ISSN No:-2456-2165

Determination of the Most Opportune Time for Industrial Circuit Breaker Replacement

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Abstract:- The establishment of a replacement strategy for all critical industrial assets is of vital necessity since it guides into proactive measures of asset management. Asset management is of vital necessity to industrialists as it guides them into decision making concerning management of industrial assets in a proper way that yields maximum productivity and minimum operational expenditures. Replacement frame works are time based as they enable timely maintenance of an asset so as to maintain or increase its remaining useful time. Replacement strategies are a measure of predictive and preventive maintenance. The failure to carry out predictive and preventive maintenance will escalate degradation of an asset and shorten its remaining useful life. This study compared three replacement models for predicting optimal replacement time of industrial circuit breaker replacement namely: the Weibull Analytical Model (WAM), Markov Analytical Model (MAM) and Equipment Inspection Method (EIM). The comparison of the models was to achieve the most accurate estimates of expected time of replacement. The optimal time of replacement was determined for ten condition based factors that determined CB reliability. These factors included: insulation integrity, Moisture, Dust, ambient temperature, inaccurate sizing, mechanical failure due to switching of the MCB, MCCB, and ACB, premature failure of the thermal magnetic trip mechanism and arcing of contacts. The EIM was discovered to be the most accurate model due to its high level of genuineness as its values of optimal replacement time were the earliest in value. Additionally, the EIM displayed a high level of reliability and criterion validity compared to other methods such as the WAM and MAM.

Keywords:- *Asset Management, Industrial Consumers, Reliability, Replacement time.*

I. INTRODUCTION

The deterioration of CBs depends on several factors including but not limited to; equipment quality, operational load stress, existing maintenance strategies, the surrounding environment with regards to temperature, moisture and pollution among others [1]. In the event of occurrence of an overload induced from connected assets such as motors, Variable Frequency Drives (VFDs) and Variable Speed Drives, (VSDs), a faulty circuit breaker will fail to open [2]. Failure to prevent the fault will lead to the property destruction, significant downtimes, reduction in; productivity, profitability and firm competitiveness [3]. [4] Also noted that CB failure threatens the functioning of other equipment, which directly affects the quantity of non-supplied electrical energy. This is one of the main reasons for the accurate prediction of a CB's Remaining Useful Life (RUL). It is therefore important for industrial consumers to know the expected time of maximum degradation of CBs and assess the impact of the driving factors. This will act as a basis for identification of symptomatic CBs and establishment of proper replacement strategies. [4] Defines a replacement strategy as one which clearly predicts the likelihood of failure, conditions behind and advocates for the opportune time. Present CB assessment strategies amongst industrial consumers apply only scheduled maintenance where reliability of the CB is ensured only by planned schedules and less consideration on its actual condition. This therefore results into hidden growth in magnitude of faults leading to unexpected deterioration upon occurrence and high cost of corrective maintenance. Thus, Condition Based Maintenance (CBM) strategies accurately predict future fault occurrence giving room for earlier remedial action [5]. A survey that was conducted in Kawempe Industrial Area noted a record of cascaded failures in CB connected systems of 73% industrial consumers of Kawempe Industrial area over the past three decades attributed to poor asset management.

Poor asset management among Kawempe industrial area consumers has also initiated increased records of unreliability of grid connected assets reported by UMEME Wandegeya branch, which is the utility in direct management of the industrial area [6]. Furthermore, CB related cascaded failures in Kawempe Industrial area have taken the largest proportion of maintenance budgets for the past decade [6]. There is thus great need to improve related asset management frameworks. The application of CBM to effectively manage systems with multiple CBs has been noted to effect asset management in Industries [7]. Furthermore, the application of CBM with consideration of CB ageing predictability models accurately represents the wearing status of the CB [8]. Predictability models have been advocated to be less costly compared to condition based equipment. This research was therefore based on assessment of the ten most critical factors that influence CB degradation over its lifetime that will guide development of replacement strategies for effective asset management.

II. THEORETICAL APPROACH AND MODEL

A. Review of Models for Prediction of Opportune Replacement Time of Industrial CBs

- *The Weibull Analytical Model*

The Weibull Analytical Model (WAM) seeks to predict the impact of circuit breaker performance in its course of life and determine the opportune replacement time. Predictors such as the probability of failure, expected number of failed assets, hazard rate and mean time to failure measure the expected performance of the industrial circuit breaker for a prescribed life as earlier discussed. Achievement of the failure rate of the circuit breaker in a given time frame will aid development of a model that determines the appropriate time of replacement. The opportune replacement time consists of predictors such as the cost of failure, cost of preventive maintenance and estimates such as the shape and scale parameters. The Weibull model is known to have the largest number of predictors for determining circuit breaker reliability which renders it accurate. However, the bottleneck lies in a need for large samples of data for more accurate prediction [9].

- *Markov Analytical Modeling*

[10], in their article on "SF6 Circuit Breaker Failure data and reliability modeling" emphasizes that reliability studies on circuit breaker failure and prediction analysis are stochastic and not deterministic in nature. This is because in the stochastic scenario, the outcome of an event does not directly depend on its inputs and is likely to take different transformations (metamorphosis). However, room for prediction of outcome is available, although the outcome is not directly predicted as opposed to a deterministic approach [11].

Markov modeling involves representing each component in a system by states namely when it's operational (normal) and when it's non-operational (faulty). It can be considered for repairable and non-repairable systems. "Transition rates to and from each state are the failure rates that occur in a component in order to reach or transition back to a particular state" [12]. The major objective behind Markov transitional modeling is to determine the maximum failure rate in a given transitional stage of time. This will guide determination of appropriate time of replacement.

According to [13], the failure level of an asset is mainly determined by unobserved factors within the system. Furthermore, the performance and reliability of a power circuit breaker in regard to normal open-close motion depends on its components working capability, control as well as operating mechanisms [1]. Unobserved factors were classified as ambient temperature, reliability of tripping and closing units, operating mechanism of internal components, damping level of devices, abnormality of monitoring and protection system and level of contamination by dust. Observable factors include but not limited to damage of auxiliary parts, low insulation integrity and fluctuation of moisture content levels indicated by rusty internal components such as contacts, among others [14].

According to [15], The Markov Model of transition is defined by the state equation below:

$$\Pr\left(X_{c,nc+m} = j \mid X_{c,o} = k, X_{c,1} = l, \ldots, X_{c,nc} = i\right) = \Pr\left(X_{c,nc+m} = j \mid X_{c,nc} = i\right) = p^{(m)}{}_{(i,j)}, \tag{1}$$

Where $\Pr\left(X_{c,nc+m} = j \mid\right.$ represents the state of transition of the future state

$X_{c,nc} = i$ Represents all states of transition in the current state

$p^{(m)}{}_{(i,j)}$ Represents the probability of transition from state i to state j

m represents the time of transition

$$Pc^{(m)}{}_{(i,j)} \forall_i \sum_{j=1}^{N_c} P^{(m)}{}_{(i,j)} = 1.0. \tag{2}$$

The technical condition of a system is characterized on a scale from 1 to 4 according to the Norwegian Electricity Industry Association (EBL). Thus, the continuous degradation of a component is simplified by dividing it into four states [16]. The state description is given in figure 1 and in the following; these four states will be denoted *main states k*. A component as-good-as-new is in state *k* = 1. When the condition is characterized as critical, the state is *k* = 4 and normally maintenance actions must be taken immediately as shown in table 1.

State	Description
1	No indication of degradation
2	Some indication of degradation. The condition is noticeably worse than "as good as new".
3	Serious degradation. The condition is considerably worse than "as good as new".
4	The condition is critical

Table 1: Technical Condition States (Main States)

- That future states depend only on the present state and not on the sequence of events that preceded it
- Assume a fixed set of states

The main objective of applying the Markov Chain and Hidden Markov model is to establish the extent of impact of different transitional stages to failure to the likelihood of deterioration of the protection asset [16].

By application of the Time dependent Markov chain, $P_i(t)$ is the probability that the system is in state *i* at time *t*. hence the Markov differential equation for the transition would be:
$$P_i(t+\Delta t) = P_i(t).(1-\lambda_i.\Delta t) + P_{i-1}(t).\lambda_{t-1}.\Delta t \quad (3)$$

Where Δt is a very small-time interval and the transitional rate of the i^{th} state is given as the reciprocal of expectation of that state *i*. Given that τ represents the different periods or phases of time in which a given transition occurs, the total number of transitional periods will be characterized by $\tau = 1$ to $\tau = 4$. In this empirical study, the total duration of time for transitional analysis of circuit breakers will be a total life of 40 years and the transitional pattern will take a negative exponential trend as shown in the figure 1:

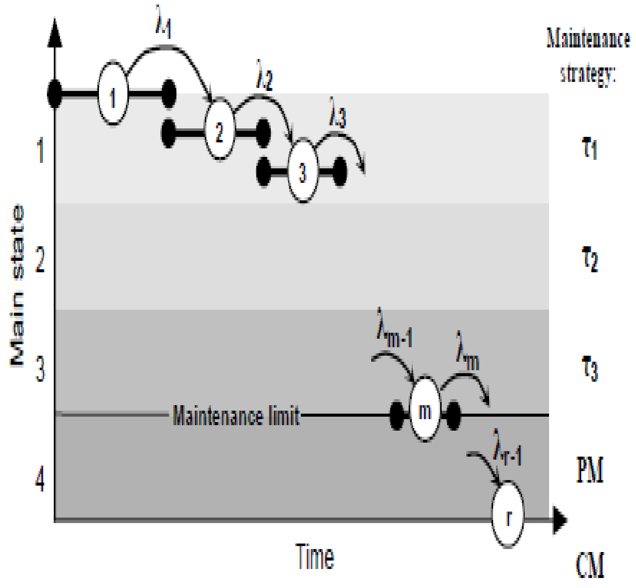

Fig. 1: Markov Model incorporating the four stages of transition

➢ *Determination of the optimal replacement time of CBs using*

- Hidden Markov Model

Optimal replacement time is the time of transition where the highest failure rate is realized. [17] Justifies that in the partially observed markov model there is a need to examine the failure rate of an asset at every stage of transition. He further emphasizes that the model will enable implementation of appropriate maintenance decisions prior to maximum failure impact on the asset: "At each time step, we are confronted with a maintenance decision. Choosing the best action requires considering not only immediate effects but also long-term effects, which are not known in advance. Sometimes action with poor immediate effects can have better long-term ramifications." Time is then viewed as an inequality constraint such that maintenance should be done before the exact time when the maximum failure rate is close to being attained. The most likely probability when the circuit breaker will exist in a given transitional state is determined by the Viterbi Algorithm as described in section 3. This will be the maximum predicted failure rate. Figure 2 shows the hidden and generated states for n observations:

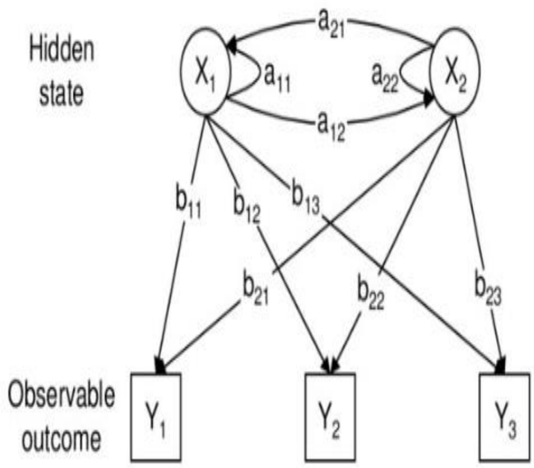

Fig. 2: HMM Processes of transition (18)

The limitation identified with the Hidden Markov Model in acquiring optimal time of replacement is that since failure patterns are discrete, they cannot accurately quantify the impact of different maintenance activities (9). Additionally, the Hidden Markov Model offers few estimates for life assessment and thus does not accurately measure the severity of failure for a given period of time as opposed to continuous distributions. This affects the accuracy of results obtained during analysis of optimal CB replacement time.

- Equipment Inspection Method (EIM)

In the EIM, three conditions are developed to determine circuit breaker reliability namely: Best, Average and Worst. The conditions are assigned a score between 0 and 1 whereby each conditional score is proportional to the working age of the circuit breaker. A score of 1 represents the worst conditional stage while a score of 0 represents the best conditional stage. The failure rate λ and optimal time of replacement t_p are then determined for a corresponding working age. $\lambda(0)$ represents the best condition failure rate, $\lambda(1/2)$ the average condition failure and $\lambda(1)$ the worst condition failure. EIM is cited the most accurate method of determining optimal time CB replacement time due to its effectiveness in asset reliability estimates (9).

B. Modeling

- *Prediction modeling and simulation of OPT using the Weibull Analytical Model*

Having achieved the shape and scale parameter β and η respectively in section 3.2, the cost parameters (predictors) were determined i.e., the cost of failure C_f, the cost of preventive maintenance C_p, the optimal time of replacement t_p and the cost function $C\left(t_p\right)$, which represents the total cost per unit time for preventive replacement (9). The equations 3.9 to 3.14 represent the formulation of the cost estimates as well as the opportune time of industrial circuit breaker replacement t_p:

$$C\left(t_p\right) = \frac{Total\ expected\ cost}{Interval}, \tag{4}$$

$$C\left(t_p\right) = \frac{C_p + C_f.H(t_p)}{t_p}, \tag{5}$$

Hence;

$$\frac{\partial C(t_p)}{\partial t_p} = \frac{\partial}{\partial t_p}\left[\frac{C_p + C_f.H(t_p)}{t_p}\right] = 0. \tag{6}$$

After differentiating the process, we get:

$$t_p = \frac{\frac{C_p}{C_f} + H(t_p)}{\frac{\partial H(t_p)}{\partial t_p}}, \tag{7}$$

Hence incorporating Weibull predictors, the optimal time of replacement was achieved as:

$$t_p = \frac{\frac{C_p}{C_f} + 1 - exp\left[-\left[\frac{t}{η}\right]^{\beta}\right]}{\frac{\beta}{η}\left[-\frac{t}{η}\right]^{(\beta-1)} exp\left[-\frac{t}{η}\right]^{(\beta)}}. \tag{8}$$

Therefore the cost function

$$C\left(t_p\right) = C_p + C_f.\frac{\left[1 - exp\left[-\left[\frac{t}{η}\right]^{\beta}\right]\right]}{\frac{\beta}{η}\left[\frac{t}{η}\right]^{\beta-1} exp - \left[\frac{t}{η}\right]^{\beta}}. \tag{9}$$

- Assumptions considered
- ✓ The total CB life is 40 years.
- ✓ $C_f \leq 35\ times\ C_p$.
- ✓ If $C_f \geq 10\ times\ C_p$ then consider replacement of the circuit breaker in the shortest time possible.
  Cost ratios of $\frac{Cp}{Cf} = \frac{1}{20}, \frac{1}{25}, \frac{1}{30}, \frac{1}{35}$ are commonly used for cost modeling to achieve accurate t_p results.

- *Prediction Modeling and Simulation of OPT using the Hidden Markov Model (HMM)*

Using Markov transitional modeling, circuit breaker degradation was compared for three industrial consumers i.e. Luuka Plastics Uganda Limited, FICA Seeds Uganda Limited and Maganjo Maize Millers Uganda Limited. The purpose of this assessment was to achieve the relationship of ten key performance indicators of the circuit breaker performance with the reliability of each industrial consumer. and findings in section 3. The implementation of the Viterbi algorithm used to determine the maximum likelihood of failure in a given stage of transition was developed using Python Software (Jupyter Notebook – Anaconda 3). The reliability parameter assessed was the failure rate considering four stages of transition of the circuit breaker throughout its life. This is shown in sections 2 and 4. The four stages of transition included: “No indication of degradation”, “Some indication of degradation”, “Serious degradation”, and “Critical degradation.”

- Assumptions considered in this study

Transitions are irreversible. This study explores a transitional algorithm which is analogous to the metamorphosis of animals where it’s not likely that they can transition back to their previous stages of growth. Considering forward probability of transition to be $\{p \in P_c\}$ while probability of reverse transition to be q, the following hypothesis was generated:

$$\textstyle\sum_{i=1}^{k} Pc = p \geq 0\ \forall_i\ Pc_{max} = 1.0, \tag{10}$$

$$\textstyle\sum_{i,j}^{i+1,j+1} q = 0,$$

But

$$\textstyle\sum_{i,i}^{i+1,i+1} q \geq 0 \text{ And } \sum_{j,j}^{j+1,j+1} q \geq 0. \tag{11}$$

As shown in figure 3, transition to maximum degradation occurs in stages 1, 2, 3….n

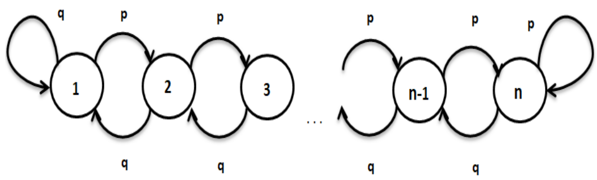

Fig. 3: Metamorphosis of an asset in its life time according to the Hidden Markov Model

- ✓ The total transition stages to failure of the circuit breakers will be four (n=4) from the time of installation to the time of complete deterioration. Hence the state equation for the empirical analysis will be:

$$k \in \mathbb{R}\,\forall;\quad k = \{1,2,3,4\} \tag{12}$$

Maximum failure rate achieved in the first and second stages of transition signified poor asset management whereas maximum failure rate achieved in the third and fourth stages of transition signified good asset management. This was aided by optimization using the Viterbi Algorithm which seeks to identify the maximum likelihood of failure after given sequence of observations as shown in section 2(b). This acted as a basis for modeling in section 3. The findings achieved in transition state modeling enabled achievement of the optimal time for replacement of the industrial circuit breakers as shown in section 3. Based on the content in section 2, the optimal time of replacement will be achieved before transitional time with the highest failure rate. The equation (13) below shows the process of Hidden Markov transition modeling:

$$p(\delta_{1:T}, x_{1:T}) = p(\delta_1)p(x_1|\delta_1)\prod_{t=2}^{T} p(\delta_t|\delta_{t-1})p(x_t|\delta_t). \quad (13)$$

The hidden markov model consists of two states i.e., the observed and the hidden states which generate the current state. The previous observable state is δ_{t-1} and current state is δ_t while δ_1 represents the observed operational state due to hidden (states) x_1. The times of transition in the hidden markov model are discrete and a transition from one state to another is described by a failure rate α. The transitional probability matrix P for life modeling is given below: modeling is a $4x4$ matrix showing four stages of transition. The total probability across all transition states is 1. Findings of the transitional Markov model are shown in section 3. Using the forward-backward algorithm, the helper function $\alpha_{t+1}(j)$ was achieved for each state of transition of the circuit breaker. The total probability of transition after 4 states was described by equation 3.31. The most likely probability of failure at a time $T-1$ after N observations was achieved using the Viterbi Algorithm. The transition matrix for the probability of failure over four transitional states is described by equation 3-19:

$$P^* = \begin{pmatrix} p_{11} & 1-p_{11} & 0 & 0 \\ 0 & p_{22} & 1-p_{22} & 0 \\ 0 & 0 & p_{33} & 1-p_{33} \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad (14)$$

- Assumptions made in the Hidden Markov model:
- ✓ Each observation δ_t is generated by a hidden state x_t.
- ✓ Transition probabilities between states p $(\delta t|\delta t-1)$ represented by a transition Matrix are constant.
- ✓ At time *t*, an observation δ_t has a certain probability distribution corresponding to possible hidden states.
- ✓ States are finite and satisfy first-order Markov property.
- ✓ Each state has a maximum number of observations.
- ✓ Every state of transition will take 10 years of CB life.

According to [19], the Hidden Markov answers three key problems:

- What is the probability that a model generated a sequence of observations?

Given a set of observations: $O = \{O_1, O_2, O_3, \dots \dots \dots \dots \dots O_T\}$ and that $\lambda = \{A, B, \pi\}$

Where A is a matrix of transition probability of moving from state i to state j.

B is a vector of probabilities of seeing different observations given that you are in a particular state.

π is the probability of starting in a particular state.

Using the forward-backward algorithm:

$$P(O|\lambda);\ \alpha_t(i) = P(O_1, O_2, O_3, \dots, O_t, q_t = S_i|\lambda), \quad (15)$$

The base cases $\alpha_1(i) = \pi_i b_1(O_1) \quad 1 \le i \le N$ where $b_i(O_1)$ is the probability of seeing the 1st observation given that we are in state 1.

Hence the probability of transition from state i to state j.

$$\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(i)\ \alpha_{ij}\right] b_j(O_{t+1}) \quad 1 \le t \le T-1 \quad (16)$$

$$1 \le j \le N$$

- What sequence of states best explains a sequence of observations?

What sequence of states did the observations happen and what is the most likely state the device would be in at a given time t given the observations?

Using the Viterbi Algorithm given a sequence of states:

$Q = \{q_1, q_2, q_3, \dots \dots q_T\}$,

The most likely state q_t where the asset would be in given observations O_i is described by a probability:

$$\gamma_t(i) = P(q_t = S_i|O, \lambda), \quad (17)$$

Where $q_t = argmax[\gamma_t(i)],\ \ 1 \le t \le T;\ 1 \le i \le N$.

Hence the probability of the most likely state i and state j given states $q_1 \dots q_t$ is:

$$\alpha_t(i) = max\ P(\{q_1, q_2, q_3, \dots q_{t-1} = q_i\}, \{O_1, O_2, O_3 \dots O_t\}|\lambda)$$

and $\alpha_{t+1}(j) = [max\delta_t(i)a_{ij}].b_j(O_{t+1})$. (18)

- Given a set of observations sequences, how do we learn the model probabilities that would generate them?

The model probabilities maximize the likelihood of generating a given set of observations. The learning process is made possible by the Baum Welch Algorithm. It first attempts to answer the probability that we are in a given state based on the observations achieved (forward Algorithm). It then answers the probability that we are in a given state i knowing the future observations without consideration of past events (Backward Algorithm). This is a basis for predictions of future transitional states. The transition probability is shown in equation 3.24:

$$\beta_t(i) = P(O_{t+1}, O_{t+2}, \ldots O_T | q_t = S_i | \lambda \quad (19)$$

Diagnosis of failure rate due to the nine deterioration factors was based on Condition Based Monitoring (CBM) and was formulated according to the flow chart in figure 3.2:

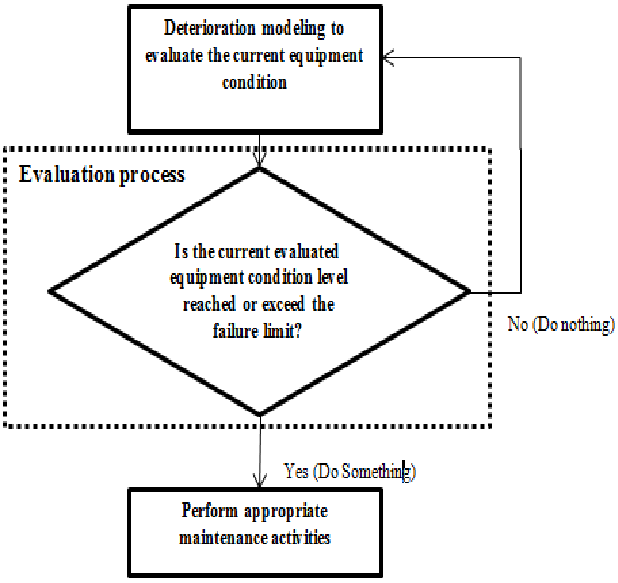

Fig. 4: The process of condition-based assessment of circuit breaker degradation factors

The predicted performance (failure rate) of the circuit breaker considered nine fault drivers i.e., premature failure of thermal magnetic trip, mechanical switching in Miniature Circuit Breaker, mechanical switching of Molded Case Circuit Breaker, mechanical switching failure in Air Circuit Breaker, ambient temperature, insulation integrity, dust, moisture/humidity, delayed tripping and arcing of contacts. The most critical fault driver was considered the factor that yields the highest failure rate.

- Determination of the appropriate time for replacement of circuit breakers

The time of maximum failure rate is Ψ_{T-1} and the optimal time of replacement is discrete and given by Ψ as shown in results section 3. Given the probability of failure at each stage is $\alpha_t(i)$, the cost of replacement C_r, the cost of failure C_f, and $R(i)$ = binary decision variable indicating whether the breaker should be replaced in state i (1 if replaced, 0 if not replaced) the objective function and constraints for determining optimal replacement time are shown in the equations 20 to 21.

The total expected cost is:

$$E(C) = \sum(\alpha_t(i) * C_f * C_r * R(i)). \quad (20)$$

Therefore the opportune replacement time Ψ_{T-1} is described by the optimization problem:

$$minimize\ C = \min(C_{replacement}, C_{failure})$$

With respect to Ψ_{T-1}, (21)

Subject to:

$0 \leq R(i) \leq 1$ This represents the binary nature of $R(i)$.

$0 \leq \alpha_t(i) \leq 1$ This represents the failure rate between 0 and 1.

$R(i) = 1$ If $28 \leq \Psi_{T-1} \leq 40$ (to replace the circuit breaker only between 28 to 40 years)

- *Prediction modeling and simulation of OPT using Equipment Inspection Method (EIM)*

As earlier discussed in section 2(a), the failure rate was determined by non-linear regression and estimated according to equations 22 to 25 but defined by constants A, B and C. Given that matrix X represents the conditional score of the industrial circuit breaker:

$$\lambda(X) = Ae^{BX} + C, \quad (22)$$

$$A = \frac{\left[\lambda\left(\frac{1}{2}\right) - \lambda(0)\right]^2}{\lambda(1) - 2\lambda\left(\frac{1}{2}\right) + \lambda(0)}, \quad (23)$$

$$B = 2Ln\left[\frac{\lambda\left(\frac{1}{2}\right) + A - \lambda(0)}{A}\right], \quad (24)$$

$$C = \lambda(0) - A. \quad (25)$$

As earlier discussed in section 2(a), the equipment inspection method is largely preferred as the most accurate for determining CB replacement time considering its large number of predictors and estimates as well as yielding high accuracy with all sample sizes. This ensures accurate results of time and cost function. The EIM is also preferable as it yields more accurate estimates of replacement time at lower cost functions. The cost of failure in EIM is slightly higher than the cost of preventive maintenance. Determining the optimal time of CB replacement is desired when it is prompt to replace the CB for a minimum cost per unit time. The optimal time of replacement for EIM is achieved as illustrated in section 3.4.1.

III. CALCULATION OF RESULTS

A. Findings of the Most Opportune Time of Replacement using the Weibull Analytical Model

The failure rate and time of replacement were determined by the shape and scale parameters and assessed for each fault driver of industrial circuit breaker failure. Analysis in this section was carried out as comparison between CBs of three industrial consumers. The results in table 2 show the prediction and time of replacement for FICA Seeds Uganda circuit breakers.

No.	Fault Driver	$\hat{\beta}$	η (years)	$\hat{t}_p$ (years)	$\lambda_{weibull}$(%)
1	Mechanical failure due to switching (MCB)	6.515146	22.542	6.20236	10.80
2	Mechanical Failure due to switching (MCCB)	6.515146	22.339	6.14979	10.90
3	Mechanical Failure due to switching (ACB)	6.515146	21.456	6.01094	11.29
4	Arcing of contacts	6.515146	26.755	7.48262	9.079
5	Delayed trip	6.515146	25.472	7.23632	9.523
6	Contamination by dust	6.515146	25.632	7.07238	9.470
7	Corrosion by moisture	6.515146	27.321	7.55499	8.870
8	Ambient temperature	6.515146	25.353	6.96858	9.570
9	Insulation failure	6.515146	21.765	6.21785	11.15
10	Premature failure of thermal magnetic trip mechanism	6.515146	21.456	6.01094	11.31

Table 2: The prediction of failure and OPT for FICA Seeds International CBs

As earlier discussed in section 2(b), the shape parameter $\hat{\beta}$ represents the level of failure of the circuit breaker whilst the scale parameter η represents the time to maximum degradation. Each fault driver has a different scale parameter due to variation in its impact on circuit breaker reliability. The highest failure rate achieved was 11.31% due to premature failure of the thermal magnetic trip mechanism. Findings also demonstrate that this fault driver requires the shortest time of replacement $\hat{t}_p$= 6.01094 years from the time of installation. Formulation of opportune replacement time is shown in section 2(b). Factors such as Mechanical failure of MCB and ACB switching mechanism as well as Insulation failure require urgent replacement as they hold the shortest time of replacement.

No.	Fault Driver	$\hat{\beta}$	η (years)	$\hat{t}_p$ (years)	$\lambda_{weibull}$ (%)
1	Mechanical failure due to switching (MCB)	1.3894	35.354	46.0353	2.08
2	Mechanical Failure due to switching (MCCB)	1.3894	35.342	45.806	2.08
3	Mechanical Failure due to switching (ACB)	1.3894	32.447	39.624	2.26
4	Arcing of contacts	1.3894	36.013	47.518	1.11
5	Delayed trip	1.3894	34.765	44.303	1.71
6	Contamination by dust	1.3894	35.435	46.035	2.07
7	Corrosion by moisture	1.3894	36.786	46.786	2.00
8	Ambient temperature	1.3894	37.624	47.624	1.95
9	Insulation failure	1.3894	33.645	39.500	2.18
10	Premature failure of thermal magnetic trip mechanism	1.3894	32.119	38.8195	2.29

Table 3: The prediction of failure and OPT for Luuka Plastics International Uganda CBs

The findings in Table 3 demonstrate that the premature failure of thermal magnetic trip mechanism and mechanical failure of the ACB switch mechanism are the highest fault drivers and require the most immediate time of replacement. This is justified by the values of the scale parameter 32.119 years and 32.447 years respectively, which is the shortest time predicted from installation to maximum degradation of the circuit breaker. The periods of replacement are far longer due to the inaccuracies in the cost ratios arising in the Weibull Analytical Model as earlier discussed. However, the appropriate value of the shape parameter 1.3894 demonstrates a very high reliability of the industrial circuit breaker since they would be in the AGAN state for quite some time.

The CBs would therefore demonstrate low failure rates and longer times of replacement. Maganjo Maize Millers and FICA Seeds Uganda CBs have a far greater value of shape parameter, which results into shorter replacement time required. The replacement time estimates for Maganjo Maize Millers Uganda Ltd are considerably accurate since all values lie within the prescribed 40-year life of a circuit breaker. The shape parameter estimates are uniform for all factors due to the fact that the time of installation of was similar for all CBs. Table 4 shows prediction of failure and replacement patterns for Maganjo Maize Millers Uganda Ltd CBs.

ISSN No:-2456-2165

No.	Fault Driver	$\hat{\beta}$	η (years)	$\hat{t}_p$ (years)	$\lambda_{weibull}$ (%)
1	Mechanical failure due to switching (MCB)	3.201423	28.253	16.030	4.402
2	Mechanical Failure due to switching (MCCB)	3.201423	27.985	15.828	4.450
3	Mechanical Failure due to switching (ACB)	3.201423	27.643	15..544	4.455
4	Arcing of contacts	3.201423	32.345	18.353	3.840
5	Delayed trip	3.201423	27.024	12.429	4.600
6	Contamination by dust	3.201423	29.767	16.863	4.170
7	Corrosion by moisture	3.201423	31.056	17.451	3.986
8	Ambient temperature	3.201423	30.232	17.023	4.115
9	Insulation failure	3.201423	27.963	13.137	4.440
10	Premature failure of thermal magnetic trip mechanism	3.201423	26.274	11.630	4.730

Table 4: The prediction of failure and OPT for Maganjo Maize Millers industrial CBs

The findings in Table 4 demonstrate accuracy in achieving the opportune time of replacement since it is required that estimates achieved do not exceed the degradation period. This is consistent with the fact that replacement of an asset should take place as a preventive maintenance strategy in order to minimize future expenditures involved in mitigating the loss impacts due to failure.

B. Findings of the most opportune time of replacement using the MAM

The Markov Analytical Model (MAM) requires that the transitional time corresponding to the highest fault driver should determine the opportune time of replacement. The key performance indicators achieved aided as a basis for modeling the transitional states of each factor that influenced circuit breaker ageing. The results in Table 5 show a summary of the HMM diagnosis of circuit breaker transitions based on three asset managers. Each of the deterioration factors was analyzed basing on four transitions based on the assumption that transition from one state to another was irreversible [20].

The cost of failure C_f and the replacement cost C_r are represented by the ratio C_p/C_f. The transition from one state to another was characterized by the failure rate α. This is shown in corresponding Tables 5, 6 and 7 below: The failure rate α was assessed for each stage of transition considering ten fault drivers. The purpose was to achieve the fault driver influenced the most significant failure impact and its corresponding stage of transition.

S/n	Ageing Factors	C_p/C_f	$\alpha(t1)_{max}$	$\alpha(t2)_{max}$	$\alpha(t3)_{max}$	$\alpha(t4)_{max}$
1	Mechanical failure due to switching (MCB)	0.020	$0.4166667s_1$	$0.60402685s_1$	$0.82443s_3$	$1s_4$
2	Mechanical failure due to switching (ACB)	0.020	$0.6637168s_1$	$0.78994614s_2$	$0.82443s_3$	$1s_4$
3	Arcing of Contacts	0.020	0	$0.17777778s_1$	$0.75016s_3$	$1s_4$
4	Delayed trip	0.020	0	0	$0.75s_2$	$1s_4$
5	Contamination by dust	0.020	0	$0.50505051s_1$	$0.78764s_3$	$1s_4$
6	Corrosion by moisture	0.020	0	$0.1s_2$	$0.66635s_2$	$1s_4$
7	Ambient Temperature	0.020	0	$0.5s_2$	$0.75048s_3$	$1s_4$
8	Insulation failure	0.020	0	$0.70607553s_2$	$0.49039s_3$	$1s_4$
9	Premature failure of thermal magnetic trip mechanism	0.020	$0.4285714s_1$	$0.75707702s_2$	$0.74184s_3$	$1s_4$

Table 5: Markov Transition Probability for FICA Seeds Uganda Ltd: β = 9.75 (x<0.5x)

Results in Table 5 show that the highest transition to failure is likely to be due to mechanical switching which exhibits a transitional probability of 0.82443 in the third stage of transition. Mechanical failure due to switching the ACB shows a likelihood of an extremely high failure of the circuit breaker in its first stage. This is indicated by a probability of 0.6637168. The stages of transition were modeled as proportions of the span of years/parameters previously achieved through Maximum Likelihood Estimation. Mechanical failure of the ACB thus requires replacement in the third stage of transition (after 30 years) of industrial CB operation. All factors exhibit a cost ratio of 0.20 since the industrial circuit breaker are considered as a single entity.

From the analysis above, stage 1 consisted of the initial years of the asset operation, stage 2 consisted of the time frame when the asset starts exhibiting symptoms, stage 3 represents the time frame when the asset is in critical condition and stage 4 consists of the time frame when the device faces serious degradation. Each stage of transition lasts 10 years of operation as earlier mentioned in section 2(b). Results also show that poor insulation of the breaker, and premature failure due to thermal magnetic trip mechanism also pose a high risk of failure as the breaker ages. The transitional probabilities include 0.70607553 and 0.75707702 respectively in the second stage of transition and thus CBs require replacement after 20 years of operation. Figure 5 shows that all ageing factors have a transitional probability of 1 in the final stages of circuit breaker aging since death is defined by complete degradation with a failure probability of one representing perfect likelihood of failure. Table 6 compares the transitional probabilities of each fault driver of the circuit breakers in their course of aging. Factors with transition probability 0 in their first stage or second stage indicate that there is no visible sign of failure of the breaker in the initial

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stage of operation. However, by the time a visible sign is identified, the circuit breaker is in its final stages of operation and is bound to face serious degradation.

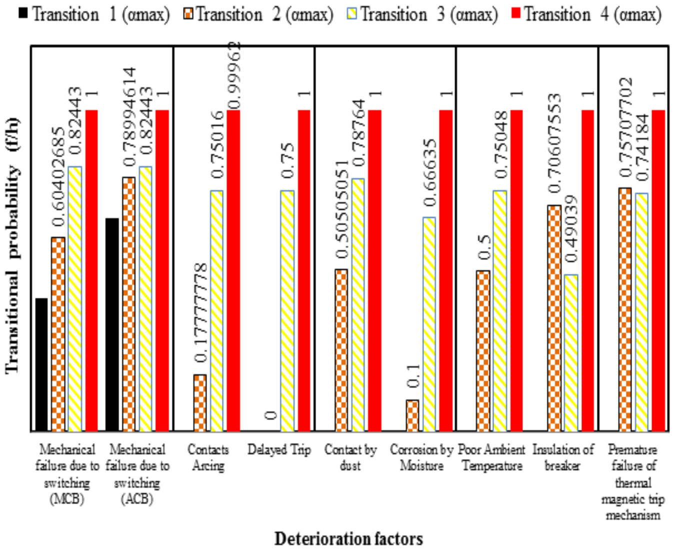

Fig. 5: Transitional probabilities of each ageing factor for FICA Seeds Uganda Limited

S/n	Ageing Factors	$\alpha(t1)_{max}$	$\alpha(t2)_{max}$	$\alpha(t3)_{max}$	$\alpha(t4)_{max}$
1	Mechanical failure due to switching (MCB)	$0.1697793s_1$	$0.3345181s_2$	$0.5717553s_3$	$1s_4$
2	Mechanical failure due to switching (ACB)	$0.2374846s_1$	$0.4258471s_3$	$0.5593653s_3$	$1s_4$
3	Arcing of Contacts	$0.359874s_1$	$0.4366812s_2$	$0.5808794s_3$	$0.99986s_4$
4	Delayed tripping	$0.4362536s_1$	$0.4376536s_1$	$0.5544006s_3$	$1s_4$
5	Contamination by dust	$0.304878s_1$	$0.4302594s_2$	$0.5544006s_3$	$1s_4$
6	Corrosion by moisture	$0.2923977s_1$	$0.4011015s_2$	$0.5211365s_3$	$0.99592s_4$
7	Ambient Temperature	$0.2467105s_1$	$0.4072473s_1$	$0.5016447s_2$	$0.99027s_4$
8	Poor Insulation integrity	$0.2741228s_1$	$0.4321809s_1$	$0.5121951s_1$	$0.99954s_4$
9	Premature failure of thermal magnetic trip	$0.4231653s_1$	$0.6088668s_1$	$0.7096327s_3$	$0.99907s_4$

Table 6: Markov Transitional Probability Model: Luuka Plastics β = 33.898 (x>0.5x)

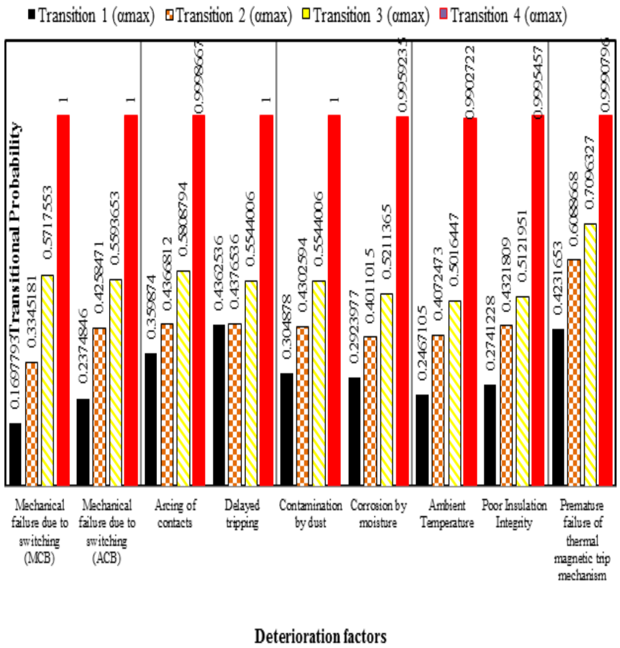

Fig. 6: Transitional probabilities of each ageing factor for Luuka Plastics Uganda Limited

According to the graphical illustration figure 6, all ageing factors have a maximum transitional probability of 1 in their final stage. This is because death of an asset is characterized by a perfect failure rate. Stages 1 to 3 for all ageing factors have a maximum probability of 0.7093627 and this is attributed to the premature failure due to thermal magnetic trip mechanism. Table 7 shows the transitional Hidden Markov probability results of Maganjo Maize Millers Limited.

S/n	Ageing Factors	α(t1)max	α(t2)max	α(t3)max	α(t4max)
1	Mechanical failure due to switching (MCB)	0.833333	0.2	0.074627	0.916667
2	Mechanical failure due to switching (ACB)	0.780488	0.218182	0.096514	0.943627
3	Arcing of Contacts	0.628931	0.2777778	0.093333	0.9375
4	Delayed tripping	0.592593	0.282828	0.099415	0.986532
5	Contamination by dust	0.698413	0.278803	0.072917	0.975
6	Corrosion by moisture	0.6	0.309524	0.07619	0.986532
7	Ambient temperature	0.133333	0.833333	0.087146	0.989583
8	Insulation Integrity	0.6	0.285714	0.153413	0.990196
9	Premature failure of thermal trip	0.948213	0.125	0.09331	0.989796

Table 7: Transitional Probability Model of Maganjo Maize Millers Limited

ISSN No:-2456-2165

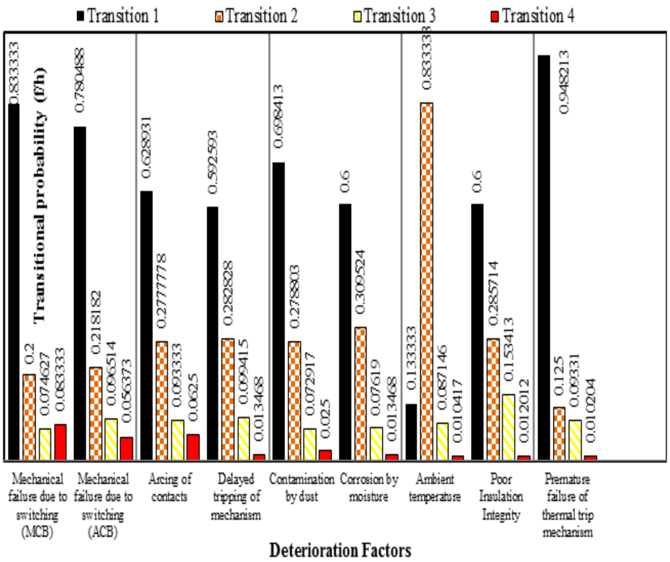

Fig. 7: Transitional probability per ageing factor for the circuit breaker ageing process

Based on Maganjo Maize Millers' simulation shown in Figure 7, the highest transitional probability/risk probability was mechanical failure due to operating mechanism with 0.948213 in the first stage of transition. This represents premature failure of the circuit breaker in its infant stages of operation. The CBs therefore require replacement in the first 10 years of operation. Premature failure due to switching poses as the second ageing factor influencing premature failure with a probability of 0.8333 in its initial stages of operation. Ambient temperature of the circuit breaker enclosing unit should also be put in consideration since in the first transitional stage; the risk of failure will not be noticed. This is characterized by a transitional probability of 0.13333. However, in the second stage of transition, the risk of failure is extremely high (0.83333) an indicator of a very quick and unexpected transition to death. This category of transition violates the life span initially set by the manufacture since the asset will deteriorate at a rapid rate as opposed to the expiry date initially allocated to it. The operator should therefore pay attention to these ageing factors prior to commissioning. Thus, the time of replacement for a circuit breaker under exposure by ambient temperature is 30 years.

C. Findings of the Most Opportune Time of Replacement using the Equipment Inspection Method

As earlier discussed in section 2(b), the Equipment Inspection Method seeks to predict the failure pattern of the industrial circuit breakers based on classification into four stages: $\lambda(0)$ when the circuit breaker is in the AGAN state showing no sign of failure: this was corresponding to a life of 0 years of the circuit breaker. The second stage is $\lambda\left(\frac{1}{2}\right)$ is a period when the circuit breaker operational life is half way maximum degradation, $2\lambda\left(\frac{1}{2}\right)$ a multiplier of the second stage and lastly $\lambda(1)$ a period when maximum degradation takes place. Formulation is shown in section 2(b). The circuit breakers of three industrial consumers namely: FICA Seeds International, Luuka Plastics Uganda and Maganjo Maize Millers were analyzed to determine the failure pattern and optimal time of replacement as in the previous case with WAM and MAM. Table 8 shows prediction and the OPT for FICA Seeds International industrial CBs:

No.	Fault Driver	$\lambda\left(\frac{1}{2}\right)$ (%)	$2\lambda\left(\frac{1}{2}\right)$ (%)	$\lambda(1)$ (%)	$\hat{t}_p$ (years)
1	Mechanical failure due to switching (MCB)	0.63	1.26	10.76	6.199
2	Mechanical failure due to switching (MCCB)	0.64	1.28	10.83	6.084
3	Mechanical failure due to switching (ACB)	0.65	1.30	10.83	5.626
4	Arcing of contacts	0.43	0.86	9.06	7.254
5	Delayed tripping	0.50	1.00	9.52	7.144
6	Contamination by dust	0.48	0.96	9.46	6.876
7	Contamination by moisture	0.48	0.96	8.90	7.245
8	Ambient temperature	0.60	1.20	9.57	6.023
9	Insulation integrity	0.62	1.24	11.15	6.1146
10	Premature failure of thermal magnetic trip mechanism	0.65	1.30	11.31	5.626

Table 8: Prediction of failure and OPT for FICA Seeds International circuit breakers

Findings in Table 9 demonstrate that the OPT values are consistent and vary less with findings using the WAM approach considering the same shape parameter $\beta = 6.515146$ years. However, findings using the EIM model are more accurate as they exhibit more urgency (a shorter time frame) for industrial circuit breaker replacement. Results for Luuka Plastics International Uganda show a longer time of replacement required due to a far lower value of the shape parameter ($\beta = 1.38942$) years as earlier discussed in the WAM model.

However, values of OPT are more accurate due to a lower cost function usually used in EIM predictions., the cost of failure is often modeled as slightly greater than the cost of preventive maintenance in multipliers such as 1.5, 2 and 5 which yields highly reliable results. It is required that the OPT should take place as a preventive maintenance strategy before maximum degradation of the circuit breaker. Table 10 shows the failure patterns and optimal replacement time for Luuka Plastics International Uganda CBs.

No.	Fault Driver	$\lambda\left(\frac{1}{2}\right)$ (%)	$2\lambda\left(\frac{1}{2}\right)$ (%)	$\lambda(1)$ (%)	$\hat{t}_p$ (years)
1	Mechanical failure due to switching (MCB)	1.84	3.60	2.08	33.655
2	Mechanical failure due to switching (MCCB)	1.85	3.70	2.09	33.785
3	Mechanical failure due to switching (ACB)	1.90	3.80	2.27	31.276
4	Arcing of contacts	1.85	3.70	2.04	35.124
5	Delayed tripping	1.90	2.00	2.11	33.865
6	Contamination by dust	1.83	1.92	2.08	34.743
7	Contamination by moisture	1.83	1.92	2.00	36.634
8	Ambient temperature	1.80	2.40	1.95	37.547
9	Insulation integrity	2.00	2.48	2.18	32.888
10	Premature failure of thermal magnetic trip mechanism	2.08	2.60	2.29	30.996

Table 9: Prediction and OPT for Luuka Plastics International industrial CBs

Findings demonstrate that the OPT values are consistent with the fundamental requirement of replacement time which emphasizes it ought to be preventive in nature and should occur before maximum degradation of the asset. Results show that replacement will be done at a minimum of 75% of the circuit breaker's life. Considering a shape parameter (1.38942) renders them highly reliable. Comparing previous results with Maganjo Maize Millers, replacement time of CBs will have to earlier considering a higher value of shape parameter (3.201423). Results are shown in table 11.

No.	Fault Driver	$\lambda\left(\frac{1}{2}\right)$ (%)	$2\lambda\left(\frac{1}{2}\right)$ (%)	$\lambda(1)$ (%)	$\hat{t}_p$ (years)
1	Mechanical failure due to switching (MCB)	1.72	3.44	4.48	15.912
2	Mechanical failure due to switching (MCCB)	1.60	3.20	4.46	15.643
3	Mechanical failure due to switching (ACB)	1.78	7.60	4.78	15.643
4	Arcing of contacts	1.90	7.40	4.66	17.876
5	Delayed tripping	1.90	3.80	4.67	11.253
6	Contamination by dust	1.74	3.84	4.25	16.232
7	Contamination by moisture	1.47	2.94	4.20	16.784
8	Ambient temperature	1.54	3.08	4.32	16.843
9	Insulation integrity	1.56	3.12	4.78	12.343
10	Premature failure of thermal magnetic trip mechanism	2.18	5.20	5.29	10.876

Table 10: Prediction and OPT for Maganjo Maize Millers Uganda industrial CBs

Results in Table 11 exhibit a need for early replacement of the industrial CBs since Maganjo Maize Millers CBs have a relatively higher shape parameter $\beta = 3.20143$ compared to Luuka Plastics Uganda. This shows that Maganjo Maize Millers Uganda CBs are predicted to have lower reliabilities in their course of life. The premature failure of the thermal magnetic trip mechanism thus poses as the most critical fault driver for all cases with the highest failure rate at maximum degradation, consequently requiring the shortest time of replacement (10.876 years).

IV. CONCLUSION

In this study, three methods of achieving optimal time of industrial circuit breaker replacement were selected namely: the Weibull Analytical Model, the Markov Analytical Model and the Equipment Inspection Method. Findings indicate that the EIM exhibited the highest level of accuracy in acquiring OPT. This is due to low cost ratio of failure to preventive maintenance thus leading to highly reliable $\hat{t}_p$ predictors with high consistency, criterion validity and minimum variance. The validity of EIM results was such that all the values of $\hat{t}_p$ where predicted to take place before the prescribed circuit breaker life as opposed to WAM which exhibited low reliability values for the case of Luuka Plastics International CBs. Other methods such as MAM yielded lower accuracy or reliability in results displayed due to accommodation of higher cost ratios of failure to preventive maintenance. This resulted into inaccurate estimates achieved for most of the fault drivers. The case of the MAM model also proved to be unreliable due to a discrete pattern of estimation for OPT. The failure of the thermal magnetic trip mechanism was identified as the most critical fault driver for MCBs and MCCBs, thus needed urgent consideration for replacement and repair respectively.

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