# Time Based Preventative Maintenance Policies for Circuit Breakers with Multiple Failure Types

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*SUMMARY*

The reliability of critical components within large test facilities, such as the Unitary Plan Wind Tunnel (UPWT), is a paramount concern, due to the significant impact of component failures which result in facility downtime and subsequent schedule increases. Testing is on the critical path of multiple aircraft and spacecraft development projects, therefore, a component failure affects not only the test facility but also many development programs which require testing prior to attaining key milestones in order to stay on schedule. Vacuum circuit breakers, which actuate electrical power during wind tunnel operations, are critical single point of failure components. The breakers have several failure mechanisms and associated repair processes. This paper models the recurrent failure and subsequent maintenance events throughout the operation life of vacuum circuit breakers as a trend renewal process. The model parameters are estimated using the maximum likelihood method. Subsequently, a generalized maintenance policy is constructed which maximizes the availability of the UPWT system. The policy establishes optimal preventative maintenance scheduling for individual circuit breakers given their unique failure history.

## *1 INTRODUCTION*

The UPWT is used by NASA to test aircraft and spacecraft. During tests, scaled physical models of aircraft and spacecraft are placed within the UPWT and subjected to airflow velocity as high as 2.5 Mach. Testing results are subsequently used to validate software models and improve the design of the tested crafts. UPWT relies on induction motors to power an axial flow compressor which generates the high velocity airflow required for testing. A significant amount of electrical power is required to generate the high velocity airflow of the wind tunnel. UPWT utilizes a high voltage system to generate the required air flowrates. However, the high voltage electrical switchgear is susceptible to arc flash, which occurs when an electric arc crosses an air gap and current flows from air to ground or to other components within an electrical system. Safety hazards, as well as extensive damage to electrical components, are common when arc flash occurs due to the high temperatures it generates. A potential mitigation for this hazard is utilizing vacuum circuit breakers within the high voltage electrical switchgear. Vacuum circuit breakers place electrical contacts inside a vacuum chamber. The reduced air pressure within the evacuated vacuum chamber significantly increases the impedance between electrical contacts and, thereby reduces the likelihood of arc flashing. However, due to the fact that some small quantity of air remains within the vacuum chamber, arc flashing may still occur when electrical contacts are in close proximity but not quite making physical contact, such as when a switch is just beginning to open or when a switch is nearly closed. During these scenarios another arc flash mitigation is frequently utilized. To mitigate this residual arc flash risk, vacuum circuit breakers employ mechanisms to rapidly open and close circuits. Opening and closing circuits with fast acting physical mechanisms reduces the likelihood and severity of arc flash by minimizing the amount of time for arcing to initiate and occur. However, these rapid physical mechanisms require increasing force which in turn increases stress, resulting in frequent failures within mechanical linkages required to rapidly actuate switches.

The UPWT utilizes twelve primary vacuum circuit breakers and four spares as arc flash hazard mitigating electrical switchgear. Each of the primary vacuum circuit breakers is required for operations. A failure in one breaker results in a nonfunctional system due to a lack of redundancy. Breaker maintenance consists of scheduled preventative maintenance, in-place corrective maintenance which does not require removing the failed breaker for repair, and corrective maintenance actions which warranted failed breaker removal with temporary use of a spare breaker. In this study, we categorize vacuum circuit breaker failures into two types. Type 1 failures can be repaired quickly and subsequently do not warrant using a spare breaker while maintenance actions are completed. Type 1 failures are addressed using the repair in place corrective maintenance action. Type 2 failures are more significant and take more time to repair. Subsequently, in order to minimize system downtime, corrective maintenance for type 2 failures requires removal of the failed breaker and temporary use of a spare breaker while the failed original breaker is repaired. Since the UPWT is a critical test facility required for design iteration and performance verification of both aircraft and spacecraft, continued UPWT operations are crucial to numerous development programs. Therefore, the reliability of the vacuum circuit breakers within UPWT is of critical importance for not only continued successful UPWT operations but also many other developmental programs which rely on data collected from UPWT testing.

### 1.1 *Problem Statement*

This paper utilizes a trend-renewal process (TRP) which incorporates the power law function as the trend process and the Weibull distribution as the renewal process in order to predict failure rates of the circuit breakers for both failure types. Three model parameters are estimated using maximum likelihood to characterize the TRP. A case study is conducted using vacuum circuit breaker data [of the UPWT at NASA Ames Research Center]. Approximately ten years of data, from sixteen circuit breakers which experienced 192 failures is used in the case study. The study provides insights into the prognostics of vacuum circuit breakers in terms of predicted failure rates in order to plan for wind tunnel operations and maintenance. The motivation for applying the TRP to the circuit breaker data is to utilize the TRP model results to predict reliability and optimize the frequency of corrective maintenance actions in order to maximize the availability of the wind tunnel.

The remaining sections of the paper are organized as follows: Section 2 reviews the relevant existing literature, Section 3 provides the model development, Section 4 presents the case study, and concluding remarks are summarized in Section 5.

## 2 *LITERATURE REVIEW*

The scope of this review includes: repairable systems, recurrent events, and renewal models. Particular emphasis is placed on describing renewal models and the trend renewal process.

Rigdon et al [1] define a repairable system as a system that upon experiencing a failure can be restored to fully operational performance by any method other than complete replacement of the entire system. Systems of this type are subjected to recurrent events. The system endures an environment which causes a failure event and a subsequent repair event. This cycle of failure followed by repair can occur repeatedly and is, therefore, composed of recurrent events.

According to Xu et al [2], several models are utilized for recurrent event analysis of repairable systems. These models may use input data including both component replacement times and dynamic covariates such as historic system usage information. The models also take into account the quality of maintenance events. Assumptions regarding the quality of maintenance events and the effective age of the repairable system vary depending upon which renewal model is used. Modeling of the maintenance and failure events enables failure prediction which subsequently can be used to improve prognostics and the scheduling of maintenance, as well as the provisioning of spare parts.

Yanez et al [3] define the renewal process (RP) as a recurrent event analysis technique used on repairable systems which assumes perfect repair. After a maintenance action is performed the system is assumed to be in an as good as new condition. The RP model results in a best case scenario where repairing a component resets the repairable systems age to new. Other renewal models are more conservative resulting in marginally degraded repaired systems following a failure.

Another renewal model, which is the opposite extreme of RP, is the nonhomogeneous Poisson process (NHPP). Majeske [4] describes the NHPP as a minimal repair model. After undergoing repair, the repairable system is treated as being as bad as old. This model results in a repairable system age that is the same immediately after a repair as it was immediately before the accompanying failure.

Yet other renewal models of maintenance events result in a remaining useful life estimation that is between the two extremes of as good as new and as bad as old. Kijuma [5] introduced recurrent event models, which incorporate virtual age through a partial reduction of the system's age after each maintenance action, resulting in a system that is better than old while worse than new. Additionally, Yang et al [7] discuss many other intermediate age models including: the modulated renewal process, inhomogeneous gamma process, modulated gamma process, modulated power law process, the Brown-Proschan model, the arithmetic reduction of age model, and the arithmetic reduction of intensity model.

Lindqvist [6] extended the work on intermediate age models by introducing the concept of a TRP for analysis of repairable systems. The TRP can accommodate both the general NHPP and the general renewal process ($\lambda(t)$ = constant intensity function) as enveloping repair cases. These include perfect repair to an equivalent to new condition in the case of the general renewal process case and minimal repair to a state equivalent to as bad as old in the general NHPP case. Additionally, Lindqvist establishes that the TRP can accommodate a more general set of models with intensity functions which vary as a function of time (t).

One scenario considered by Lindqvist, which TRP modeling is particularly well suited for, is the following. Suppose the primary failure mode of a system is due to a single component. That component is replaced at failure; however, no maintenance is performed on the other components of the system. A renewal model (perfect repair) is useful only when mechanical wear and fatigue are neglected. However, if wear and fatigue are included an increased failure frequency should be anticipated. This increased failure rate is captured in the TRP model through the cumulative intensity function of $\lambda(t)$, $\Lambda(t) = \int\lambda(u)du$ (integrated from 0 to t) which accounts for the cumulative mechanical wear and fatigue experienced by the components which have not been replaced up to time t.

Yang et al [7] extended the TRP model by considering relative failure frequencies when multiple failure modes are observed within a repairable system. The highest frequency failure modes are essentially bottle necks for system reliability. Therefore, failure modes which statistically occur more frequently warrant additional resources and mitigations. Additional resources may include redundancy, smaller preventative maintenance intervals, higher reliability components, and sensors to detect degraded conditions. Yang's proposed general method to analyze failure frequencies with imperfect maintenance actions for a single repairable system is discussed in detail within the TRP Model section.

Franz et al [8] study the RP through conducting simulations in order to compare the predicted failure times and failure intervals from an unknown renewal distribution with results from a TRP which incorporates a Weibull renewal distribution and a power law type trend function. Qiuze et al [9] provide an alternative method to the simulation technique of Franz by proposing an analytical approach. The analytical approach proposed by Qiuze can provide failure predictions as accurate as the alternative simulation technique.

Additionally, the authors leverage and extend prior work performed by themselves in [10].

## 3 MODEL DEVELOPMENT

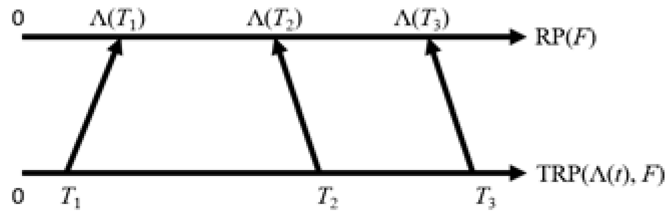
### 3.1 *System Description*

By definition a failure of a vacuum circuit breaker occurs during two situations, first when a breaker is commanded to close a circuit but fails to do so, and second when a breaker is commanded to open a circuit but fails to do so. Both of these events are logged by maintenance technicians when they occur. In some instances of breaker failure, nominal functioning is regained by issuing a second command to either open or close. This type of failure, which does not require subsequent repair, is omitted from further analysis and discussion. Other more significant failures require corrective maintenance actions to repair misaligned or failed components. These actions are grouped into two sets. Failures which involve adjustment, alignment and minimal component replacement are defined as type 1 failures. This type of failure is repaired in place and does not warrant the use of a spare circuit breaker. Failures which require significant component replacement as well as adjustment and alignment are defined as type 2 failures. This type of failure results in using a spare circuit breaker while repair actions are performed. The previous failure descriptions contain all failures which the repairable system experiences.

Failure times and maintenance records for sixteen circuit breakers are available (twelve primary and four spares). This data encompass a total of roughly ten years of operations and 55,135 cumulative operating cycles. The failure times are recorded as functions of time and cumulative number of cycles at time of failure. Each breaker undergoes recurrent failure events and subsequent corrective maintenance repairs through its lifetime. Failures of type 1 and 2 require corrective maintenance which results in a better than old while worse than new condition. This intermediate age condition is modeled using the TRP. The TRP model is suited for repairable systems with multiple failure modes when recurrent event data is available. Each failure type is modeled independently, since type 2 failures by definition involve significantly more corrective maintenance than type 1 failures. Additionally, the TRP model could be modified to model component and system enhancements which result in a better than new condition, due to the increased reliability of enhanced components.

### 3.2 *TRP Model*

According to Yang et al [7], the primary concept behind the TRP is to generalize a property of the NHPP. Let the failure times of a repairable system be T1 , T2 , … be modeled with a NHPP with intensity function, λ(t) , then the corresponding time-transformed process (Λ(T1) , Λ(T2) , …) is a homogeneous Poisson process (HPP) with an event rate equal to 1, denoted as HPP(1). HPP(1) is expanded by the TRP to be any renewal process RP(F). Here F is a cumulative distribution function (CDF). The characterization of a TRP therefore




includes Λ(t ; θλ), and F(z ; **θF**) where: t is the total time since observation began, θλ is the vector containing the parameters of the trend function, z is the inter-event time, and θF is the vector containing the parameters of the renewal function. Figure 1 illustrates the TRP definition.

Figure 1. TRP model illustration.

The TRP model requires two components, a trend function used to model failures and a renewal function used to model the quality of repair after a failure. The formal TRP definition, according to Yang [7], places four constraints on the CDF of the trend function, Λ(t ; θλ):

1. Must be a nonnegative, monotonic increasing function of t
2. Λ(t ; **θλ**) < ∞ for each t ≥ 0 , the cumulative of observed failures is finite, if t is finite
3. Λ(∞ ; θλ) = ∞ , the cumulative number of failures approaches infinity as t approaches infinity
4. Λ(0 ; θλ) = 0, at t equal to 0, no failures have occurred

If T1, T2, …, are independent and identically distributed (iid), T0 = 0 and i = 1, 2, …, then Zi = Λ(Ti ; θλ) - Λ(Ti-1 ; θλ) is a TRP with a CDF equal to F(z ; θλ).

Additionally, the formal TRP definition places two constraints on the CDF of the renewal process F(z ; θF):

1. The CDF must be a positive random variable with F(0 ; θF) = 0
2. The expected value of the CDF must equal 1

The probability density function (PDF) of the renewal function is f (z ; θF). The hazard function of the renewal function is h (z ; θF) = f (z ; θF) / [1 - F(z ; θF)] and the cumulative hazard function is H(z ; θF) = ∫ h (s ; θF) ds (integrated from 0 to z).

The power law function is used as the trend function within this model in the format provided below in (1):

$$\lambda(t;\boldsymbol{\theta}_\lambda) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \quad (1)$$

Here θλ = (β / η)T is the parameter vector.

The Weibull distribution is used by the model as the renewal function. The Weibull distribution PDF is provided in (2) and the CDF is provided in (3):

$$f(z;\boldsymbol{\theta}_F) = \frac{\mu}{\sigma}\left(\frac{z}{\sigma}\right)^{\mu-1} e^{(z/\sigma)^{\mu}} \quad (2)$$

$$F(z;\boldsymbol{\theta}_F) = 1 - e^{(z/\sigma)^{\mu}} \quad (3)$$

Here the Weibull shape parameter is μ and the Weibull scale parameter is σ. By definition the expected value of the renewal distribution is 1. Therefore, the shape parameter, μ is determined by setting the expectation of the Weibull distribution to 1. This constraint results in a shape parameter, estimated by μ = - log [Gamma (1 + σ)]. Subsequently, only 1 parameter, θF = σ is required in (2) and (3).

### 3.3 *Reliability Model*

The following definition applies to a single repairable system which is instantly repaired upon failure (assume repair time is negligible). The system has K different types of s, independent failure modes. The system observation time starts at t = 0 and ends at a predetermined time t = τ. The failure count is defined thusly: Nk(t) is the cumulative number of k type failures observed in the time interval (0, t ] where k = 1,2, …,K. N(t) is the cumulative number of failures of all types observed in the time interval (0, t ] calculated by N(t) = ∑ Nk(t) (evaluated from k = 1 to k = K). Observed failure times are defined by Tk,i where i = 1, 2, …, Nk(τ) such that the ordered failure times for a particular failure type k are always increasing, 0 < Tk,1 < Tk,2 < , …, < Tk,N(t) < τ.

The failure time-history from the start of observations up to but not including time t, (0, t ] is defined as Ƒt- = { Tk,i ; i = 1, 2, … , Nk(t-) and k = 1, 2, … , K}. Nk(t-) represents the number of type k failures which occur prior to time t. All failure times for all failure types which occur prior to time t are contained within Ƒt- .

The failure counting process Nk(t) has a condition intensity function denoted as γk (t ; θk) where θk is the vector containing parameters for failure type k as illustrated in (4) below:

$$\gamma_k(t;\boldsymbol{\theta}_k) = \lim_{\Delta t \to 0} \frac{Pr(\text{an event of type } k \text{ occurs in}[t, t+\Delta t) \mid \mathcal{F}_{t-})}{\Delta t} \quad (4)$$

Given Ƒt- the failure history, the term γk (t ; θk)Δt provides an approximation of the probability of an occurrence of failure type k during [t, t + Δt). Additionally, when considering failure of all types 1 through K, let γ (t ; θ) = ∑ γk (t ; θk) where the vector containing parameters for all failure types is θ = ( $\theta_{1T}$ , … , $\theta_{KT}$ )T. Therefore the term γ (t ; θ)Δt provides an approximation of the probability of an occurrence of failure of any type [t, t + Δt).

Utilizing (4) the cumulative expected number of type k failures during the time interval (t1 , t2] is denoted by Γk ( t1 , t2 ; θk) which is a deterministic function of unknown failure type k parameters, and determined by (5) and (6):

$$\begin{aligned}\Gamma_k(t_1,t_2;\boldsymbol{\theta}_k) &= \boldsymbol{E}\Big(\int_{t_1}^{t_2}\gamma_k(s;\boldsymbol{\theta}_k)ds\Big) \quad (5)\\ &= \boldsymbol{E}\Big(\int_{0}^{t_2}\gamma_k(s;\boldsymbol{\theta}_k)ds\Big) - \boldsymbol{E}\Big(\int_{0}^{t_1}\gamma_k(s;\boldsymbol{\theta}_k)ds\Big)\\ &= \boldsymbol{E}\big(\tilde{\Gamma}_k(t_2;\boldsymbol{\theta}_k)\big) - \boldsymbol{E}\big(\tilde{\Gamma}_k(t_1;\boldsymbol{\theta}_k)\big)\end{aligned}$$

where:

$$\tilde{\Gamma}_k(t;\boldsymbol{\theta}_k) = \int_0^t \gamma_k(s;\boldsymbol{\theta}_k)ds \quad (6)$$

Additionally, let the summation from k = 1 to k = K of the expected individual failures equal the expected total failures such that ∑ Γk ( t1 , t2 ; θk) = Γ ( t1 , t2 ; θk). Here Γ ( t1 , t2 ; θk) is the expected total number of failures during time interval (t1 , t2]. The failure profile for a single repairable system with K types of failures within time interval (t1 , t2] is a vector, R( t1 , t2 ; θk) defined by (7):

$$\boldsymbol{R}(t_1,t_2;\boldsymbol{\theta}) = \left[\frac{\Gamma_1(t_1,t_2;\boldsymbol{\theta}_1)}{\Gamma(t_1,t_2;\boldsymbol{\theta})},..,\frac{\Gamma_1(t_1,t_2;\boldsymbol{\theta}_k)}{\Gamma(t_1,t_2;\boldsymbol{\theta})},..,\frac{\Gamma_1(t_1,t_2;\boldsymbol{\theta}_K)}{\Gamma(t_1,t_2;\boldsymbol{\theta})}\right]^T \quad (7)$$

Here the relative failure frequency of failure type k is denoted by Rk ( t1 , t2 ; θk).

### 3.4 *Parameter Estimation*

This paper applies the TRP to a single repairable system with multiple failure types. Each failure type is assumed to be independent and each is modeled separately using a TRP. The conditional intensity function described in (4) for a particular failure type k is provided in (8):

$$\gamma_k(t;\boldsymbol{\theta}_k) = h[\Lambda(t:\boldsymbol{\theta}_{\lambda_k}) - \Lambda(T_{k,N_k(t-)};\boldsymbol{\theta}_{\lambda_k});\boldsymbol{\theta}_{F_k}]\lambda(t;\boldsymbol{\theta}_{\lambda_k}) \quad (8)$$

Within this model the forms of h and Λ are the same for all failure types. However, the failure parameters vary as a function of failure type. The conditional cumulative intensity function term defined in (6) is calculated using (9):

$$\begin{aligned}\tilde{\Gamma}_k(t;\boldsymbol{\theta}_k) &= H[\Lambda(t;\boldsymbol{\theta}_{\lambda_k}) - \Lambda(T_{k,N_k(t-)};\boldsymbol{\theta}_{\lambda_k}) \quad (9)\\ &+\mathbf{1}_{[N_k(t-)>0]}\sum_{i=1}^{N_k(t-)} H[\Lambda(T_{k,i};\boldsymbol{\theta}_{\lambda_k})\\ &-\Lambda(T_{k,i-1};\boldsymbol{\theta}_{\lambda_k});\boldsymbol{\theta}_{F_k}] \text{ where:}\end{aligned}$$

$\mathbf{1}_{(\bullet)}$ is an indicator variable and $H(z;\boldsymbol{\theta}_{F_k}) = \int_0^z h(s;\boldsymbol{\theta}_{F_k})ds$

Maximum likelihood is utilized to estimate the model parameters. Equation (10) is used to estimate the likelihood of parameter θ from the general model in (4):

$$L(\boldsymbol{\theta} \mid \text{DATA}) \prod_{k=1}^{K}\left[\prod_{i=1}^{N_k(\tau)}\gamma_k(T_{k,i};\boldsymbol{\theta}_k)\right] \text{ x exp}\left[-\int_0^{\tau}\gamma(u;\boldsymbol{\theta})du\right] \quad (10)$$

The likelihood function for parameter θ is determined through substituting (8) into (10) which results in (11):

$$L(\boldsymbol{\theta} \mid \text{DATA}) = \prod_{k=1}^{K} \left\{ \prod_{i=1}^{N_k(\tau)} h[\Lambda(T_{k,i};\boldsymbol{\theta}_{\lambda_k}) - \Lambda(T_{k,i-1};\boldsymbol{\theta}_{\lambda_k});\boldsymbol{\theta}_{F_k}]\lambda(T_{k,i};\boldsymbol{\theta}_{\lambda_k}) \right\} \text{x exp} \left( -\int_0^{\tau} \sum_{k=1}^{K} \{h[\Lambda(t;\boldsymbol{\theta}_{\lambda_k}) - \Lambda(T_{k,N_k(t-)};\boldsymbol{\theta}_{\lambda_k});\boldsymbol{\theta}_{F_k}] \text{ x } \lambda(t;\boldsymbol{\theta}_{\lambda_k})\} dt \right) \quad (11)$$

The maximum likelihood estimation of parameter θ is the value of θ which maximizes L(θ | DATA) from (11). Since each failure type is assumed to be independent (11) can be maximized separately for each failure type as shown in (12) where L(θ) = log[ L(θ | DATA)]:

$$I(\hat{\boldsymbol{\theta}}) = -\left.\frac{\partial^2 L(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}\partial\boldsymbol{\theta}^T}\right|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}} \quad (12)$$

The estimated parameter values for each failure type is substituted into (7) in order to obtain the individual failure profiles. This substitution is shown in (13).

$$\boldsymbol{R}(t_1,t_2;\hat{\boldsymbol{\theta}}) = \left[\frac{\Gamma_1(t_1,t_2;\hat{\boldsymbol{\theta}}_1)}{\Gamma(t_1,t_2;\hat{\boldsymbol{\theta}})},..,\frac{\Gamma_1(t_1,t_2;\hat{\boldsymbol{\theta}}_k)}{\Gamma(t_1,t_2;\hat{\boldsymbol{\theta}})},..,\frac{\Gamma_1(t_1,t_2;\hat{\boldsymbol{\theta}}_K)}{\Gamma(t_1,t_2;\hat{\boldsymbol{\theta}})}\right]^T \quad (13)$$

### 3.5 *Time Based Preventative Maintenance Model*

In this application circuit breakers have two defined failure modes, which require different types of maintenance. It is desirable to develop an availability maximizing maintenance strategy for the circuit breakers. In this paper, we consider age-based maintenance policy for flowmeters based on the estimated reliability model. To address both failure modes, three different types of maintenance are defined as follows.

- Preventive maintenance (PM). PM is a periodic practice and is scheduled after every τ units of time. It is performed with a fixed cost cPM, which instantly returns the circuit breaker to a like-new condition.
- Corrective maintenance (CM1). When a critical part fails (i.e., failure mode 1), and the repair warrants the use of a spare.
- Corrective maintenance (CM2). When a critical part fails (i.e., failure mode 2), and the repair is performed in place and does not warrant the use of a spare.

All types of maintenance are assumed to be performed instantaneously since the maintenance times are negligible in one renewal cycle. Each renewal cycle ends with either a PM or a CM.

The expected cycle length, denoted by μ, is derived as

$$\mu = \int_0^{\tau} t f_K(t)\,dt + \tau R_K(\tau) = \int_0^{\tau} R_K(t)\,dt = \int_0^{\tau} e^{-\int_0^t \lambda_K(u;\beta_K,\eta_K,\boldsymbol{\alpha}_K)du}\,dt = \int_0^{\tau} e^{-\Lambda_K(t;\beta_K,\eta_K,\boldsymbol{\alpha}_K)}\,dt. \quad (14)$$

The expected cost for each renewal cycle is given by

$$C = R_K(\tau)\left(c_{PM} + \sum_{k=1}^{K-1} c_{MR,k}\Lambda_k(\tau)\right) + (1-R_K(\tau))\left(c_{CM} + \sum_{k=1}^{K-1} c_{MR,k}\Lambda_k(\mu - \tau R_K(\tau))\right) \quad (15)$$

Finally, the long-run expected cost rate is given by

$$\eta = \frac{C}{\mu}. \quad (16)$$

The optimal age-based PM policy τ* is then obtained by minimizing η.

## 4 *CASE STUDY*

This study models circuit breaker failures using a TRP with a power law trend function and a Weibull renewal distribution. The failures are divided into two types; type 1 which requires minor repair and type two which requires more significant repair. The data analyzed was collected from sixteen circuit breakers. Each circuit breaker is modeled separately as an individual repairable system. Figure 2 illustrates the type 1, type 2 and combined total failure rate as a function of the cumulative number of cycles which an individual circuit breaker has been subjected to. Additionally, figure 2 provides the predicted total failure rate generated by the TRP model.

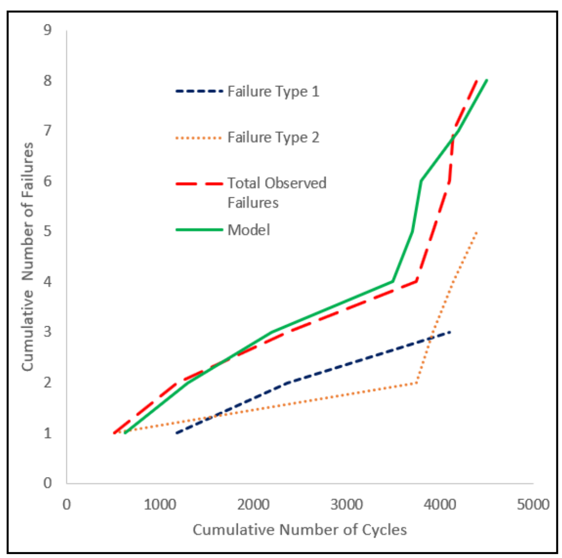


Figure 2. TRP model fitting results with power law trend function and Weibull renewal distribution.

Throughout the period of observation 193 failures occurred including 125 type 1 failures, representing 65% of total failures, and 67 type 2 failures, representing the remaining 35% of total failures. Data from these failure times was used as an input to the TRP model through the failure-time history variable, Ƒt-.within (1). Subsequently maximum likelihood estimation of the parameters within (11) was performed. Table 1 provides the maximum likelihood parameter estimates for 1 of the circuit breakers which include σ for the Weibull renewal distribution as well as β and η for the power law trend function. These parameter estimates were utilized to generate the Model curve fit provided within Figure 2. The results indicate that initially failure type 1 occurs more frequently. However, towards the end of the observation period failure type 2 increases in frequency.

*Table 1 – Parameter estimates for type 1 & 2 failures*

| Failure Type | Parameter | Estimates |
|---|---|---|
| 1 | $\beta$ | 1.884 |
| | $\eta$ | 23.308 |
| | $\sigma$ | 0.565 |
| 2 | $\beta$ | 3.150 |
| | $\eta$ | 44.454 |
| | $\sigma$ | 4.948 |

This study encountered several issues with available data. The majority of events were recorded as a function of calendar date without an accompanying cumulative cycle count. When this occurred, a linear interpolation is performed from the nearest known cycle number. This assumes that the date and cycle count are linear functions of one another. Another observed data issue is that a record of when functional breakers are replaced with freshly repaired spare breakers is not available. These replacement actions are performed without an accompanying failure occurring and subsequently are not captured within the model.

## 5 CONCLUSIONS

The trend renewal process using the power law function as the trend process and the Weibull distribution as the renewal process is an appropriate model for predicting future failure rates for repairable systems with multiple failure modes. The contribution of this paper is the application of the TRP to a data set of component failure times as a function of cycle number with two unique failure types. Areas of future study for this application include incorporating covariate data to increase the robustness of the model. Maximizing availability is a useful proxy for costs minimization when cost data is not available.

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