.9 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0 & 0 & 0 & 0.5003 & 0.4997 \\ 0 & 0.1 & 0 & 0 & 0.9 \end{bmatrix}$ |
| **5 to 1** | $P_R = \begin{bmatrix} 0.9348 & 0.0652 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.5493 & 0.4507 & 0 \\ 0 & 0 & 0 & 0.9900 & 0.0100 \\ 0.1 & 0 & 0 & 0 & 0.9 \end{bmatrix}$ | $P_R = \begin{bmatrix} 0.7515 & 0.2485 & 0 & 0 & 0 \\ 0 & 0.9900 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.9900 & 0.0100 & 0 \\ 0 & 0 & 0 & 0.5003 & 0.4997 \\ 0.1 & 0 & 0 & 0 & 0.9 \end{bmatrix}$ |

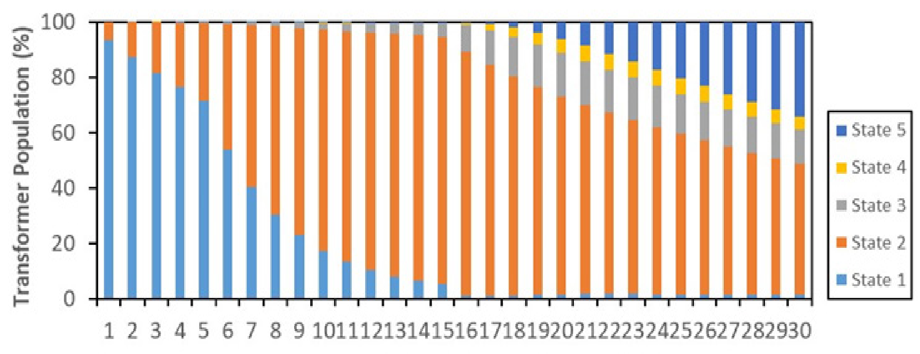
Figure 4 illustrates the transformer population distribution based on various state transitions utilizing a 10% pre-determined maintenance repair rate. An obvious improvement in transformer distribution is observed once the pre-determined maintenance repair rate is implemented during the transition from state 2 to state 1. There is a 46.18% increment in the transformer population in state 1. The transformer population in states 2, 3, 4 and 5 decrease by 9.48%, 16.21%, 16.27% and 19.69% respectively.


Transformer Population (%)
100
80
60
40
20
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
Age (Year)
State 5
State 4
State 3
State 2
State 1

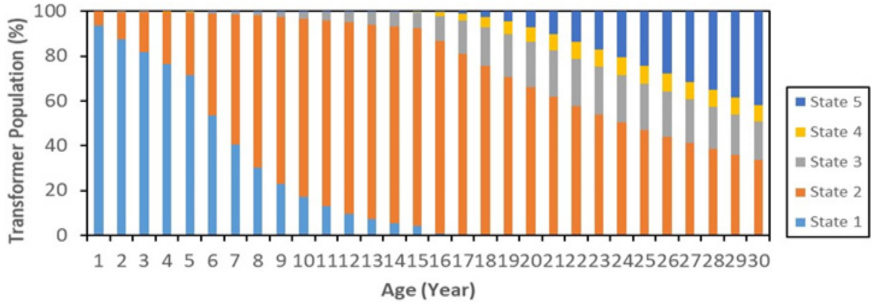
(a)


Transformer Population (%)
100
80
60
40
20
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
Age (Year)
State 5
State 4
State 3
State 2
State 1

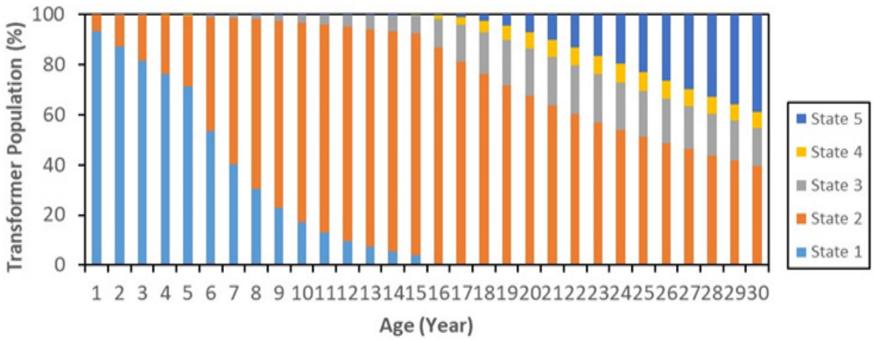
(b)


Transformer Population (%)
100
80
60
40
20
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
Age (Year)
State 5
State 4
State 3
State 2
State 1

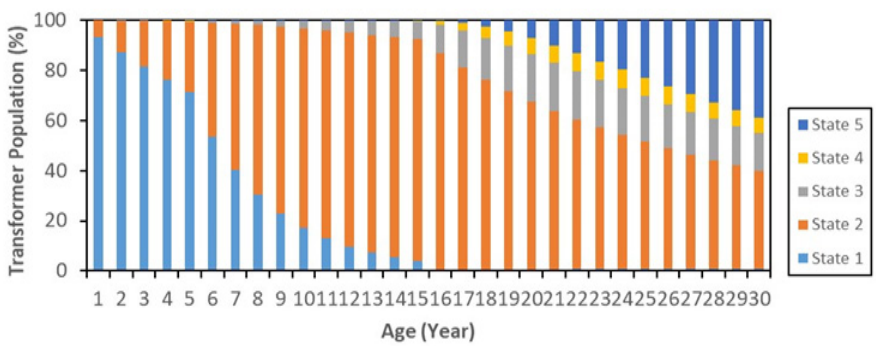
(c)


Transformer Population (%)
Age (Year)
State 5
State 4
State 3
State 2
State 1

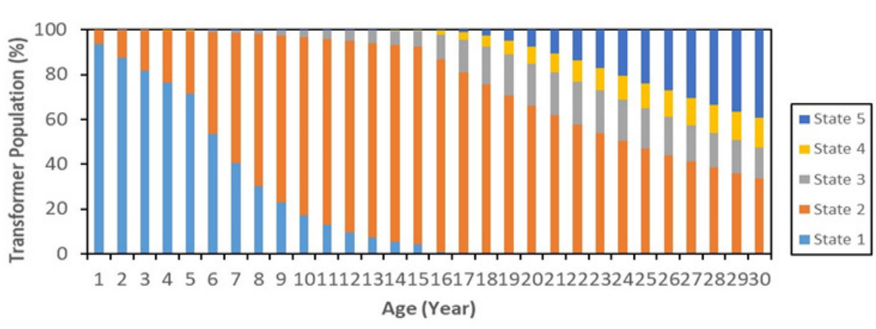
(d)


Transformer Population (%)
Age (Year)
State 5
State 4
State 3
State 2
State 1

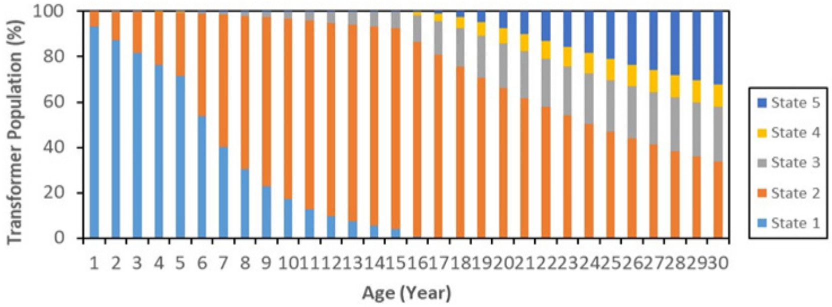
(e)


Transformer Population (%)
Age (Year)
State 5
State 4
State 3
State 2
State 1

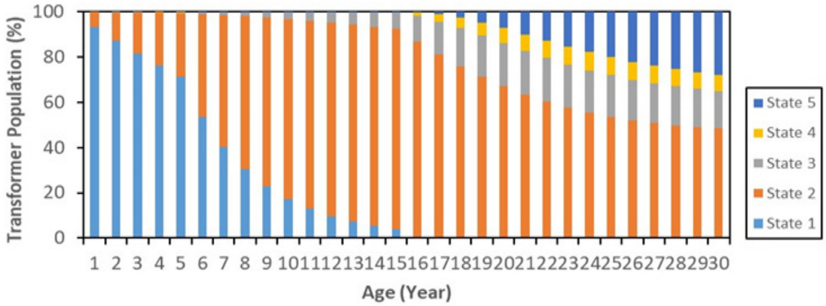
(f)


Transformer Population (%)
Age (Year)
State 5
State 4
State 3
State 2
State 1

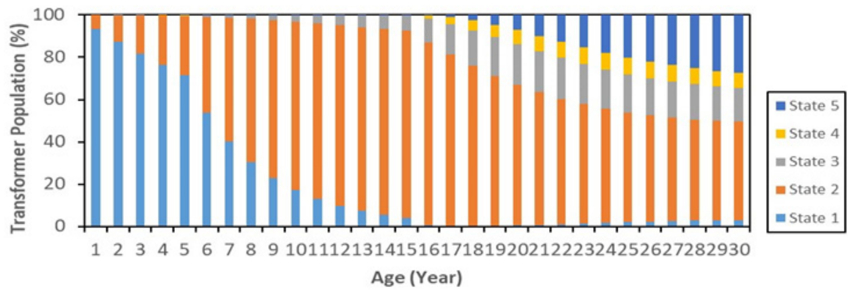
(g)




(h)




(i)




(j)

*Figure 4.* The transformer population distribution utilizing a 10% pre-determined maintenance repair rate perform at state transitions of (a) state 2 to state 1; (b) state 3 to state 2; (c) state 3 to state 1; (d) state 4 to state 3; (e) state 4 to state 2; (f) state 4 to state 1; (g) state 5 to state 4; (h) state 5 to state 3; (i) state 5 to state 2; (j) state 5 to state 1

The failure rate performance curves with a 10% pre-determined maintenance repair rate on different state transitions are shown in Figure 5. During the first 5 years, there was no significant impact on the failure rate reduction among the various states. However, for the next 5 years, it is observed that the transition from state 2 to state 1 significantly impacts the failure rate reduction up to 4.77%. In addition, throughout the prediction period, it is found that significant reductions in failure rate occur from the age of 9 to 18 years.

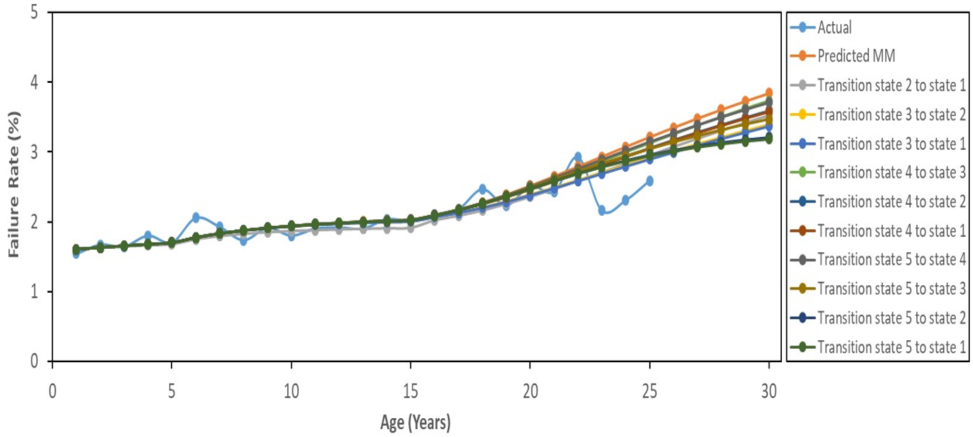



*Figure 5.* Failure rate performance curves with a 10% pre-determined maintenance repair rate performed at different states

The same adjustment of transition matrices as Table 2 was performed for maintenance repair rates of 20% and 30%. The failure rate performance curve and distribution of the transformer population were determined using the same methodology. The failure rate state distributions and trends of the failure rate performance curves are similar for 10%, 20%, and 30% pre-determined maintenance repair rates. For all rates, the transition from state 2 to state 1 significantly affects the failure rate state distribution and results in the highest failure rate reduction in the performance curve. The comparison of the failure rate performance curves for various pre-determined maintenance repair rates is shown in Figure 6. The pre-determined maintenance repair rate of 30% has the highest impact on the failure rate state distribution of the transformer population.

According to the case study, it is found that updating transition matrices with selected pre-determined maintenance repair rates at various states could reduce the failure rate. The comparison of average failure rate reduction with 10%, 20% and 30% pre-determined maintenance repair rates performed at all states for 30 years can be seen in Figure 7. The transition from state 2 to state 1 with 10 %, 20% and 30% pre-determined maintenance repair rates have the highest impact on the average failure rate reductions with percentages of 4.77%, 8.47% and 11.47%, respectively. It is followed by a transition from state 3 to state 1 with percentages of 4.00%, 6.75% and 8.24%, respectively. The lowest impact on the average failure rate reductions with 10 %, 20% and 30% pre-determined maintenance repair rates occur at the transition from state 5 to state 4 with percentages of 0.79%, 1.42% and 1.92%, respectively. It is followed by a transition from state 4 to state 3 with percentages of 0.99%, 1.98% and 2.95%, respectively. It is observed that the changes for each failure rate state distribution are influenced not only by the percentage of the pre-determined maintenance repair rate but also by the transition of failure rate state improvement in the MM.

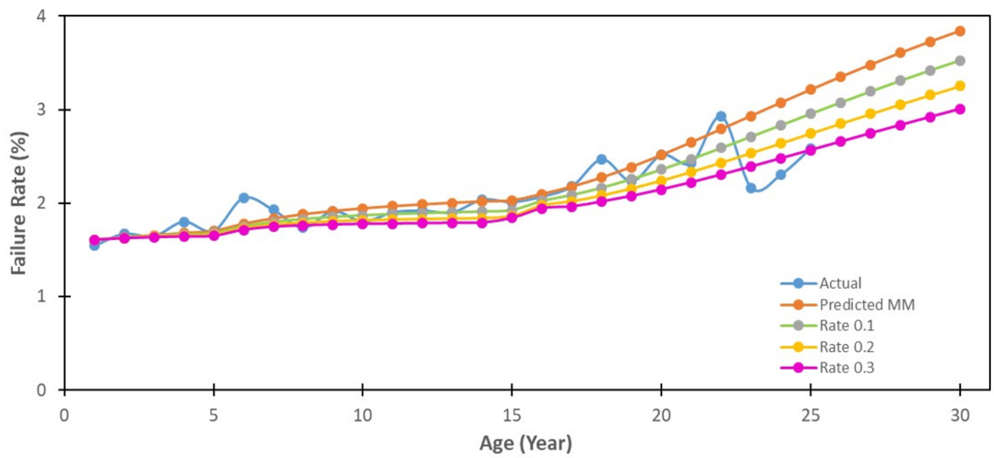



*Figure 6.* Failure rate performance curves with 10%, 20% and 30% pre-determined maintenance repair rates

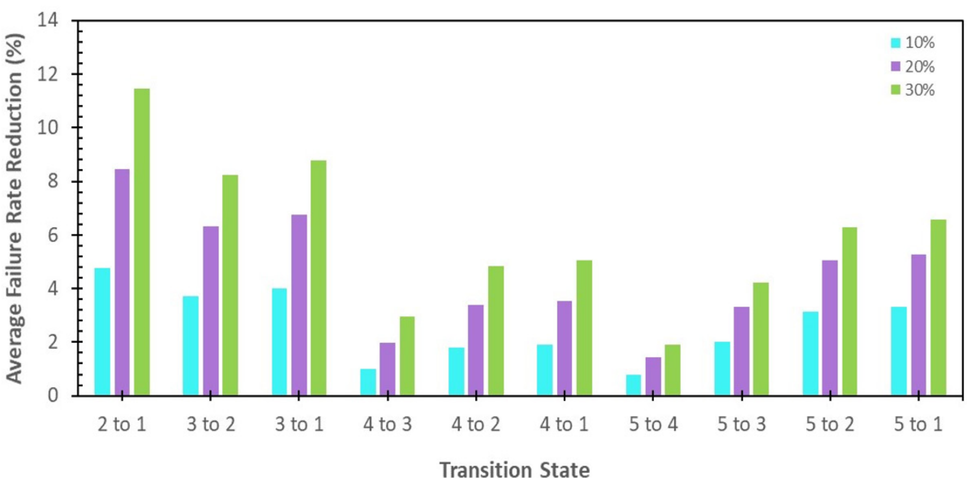
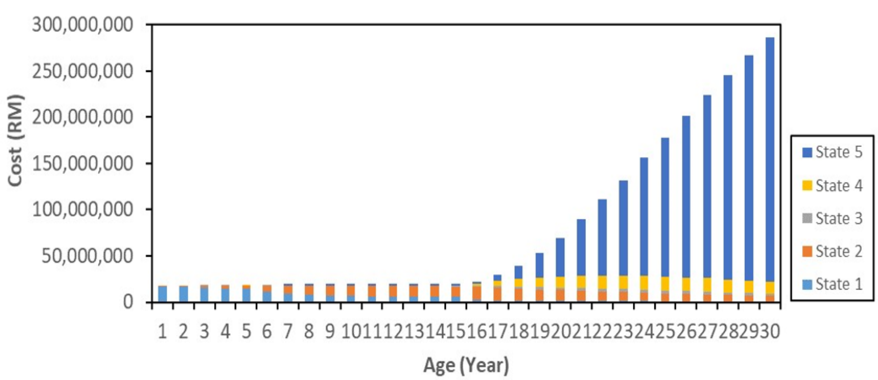



*Figure 7.* Comparison of failure rate reduction for all states

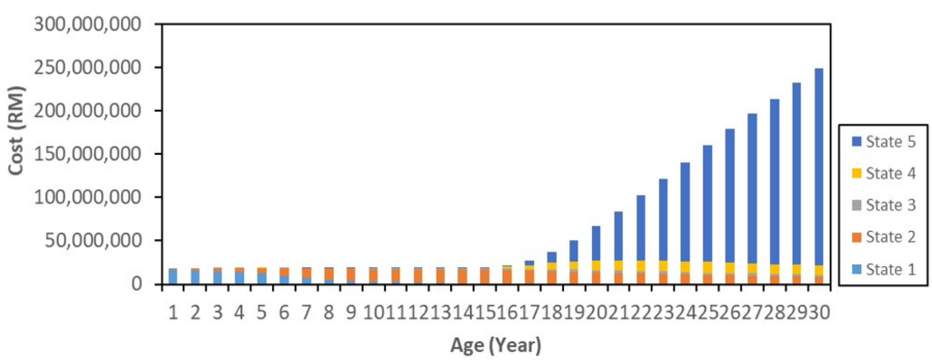
## Maintenance Policy and Cost Study

The analysis of maintenance costs was performed using the transition matrices computed from the generated MPM, as shown in Equations 12 and 13. In addition, as indicated in Equation 8, the future state distributions were updated depending on the maintenance policy model and the combined effect of deterioration. Finally, the cost of maintenance for each of the state distributions was plotted using Equation 9 and the cost estimation defined by Yahaya et al. (2018b).

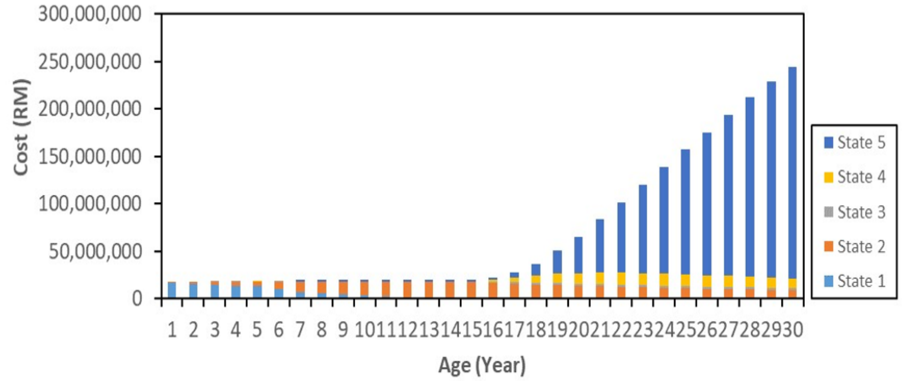
The 10% pre-determined maintenance policy was assigned to each state to simulate the impact of the maintenance cost of the transformer. The distribution of transformer maintenance costs by the state is shown in Figure 8. The costs in states 4 and 5 contribute the most to the total maintenance cost. Over the 30 years, there has been no significant increment in the maintenance costs for states 1, 2, and 3. However, it is observed that the estimated costs for the transformer gradually increase, and there is a significant increment in the cost in state 5 once the age reaches 17 years. Furthermore, the total maintenance costs rise by an average of RM 18.32 million to RM 251.87 million.




(a)

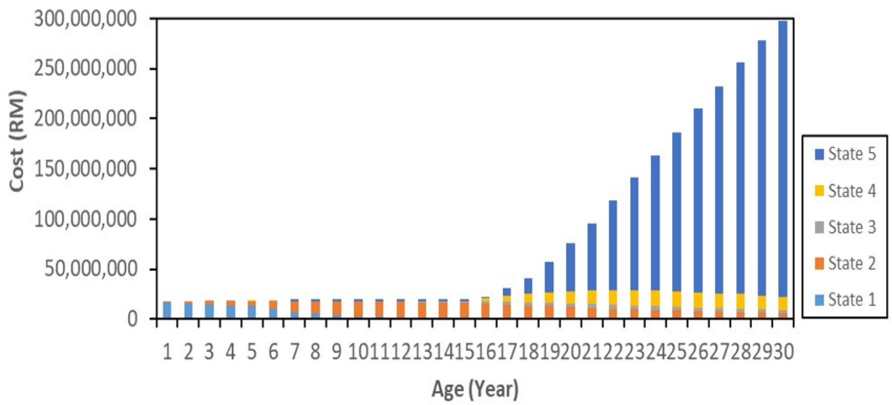



(b)



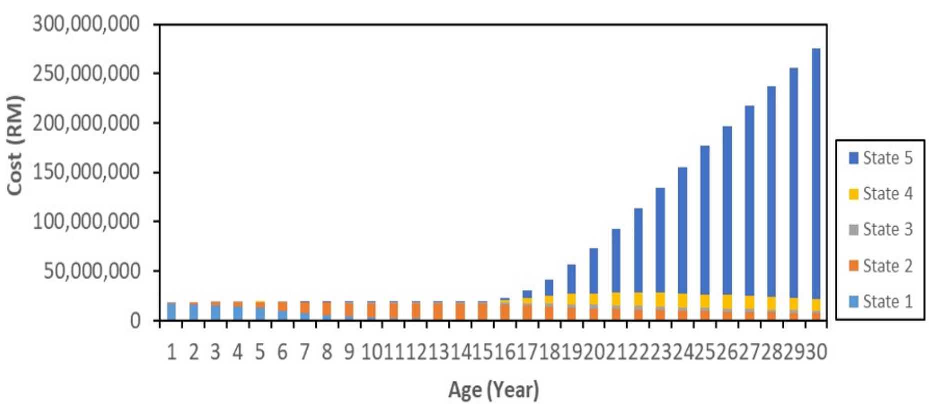
Cost (RM)
Age (Year)
State 5
State 4
State 3
State 2
State 1


(c)



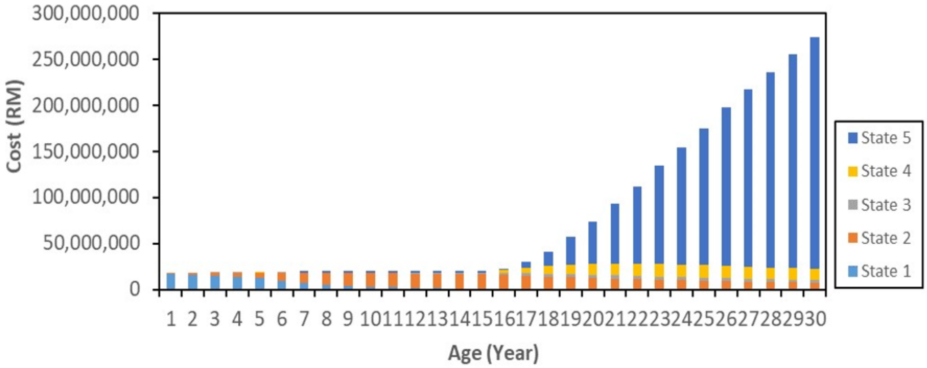
Cost (RM)
Age (Year)
State 5
State 4
State 3
State 2
State 1


(d)

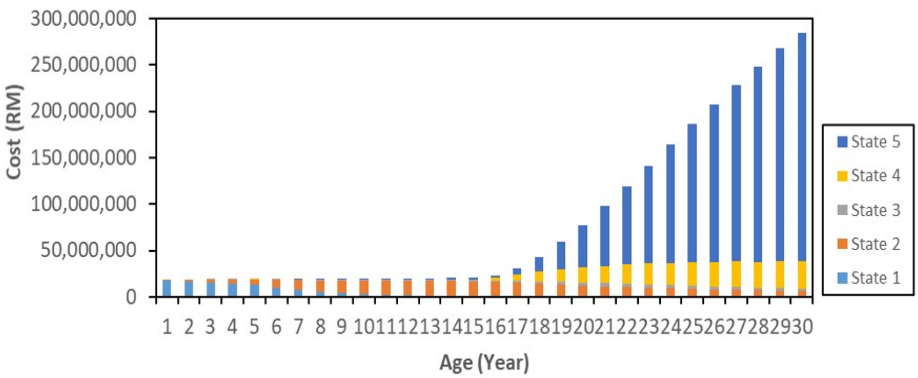


Cost (RM)
Age (Year)
State 5
State 4
State 3
State 2
State 1

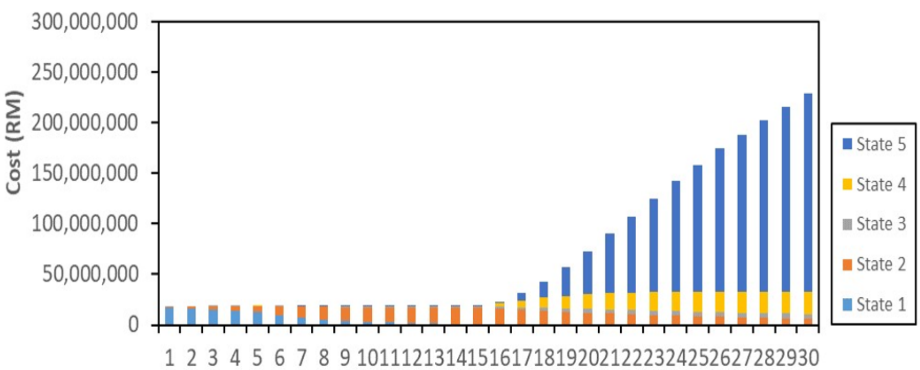

(e)


300,000,000
250,000,000
200,000,000
150,000,000
100,000,000
50,000,000
0
Cost (RM)
1 2 3 4 5 6 7 8 9 10111213141516171819202122232425262728293
Age (Year)
State 5
State 4
State 3
State 2
State 1

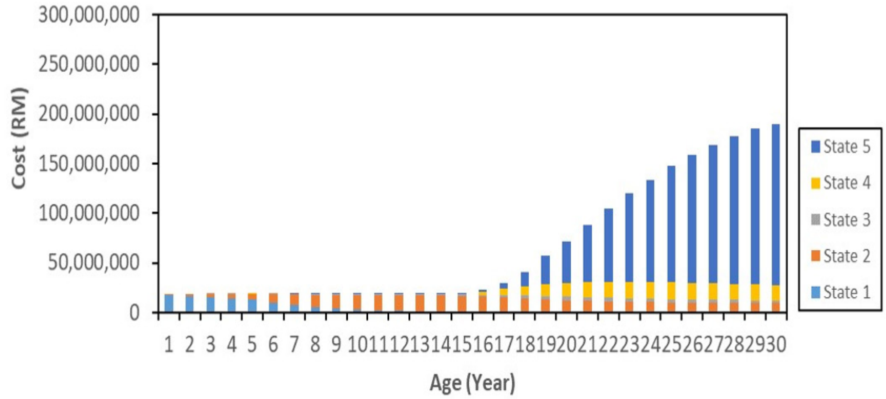
(f)


300,000,000
250,000,000
200,000,000
150,000,000
100,000,000
50,000,000
0
Cost (RM)
1 2 3 4 5 6 7 8 9 10111213141516171819202122232425262728293
Age (Year)
State 5
State 4
State 3
State 2
State 1

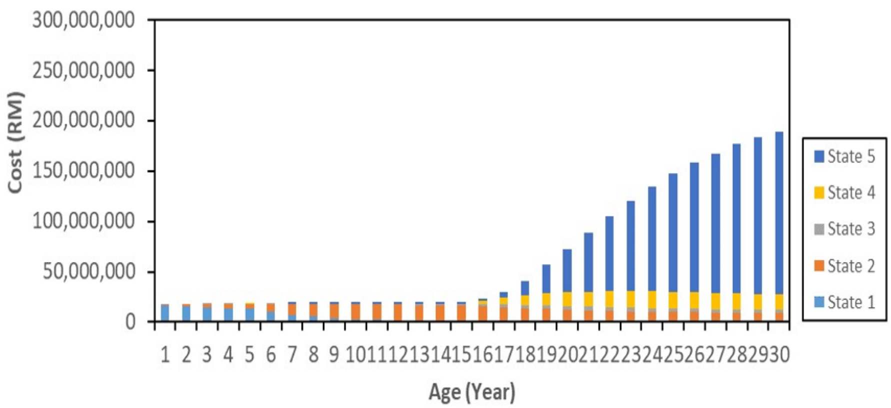
(g)


300,000,000
250,000,000
200,000,000
150,000,000
100,000,000
50,000,000
0
Cost (RM)
1 2 3 4 5 6 7 8 9 10111213141516171819202122232425262728293
Age (Year)
State 5
State 4
State 3
State 2
State 1

(h)




(i)




(j)

*Figure 8.* The transformer maintenance cost distribution with a 10% pre-determined maintenance policy calibrated at (a) state 2 to state 1; (b) state 3 to state 2; (c) state 3 to state 1; (d) state 4 to state 3; (e) state 4 to state 2; (f) state 4 to state 1; (g) state 5 to state 4; (h) state 5 to state 3; (i) state 5 to state 2; (j) state 5 to state 1

## Maintenance Policy and Preventive Maintenance Frequency

The maintenance frequency analysis was performed using the transition matrices obtained from the generated MPM, as illustrated in Equations 12 and 13. The future state distributions are updated based on the maintenance policy model and the combined effect of deterioration, as shown in Equation 11. The frequency of maintenance was calculated for each state distribution using Equation 11 and the frequency of maintenance test as specified in Table 1.

The distribution of transformer population in each maintenance frequency over the 30 years of prediction is presented in Figure 9. The maintenance frequency for every nine months contributes the highest portion of the maintenance frequency. The maintenance frequency for every six months contributes a lesser portion of the maintenance frequency than every nine months. The maintenance frequency for every three months contributes the lowest portion of the maintenance frequency. In practice, the maintenance frequency for every three months is quite difficult. A comprehensive examination and expert judgment are required to obtain necessary information, such as transformer reliability requirements. Nonetheless, this study can help utilities plan for maintenance by adjusting the maintenance policy and frequency of maintenance to optimize the asset management of the transformer population.

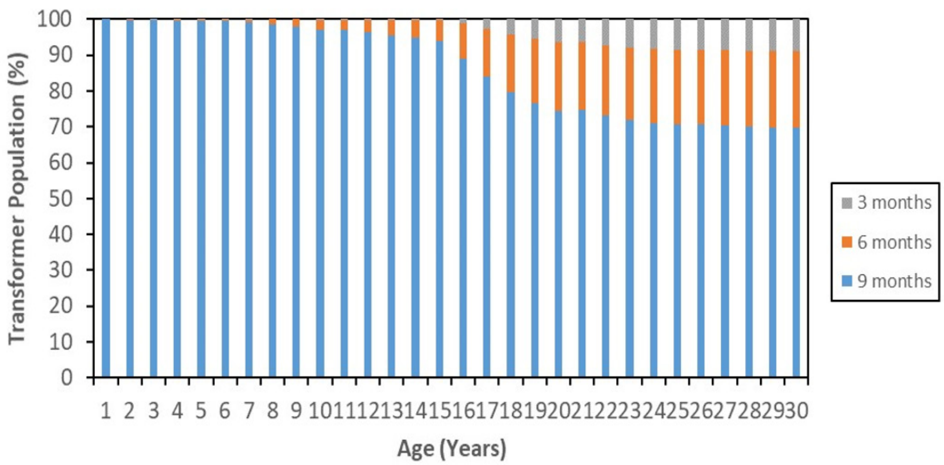



*Figure 9.* Distribution of transformer population according to maintenance frequency

The estimation of the maintenance frequency by months for 370 transformers is shown in Figure 10. It is observed that 316 transformers would be required to be maintained every nine months, 41 transformers every six months and 13 transformers every three months. The maintenance frequency for every nine months contributes the highest portion of the maintenance frequency since 85% of the transformer population is in states 1 and 2.

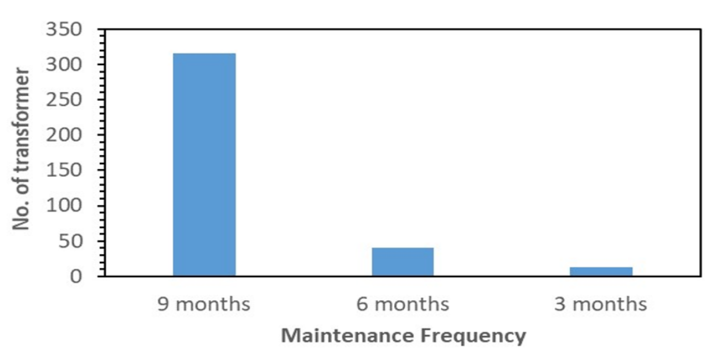



*Figure 10.* Estimated maintenance frequency for the transformer

## CONCLUSION

It is found that MM can be used to aid utilities in planning and to implement maintenance strategies. Pre-determined maintenance repair rate and policy model is considered one of the maintenance strategies that can be carried out by updating the MM. The effect of various pre-determined maintenance repair rates and maintenance cost studies on the failure rate based on MM are investigated in this study. It is found that the updated transition matrices with selected pre-determined maintenance repair rates at various states can reduce the failure rate. The results of this study show that the adjustment of transition matrices from state 2 to state 1 has the highest impact on the failure rate reduction. The pre-determined maintenance repair rate of 30% has the highest impact on the transformer population's failure rate state distribution and failure rate performance curve. Over the 30 years of forecasting, it is observed that the estimated cost for the transformer population gradually increases, and there is an apparent increment of costs in state 5 once the age reaches 17 years. Moreover, the total maintenance costs are expected to rise by an average of RM 18.32 million to RM 251.87 million. Most transformers require maintenance every nine months to prevent the transformer from degrading to state 5, which is very poor. Overall, the findings of this study could help utilities plan and optimize their asset investments.

## ACKNOWLEDGEMENTS

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