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A Maintenance Cost Study of Transformers Based on Markov Model Utilizing Frequency of Transition Approach

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Abstract: In this paper, a maintenance cost study of transformers based on the Markov Model (MM) utilizing the Health Index (HI) is presented. In total, 120 distribution transformers of oil type (33/11 kV and 30 MVA) are examined. The HI is computed based on condition assessment data. Based on the HI, the transformers are arranged according to its corresponding states, and the transition probabilities are determined based on frequency of a transition approach utilizing the transformer transition states for the year 2013/2014 and 2012/2013. The future states of transformers are determined based on the MM chain algorithm. Finally, the maintenance costs are estimated based on future-state distribution probabilities according to the proposed maintenance policy model. The study shows that the deterioration states of the transformer population for the year 2015 can be predicted by MM based on the transformer transition states for the year 2013/2014 and 2012/2013. Analysis on the relationship between the predicted and actual computed numbers of transformers reveals that all transformer states are still within the 95% prediction interval. There is a 90% probability that the transformer population will reach State 1 after 76 years and 69 years based on the transformer transition states for the year 2013/2014 and 2012/2013. Based on the probability-state distributions, it is found that the total maintenance cost increases gradually from Ringgit Malaysia (RM) 5.94 million to RM 39.09 million based on transformer transition states for the year 2013/2014 and RM 37.56 million for the year 2012/2013 within the 20 years prediction interval, respectively.

Keywords: transformers; Health Index (HI); Markov Model (MM); transition probabilities; frequency of transition; prediction interval; maintenance cost; maintenance policy model

1. Introduction

One of the vital elements in power system planning is management of transformer asset. Condition Based Monitoring (CBM) has been introduced by utilities as part of an asset management scheme to monitor the characteristics of operational parameters and provide a comprehensive diagnosis on transformers. Condition trends that indicate abnormality can be detected early and can be used to determine health conditions of transformers [1].

Multiple condition data are normally considered to diagnose the condition of transformers, such as oil quality, dissolved gases, furanic compounds, power factors, winding resistances, winding ratios, temperature, partial discharges, physical conditions and load tap changer conditions [2,3]. This information is embedded in a single quantitative value known as Health Index (HI), which can give overall condition status of transformers [4–8]. The HI can be utilized to evaluate transformer deteriorations that require diagnosis, maintenance and approaching end of life [9,10].

The HI of transformers has been identified for its potential in predicting the future states of transformer population. Presently, there are fewer studies on modelling the deterioration of transformers using the HI [11,12]. A few techniques based on extrapolation, regression, trend forecasting and curve fitting analysis have been implemented to achieve this purpose [13,14]. However, due to the scattering nature of HI, a reliable prediction is quite difficult to be achieved based on these techniques [7,14,15].

One of the possible approaches that can be used to evaluate the future condition of transformers is the Markov Model (MM). It is a stochastic approach, where the transition probabilities can be identified based on existing condition data. The MM has been widely applied to forecast the conditions of bridges, bridge elements, pavements, storm water piping components and steel hydraulic structures in civil engineering [16–20]. The MM has also been used to predict the deterioration states of switchgear populations, spare units and fault occurrence of transformers [21–24]. Based on the MM, the maintenance cost can be estimated to assist asset managers in planning their future budgetary [25–27]. The financial aspect of the CBM needs to be planned appropriately whereby it can be achieved by maintenance cost analysis.

In this paper, the MM is applied to predict the deterioration states of the transformer population based on the HI. In total, 120 distribution transformers of oil type (33/11 kV and 30 MVA) are used for the case study. The first part is the modelling of deterioration states of the transformer population based on the MM and the HI. The second part is the sensitivity analysis on the transformer deterioration model based on a pre-determined maintenance policy model. The final part is the assessment of cost impact based on the pre-determined maintenance policy model.

2. Health Index of Transformer

The HI is defined as a method to measure the overall health of an asset by quantifying the condition monitoring information [28]. It is based on scoring, rating and ranking techniques, which considers theoretical knowledge, standards, guidelines and expert judgments. Most of the electrical power utilities adopt HI for management of transformers, such as Kinectrics Incorporate, DNV KEMA, Hydro Quebec, EDF Energy, TERNA, Electricity Generating Authority of Thailand and Tenaga Nasional Berhad [6–8,29]. Figure 1 shows an example of a basic framework of HI formulation, which is dependent upon the weighting factors in order to determine the final HI [28].

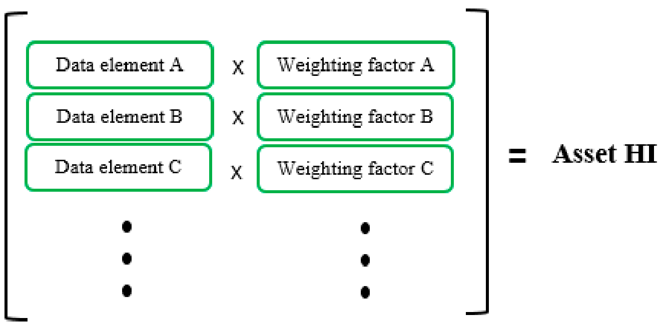

Figure 1. A basic framework of health index formulation.

Equation (1) shows the common HI formulation introduced in [9,10], which was adopted in this study:

$$HI = A\% \frac{\sum_{j=1}^{21} K_j HIF_j}{\sum_{j=1}^{21} 4K_j} + B\% \frac{\sum_{i}^{24} K_j HIF_j}{\sum_{j=22}^{24} 4K_j} \tag{1}$$

where K_j is the assigned rating given for each factor, HIF_j is the assigned score for each factor and j is the number of condition data. According to [9,10], the constant values of A and B are 60% and 40%, respectively, which correspond to parameters of transformers and tap changers. In this study, the constants, A and B, were not considered since only transformer condition data are available for analysis. Furthermore, due to the limitation of data in the database, only oil quality, dissolved gases and furanic compounds were considered and the updated formulation of HI can be seen in Equation (2):

$$HI_{adjusted} = \frac{K_{DGA} HIF_{DGA}}{4K_{DGA}} + \frac{K_{OQA} HIF_{OQA}}{4K_{OQA}} + \frac{K_{FA} HIF_{FA}}{4K_{FA}} \tag{2}$$

Based on the HI score, several indicator scales can be determined, which can be seen in Table 1 [9,10,30].

Table 1. Health Index indicator scales.

Condition	Health Index	Description
Very Good	85–100%	Some aging or minor deterioration of a limited number of components.
Good	70–84%	Significant deterioration of some components.
Fair	50–69%	Widespread significant or serious deterioration of specific components.
Poor	30–49%	Widespread serious deterioration.
Very Poor	0–29%	Extensive serious deterioration.

3. Markov Model Structure with Health Index

3.1. Markov Chain Concepts

The MM is known as a probabilistic approach based on the Markov chain decision process that can be used to predict the future condition of equipment. It can be evaluated through state transition in a specific interval [15]. Since the MM does not rely heavily on historical conditions of equipment which are normally limited, the uncertainty effect due to constraints of a long-term data record could be minimized. Thus, the decision process is considered as a memoryless process [31]. Figure 2 illustrates the representation of the Markov chain for this study, which considers 5 states as stated in Table 1.

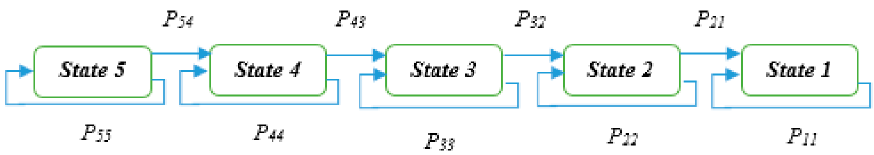

Figure 2. Five-state Markov chain model.

Generally, the Markov chain is determined by transition probabilities given as P_{ij} [32,33]. Transition matrix, $\boldsymbol{P}$, represents the transition probabilities. The corresponding transition matrix, $\boldsymbol{P}$, for 5 states of MM used in this study is shown in Equation (3) as following:

$$\boldsymbol{P} = \begin{bmatrix} P_{55} & 1-P_{55} & 0 & 0 & 0 \\ 0 & P_{44} & 1-P_{44} & 0 & 0 \\ 0 & 0 & P_{33} & 1-P_{33} & 0 \\ 0 & 0 & 0 & P_{22} & 1-P_{22} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

In order to analyze the MM based on the HI of transformers, several assumptions were made. First, a monotonic process was assumed where the states of transformers either remained at its current state or moved to the next state. The assumption was made based on the fact that ageing of transformers was irreversible, of which data screening was carried out to filter transformers that have been refurbished either through rewinding or oil regeneration. In order to further simplify the Markov chain process, the transition probabilities were assumed to be stationary and maintain over time. Thus, the same value of probability P_{ij} *(t)* was considered in a particular year. In addition, each state probabilities should be equal to one, for example, $P_{55} + P_{54} = 1$, $P_{44} + P_{43} = 1$, $P_{33} + P_{32} = 1$ and $P_{22} + P_{21} = 1$. The final state was set as 1, assuming that all transformers would end up in the poorest condition and remained at the last state. This concept of the MM is known as an absorbing model. Once the transition matrix has been developed, the future states of the HI of transformers can be determined based on the current state shown in Equation (4):

$$\boldsymbol{H}_{n+1} = \boldsymbol{H}_n \cdot \boldsymbol{P} \tag{4}$$

where $\boldsymbol{H}_{n+1}$ is the next state in a particular interval and $\boldsymbol{H}_n$ is the current state. The future state of the HI can also be determined by the MM based on the following equation:

$$\boldsymbol{H}_t = \boldsymbol{H}_0 \cdot \boldsymbol{P}^t \tag{5}$$

where t is the number of intervals,$\boldsymbol{H}_0$ is the initial state and $\boldsymbol{H}_t$ is the future deterioration state in t.

3.2. Transition Probability Derivation

Transition probabilities are the core element of the MM process, which can be determined by heuristic or statistical approaches. A heuristic approach utilizes knowledge from the degradation characteristic of a component. The statistical approach uses statistical techniques, such as frequency of transition, Maximum Likelihood Estimator (MLE), Least Square (LS), time spent and regression. In this study, the transition probabilities were computed based on the frequency of the transition approach, which was implemented according to the HI and the state classification. The transition probabilities for each state in the transition matrix can be seen in Equations (6) and (7) as following:

$$P_{ij} = Prob[H(t+1) = j \big| H(t) = j] \tag{6}$$

$$1 - P_{ij} = Prob[H(t+1) = j - 1 \big| H(t) = j] \tag{7}$$

where P_{ij} is the transition probability for equipment remaining at the existing state and $1 - P_{ij}$ is the probability for equipment moving to the next state. Both probabilities depend on the present state j. In order to determine the future state for the next interval, $t + 1$, the transition probabilities were calculated, where each iteration fulfilled the Chapman-Kolmogorov rules and can be seen in Equations (8)–(12):

$$P_5(t+1) = P_5(t) * (1 - P_{54}) \tag{8}$$

$$P_4(t+1) = P_5(t) * (1 - P_{54}) + \ P_4(t) * (1 - P_{43}) \tag{9}$$

$$P_3(t+1) = P_4(t) * (1 - P_{43}) + \ P_3(t) * (1 - P_{32}) \tag{10}$$

$$P_2(t+1) = P_3(t) * (1 - P_{32}) + \ P_2(t) * (1 - P_{21}) \tag{11}$$

$$P_1(t+1) = P_2(t) * (1 - P_{21}) + \ P_1(t) \tag{12}$$

Frequency of Transition

Frequency of transition is among the common approaches to determining the transition probabilities [16,34]. This method takes into consideration the number of equipment residing in each state between time intervals. In this study, 2 consecutive snapshots of HI were used to determine the frequency of transition. A set of transformer data from the year 2012 to 2015 was utilized. Two transition probabilities were computed using the frequency of the transition approach utilizing transformer transition states for the year 2013/2014 and 2012/2013. The transition probabilities can be obtained by Equation (13):

$$P_{ij} = \frac{n_{ij}}{n_i} \quad (13)$$

where n_{ij} is the number of transformers transit from a state i to j in one year period and $n_i = \sum_j n_{ij}$ is the number of transformers in state i before the transition.

Once the transition probabilities were established, the transition matrix was determined based on Equation (3), and the deterioration probability rate was calculated according to Equation (5) based on the assumption that the initial condition state vector, $\boldsymbol{H}_0$ equal to [1 0 0 0 0].

4. Maintenance Policy and Cost

The maintenance cost is associated with the cost spent for the maintenance actions by utilities to ensure transformers to operate at the optimum level [35]. Based on the future state probabilities of the transformer model obtained by the MM, the maintenance policy can be determined. The rehabilitation can be modelled by allowing the current state of transformers to return to its preceding state [25–27]. A new transition matrix to represent the effect of rehabilitation actions has been introduced in this study, whereby appropriate maintenance approaches were considered, since it was quite difficult to obtain detailed information on the generic maintenance policy model. Based on [36], there are 3 main maintenance approaches that can be used for transformer operation and maintenance actions known as Condition Assessment (CA), minor work that involves Corrective Maintenance (CM) and major work which consists of refurbishment and replacement. In this study, several assumptions were made for the maintenance policy model. The CA was conducted for transformers in all states. It was performed annually to monitor the transformer condition without improving the condition state. For any transformer at State 2 (poor), CM was carried out to improve the condition to State 5 (very good), while for any transformers in State 1 (very poor), major work was carried out to improve the condition to State 5 (very good). The maintenance actions, intervention states, maintenance activities and estimated cost breakdowns can be seen in Table 2. The average cost for each maintenance activity from 3 different Original Engineering Manufacturers (OEMs) was used in this study.

Table 2. Maintenance action, intervention state, maintenance activity and cost estimation breakdown.

Maintenance Action	Intervention State	Activity	Estimated Cost (RM)
Condition assessment	5, 4, 3, 2, 1	Annual routine monitoring [1]	49,500.00
Minor work	2	Oil regeneration + major parts restoration [2]	30% from new unit
Major work	1	Replacement	1,700,000.00

[1] Annual routine monitoring by OEM will consider physical inspection, dissolved gases, oil quality and furanic compounds. [2] It may include the tap changers, bushing, labor, oil drying, tank and sealing, wiring and control systems. Rewinding and core replacement are not included [36].

Based on the given transition-state probability matrices for the year 2013/2014 and 2012/2013, the future-state probability distribution of the transformer was simulated based on 10% pre-determined maintenance policy model. The matrix of the corresponding maintenance policy model for each of the states, $\boldsymbol{R}$, is given by:

$$\boldsymbol{R} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0.1 & 0 & 0 & 0.9 & 0 \\ 0.1 & 0 & 0 & 0 & 0.9 \end{bmatrix} \quad (14)$$

The combined effect of the normal deterioration and the maintenance policy model is expressed as $\boldsymbol{PR}$ [27]. These Markov chain models were solved to find future-state probabilities at a certain year, n, by iterating the initial-state distribution matrix with the combined effect of deterioration and maintenance policy matrices, as shown in Equation (15):

$$\boldsymbol{H}_n = \boldsymbol{H}_0(\boldsymbol{PR})^n \tag{15}$$

Next, the model was evaluated to assess the relative cost impact throughout the life cycle term based on the information in Table 2. Since each of the state j is associated with the maintenance cost known as $\boldsymbol{C}$, and hence, the expected maintenance cost of each future state for each year, n, can be determined based on Equation (16):

$$Expected\ Cost = \boldsymbol{H}_0(\boldsymbol{PR})^n \boldsymbol{C}_n \tag{16}$$

The overall workflow on the maintenance cost study can be seen in Figure 3. The model can be updated based on yearly historical data of the transformer population. In this study, the percentage of pre-determined maintenance policy has been determined based on assumptions in order to simulate the cost sensitivity for the maintenance policy. Dependent upon the budgetary, utilities can plan the percentage of the pre-determined maintenance policy in order to optimize the asset management of the transformer population.

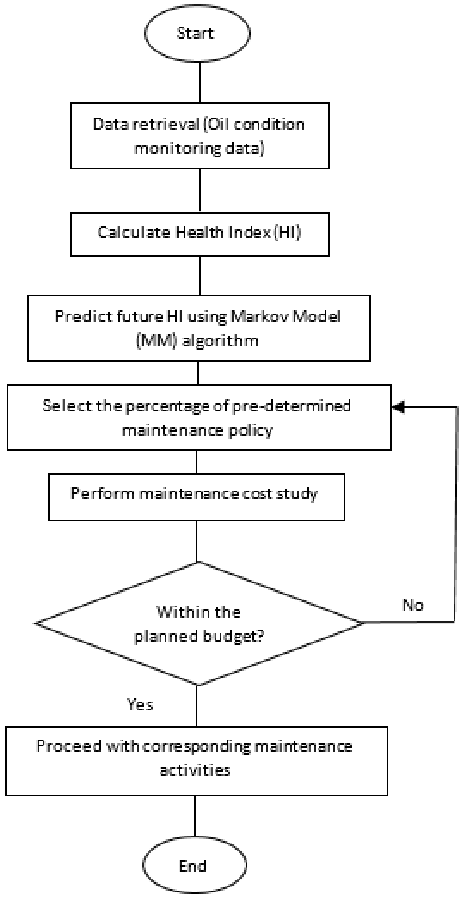

Figure 3. An overall workflow on the maintenance cost study.

5. Application of Markov Model for 33/11 kV Distribution Transformers

In this study, 120 transformers (33/11 kV and 30 MVA) were analyzed for MM. First, the states of all transformers obtained by the MM were defined based on the HI indicator scale in Table 1. The classification of transformers is tabulated in Table 3.

Table 3. Classification of transformer states based on health index.

Markov Model State	Corresponding HI Range
State 5	85–100%
State 4	70–84%
State 3	50–69%
State 2	30–49%
State 1	0–29%

Next, the numbers of transformers in its consecutive states were clustered according to its corresponding years, which can be seen in Table 4.

Table 4. Numbers of transformers in its consecutive states from 2012 to 2015.

State	Year 2012	Year 2013	Year 2014	Year 2015
State 5	23	19	17	7
State 4	25	23	15	12
State 3	46	46	42	42
State 2	21	26	39	44
State 1	5	6	7	15

Since the condition monitoring of transformers was conducted annually, a yearly time period was used as the transition interval. The transformer transition states for the year 2013/2014 and 2012/2013 can be seen on Tables 5 and 6. The transition probability matrices were determined based on the frequency of a transition technique that utilized the transformer transition states for the year 2013/2014 and 2012/2013 and can be seen in Equations (17) and (18) respectively:

$$\boldsymbol{P} = \begin{bmatrix} 0.8947 & 0.1053 & 0 & 0 & 0 \\ 0 & 0.5652 & 0.4348 & 0 & 0 \\ 0 & 0 & 0.7391 & 0.2609 & 0 \\ 0 & 0 & 0 & 0.9615 & 0.0385 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{17}$$

$$\boldsymbol{P} = \begin{bmatrix} 0.8261 & 0.1739 & 0 & 0 & 0 \\ 0 & 0.7600 & 0.2400 & 0 & 0 \\ 0 & 0 & 0.8696 & 0.1304 & 0 \\ 0 & 0 & 0 & 0.9524 & 0.0476 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{18}$$

Table 5. Transition of transformer states for the year 2013/2014.

To From	State 5	State 4	State 3	State 2	State 1
State 5	17	2	0	0	0
State 4	0	13	10	0	0
State 3	0	0	34	12	0
State 2	0	0	0	25	1
State 1	0	0	0	0	1

Next, the future states of transformers were calculated according to Equation (4). Figure 4 shows the state probabilities of transformers over the years predicted based on transformer transition states for the year 2013/2014. The number of transformers in its consecutives states can be determined through multiplication with its corresponding probabilities. The probability of State 1 is regarded as a critical state for transformers since the risk of failure is high. Based on this study, it is found that there is a 90% probability that the population of transformer will reach State 1 after 76 years based on the transformer transition states for the year 2013/2014.

Table 6. Transition of transformer states for the year 2012/2013.

To From	State 5	State 4	State 3	State 2	State 1
State 5	19	4	0	0	0
State 4	0	19	6	0	0
State 3	0	0	40	6	0
State 2	0	0	0	20	1
State 1	0	0	0	0	1

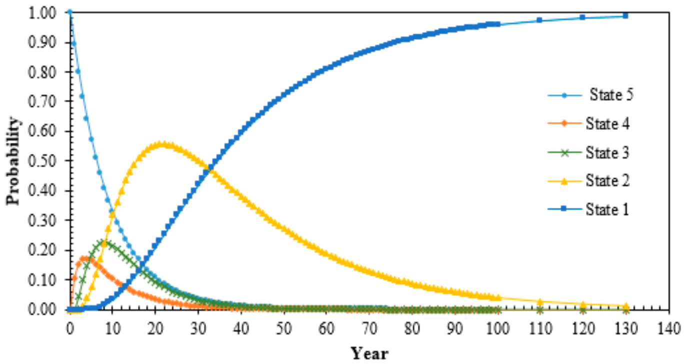

Figure 4. State probabilities in the year 2015 based on transformer transition states for the year 2013/2014.

The maintenance cost analysis was carried out based on the transition matrices computed from the MM. The future-state distributions were adjusted based on the maintenance policy model that utilized transition states for the year 2013/2014 and Equation (15). Table 7 shows the distribution of 120 transformers residing in each state for the period of 20 years. The maintenance cost for each of the state distributions was plotted based on Equation (16) and estimated cost defined in Table 2.

The relationship between the predicted and actual computed numbers of transformers was further analyzed based on a linear regression technique, which can be seen in Figure 5. The r^2 value of the line fitting was 0.8826. It is found that the data exceeded the confidence interval, but were still within the prediction interval.

An analysis was also carried out based on transformer transition states for the year 2012/2013. A comparison was carried out between the predicted and actual computed numbers of transformers for the year 2014 and 2015, as shown in Figures 6 and 7. A similar finding was observed in Figure 5, where the data exceeded the confidence interval but were still within the prediction interval. For both fittings, the r^2 values were 0.8864 and 0.8619 for the year 2014 and 2015, respectively.

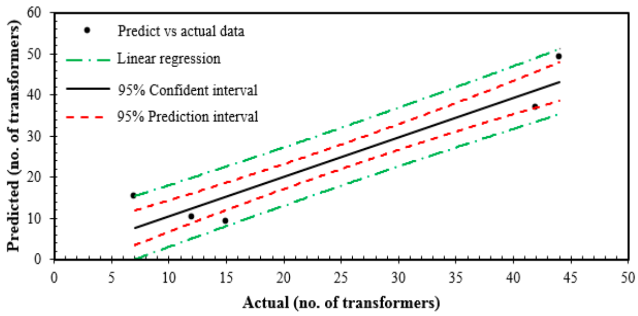

Figure 5. Predicted versus actual numbers of transformer in the year 2015 based on transformer transition states for the year 2013/2014.

Table 7. Numbers of transformers in each of the states based on transition states for the year 2013/2014 with the maintenance policy model.

Age	State 5	State 4	State 3	State 2	State 1
0	120	0	0	0	0
1	107	13	0	0	0
2	96	18	6	0	0
3	86	21	12	1	0
4	77	21	18	4	0
5	70	20	22	8	0
6	64	19	25	12	0
7	59	17	27	16	1
8	55	16	27	21	1
9	52	15	27	24	2
10	50	14	26	28	2
11	49	13	26	29	3
12	47	13	25	31	4
13	47	12	24	32	5
14	46	12	23	34	5
15	46	11	22	35	6
16	46	11	21	35	7
17	46	11	21	35	7
18	46	11	20	35	8
19	46	11	20	35	8
20	46	11	19	35	9

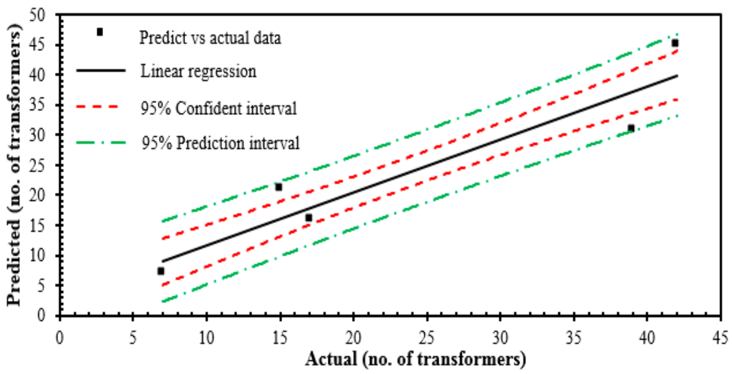

Figure 6. Predicted versus actual numbers of transformer in the year 2014 based on transformer transition states for the year 2012/2013.

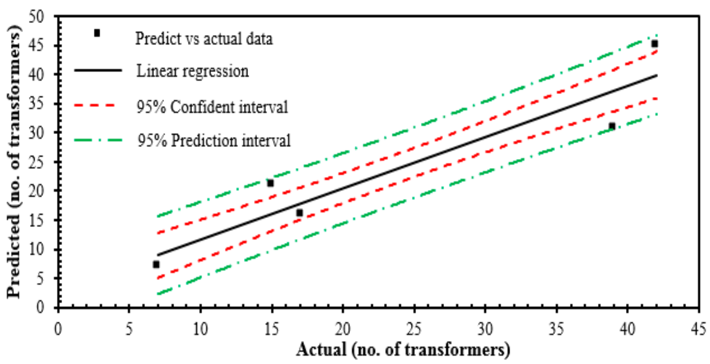

Figure 7. Predicted versus actual numbers of transformer in the year 2015 based on transformer transition states for the year 2012/2013.

The predicted state probabilities over the years for State 1 in the year 2015 based on transformer transition states for the year 2013/2014 and 2012/2013 are shown in Figure 8. The percentage of differences for states probabilities for different years were in the range from 0% to 4.87%. Based on the transformer transition states for the year 2012/2013, there is a 90% probability that the population of transformer will reach State 1 after 69 years, which are lower than the prediction based on transformer transition states for the year 2013/2014.

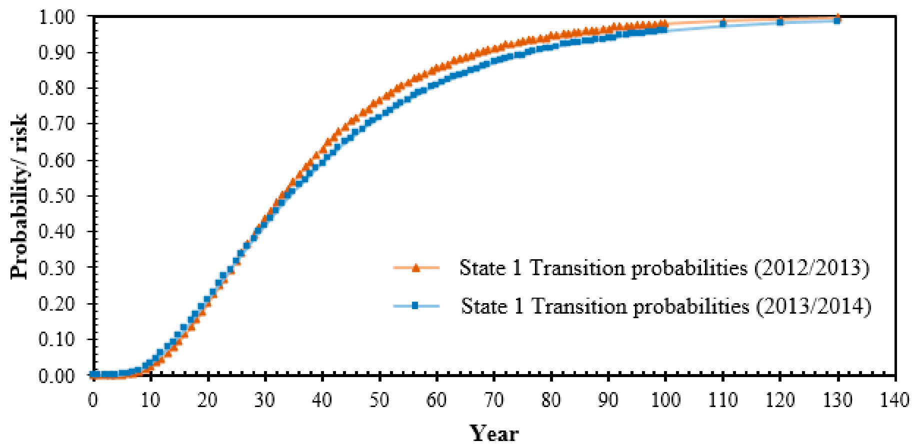

Figure 8. Predicted state probabilities for State 1 in the year 2015 based on transformer transition states for the year 2013/2014 and 2012/2013.

It is apparent that there was a slight deviation between the actual and predicted numbers of transformers for each state, as shown in Figure 9. Based on transformer transition states for the year 2013/2014, State 5 showed the highest deviation followed by State 1, State 4, State 3 and State 2. On the other hand, State 2 showed the highest deviation followed by State 5, State 4 and State 1 and State 3 based on transformer transition states for the year 2012/2013. For State 2 and State 4, the number of transformers predicted by transformer transition states for the year 2013/2014 is much closer to the actual computed number of transformers than that for the year 2012/2013. It was found that for State 3 and State 5, the number of transformers predicted based on transformer transition states for the year 2012/2013 is closer to the actual computed number of transformers than that for the year 2013/2014. For State 1, the number of transformers predicted based on transformer transition states for the year 2013/2014 is the same as that for the year 2012/2013.

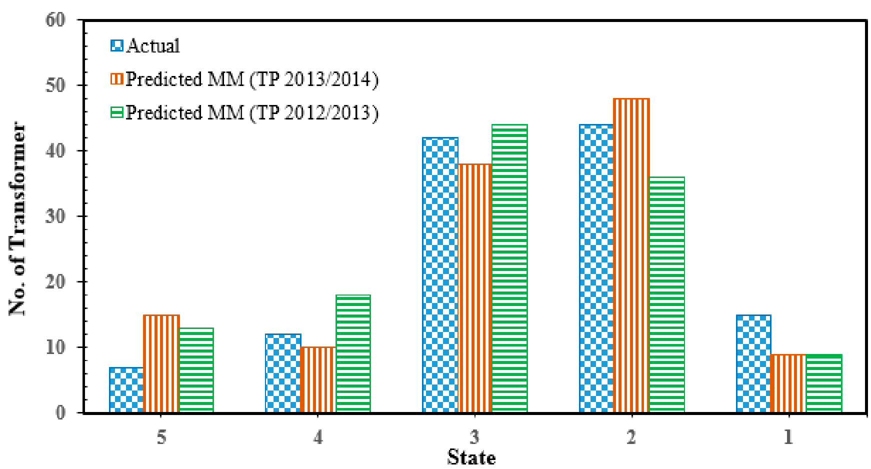

Figure 9. Actual and predicted transformer populations in the year 2015 based on transformer transition states for the year 2013/2014 and 2012/2013.

The maintenance cost distribution for transformers in each of the states for transformer transition states for the year 2013/2014 and 2012/2013 can be seen in Figures 10 and 11, respectively. The costs in State 2 and State 1 contributed to the highest portion of the maintenance cost. There was no significant increment of the maintenance cost for State 5, State 4 and State 3 over the past 20 years of prediction. The estimated total costs for transformer transition states for the year 2013/2014 and 2012/2013 will gradually increase, as shown in Figure 12. The estimated total cost for transformer transition states for the year 2013/2014 will increase from RM 5.94 million to RM 39.09. On the other hand, based on the transformer transition states for the year 2012/2013, the maintenance cost will increase up to RM 37.56 million.

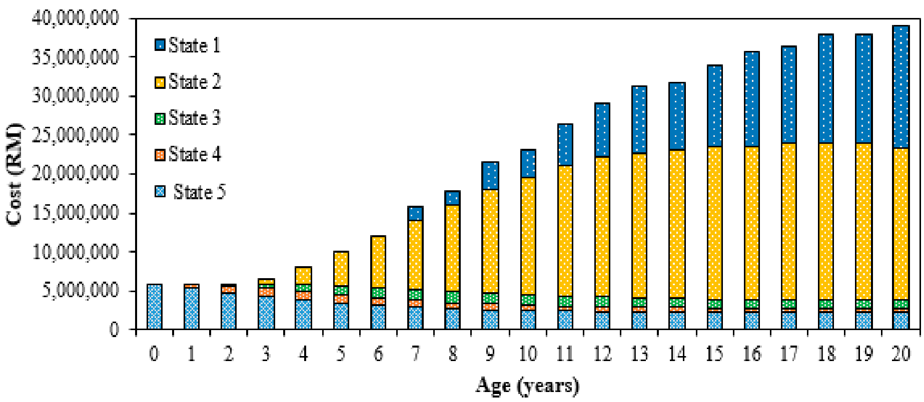

Figure 10. Maintenance cost for transformers in each state for transition states for the year 2013/2014.

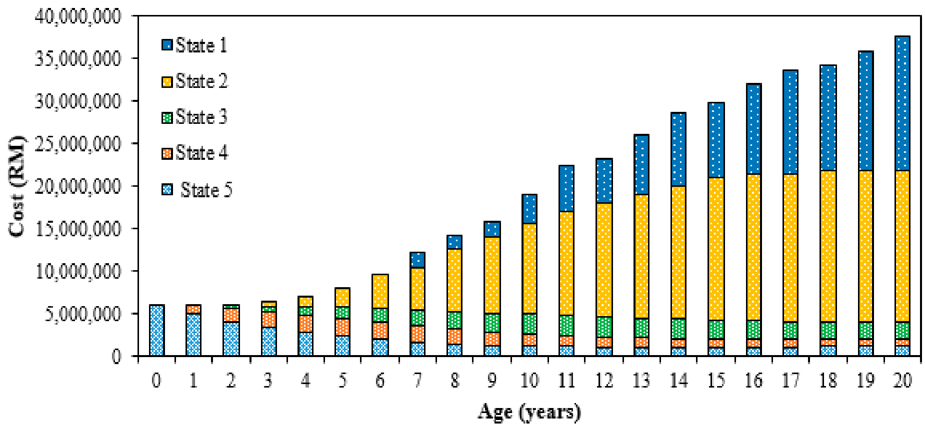

Figure 11. Maintenance cost for transformers in each state for transition states for the year 2012/2013.

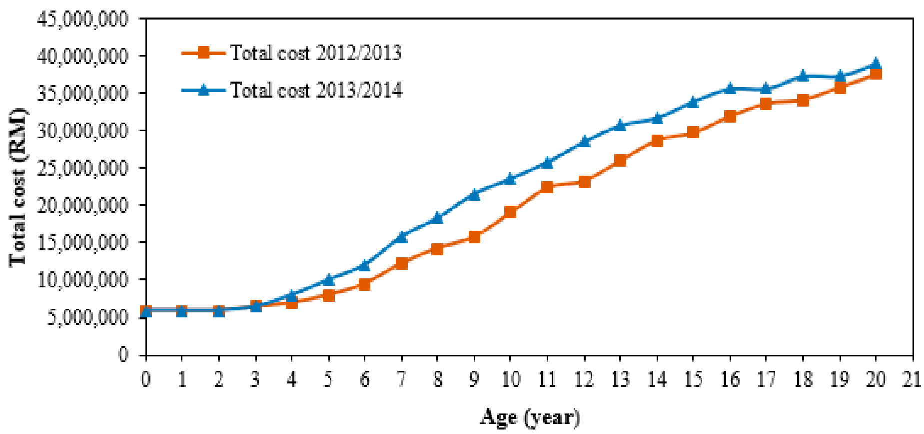

Figure 12. Total estimated maintenance cost for transformers in each year based on transformer transition states for the year 2012/2013 and 2013/2014.

6. Conclusions

The application of the MM based on frequency of a transition method derived using HI was carried out in this study to predict the transformer state distribution and the maintenance cost. It was implemented by determine the deterioration states of the transformer population and their future states based on transformer transition states for the year 2013/2014 and 2012/2013. Analyses on the relationship between the predicted and actual numbers of transformers revealed that the data exceeded the 95% confidence interval plots, but were still within the 95% prediction interval plots. Based on the probability state plots, there is a 90% probability that population of transformers will reach State 1 after 76 years and 69 years based on transformer transition states for the year 2013/2014 and 2012/2013, respectively. Over the 20 years of the prediction interval, the total estimated maintenance costs would increase from RM 5.94 million up to RM 37.56 and RM 39.09 million for transformer transition states for the year 2012/2013 and 2013/2014, respectively.

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Nomenclature

CA	Condition Assessment
CBM	Condition Based Monitoring
CM	Corrective Maintenance
DGA	Dissolved Gas Analysis
FA	Furfural Analysis
HI	Health Index
HIF	Health Index Factor
MM	Markov Model
OEM	Original Engineering Manufacturer
OQA	Oil Quality Analysis
RM	Ringgit Malaysia

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