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Smart Maintenance Decision Support Systems (SMDSS)

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by

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ABSTRACT

Computerized information systems are used in all contemporary industries and have been applied to track maintenance information and history. To a lesser extent, such information systems have also been used to predict or simulate maintenance decisions and actions. This work details two models, a population data analysis, and a system infrastructure, to aid operations and maintenance managers with the difficult resource allocation decisions they face in the field. The first model addresses the consideration of component dependency for series network connections using a Markov Decision Process model and solution algorithm. The second model addresses the prioritization of maintenance activities for a fleet of equipment using an Analytical Hierarchy Process and solution algorithm. A recurrent event data analysis is performed for a population data set. The final element is the information system architecture linking these two models to a marketing information system in order to provide quotations for maintenance services. The specific industry of interest is the electrical power equipment industry with a focus on circuit breaker maintenance decision actions and priorities and the development of quotations for repair and replacement services. This dissertation is arranged in a three paper format in which each topic is self contained to one chapter of this document.

CHAPTER 1. OVERVIEW

1.1 Introduction

The four primary contributions of this dissertation are (1) a dependent component transformer / circuit breaker model to provide a maintenance decision policy [actions] which can be increased in scope to include other components and scaled to other applications, (2) a recurrent data analysis for production population data, (3) a maintenance prioritization model which can be used for planning predictive maintenance rather than via traditional time or condition based programs, and (4) a system to integrate this data output into a maintenance service quotation.

Reliability and maintenance research focuses on maintenance decision making for discrete components, such as a single piece of equipment, or system wide resource allocation, such as operations and maintenance (O&M) scheduling or budgeting. The problems faced are how to decide what maintenance actions to take, how to prioritize maintenance across a fleet of equipment, and how to provide a quotation for recommended maintenance services. In system network architectures, components are often linked together which creates the potential for component dependency. Dependent components are two or more items which are connected in a network, whereby the condition of one or more items can impact the performance, or condition, of other dependent component(s). While these dependency considerations are mentioned in some literary contributions, there are notable gaps in the models that attempt to incorporate such considerations. In order to address this, an analytical model has been developed to provide maintenance decision actions for dependent components. This topic is explored in greater depth in Chapter 2 of this document.

Since component dependency has not been comprehensively studied, the majority of work related to providing products and services has been focused on discrete, individual, components. In order to provide more comprehensive maintenance service, a solution must consider a network as a group of inter-connected pieces of equipment which interact with one another. This type of systems based approach has not been implemented in maintenance programs for industrial equipment which must be extensively maintained in order to operate electrical generation sites and industrial facilities. Service providers provide quotations for parts and field service to keep such equipment in good working condition. However, such systems rely on human experts and manual preparation of documents and bid materials. While there has been research related to capturing human expert knowledge in a computer application or system, there has not been research in the automatic generation of service quotations from predictive maintenance decision models for dependent component networks.

The final deliverable or end product of this research is the framework herein referred to as a *Smart Maintenance Decision Support System* (SMDSS). This system is very useful in the preparation and tracking of business documentation such as quotations, purchase orders, and invoices.

The documented system provides steps to effectively *predict* the recommended maintenance action(s) on a piece of equipment, provide prioritization of units within a fleet, and provide quotation information in such a manner that it has substantial value to business and industry. The potential commercial viability of such a system is high and is already being discussed with software developers. There is a desire in industry to establish maintenance programs for equipment fleets such as small power and distribution transformers, circuit breakers, etc. Maintenance decision making in power system planning is of extreme importance to energy providers and users; the assets making up the U.S. power system are valued at roughly $300B per McCalley et al [1]. Most of the previous work in this area has focused on single component systems, i.e., a transformer or a breaker, and not on multiple dependent component network systems.

1.2 Dissertation Organization

The dissertation is arranged in a three paper format with the following papers:

- Optimal Maintenance of Serially Dependent Power System Components
- Maintenance and Recurrent Event Analysis of Circuit Breaker Population Data
- Smart Maintenance Decision Support Systems (SMDSS): Application of an Analytical Hierarchy Process Model Integrated with a Marketing Information System

This research is unique because it introduces the issue of system component dependency; it provides a maintenance model to consider two inter-connected pieces of equipment, a detailed statistical analysis of a fleet population, a prioritization model to order maintenance across a fleet, and an information system to integrate these models with various software applications and databases. While the analytical tools utilized (e.g., Markov decision process model solution algorithms, recurrence event statistical analysis, and analytical hierarchy process method, and marketing information system) are not 'new' the data collection, data formatting, model development, system requirement definition, implementation, analyses, and questions answered are a unique contribution in each of the three papers.

1.3 References

1. McCalley J, Honavar V, Pathak J, Jiang Y, Kezunovic M, Natti S, Singh C, Panida, J. Integrated Decision Algorithms for Auto-Steered Electric Transmission System Asset Management. *Power Systems Engineering Research Center (PSERC) and Iowa State University* 2006. PSERC Publication 06-04. Available: www.pserc.org.

CHAPTER 2. OPTIMAL MAINTENANCE OF SERIALLY DEPENDENT POWER SYSTEM COMPONENTS

A paper submitted to *Quality and Reliability Engineering International*

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Abstract

This paper is a case study investigating the importance of relationship or interaction between series-connected dependent system components in maintenance decisions. A continuous-time Markov decision model is applied to find minimum cost maintenance policies in the case of electrical power equipment. Two models are formulated, one considering an independent and a dependent component, and the other considering only the independent component, to compare the optimal maintenance policies for the independent component. Maintenance of the dependent component is included implicitly in terms of the costs associated with certain state-action pairs. A circuit breaker is considered as the independent component and a transformer is considered as the dependent component. Data to specify the models are based on mean times for failure and repair of the system components obtained from industry. After uniformizing the continuous-time models to discrete time, standard methods are used to solve for the average-cost-optimal policies of each model. The importance of considering the component dependency or interaction is

quantified by evaluating, in the dependent-component model, the policy obtained from the single-component model.

Keywords: Dependent components, Continuous-time Markov decision model, Electrical power system maintenance

I. Introduction

In this paper, we investigate the impact of the dependency of electrical power system components on field maintenance decision making. Specifically, we consider the case of maintenance decisions for a degrading circuit breaker whose failure could possibly cause an in-line transformer outage. This type of maintenance policy decision logic is useful in planning operating budgets and resource allocations. Typical maintenance decisions include:

- When to perform maintenance, based on time or condition or both?
- What type of maintenance should be performed (none, minor repair, major overhaul, or replacement)?

A maintenance policy specifies both the choice and timing of maintenance actions. The objectives of this paper are to formulate a model to address dependent components and evaluate the importance of considering the dependence by comparing its results with those from a corresponding model that considers only a single component. Our hypothesis is that component dependence is not negligible in this application. By taking dependency into account, better decisions can be made and costs can be reduced. A numerical case study derived from real data obtained from a transformer manufacturer provides support for our hypothesis.

The terms "dependent components" or "component interactions" are often used to describe the impact components have on the condition of one another. In this paper, the word "dependent" means that one piece of equipment depends on the other in some way. The objective is to determine whether this relationship of dependence between the components is negligible or whether these interactions are important in the maintenance decision making process. In this model, all maintenance decision actions are made with respect to the circuit breaker, the independent component, and no maintenance recommendations are provided for the transformer, the dependent component. The specific dependency considered is the impact of transformer costs on the optimal maintenance policy for the circuit breaker. The circuit breaker was selected for study because the breaker has more mechanical components and more frequent maintenance cycles than the transformer.

This research concerns the maintenance of the electro-mechanical equipment in power system circuits. Circuit breakers and other equipment (e.g., reclosers, panelboards, switches, etc.) are used in-line on the primary and secondary load sides of transformers as shown in figure 1, which represents a simplified example of the generation, transmission and distribution of electricity across a power grid. Generator step-up (GSU) transformers, extra high voltage (EHV) circuit breakers, and medium voltage (MV) and low voltage (LV) circuit breakers are included. The functional requirements of these circuit breaking devices are two-fold: (1) to act as a perfect conductor when closed and (2) to act as a perfect insulator when open (tripped). Since all systems have imperfections or variability there is some level of inefficiency in fulfilling this functional requirement. For example, in power systems we observe load losses and continuous current or fault current ratings which may be exceeded instantaneously and acutely in case of an external transient event or in a longer term steady-state condition, e.g., due to false system monitoring. Because the circuit breaking device allows for current to flow downstream to the transformer, the condition of the breaker can directly impact the condition of the transformer. Only conductors such as cables and terminations such as leads typically are located between the circuit breaking device and the transformer. The model in this paper considers a single breaker-transformer pair. It is reasonable to assume independence among such pairs because they share a common voltage rating, are located in the same substation, and are isolated from other substation pairs by high voltage disconnect switches. Therefore, a maintenance policy for a more complicated system could be constructed as the combination of (not necessarily identical) policies derived for each pair.

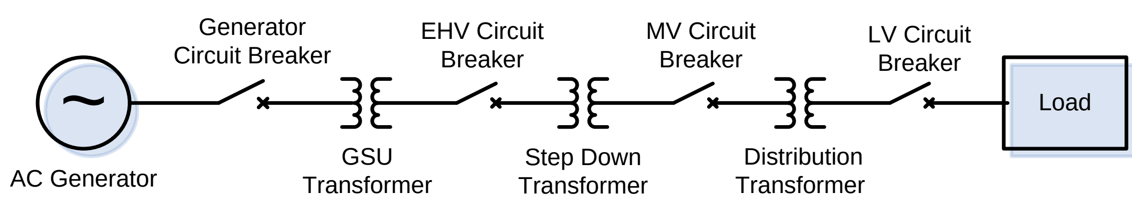

Figure 1. One-Line Diagram for a Typical Power System

The maintenance decision to be made is whether to replace, repair, maintain, or take no physical action on (i.e., assess or monitor) a component, based on the component states. The objective is to minimize total cost over an indefinite time horizon. Component maintenance policies can be used in the context of system management to decide where to allocate resources across sets of components. In this paper, we consider a dependent component, a transformer, and an independent component, an adjacent circuit breaker. The independent component can be replaced, repaired, maintained, or assessed based on the state of the dependent component as well as its own deterioration level as determined by inspection or condition monitoring.

Asset management techniques are a primary focus for organizations that operate equipment in the North American electrical power grid. One contemporary aid that has been implemented is the use of condition monitoring (CM) devices which can collect and transmit field data to a centralized location. CM apparatus typically are purchased and installed by an end user or leased from an equipment supplier that acts as a contractor. Tarakci et al. [1] and Lugtigheid et al. [2] consider outsourcing of maintenance operations to external contractor(s) who provide preventive maintenance which is performed periodically and corrective maintenance which is performed upon failure with the objective to select a maintenance policy that maximizes the total profit for both the equipment owner and contractor. There is a desire in industry to establish maintenance programs for equipment fleets such as small power and distribution transformers, circuit breakers, etc. as the assets making up the U.S. power system are valued at roughly $300B per McCalley et al. [3]. Schlabbach and Berka [4] acknowledge dependency of power system components stating, "It should be noted that the location of the circuit-breaker and by this the importance for the system operation has to be weighted different[ly], e.g. the importance of a circuit-breaker installed in a transformer of line feeder in a feeding substation is higher as compared with the installation for a reactive power compensation device [4]."

Section II summarizes the existing literature related to this work, followed by the formulation of an analytical model in Section III. Section IV summarizes the computational steps and a detailed numerical case study is presented in Section V. Finally, potential future work on dependent component modeling for electrical power systems is discussed in Section VI.

II. Background

A review of the literature reveals trends in maintenance and reliability research that apply to this problem. The Markov decision process method for formulating maintenance models using condition monitoring information is the most prevalently used in the literature. One common alteration is the use of the partially observed Markov decision process (POMDP) model. While the objective functions used by researchers have slight distinctions, the basis for each model optimization is to minimize some total cost function measured in time or dollars including replacement cost, maintenance cost, down-time, etc., or to maximize some total benefit function including metered revenues, utility profit, in-service time, etc.

II.A. Non-Dependent Markov Decision Process Models

The most prevalent modeling technique for such industrial cases is the Markov Decision Process (MDP) model. Most work is this area does not consider component dependency. Chan and Asgarpoor [5] described the key considerations and concerns facing electric utilities related to O&M budgeting, planned and unplanned outages, and preventive maintenance (PM) versus predictive maintenance (PdM). Using a Markov chain they establish an optimal policy for a single unit; however this model does not consider equipment interactions or the option to replace units in service. Unplanned outage activities were also considered by Sim and Endrenyi [6] who formulated a Markov process model and calculated the optimal mean time to preventive maintenance (PM) by minimizing unavailability of objects or systems. Minor and major maintenance actions were considered with minor maintenance being defined as those tasks which move the equipment back one state, not to the initial new state. When the unplanned failure rate dominates the deterioration rate, there is little or no need for minimal PM. For example, if a circuit breaking device is causing unplanned outages, PM on the transformer still might be worthwhile.

Zheng et al. [7] considered a two-state Markov repairable system to determine production availability to assess reliability of a single object or system; the states utilized by the authors are 'operating' and 'failed'. However, the assumption that systems having undergone a silent failure can still operate, albeit at a higher cost, is typically not practical for a power system network. If a line is down, power is not flowing across the line and the operating companies are therefore losing revenues. This typically occurs during an outage or repair downtime which can be planned or unplanned. Chiang and Yuan [8] expand the maintenance decision model to a multi-state Markov repairable system. This model provided output related to the optimal inspection interval and optimal maintenance action; however, it does not consider the interactions of components or the severity of the failure. For example, there is only one repair action for all failure types.

Maillart and Pollock [9] explored condition monitors which were allocated based on preventive maintenance value (cost minimization), with monitor usage time and allocation deployment as the criteria for an optimal maintenance policy. A finite time horizon POMDP was used by Ivy and Pollock [10] to model a system with monitoring capabilities. Maillart [11] utilized condition monitoring data to observe parameters over the lifetime of an object or system to assess the degree of deterioration which can be used to establish predictive maintenance policies. Models with obvious failures and silent failures made use of reactive and preventive maintenance as formulated in a cost minimization POMDP model.

Yong et al. [12] developed a method to select and schedule maintenance actions from probabilistic failure rates including instantaneous failure probabilities from condition monitors. A multi-state Markovian probability model was used where each state was defined as a level of deterioration. Trending of data collected via condition monitoring was important as was the historical performance of various vintages of original equipment manufacturer (OEM) supplied equipment. The decision policy concerned the allocation of resources to pre-defined feasible maintenance tasks (e.g. tree-trimming, transformer maintenance, etc.) across the entire power system network. Zhang and Nakamura [13] also explored optimal maintenance task scheduling by developing a method and simulation to reduce operations and maintenance costs.

Yang [14] and Lu et al. [15] utilized failure prediction modeling as a tool to estimate equipment state(s) for use in a condition based preventive maintenance policy. Kharoufeh and Cox [16], Gebraeel et al. [17], and Guida and Pulcini [18] utilized condition monitoring data to establish stochastic lifetime distributions for a single object in a stochastic system. These lifetime distributions were then used in maintenance planning to prevent failures and to optimize preventive maintenance policies. The number of states defined in the model formulation was subject to the type of equipment and the number(s) of processes which were inherent to operation of the equipment.

II.B. Component Dependency Models

Barros et al. [19] considered imperfect monitoring information (i.e., non-detection of events) as a practical constraint because condition monitoring data are prone to errors just as in any other data collection process. The authors used the observed system failure rate as a correction factor in their stochastic cost maintenance model. Various failure rates were used to represent the dynamic condition created by the impact from failure of other system components. Dependency was considered for parallel equipment arrangements (i.e., redundancy such as ring-bus network), but not for series configurations. In power systems, both parallel and series circuits must be considered and dependency can occur on any in-line portion of the system.

Albin and Chao [20] formulated a dependency model for series connected micro-electronic circuits and solved for an optimal maintenance policy when optimizing a special case considering two components. They considered only two decisions; to monitor or to replace components. Microelectronic devices typically modify the flow of electricity in an expendable form, in that the components such as resistors can be easily replaced, and are not subjected to strenuous ambient situations, extreme mechanical loads (with moving parts), or large electrical transients. Considering only replacement and not repair is not suitable for circuit breakers because the cost of replacement is too high [3]. In addition, the assumption that unexpected damage following repairs cannot occur is invalid in power system maintenance applications which are subject to energization failures. In the case of the electric power system, we cannot assume that a replacement always returns the circuit to a new or equivalent to new state. Since electrical power systems are very expensive compared to micro-electronic circuits, contemporary condition monitoring is relevant regardless of the equipment deterioration rate.

Many works have addressed parallel redundant systems. For example, Kotz et al. [21] provided some insight on the usefulness of statistical distributions for dependent component reliability models. They specifically addressed the area of parallel component redundancy (e.g., ring bus topology). The parallel component assumption must be relaxed when considering power system component dependency. Levitin and Lisnianski [22] also provided a model for parallel systems and Lisnianski et al. [23] considered many practical elements of maintenance decision making and modeling for aging industrial systems by using a Markov Decision Process model to minimize "reliability-associated cost (RAC)," which includes downtime costs. The authors modeled a system with multiple pieces of interconnected equipment (e.g., air conditioners); however, the model did not consider the impact of one unit based on another unit's condition. This type of model again assumes equipment is connected in a redundant parallel network rather than an in-line series network.

A semi-Markov process (SMP) was used by Tomasevicz and Asgarpoor [24] to establish a preventive maintenance policy to maximize availability. The Tomasevicz and Asgarpoor model accounted for unexpected failures and deterioration failures with an objective to minimize the amount of maintenance time spent repairing or replacing equipment while acknowledging that neglecting maintenance could lead to a deterioration type failure. The SMP model was used to incorporate the amount of time spent in a particular state and to find steady-state probabilities. The output is the optimal rate of PM to maximize availability of the transformer. Sensitivity analysis was used to explore the effects of various parameters but did not include the condition of in-line components. By implying that time minimization will also minimize costs, the authors did not consider other cost sources. In power systems, material costs must also be considered as they impact capital expenditures.

Castanier et al. [25] define stochastic dependence as the case “that the state of a system component (e.g., its age, degradation rate, degradation level) influences the states of others whereas structural dependence exists e.g. in case of physically interconnected components when the maintenance of a component affects the state of others.” However, their model included only economic dependence and did not allow the condition of one component to influence the state of the other component. Gupta and Lawsirirat [26] and Nepal et al. [27] used Failure Modes and Effect Analysis (FMEA) to account for component interaction. Gupta and Lawsirirat’s model does not consider maintenance set-up costs (e.g., mobilizations) or repair times which are both critical elements of electric power system maintenance. Nepal et al. acknowledged the need to explore “dependency relationships and interactions of components in a complex system…,” supporting the assertion that existing models and tools do not consider such interactions. Their model is suited for consumer and commercial applications (e.g., coffeemaker) but is limited for use in heavy industrial systems due to the assumptions that components have assembly-like interactions and arcing occurs at only discrete connection points. In electric power systems, while transient electrical failures occur, gradual degradation over time takes place and occurs almost exclusively at the higher end of the developed severity ranking. For example, the condition of a high voltage apparatus depends on the insulation level and integrity of the insulating medium.

This paper explores component interaction by providing the formulation of a model which accounts for the interaction between two pieces of equipment when determining an optimal maintenance policy. The interactions are modeled in terms of costs rather than transition rates as in previous works such as Albin and Chao [20]. While many papers acknowledged the need to consider interactions, many models neglected interactions by assuming that they do not impact the maintenance decision policy. The results of our case study indicate that this is an invalid assumption in power transmission systems.

III. Model Formulation and Notation

We represent the component condition as a continuous-time Markov chain. By including a set of feasible actions for each state, along with transition rates and costs that depend on the state and action taken, we formulate a continuous-time Markov decision process (CTMDP) to identify an optimal preventive maintenance policy. We formulate two models to validate the hypothesis that dependency is not negligible. The primary focus of this paper is the first model which was developed for a system with dependent components (i.e., in-line circuit breaker (*CB*) and transformer (*T*) pair). For validation purposes, this is compared to a second model which considers only a circuit breaker as a stand-alone apparatus.

<u>Notation:</u>

S: state space

A: action space

$\lambda(s,a)$: transition rate out of state s if action a is chosen

$\lambda(j|s,a)$: rate of transition to state j if action a is chosen in state s

$\Phi(s,a)$: expected time required to perform action a in state s

$P(j|s,a)$: discrete probability of transition to state j if action a is chosen in state s; also referred to as the probability of state deterioration or repair success

$c(s,a)$: cost in state s if action a is chosen

$\pi(s)$: action to take in state s, according to policy π

$P^*(j|s,a)$: uniformized probability of transition to state j if action a is chosen in state s

$P^{\pi*}$: uniformized transition probabilities for a given policy π

$c^*(s,a)$: uniformized cost in state s if action a is chosen

g^π: gain (average cost per unit time) of policy π

$h^\pi(s)$: bias of state s (relative cost if initial state is s) for policy π

III.A States

The transformer is either operating (online), denoted as T_u, or not operating (offline), denoted as T_d. In this model, whether the transformer is online or offline is based on the breaker's position (open or closed). For instance, the state T_u, CB_0 represents the case in which the circuit breaker has failed in the closed position; thus, the transformer remains online. While there is no immediate impact on outage downtime, this is a risky failure state as the transformer remains energized in an unprotected state which is a dangerous situation. Conversely, T_d, CB_0 represents the circuit breaker having failed in the open position so that the transformer is offline. This has an immediate cost impact as downtime is now a factor since power flow is interrupted. In this model, the transformer can be down only when the breaker has failed in the closed position. The breaker is assumed to be closed with the transformer online in all other condition states.

The circuit breaking device is limited to four condition states in the model: CB_0 = failure, CB_1 = poor, CB_2 = good, CB_3 = excellent. The condition of the circuit breaker could be ascertained by visual external or internal inspection, remote monitoring, or condition monitoring data. Examples of external inspection could be observing the trip counter, lubricant applications, evidence of oxidation from moisture ingress, etc. Examples of internal inspection would require de-energization (i.e., lock-out, tag-out) and opening of the breaker enclosure or housings. An internal inspection would include observation of any contact degradation, arc-tracking, contamination, etc. Remote monitoring would include SCADA operations and alarm contact response. Finally, condition monitoring would include data collected automatically on parameters of interest such as coil continuity, gas purity, moisture, etc. There are five feasible states: $S = \{T_d, CB_0; T_u, CB_0; T_u, CB_1; T_u, CB_2; T_u, CB_3\}$

For the maintenance model that considers only the circuit breaker, the transformer is not considered in the state definition. The feasible states for the circuit breaker only model are $S_{CB} = \{CB_0; CB_1; CB_2; CB_3\}$.

III.B. Circuit Breaker Maintenance Actions and Transition Rates

Only circuit breaker maintenance actions are considered in this dependent component model. While transformer maintenance actions are also important (and could be considered in future work), this model considers the dependency between the transformer and breaker to determine breaker maintenance tasks. By considering the transformer condition we extend the scope of a traditional maintenance models which consider only a single component. The dependency is accounted for in the input data as described in Section III.C.

There are five possible actions: $A = \{a_{NA}, a_{RF(mn)}, a_{RF(mj)}, a_M, a_{RP}\}$, defined as:

- a_{NA}: No Action
- $a_{RF(mn)}$: Repair after Failure – minor repair
- $a_{RF(mj)}$: Repair after Failure – major overhaul
- a_M: Maintain
- a_{RP}: Replace

No action (a_{NA}) means that the circuit breaker is left in service with no maintenance performed. There is a cost savings realized when no field maintenance is conducted as there is no cost associated with no action. Repairs (a_{RF}) can be either minor (*mn*) in nature, such as expendable component replacement or major (*mj*) such as an overhaul or rebuilding. Possible actions at failure are minor repair, major repair, or replacement. Their costs are such that $c(s, a_{RF(mn)}) < c(s, a_{RF(mj)}) < c(s, a_{RP})$.

Maintenance (a_M) can be performed either preventively (time or condition based) or by prediction (statistically). Taking no action may be warranted under some conditions. By removing critical maintenance operations based on an assessment, time and cost can be reduced. In our model, this is a by-product of the optimal decision making policy model output (e.g., in some cases no action is optimal).

It is assumed that actions can only be performed when state transitions occur and that condition cannot improve without maintenance, repair, or replacement actions. Both of these assumptions are practical and reasonable. For the circuit breaker only model, the action space remains the same. Figures 2 and 3 are state transition diagrams for each model showing the feasible state space and decision actions which can lead to state transition; each transition has an associated rate (λ) and cost (c).

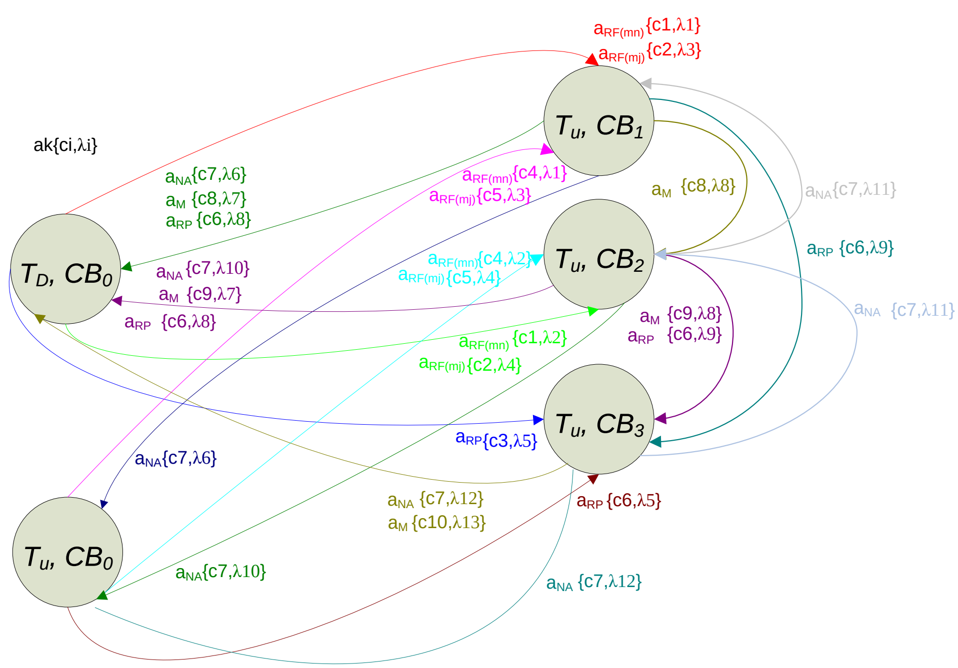

Figure 2. State Transition Diagram – Transformer / Circuit Breaker Model

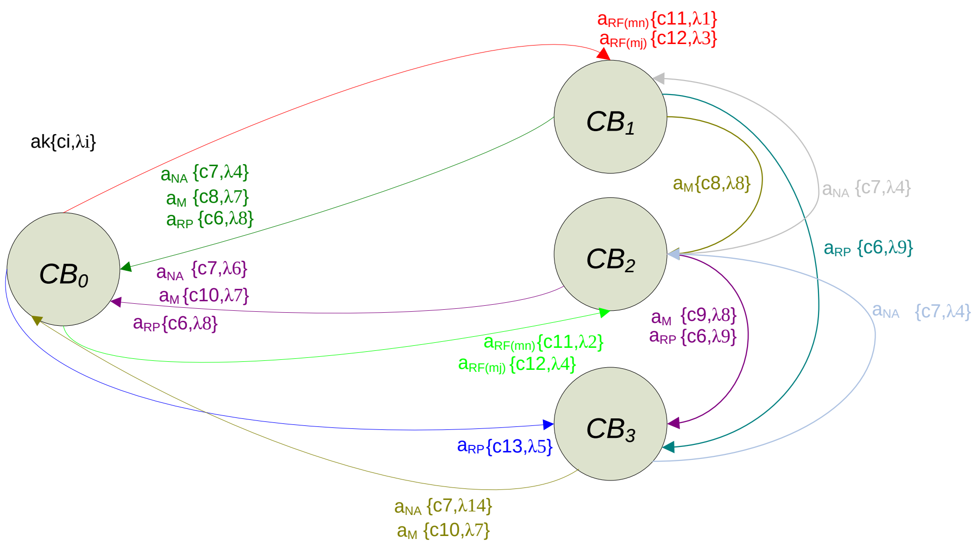

Figure 3. State Transition Diagram – Circuit Breaker Only Model

Tables 1 and 2 provide the model transition rates and costs for states and actions in the dependent component and circuit breaker only models. Continuous-time rates are defined for the transitions between condition states based on maintenance decision actions. The parameters in these tables were collected from internal time estimates, $\Phi(s,a)$, developed by subject matter experts in the field based on historical operating data, field service event data, and industry standards. These include the estimated time until a breaker in any condition state will fail and the estimated time it will take to return a breaker to service during an outage maintenance action (repair time). For example, if a breaker failed bringing the transformer down, the estimated time to return the breaker to service was used as the basis for the transition rate. Such a repair can either succeed or fail. Energization failure rates were used to determine the probability of successful and unsuccessful repairs. Sections

III.D and III.E elaborate on the data collection methodology for these rates and costs and provide examples of how the values were calculated.

Table 1. Transition Rates $\lambda(j|s,a)$ and Costs for States and Actions in Dependence Component Model

s	a	T_d,CB_0	T_u,CB_0	T_u,CB_1	T_u,CB_2	T_u,CB_3	$c(s,a)$
T_d,CB_0	$a_{RF(mn)}$			λ_1	λ_2		c_1
T_d,CB_0	$a_{RF(mj)}$			λ_3	λ_4		c_2
T_d,CB_0	a_{RP}					λ_5	c_3
T_u,CB_0	$a_{RF(mn)}$			λ_1	λ_2		c_4
T_u,CB_0	$a_{RF(mj)}$			λ_3	λ_4		c_5
T_u,CB_0	a_{RP}					λ_5	c_6
T_u,CB_1	a_{NA}	λ_6	λ_6				c_7
T_u,CB_1	a_M	λ_7			λ_9		c_8
T_u,CB_1	a_{RP}	λ_8				λ_{10}	c_6
T_u,CB_2	a_{NA}	λ_{11}	λ_{11}	λ_{12}			c_7
T_u,CB_2	a_M	λ_7				λ_9	c_9
T_u,CB_2	a_{RP}	λ_8				λ_{10}	c_6
T_u,CB_3	a_{NA}	λ_{13}	λ_{13}		λ_{12}		c_7
T_u,CB_3	a_M	λ_7					c_{10}

For the circuit breaker only model, the transition rates are modified as shown in table 2. The values of many of the rates between states are identical; therefore, they have the same values as in the dependent component model. Only one additional rate is utilized in the circuit breaker only model, λ_{14}, which represents the time to failure from excellent condition. This value differs from λ_{13}, since failure is not subrogated into an open or closed failure as in the dependent component model. Therefore, λ_{13} is half of λ_{14} since there is an equal probability of the breaker failing in the open or closed position in the dependent component model and this distinction is not made in the circuit breaker only model. The aggregation of the states T_d, CB_0 and T_u, CB_0 into the single state, CB_0, eliminates the dependency consideration making this a traditional maintenance model for a single piece of equipment. Alternative costs were defined to reflect only cost considerations for circuit breaker repair, replacement, and no action when the transformer is no longer considered. This is the main distinction between the two models.

Table 2. Transition Rates $\lambda\left(j\,|\,s,a\right)$ and Costs for States and Actions in Circuit Breaker Only Model

s	a	CB_0	CB_1	CB_2	CB_3	$c(s,a)$
CB_0	$a_{RF(mn)}$		λ_1	λ_2		c_{11}
CB_0	$a_{RF(mj)}$		λ_3	λ_4		c_{12}
CB_0	a_{RP}				λ_5	c_{13}
CB_1	a_{NA}	λ_{12}				c_7
CB_1	a_M	λ_7		λ_9		c_8
CB_1	a_{RP}	λ_8			λ_{10}	c_6
CB_2	a_{NA}	λ_6	λ_{12}			c_7
CB_2	a_M	λ_7			λ_9	c_9
CB_2	a_{RP}	λ_8			λ_{10}	c_6
CB_3	a_{NA}	λ_{14}		λ_{12}		c_7
CB_3	a_M	λ_7				c_{10}

III.C. Model Input Data

The data used in the model were collected from various sources including transformer and circuit breaker manufacturers and used to estimate the breaker failure time. These estimates were based on field incident, manufacturer, and industry data as well as standards for medium voltage breakers, high voltage circuit breakers, and transformers. Production, service, and warranty databases were searched for all failure related activities for a production population. This population consisted of breakers manufactured from 1997-2009 and included all recorded unplanned outage events which required a service or warranty action in the field. The field incident rate is the ratio of the number of breakers causing forced outages divided by the total number of breakers in service. A forced outage is defined as an outage that is unplanned. This is computed by taking the total number of warranty related forced outages caused by breakers from some time in the past (e.g., shipment or installation) up to the present divided by the total number of breakers that were in service during that time interval. This ratio could be considered as an expected number of forced outages that an individual breaker would cause during its life. In this paper we derive transition probabilities from various data, but the model validity would be improved using condition monitoring (CM) data from a field fleet to more realistically represent the field incident rates. Such data are not readily available as detailed in Section V and Section VI. The data collection method for field incident rates and mean time between failures is dictated by ANSI/IEEE Standard C.57.117 [28].

Repair times, replacement times, and outage durations were based on average field repair times for high voltage breaker services. The cost of downtime was estimated assuming a generation or production penalty is incurred for an outage. The manufacturer field incident rate data were verified by comparison to International Council on Large Electric System (CIGRE) failure statistics [29] and data from transformer failure surveys conducted in Australia and New Zealand. The expected numbers of days to failure were based on typical design standards for transformers and breakers, or a 30 year useful life as used by the International Electro technical Commission (IEC) [30]. The IEC useful life is longer than the IEEE standard useful life estimation of 180,000 hours [31]. This 30 year useful life is an industry standard guideline for the estimated life of a circuit breaker. Cost data were collected based on expected costs to perform minor maintenance, major maintenance, replacement, and no action. A more detailed discussion of the cost inputs is provided in Section III.E.

From these data, the number of days to failure or the number of days to return a unit to service was estimated for each condition state and action. The reciprocals of these estimates become the transition rates for each state and action pair. Transition probabilities were established based on the field incident rate information and mean time to failure data which projects the likelihood of general failures, energization failures, successful repairs, successful replacements, and successful maintenance activities.

III.D. Transition Rate Data Analysis, Assumptions, and Calculation Example

This section describes how transitions rates between states are defined and how the applicable data were collected. A fundamental assumption of the Markov model is that the transition times are exponentially distributed. Verifying this assumption is difficult because some of the breakers remain in service and their remaining useful life is unknown; thus, we have a censored data set. Statistical methods exist to address such censored or truncated data sets and are applied to this problem in [32]. The transition rates defined in the model are based on a series of assumptions, as follows:

(1) Maintenance either yields a condition improvement (of one state) or can worsen the condition, e.g., by introduction of contaminants. The condition cannot improve beyond excellent.

(2) Repair yields a condition improvement and is feasible only in states T_d, CB_0 or T_u, CB_0. The state that results from a repair action depends on the type (minor or major) and quality of repair (success or energization failure).

(3) Replacement yields a transition to excellent condition state CB_3 or it can result in transition to a failure state T_d, CB_0 or T_u, CB_0 unless the circuit breaker is already in a failure state.

(4) The condition is known perfectly at all times.

(5) When the breaker fails, it is equally likely to be in the open or the closed position.

(6) In some cases, a transition is infeasible or has a zero probability of occurrence in the given model. For example, no transition rate (λ) is given for the state and action

pair of CB_1, a_M to state T_u, CB_0 because the transformer cannot be online when the circuit breaker is replaced and re-energized as it is assumed the transformer is isolated. This is a realistic assumption since an outage must be taken to replace the breaker.

At failure states T_d, CB_0 or T_u, CB_0, the decision maker can choose to perform a minor repair or a major overhaul repair, which will restore the breaker to poor or good condition, respectively. There are probabilities associated with the repair quality, either success or failure, to reach each condition state by performing either type of repair. For example, among the state transition rates, λ_1 and λ_2 reflect the minor repair rates and probability of restoring the unit to good or poor condition, respectively. This is done by multiplying the repair rate by the probability of a partially successful repair, which results in a transition to the poor condition state, or a fully successful repair, which restores the breaker to the good condition state.

Next, the transition probability of moving between states dependent on the action taken were determined by subject matter expert using usage data for energization failures and repair success rates. Using the reciprocal of the transition time, $\lambda(s,a)$, multiplied by the probability of the success or failure, $P(j|(s,a))$, we computed the rate of transitions among states, $\lambda(j|s,a)$.

For example, the scaled mean time to failure for a CB in excellent condition is $\phi\left(\left(T_u, CB_3\right), a_{NA}\right) = 1/\left(2L\right)$ days. Because there is an equal likelihood of the breaker being in the open or the closed position when it fails,

$P\left((T_d, CB_0)\middle|(T_u, CB_3), a_{NA}\right) = P\left((T_u, CB_0)\middle|(T_u, CB_3), a_{NA}\right) = 1/2$. Therefore,

$\lambda_{13} \equiv \lambda\left((T_d, CB_0)\middle|(T_u, CB_3), a_{NA}\right) = 2L/2 = L$ per day. Note that, for convenience, the smallest transition rate was scaled to L after all of the transition rates were computed.

This process was completed for the model states and actions identified in sections III.A and III.B and the results make up tables 1 and 2. Here, average times are used to estimate the expected value of the random variable. Table 3 shows data sources and relative magnitudes of the transition rates. Rates are scaled so that L denotes the slowest rate (λ_{13}) and $18{,}179L$ denotes the fastest rate (λ_9). The rates λ_{11} and λ_{13} are not used in the circuit breaker only model. The rate λ_{13} is the critical path rate in the dependent component model since it is the slowest rate in that scenario. The rate λ_{14} is the critical path rate in the circuit breaker only model since it is the slowest rate in that scenario.

Table 3. Transition Rates (λ) Considered in the Models

Rate	Estimation	Scaled
λ_1	Reciprocal of the mean time to perform minor repair times the probability that the condition changes to poor	$8145L$
λ_2	Reciprocal of the mean time to perform minor repair times the probability that the condition changes to good	$2715L$
λ_3	Reciprocal of the mean time to perform major overhaul times the probability that the condition changes to poor	$1086L$
λ_4	Reciprocal of the mean time to perform major overhaul times the probability that the condition changes to good	$6154L$
λ_5	Reciprocal of the mean time to perform replacement times the probability of a successful replacement	$4344L$
λ_6	Reciprocal of the mean time to failure in poor condition times ½ since there is an equal likelihood of the breaker failing in the open or closed position.	$3L$
λ_7	Expected energization failure rate from maintenance action.	$3540L$
λ_8	Expected energization failure rate from replacement action.	$354L$
λ_9	Reciprocal of the mean-time to perform maintenance times the probability it is successful.	$18179.6L$
λ_{10}	Reciprocal of the mean-time to perform a replacement times the probability it is successful.	$3990L$
λ_{11}	Reciprocal of the mean time to failure in good condition times ½ since there is an equal likelihood of the breaker failing in the open or closed position.	$1.5L$
λ_{12}	Reciprocal of the mean time to deteriorate one condition state.	$6L$
λ_{13}	Reciprocal of the mean time to failure in excellent condition times ½ since there is an equal likelihood of the breaker failing in the open or closed position.	L
λ_{14}	Reciprocal of mean time to failure for a unit in excellent condition	$2L$

III.E. Costs

Industry data were utilized in this model to provide an accurate portrayal of repair costs and times. The first step in the process was to assemble cost data for each state and action pair, $c(s,a)$. The costs were determined based on typical field service estimations for a breaker in that condition state given the desired action. Costs incurred from production downtime when the transformer is offline were also considered (backup generation is not considered). For instance, if the transformer was online, the breaker had failed and was out of service requiring a minor repair; a field service estimate for this service was used based on the current condition criteria. In this example, the cost value for this repair is c_4. The only way the breaker can fail keeping the transformer online is with some form of system redundancy such as ring-bus network, therefore, we assume system redundancy for some costs where noted in table 4. However, if the transformer is taken offline by the breaker failure, the cost value for this repair is now c_1 which is nearly 25 times larger than c_4 since the transformer has now been taken out of service. The estimated costs used in the numerical case example below are based upon manufacturer support pricing for repair services and generation and transmission downtime. The data were collected from subject matter experts and multiple industry production, service, and repair databases.

Specifically, labor, materials, equipment, and production loss are variable costs used in the model. Fixed, sales, general, administrative costs are not considered. The costs associated with all states and actions are shown in tables 1 and 3. For example, data collected for the cost of minor repairs on a failed circuit breaker with a transformer online, c_4, were from historical estimates for such a repair from industry databases.

Quantitative data were used in the model, and a qualitative description of each cost is provided in table 4 for illustrative purposes. The actual data utilized in the model was analyzed using a Program, Evaluation, Review Technique (PERT) approach. The PERT approach scales the expected costs in the network states and averages them for each action in the action set (i.e., worst, moderate, and best case scenarios). There is an equal likelihood of the worst, moderate, and best case scenario occurring. Costs are scaled so that X denotes the lowest non-zero cost (c_{10}) and 216.40X denotes the highest cost (c_3).

For example, the cost for a CB in excellent condition is $c((T_u, CB_3, a_{NA})) = c_7 = 0$ because there is no cost to do nothing when the transformer is online. Because the lowest cost action for a CB in excellent condition, other than no action, is the cost of performing breaker maintenance with the transformer online, c_{10} is the base of all scaled costs; i.e., $c((T_u, CB_3, a_M)) = c_{10} = X$. As was the case with the transition rates, the smallest cost was scaled to X after all of the costs were computed. All other costs were determined by summing the estimated costs for actions taken in a given state.

Assuming the cost of a minor repair on the breaker is \$3,000; this value would be used as the base valuation (in the moderate case). However, to account for dependency we must consider the impact on transformer productivity caused by a breaker event taking the transformer offline. The lost production time for the transformer, i.e., the dependent component needs to be considered and for this example is said to be \$15,000 per day.

However, there is variability in both the repair cost and the duration of outage. Suppose that the actual cost could be as little as \$500 or as much as \$10,000. We now have a worst case scenario (\$10,000), moderate case scenario (\$3,000) and best case scenario (\$500) for the breaker repair cost. Assuming equal probabilities, the expected cost is \$4,500 which would be used as the repair cost estimate for the breaker only model. Now considering the transformer productivity loss at \$15,000 per day, assume we have a worst case repair time of five days (the \$10,000 breaker repair cost plus \$75,000 transformer lost time cost for a total of \$85,000), moderate case of two and a half repair days (\$40,500) and a best case of one repair day (\$15,500). When considering dependent component maintenance for the entire system (breaker and transformer), the total cost impact must be considered. For example, the total cost of being in state T_d, CB_0 and taking action $a_{RF(mn)}$ is the expected value of $47,000, again assuming equal probabilities. The electrical equipment case example in sections VI and V utilizes transformer downtime costs as determined based on typical generation downtime estimates from industry subject matter experts.

Table 4. Cost Impacts Considered in the Models

Rate	Estimation	Scaled
c_1	cost for minor repair of a failed circuit breaker, transformer offline	55.50X
c_2	cost for major repair of a failed circuit breaker, transformer offline cost for major repair of a failed circuit breaker, circuit breaker only	111X
c_3	cost of outage downtime and cost to replace failed circuit breaker, transformer offline	216.40X
c_4	cost for minor repair of a failed circuit breaker, transformer online (assumes system redundancy)	2.25X
c_5	cost for major repair of a failed circuit breaker, transformer online (assumes system redundancy)	3.00X
c_6	cost to replace failed circuit breaker (assumes system redundancy)	4.00X
c_7	cost of no action on poor, good, excellent condition unit	0
c_8	cost of performing maintenance on poor condition unit	1.60X
c_9	cost of performing maintenance on good condition unit	1.30X
c_{10}	cost of performing maintenance on excellent condition unit	1.00X
c_{11}	cost of minor repair of failed circuit breaker (circuit breaker only)	1.75X
c_{12}	cost of major repair of failed circuit breaker (circuit breaker only)	2.25X
c_{13}	cost to replace a failed unit (circuit breaker only)	7.50X

IV. Computation

An infinite horizon continuous-time Markov decision process model (CTMDP) is formulated to evaluate the optimal policy. For an infinite time horizon model, the cost of any policy will be infinite. Therefore, policy costs must be either averaged over time or discounted to time zero for decision making. We minimize the average cost per unit time in this paper to find the optimal decision policy. One can compute the optimal policy using various methods. In this paper, we used two algorithms to confirm the optimal policy: policy improvement and value iteration. The structure of the optimal policy is obtained under both models and a sensitivity analysis is performed. Alternatively, the model could be solved using a failure minimization or outage downtime objective function.

To facilitate computation of the optimal policy, data transformation or uniformization is used to convert the continuous-time model to discrete time for solution by established methods. The uniformized model includes actual and "fictitious" or "virtual" transitions as noted by Puterman [33] and Kao [34]. The use of uniformization transforms from state transition rates to state transition probabilities denoted as P^{π^*} (see Puterman [33] or Ross [35] for more details on the uniformization process).

Let v be an upper bound on the transition rate out of any state given any action is selected, i.e.,

$$\left[1-P(s|s,a)\right]\lambda(s,a) \le v < \infty, \text{ for all states } s \text{ and actions } a.$$

Following Puterman, the costs and transition probabilities were uniformized as follows:

$$c^*(s,a) = c(s,a)\lambda(s,a)$$

$$P^*(j|s,a) = \begin{cases} 1-\dfrac{\left[1-P(s|s,a)\right]\lambda(s,a)}{v}, & j = s \\ \dfrac{P(j|s,a)\lambda(s,a)}{v}, & j \ne s \end{cases}$$

It should be noted that $P^*(j|s,a)$ differs from $P(j|s,a)$; $P(j|s,a)$ is the probability of state deterioration or repair success while $P^*(j|s,a)$ accounts for both $P(j|s,a)$ *and* the expected time, $\Phi(s,a)$, required to perform action a in state s. The uniformized process moves from state to state with a probability based on the rate of transition (i.e., there is a higher likelihood of going to states among which the transition rates are larger).

An optimal policy solves the optimality equation for each state:

$$0 = \min_{a} \left\{ c^{*}(s,a) - g + \sum_{j \in S} P^{*}(j | s,a) h(j) - h(s) \right\}$$

The scalar g represents the minimum average cost per unit time, or gain, of the process, while the difference between bias values $h(i)$ - $h(j)$ represents the increase in cumulative cost if the initial state of the process is i rather than j. In graphical terms, the gain is the slope of the cumulative cost over time and the difference in bias values between states is the difference in the vertical intercepts of the cumulative costs starting from each state as the initial one.

The uniformized cost values c^{*} are shown in table 5 for both models and discrete transition probabilities P^{*} appear respectively in table 6 for the dependent component model and in table 7 for the circuit breaker only model. A scale factor of U was used for all uniformized cost values.

Table 5. Scaled Uniformized Costs

Dependent Component Model		Circuit Breaker Only Model	
s,a	$\tilde{c}(s,a)$	s,a	$\tilde{c}(s,a)$
$\tilde{c}$ $T_d,CB_0,a_{RF(mn)}$	170.25 U_1	$\tilde{c}$ $CB_0,a_{RF(mn)}$	5.37 U_1
$\tilde{c}$ $T_d,CB_0,a_{RF(mj)}$	226.99 U_1	$\tilde{c}$ $CB_0,a_{RF(mj)}$	4.60 U_1
$\tilde{c}$ T_d,CB_0,a_{RP}	265.52 U_1	$\tilde{c}$ CB_0,a_{RP}	9.20 U_1
$\tilde{c}$ $T_u,CB_0,a_{RF(mn)}$	6.90 U_1		
$\tilde{c}$ $T_u,CB_0,a_{RF(mj)}$	6.13 U_1		
$\tilde{c}$ T_u,CB_0,a_{RP}	4.91 U_1		
$\tilde{c}$ T_u,CB_1,a_{NA}	0	$\tilde{c}$ CB_1,a_{NA}	0
$\tilde{c}$ T_u,CB_1,a_M	9.82 U_1	$\tilde{c}$ CB_1,a_M	9.82 U_1
$\tilde{c}$ T_u,CB_1,a_{RP}	4.91 U_1	$\tilde{c}$ CB_1,a_{RP}	4.91 U_1
$\tilde{c}$ T_u,CB_2,a_{NA}	0	$\tilde{c}$ CB_2,a_{NA}	0
$\tilde{c}$ T_u,CB_2,a_M	7.98 U_1	$\tilde{c}$ CB_2,a_M	7.98 U_1
$\tilde{c}$ T_u,CB_2,a_{RP}	4.91 U_1	$\tilde{c}$ CB_2,a_{RP}	4.91 U_1
$\tilde{c}$ T_u,CB_3,a_{NA}	0	$\tilde{c}$ CB_3,a_{NA}	0
$\tilde{c}$ T_u,CB_3,a_M	U_1	$\tilde{c}$ CB_3,a_M	U_1

Table 6. Uniformized Probabilities – Dependent Component Model

	$P^*(j\|s,a)$				
s,a	T_d,CB_0	T_u,CB_0	T_u,CB_1	T_u,CB_2	T_u,CB_3
$T_d,CB_0,a_{RF(mn)}$	0.500	0	0.375	0.125	0
$T_d,CB_0,a_{RF(mj)}$	0.667	0	0.050	0.283	0
T_d,CB_0,a_{RP}	0.800	0	0	0	0.200
$T_u,CB_0,a_{RF(mn)}$	0	0.500	0.375	0.125	0
$T_u,CB_0,a_{RF(mj)}$	0	0.667	0.050	0.283	0
T_u,CB_0,a_{RP}	0	0.800	0	0	0.200
T_u,CB_1,a_{NA}	0.000138	0.000138	0.999724	0	0
T_u,CB_1,a_M	0.163	0	0	0.837	0
T_u,CB_1,a_{RP}	0.0163	0	0.800	0	0.1837
T_u,CB_2,a_{NA}	6.91E-05	6.91E-05	0.000276	0.999586	0
T_u,CB_2,a_M	0.163	0	0	0	0.837
T_u,CB_2,a_{RP}	0.0163	0	0	0.800	0.1837
T_u,CB_3,a_{NA}	4.60E-05	4.60E-05	0	0.000276	0.999632
T_u,CB_3,a_M	0.163	0	0	0	0.837

Table 7. Uniformized Probabilities – Circuit Breaker Only Model

	$P^*(j \mid s,a)$			
s,a	CB_0	CB_1	CB_2	CB_3
$CB_0,a_{RF(mn)}$	0.500	0.375	0.125	0
$CB_0,a_{RF(mj)}$	0.667	0.050	0.283	0
CB_0,a_{RP}	0.800	0	0	0.200
CB_1,a_{NA}	0.000276	0.99724	0	0
CB_1,a_M	0.163	0	0.837	0
CB_1,a_{RP}	0.0163	0.800	0	0.1837
CB_2,a_{NA}	0.000138	0.000276	0.999586	0
CB_2,a_M	0.163	0	0	0.837
CB_2,a_{RP}	0.0163	0	0.800	0.1837
CB_3,a_{NA}	9.21E-05	0	0.000276	0.999632
CB_3,a_M	0.163	0	0	0.1837

These computational methods are valid if the sequence of states for any stationary policy follows a unichain weakly communicating Markov chain. The unichain structure, defined as a "closed irreducible set and a (possibly empty) set of transient states [33]," was verified by visual inspection of the state transition diagrams for both models. Kao [34] presents a formal algorithm to verify whether an MDP is unichain or multichain manually or using MatLab coding to automate the procedure. Puterman [33] also presents a similar method to classify an MDP using the Fox-Landi algorithm.

Next, we used value iteration on this communicating unichain average cost model to solve the optimality equation. The value iteration algorithm is a commonly used computational method for large Markov decision process models as noted by Tijms [36].

The average cost value iteration algorithm followed the form presented by Puterman [33] and stops when the span of the difference between successive cumulative cost vectors is less than some constant, ε. A small value of the span indicates that this difference has become nearly constant over the states and approximately equals the gain. Using ε = 0.001, convergence occurred in approximately 15,000 iterations for the dependent component model and 22,000 iterations for the circuit breaker only model. We also solved the model using a policy improvement algorithm to confirm the results.

V. Numerical Results / Examples

The optimal policy for each model and resulting costs are shown in table 8. The steady-state average cost per unit time, or gain, is given for each optimal policy. The gain, g^{π}, is scaled by scalar G, and the bias, $h^{\pi}(s)$, is scaled by a positive scalar Y.

Table 8. Results of Value Iteration for CTMDP for Typical Maintenance Valuations

Dependent Component Model				Circuit Breaker Only Model			
State (s)	Action (a)	Gain (g^{π})	Bias ($h^{\pi}(s)$)	State (s)	Action (a)	Gain (g^{π})	Bias ($h^{\pi}(s)$)
T_d,CB_0	$a_{RF(mn)}$	10.679G	0.000	CB_0	$a_{RF(mn)}$	G	0.000
T_u,CB_0	a_{RP}		-0.938Y_1				
T_u,CB_1	a_{RP}		-0.856Y_1	CB_1	a_{NA}		-0.025Y_1
T_u,CB_2	a_{NA}		-0.907Y_1	CB_2	a_{NA}		-0.034Y_1
T_u,CB_3	a_{NA}		-1.000Y_1	CB_3	a_{NA}		-0.044Y_1

Note that the optimal decision policy differs in the dependent component model (states T_u, CB_0 and T_u, CB_1) when compared to the circuit breaker only model (states CB_0 and CB_1). From this, it can be deduced that the transformer-circuit breaker dependency relationship does influence maintenance decision making in the circuit breaker maintenance model. Here, we see that when the transformer is present and online, the maintenance decision is to replace the breaker, while when only the breaker is considered the optimal action is to perform a minor repair of the breaker in state CB_0 or no action in state CB_1. This outcome seems rational as the circuit breaker only model's minimum single transition cost would be to perform a minor repair of the breaker upon failure or to perform no action while operating. Conversely, when the cost of failure is increased by incorporating the transformer, the decision to replace the breaker is a more cost effective strategy when all risks are considered. By updating costs and re-evaluating, the resulting decision policy, gain, and bias valuations are subject to change as shown in the sensitivity analysis.

Intuitively, the bias values (relative costs for different initial states) should be lower for equipment in better condition (i.e., the lowest bias value should correspond to state CB_3 or excellent condition). This trend can be observed in the circuit breaker only model where policy iteration and value iteration agree on decision policy $a_{RF(mn)}, a_{NA}, a_{NA}, a_{NA}$ with gain G and the following bias relationship: $h^{\pi}(CB_3) < h^{\pi}(CB_2) < h^{\pi}(CB_1) < h^{\pi}(CB_0)$. In the dependent component model, policy iteration and value iteration agree on decision policy $a_{RF(mn)}, a_{RP}, a_{RP}, a_{NA}, a_{NA}$ with gain 10.679G and the following bias relationship: $h^{\pi}(T_u,CB_3) < h^{\pi}(T_u,CB_0) < h^{\pi}(T_u,CB_2) < h^{\pi}(T_u,CB_1) < h^{\pi}(T_d,CB_0)$. Note that in the dependent component model, when the transformer is online in state T_u, CB_0 the bias value is smaller than T_u, CB_2 and T_u, CB_1. This can be explained by the fact that there is a zero probability of transition from T_u, CB_0 to T_d, CB_0 while there is a positive probability of transition from T_u, CB_1 or T_u, CB_2 to T_d, CB_0. The fact that T_d, CB_0 is the worst case scenario in the model skews the bias values since the bias is a "transient reward" during the initial state transitions [33]. The same observation applies to replacing the breaker. There is a higher probability of replacement from T_u, CB_0 (probability equal to 0.2) than T_u, CB_1 (probability equal to 0.1837). Therefore, over the long run, the steady-state stationary policy bias values may not be lowest for the best condition state. These can be attributed to cost considerations such as salvage value under catastrophic failure conditions, i.e., the scenario in which the transformer remains online and the circuit breaker fails.

A sensitivity analysis was performed to assess changes to the gain valuations based on an increase in the cost of the transformer going down. This cost was selected for study because transformer outage cost is highly variable across applications and industries and, therefore, is very difficult to estimate. This value can also change over time if system usage is modified such as in load increase and load shedding scenarios. The sensitivity analysis was accomplished by increasing the cost associated with all actions from state T_d, CB_0 and re-optimizing. The cost was adjusted to simulate an increase in the cost of the circuit breaker failing in the closed position to reflect a change to the condition of the transformer. The results from a 25 percent increase are shown in table 9. The increase in outage cost does not change the optimal policy; however, we do see an increase in the gain, and a decrease in the bias values associated with taking no action. The results indicate that the total cost of the optimal maintenance policy increased by 20.27 percent and that the bias, the transient cost from starting in a particular state rather than an "average" state as defined by the Markov chain's limiting probabilities, decreased on average by 24.55 percent.

Table 9. Sensitivity Analysis for Dependent Component Model (25 Percent)

State (s)	Gain (g^{π})	Bias ($h^{\pi}(s)$)	Percent Change
T_d,CB_0	12.844G	0.000 Y_1	
T_u,CB_0		-1.173 Y_1	-25.12%
T_u,CB_1		-1.073 Y_1	-25.27%
T_u,CB_2	Δ = 20.27%	-1.127 Y_1	-24.25%
T_u,CB_3		-1.235 Y_1	-23.55%

The circuit breaker only model includes the cost of breaker failure as an isolated event. This cost is lower than the failure risk in the dependent component model which includes both components. Table 10 shows the sensitivity results of increasing the breaker failure cost in the circuit breaker only model. Similar to the dependent component model, the policy did not change, the gain increased, and the bias values decreased for the circuit breaker only model. In the circuit breaker only component model the results indicate that the total cost of the optimal maintenance policy increased 25 percent and that the bias also decreased on average 25 percent. This is the expected result since a change to the cost structure has a direct influence on the optimal maintenance policy cost since the transformer is not being considered.

Table 10. Sensitivity Analysis for Circuit Breaker Only Model (25 percent)

State (s)	Gain (g^{π})	Bias ($h^{\pi}(s)$)	Percent Change
CB_0	1.250G	0.000	
CB_1		-0.032Y_1	-24.99%
CB_2	Δ = 25.00%	-0.042Y_1	-25.00%
CB_3		-0.055Y_1	-25.00%

Additional sensitivity calculations were performed by increasing the cost of the actions associated with state T_d, CB_0. The cost associated with each action from state T_d, CB_0 was increased from 15 to 200 percent as shown in table 11 and table 12. Again, the optimal policies remained unchanged. While the optimal policy remains unchanged, it is noteworthy that there is a diminishing gain associated with a cost increase; when the cost is increased 200 percent, the associated gain does not increase by the same amount as at 45 percent. Therefore, the cost of the transformer has a larger impact on the gain for smaller cost increases.

Table 11. Sensitivity Analysis for Dependent Component Maintenance Model

Percent Increase T_d, CB_0	Gain (g^{π})	Percent Change
15	11.978G	12.16%
25	12.844G	20.27%
35	13.710G	28.38%
45	14.576G	36.49%
200	19.338G	81.08%

Table 12. Sensitivity Analysis for Circuit Breaker Only Model

Percent Increase T_d, CB_0	Gain (g^{π})	Percent Change
15	1.150G	15.00%
25	1.250G	25.00%
35	1.350G	35.00%
45	1.450G	45.00%
200	2.000G	100.02%

To test the impact of component dependency, the optimal policy from the circuit breaker only model was evaluated in the dependent component model. This was accomplished by modifying the actions taken in state T_u, CB_0 from a_{RP} to $a_{RF(mn)}$ and in state T_u,CB_1 from a_{RP} to a_{NA}. The expected total costs were compared for each policy as shown in table 13 which summarizes the results from this analysis. The optimal policy saves 5.824G or 54.53 percent in the dependent component model compared to the policy derived by considering the circuit breaker only.

Table 13. Cost Comparison of Optimal versus Non-Optimal Policy

State, s	Optimal $\pi^*(s)$	$h^{\pi^*}(s)$	Non-optimal $\pi'(s)$	$h^{\pi'}(s)$
T_d,CB_0	$a_{RF(mn)}$	0.000	$a_{RF(mn)}$	0.000
T_u,CB_0	a_{RP}	-0.938Y_1	$a_{RF(mn)}$	-0.834Y_1
T_u,CB_1	a_{RP}	-0.856Y_1	a_{NA}	-0.834Y_1
T_u,CB_2	a_{NA}	-0.907Y_1	a_{NA}	-0.973Y_1
T_u,CB_3	a_{NA}	-1.000Y_1	a_{NA}	-1.147Y_1
Gain	g^{π^*}	10.679G	$g^{\pi'}$	16.503G

These results confirm the hypothesis that the transformer can influence circuit breaker maintenance decision making policy, thus they are dependent system components and that dependency does not appear to be negligible. Future validation can be accomplished when actual field data can be captured from in-line transformers and circuit breakers. Since condition monitoring (CM) for circuit breakers is still relatively new, it is difficult to amass field data for an installed base or population of breakers. In addition, since a large number of parameters could be measured, filters would need to be applied to the field data (e.g., consider only age and insulation integrity). The model results could be compared to this type of field data to verify the model. Furthermore, in practical applications fault or switching currents during operation should be considered as noted in the future work Section VI.

VI. Conclusions and Future Work

These results extend the findings from previous work which addresses operations and maintenance decision making for industrial equipment. In this case, two models are compared, (1) a multi-component network system which is modeled to assess maintenance actions of one component based upon the considerations of the larger system, and (2) an independent component model. The primary contribution of this work is that this model considers transformer presence when evaluating a maintenance policy based on circuit breaker condition using a more comprehensive system-wide maintenance approach. More specifically, it considers what action should be taken if a circuit breaker fails in the open or closed position when an in-line transformer is in service.

For future research, some of the assumptions could be relaxed to replicate specific field operations. In such applications the time intervals between transitions could be considered independent and random, but not necessarily exponentially distributed. Therefore, further research could include the development of a similar model based on a semi-Markov Process (SMP). The SMP would be useful in exploring additional practical considerations since it allows for random time intervals between transitions which are not dependent on the past. While the CTMDP provides a good modeling framework, an SMP model could make use of more sophisticated failure prediction models and tools. In addition to incorporating costs associated with transformer failure in the circuit breaker maintenance model, a more elaborate model could account for the transformer failure time distribution on the circuit breaker condition. For example, in the model of Albin and Chao [20], "the statistically dependent components do not deteriorate; however, their life distributions depend on the state of the statistically independent component." However, data to support such models of transformer life dependence on the circuit breaker are not yet available. Statistical tools include advanced aging studies and statistical failure mode prediction models for individual components such as a transformer. Much work has been done in the area of statistical life prediction for transformers and such life cycle models could make use of circuit breaker condition state information for a more accurate system representation. This could improve model validity by relaxing assumptions about model inspection times or could be adapted using an optimal inspection time modeling technique, such as the redundant component model developed by Courtois and Delsarte [37]. Tijms discusses data transformations for such models [36].

Another extension could be the incorporation of transformer maintenance activities and electro-mechanical and material considerations for electrical equipment degradation. This could include a change to incorporate direct transformer damage caused by circuit breaker failure. It is possible that a comparison could be made between the optimal decisions from these models versus a model with two individual components clustered into one maintenance decision policy. More specifically for this case, the effects of loading cycle, short circuit currents, and through-faults [38] on a transformer could be considered. For example, a model analyzing only a transformer, only a circuit breaker, and a circuit-breaker transformer model could be compared. This could further verify the hypothesis that breaker condition impacts transformer operation and maintenance considerations. Maintenance actions could be elaborated on by considering differences in maintenance planning (e.g., preventative versus predictive maintenance). An example would be incorporating an inspection action item which would yield a benefit over no action, but a cost savings compared to a minor or major maintenance action. Transition rates for transformer failures could be established using existing models and methods. Budgetary constraints which limit feasible decisions could also be incorporated; e.g., when budgets will only allow for a finite number of replacement actions in a given time interval. These functions and constraints could be added in future work to increase model validity.

Once circuit breaker condition monitoring data are more readily available, it would be useful to track trends in electrical dielectric characteristics of equipment insulation. For example, in liquid filled transformers it is useful to observe dissolved metal gas levels in the fluid and for circuit breakers it is useful to observe sulfur-hexafluoride (SF_6) gas composition purity. This would be useful information for model input as well as model verification, but it relies on the field retro-fit of monitors to the installed population base.

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CHAPTER 3. MAINTENANCE AND RECURRENT EVENT ANALYSIS OF CIRCUIT BREAKER POPULATION DATA

A paper submitted to *International Journal of Quality and Reliability Management*

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Abstract

This paper reviews cotemporary maintenance programs and analyzes factory data for an SF_6 gas filled circuit breaker population. Various maintenance techniques and studies are reviewed to understand the reliability of various models and the impact manufacturing can have on long term maintenance consideration. Production and field event data were analyzed using statistical analysis tools. The population data was formatted so that a *recurrent event analysis could be conducted to establish the mean cumulative function (MCF) by model and product family (class). Average Field Two-year Recorded Event Rate (AFTRER) is introduced and compared to commonly used Field Incident Rate (FIR) and Mean-Time between Failure (MTBF) measures. Common managerial operating questions can be answered as exhibited for the provided circuit breaker population. This includes the longevity of field issues, the anticipated life cycle of a model or class, and AFTRER for models or classes of interest. These statistical analysis tools are used to make critical production quality and asset management observations and aid in decision-making.*

Keywords: reliability, asset management, electric power equipment, mean cumulative function, power system maintenance

I. Introduction

In this paper, we describe an analysis of maintenance techniques and a review of factory data for an SF_6 gas circuit breaker population. Specifically, we consider events that take the circuit breakers offline when subjected to operating mechanical and electrical loads. It is common for an electric utility system network to consist of a diverse profile of circuit breaker installations. Circuit breakers require some combination of time, condition, and/or reliability based maintenance programs and are often constrained by operating and maintenance (O&M) budgets. Therefore, an asset manager must attempt to optimize expenditures and minimize downtime across a fleet of equipment by making maintenance decisions based on available information. This work helps provide a summary of common maintenance considerations and a format by which such an asset manager could assess a fleet of breakers based on recurrent event data analysis.

SF_6 gas circuit breakers interrupt current with a chamber that extinguishes an arc created during an over voltage event. SF_6 gas circuit breakers can be enclosed in a pressure vessel, referred to as a dead-tank breaker, or open to the atmosphere, referred to as a live-tank circuit breaker. For both breaker types, SF_6 gas is used to insulate the surrounding system when the breaker opens to allow for separation of the contacts. When an arc is exhausted by SF_6 gas pressure, the interruption is referred to as a puffer system.

Circuit breakers have gone through an evolution from the advent of the first oil circuit breaker to today's SF_6 puffer style breaker. Just as new product technologies have evolved, so have maintenance techniques. Maintenance activities have gone from time based external and internal invasive inspections to full scale noninvasive maintenance including procedures such as SF_6 leak detection, thermal imaging, radiography (x-ray), corona recording, etc.

Section II summarizes the published literature related to this work in the public domain, followed by a brief description of the recurrent event data analysis methodology in Section III. Section IV summarizes the computational steps and an example applying the method. Finally, conclusions and potential future work are provided in Section V.

II. Background

A review of the literature illustrates the increased level of awareness of electrical power system operation and the impact of maintenance given the ever increasing usage of electricity globally. (Johal and Mousavi, 2008) discuss the increased visibility of electric power grid maintenance since the 2003 cascading event that occurred in the Northeastern United States. This event re-framed the importance of power system equipment condition and maintenance and re-vitalized a stagnate industry which had not seen high growth rates since the 1970's. The aging fleets of transformers and circuit breakers have been heavily scrutinized as much of the installed base for this type of equipment now exceeds its original design life. (Ma et al., 2007) cited a 2006 U.S. Department of Energy study which states that 70 percent of power transformers are older than 24 years and 60 percent of circuit breakers are over 30 years old. SF_6 circuit breakers now make up a large share of the installed base in the U.S. power grid. As stated by (TJ/H2b Analytical Services Inc., 2010),

> "First introduced in the 1960's, SF_6-filled equipment gained substantial popularity by the 1980's. Today as utility infrastructures are reaching middle age and the number of equipment replacements is growing, oil-filled breakers are being replaced almost exclusively with SF_6-filled equipment. SF_6 now dominates the higher voltage classes, and all indications are that this trend will continue through the lower voltage classes."

Circuit breaker maintenance related activities and life cycle analysis are of great interest to industry because there are great costs and social implications associated with the reliable delivery of electricity. (Parthasarathy, 2004) provides an excellent overview of power circuit breaker theory and (Parathasarathy and Heising, 2004) provide a statistical review of an oil circuit breaker fleet. The premise of maintenance for such equipment has evolved from time based maintenance to condition based maintenance and reliability centered maintenance programs.

Time based maintenance typically involves monthly, quarterly, or yearly activities. According to CIGRE (13.06), the average interval between scheduled overhaul maintenance is 8.3 years with a portion of these overhauls being unsuccessful; 6.1 percent of major failures and 13.7 percent of minor failures are related to such maintenance activities (Janssen et al., 1996). These survey data suggests that maintenance induces a significant number of failures. (Burgin et al., 1994) went on to categorize two types of maintenance-related errors: unnecessary maintenance and failing to perform maintenance when due. For example, SF_6 gas breaker systems are often subjected to contamination during field overhaul maintenance when atmospheric elements are introduced into ASME certified pressure vessel tanks. The focus of this work is on predictive maintenance techniques to avoid such unnecessary introduction of environmental hazards. The objective of predictive maintenance is to extend the maintenance interval by predicting which units should be serviced based on defined criteria. One way to accomplish this is to identify poor performers in a circuit breaker fleet and focus maintenance programs around such units. As noted in the CIGRE (13.06) report conclusions, "…although the number of failures due to incorrect maintenance has decreased [since first enquiry], there is still room for improvement in this area (Janssen et al., 1996)."

(Shoureshi et al., 2003) note that "Transformers, circuit breakers and other substation equipment should be enabled to detect their potential failures and make life expectancy prediction without human interference." They should also be able to provide a simulated predictive maintenance recommendation based on field condition data and maintenance history. This can be done while the equipment is energized and on-line as opposed to most maintenance information acquisition which focuses on de-energized inspections and overhaul maintenance.

(Kayano et al., 2004) note that there are significant differences in maintenance decision making based on interrupter technology and insulating media (e.g., oil, SF_6, air, etc.). In addition, the installation of condition monitors on existing legacy equipment remains a major challenge for data collection and predictive maintenance modeling. The major challenge associated with field installation is the unique dynamics of breaker components such as mechanism type (mechanical, spring, hydraulic, etc.) and insulating material. This makes any field retrofit specific to a given model or style in terms of measurement devices, probes, gauges, and decision logic. Section VI further elaborates on this subject. (Shoureshi et al., 2004) introduce the notion of "self-diagnosing" equipment to determine maintenance actions. (Sheng et al., 2005) support the position of (Kayano et al., 2004) regarding field retrofit of monitors as being economically and time prohibitive and introduce the important issue of selecting a finite number of parameters to monitor to prevent information overload. Mladen Kezunovic's research team at PSERC and Texas A&M University (TAMU) has conducted a great deal of research in the area of automated condition monitoring for circuit breakers. As noted by Natti and Kezunovic, "More research is needed towards relating these individual parameter distributions to the health of the breaker and anticipated condition levels (Natti and Kezunovic, 2007)."

(Snyman and Nel, 1993) note that future work is needed in the area of "…cost effective predictive maintenance on large electro-mechanical power circuit breakers." In the context of this research, recurrent data analysis helps to identify individual or groups of units upon which maintenance decisions should be focused. Previous work includes the development of a condition or health ranking method for transformers (Gao et al., 2009) and ABB Inc. has a proprietary method and process referred to as the Mature Transformer Maintenance Program (MTMP™) as discussed in section III. However, such methods have not been applied to circuit breaker assessment. Recurrent event data analysis techniques have been well documented in texts such as (Nelson, 2003) and (Meeker and Escobar, 1998). The application of such methods to industrial applications, specifically high voltage electrical equipment, has been limited and is of great interest to the industry.

III. Maintenance Profiling and Recurrent Data Analysis

The contemporary maintenance paradigm is based on the concept that activities are shifting from time, to condition, to predictive maintenance. (Natti et al., 2004) provides a good summary of basic maintenance, component replacement, and inspection testing for circuit breakers. Our analysis of field event databases allowed us to determine parameters of interest to aid in monitoring and maintenance decision making. This analysis includes all service and warranty related events for a population of circuit breakers in order to define parameters of interest. (Velasquez et al., 2007) has done some work in this area. The first author of this article worked with scientists, engineers and managers at ABB Inc. to review data and remote condition monitoring technologies relevant to this project. Some work has been done in the area of wireless communication and remote monitoring and SF_6 gas emission reduction by (Willard, 2006). (Schlabbach and Berka, 2001) introduce the concept of an importance index used in reliability centered maintenance. This index could be updated to include a more accurate age representation (by transformer or breaker type & age).

III.A. Maintenance and Fleet Profiling

Circuit breakers are sophisticated electro-mechanical devices and require periodic or other preventative maintenance. Instruction booklets for circuit breakers can be used as a baseline for current maintenance procedures. Historically, circuit breaker maintenance procedures have been time based, meaning that maintenance operations are performed periodically (e.g., check operating gauges weekly, take oil or gas sample monthly, etc.). Manufacturers provide procedures and checklists for visual inspections and more invasive internal inspections. Table 14 is an example of a periodic maintenance schedule found in some product instruction booklets (ABB Inc., 2003 and 1999). Table 14 illustrates the typical minimum maintenance requirements for a unit substation transformer or circuit breaker.

Table 14. Example Recommended Minimum Maintenance Schedule (ABB Inc., 2003 and 1999)

Check Period	One Month After Energization	Once Year After Energization
Gauge Readings	X	X
Tank Leaks		X
Fan Operation		X
Control Wiring & Circuits		X
Paint Finish		X
Dielectric [Insulation] Test		X
Temperature Scan Bushing Terminal & Surface	X	X
Insulator Cleanliness Inspection		X

Because circuit breakers are valuable assets subjected to electrical loading, they require steadfast maintenance. In addition, owners of such equipment usually have large equipment fleets; therefore fleet assessment methodologies have become popular in industry. However, the processes in place to assess electrical equipment have been primarily limited to medium and large power transformers (i.e., those rated above 20MVA). For example, ABB developed a program referred to as the Mature Transformer Management Program ® or MTMP™ (Steigemeier, 2004). There is also a desire to establish such maintenance programs for circuit breaker fleets.

Assessments make use of historical data and condition monitoring data, when available, to review the current state of units in the field (e.g., communication equipped temperature monitor, automatic meter reading (AMR), etc.). These types of apparatus are often referred to as ‘Smart Grid’ technologies and are included in the U.S. Federal Government’s ARRA stimulus package as described in (U.S. Federal Government, 2010) and (EEI, 2009). Today, physical inspections are traditionally used to collect field data while some companies have upgraded to remote monitoring systems or outsourced to third party contractors. One specific example of interest is in remote diagnostic monitoring of circuit breakers (e.g., circuit breaker sentinel) [ABB, 2004] which is an example of an ‘intelligent electronic device (IED)’ being utilized in Smart Grid applications (Wang et al., 2009).

Similar to transformer maintenance, circuit breaker maintenance is also traditionally time based but is more detailed in terms of mechanical and electrical checklists. Circuit breaking devices consist of many components two of which make up the key functional elements of the breaker: the mechanism and the interrupter. The mechanism is the device that trips or closes the breaker and the interrupter is the apparatus that breaks the electrical connection (i.e., interrupts in fault and over current situations). Routine maintenance for circuit breaking devices typically includes the monitoring of various mechanism parameters such as the trending of motor starts using an operation counter with control limits of 20 starts per day (ABB, 2004). The interrupting device has a very detailed maintenance plan which includes condition-based maintenance recommendations in addition to the time based maintenance suggestions (ABB, 2004). Internal inspections and tear-downs can be very expensive and time consuming. Therefore, maintenance techniques using a method such as recurrent data analysis is highly desirable.

Condition based maintenance is gaining popularity in many industrial applications. The ABB instruction booklet recommends an internal inspection be performed after 10 years of service or per Table 15 (ABB, 2004). This table represents the estimated permissible number of operations, relative to current load, before an inspection of the breaker's interrupters and contacts should be performed. Interrupter wear depends largely on current load and frequency. These values are only a guideline to help assess when to perform interrupter maintenance. The interrupter may require less or more maintenance depending upon breaker activity.

Table 15. Recommended Conditional Maintenance (ABB, 2004)

Interrupter Maintenance Table	
Switching Current (kA)	Recommended Number of Operations
Up to 3	2000
5	1000
10	280
20	65
30	30
40	16
50	8
63	4

To fully understand breaker maintenance activities it is useful to profile the models on the electrical network. The typical utility system consists of various breaker models manufactured by multiple third parties over a vast time period. For example, most utilities still have oil circuit breakers in service that are well over their 30 year design life manufactured by a dozen manufacturers. A method to perform such an analysis is provided for a breaker population data consisting of 26 different models. This information is useful in fleet risk profiling.

III.B. Recurrent Event Data Analysis

A recurrent event data analysis was conducted for field incident events for a circuit breaker population. The mean cumulative function (MCF) of this population estimates the average (over the population) cumulative number of field incident event occurrences per unit as a function of time in service based on the event data. The mix of ages of units in this population of circuit breakers is a result of staggered entry; that is some units from this population have been in service for a long period of time, e.g., 12 years, while others have just recently been installed, (e.g., December 2009). Most units are repaired and returned to service (e.g., after a minor event) but in some cases units may need to be replaced (e.g., when there is a catastrophic failure). The event data were sorted by unit ID (or group) and start dates, end dates, and incident dates. The data were also compiled to develop an MCF for each specific model. The population data utilized to estimate the MCFs was obtained from manufacturer databases and represents reported field incident events for the entire production run of a factory that manufactured 26 different models of circuit breakers. The data contain records of all units produced and shipped from 1997 to 2009 and any associated warranty or service claims by unit identification number.

The structure of the data extracted from production and field service databases is shown in Table 16. Both service and warranty events cause an unplanned outage. While events were originally classified as service events or warranty events, for the purposes of this recurrent event analysis both types of events are considered to be the same since either causes an unplanned outage and the warranty period may vary from a standard factory warranty. No distinction is made between the types of event in calculating the MCF.

Table 16. Circuit Breaker Population Data Format Summary

Service Events					
Job #	**Create Date**	**Breaker Type**	**Manufacture Date**	**Problem Area**	**Work Done**
Warranty Events					
Ship Date	W#O#	Report Date	Breaker Type	Description	Main / Sub / Micro Components Defect Type
Shipment History					
Breakers Shipped Total Type/Year	Breaker Line	Year			

The data were then formatted to provide the initial clock-time and end clock-time to determine the in-service time and time to events. Each entry was sorted by unit ID (e.g., serial number) and a start date was established. The time was clocked from ship date to the event including the age at the data freeze time (set as 12.31.2009). Status (indicating whether a record is an end time or failure event time), model number or product family classification, and a count were also established. In this case, the count, required by the JMP software, is zero to indicate an end of observation time or one to denote an event. Table 17 provides a summary of the re-formatted recurrent event data.

Table 17. Circuit Breaker Population Data Recurrent Analysis Format

Unit.ID	Start.Date	Days.to.Event	Age.on.12.31.2009	Status	Model	Count
7JJ2222-JN	8/11/2004	1968	1968	End	E	0
7JJ2222-JP	8/10/2004	1969	1969	End	E	0
7JJ2NP2-JN	4/4/2006	29	1367	Fail	S	1

IV. Computation / Numerical Results / Example

The JMP statistical software was utilized to compute and plot the mean cumulative functions (MCF) and produce event plots of the data for each model and product family (class). A class is a pooled group of units which are manufactured on the same production line, using the same design and manufacturing techniques. Actual model numbers were replaced by a letter A- Z. Figure 4 shows the MCF for all 27 models. There are not a uniform number of units in the population for each production model as each model has a unique number of units in the population based on manufacturing output.

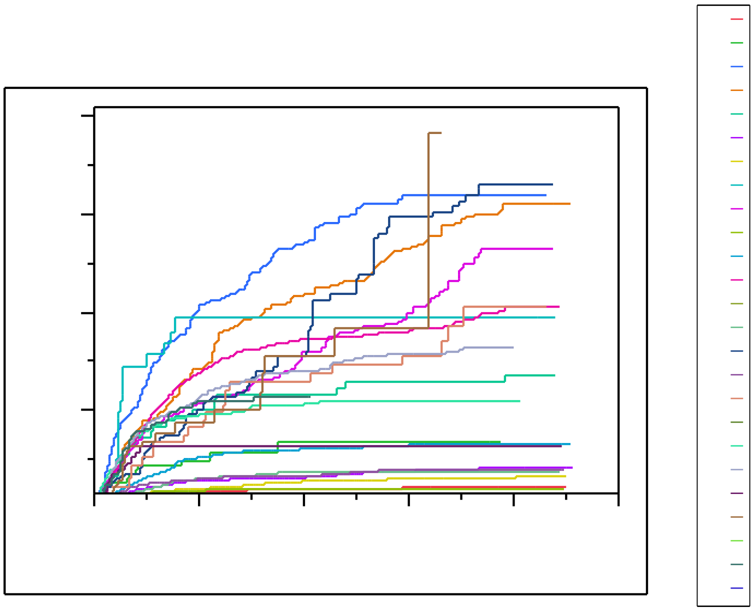

Figure 4. MCF for Each Model based on Days in Service (mean number of recurrences over time)

In analyzing the raw data, one observation is that for most models there is a high rate of field incident events in early life. Such higher-than-usual rates are not uncommon for a newly designed model and the problem or problems causing such events are usually quickly remedied in the field during the commissioning and testing phases. For example, our initial review showed that model G had two units manufactured from 1997-1998 while there were 43 units manufactured from more recent 2007-2009 production years. One hypothesis was that the two units from 1997-1998 may have been prototypes, however, it was later determined that the shift was customer driven. Production shifted from model G in the late 1990's to models D and U from 1998-2007 which are in the same class or product family. In

2007, customer demand for model G grew explaining the shift in production volume of this model during 2007-2009. Table 18 shows the production volume of models G, D, and U from 1997-1998, 1999-2006, and 2007-2009

Table 18. Production of Models G, D, and U

Units Produced	1997-1998	1999-2006	2007-2009
Model G	2	1	43
Model D	25	11	0
Model U	0	522	128

Model Q had a design issue that was quickly remedied, so once this fix was made it was expected that the rate of events would decline significantly. To verify this claim, an event plot for model Q where "days to event" indicates the number of operating days in service as illustrated in Figure 5. The circular markings indicate the event occurrences. One question of interest is when model Q stopped showing signs of problems. Figure 5 illustrates the disparity between the two specific units and the rest of the production fleet. Unit number 7JJJXJR-JP and 7JJJRNR-JP in Figure 5 (indicated with arrows) performed poorly. This is an important finding in terms of validation and verification as it exhibits that the data analysis method matches the real field phenomenon.

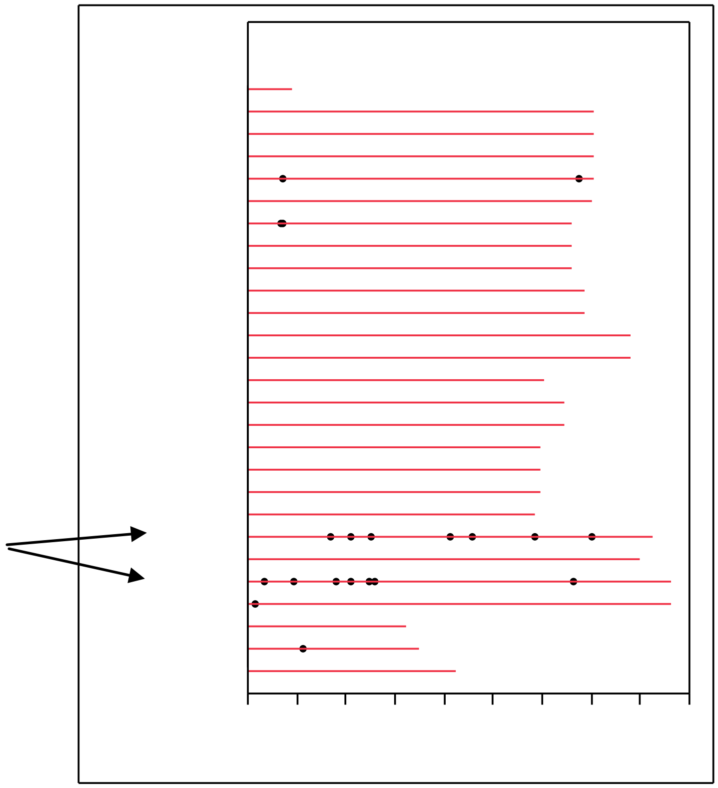

Figure 5. Event Plot for Model Q (Days in Service)

As shown in Table 19, only two of three model Q units that were produced in 1998 (the first production year) accounted for the majority of the incidents. Coincidentally, all of these events occurred in the first year of production which equalizes the amount of time (i.e., events all occurred within one year of shipment). Note that in 1998 there were 17 recorded events (for three units) compared with just four events in 2000, two events in 2005, and no events in all other years. This data set shows two trends: (a) that production of this model declined from a peak in 2000 and (b) that the number of events observed for this model declined following the initial repairs of the 1998 shipments.

Table 19. Production Volume and Events for Model Q from 1998 to 2008

Model Q	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Total
Qty Produced	3	3	10	7	0	0	1	2	0	0	1	27
Events	17	0	4	0	0	0	0	2	0	0	0	23

Another question of interest is how product families (classes) perform in the field. Classes 1, 2, 3, 4, 5 are defined in Table 20 along with the number of events observed from each class, the number of units produced, and the field incident rate (FIR). The FIR is calculated as follows:

$$FIR(\%) = \frac{\sum Number\ of\ Events}{\sum Number\ of\ Units\ Manufactured}$$

Industry relies heavily on FIR and Mean-Time between Failure (MTBF) metrics. However, these FIR calculations can be misleading such as the case where a large part of the FIR was infant mortality, then the relevant comparison would be the slope of the MCF for the average age of the units today (data freeze time). A commonly referenced standard in the electric industry is ANSI / IEEE Standard C57.117 – 1986 which is used by industry to establish Mean Time between Failures (MTBF) values. As noted in (ANSI/IEEE Standard C57.117 – 1986, 1998) “MTBF…[is] considered to be the reciprocal of the failure rate for purposes of estimating reliability.” The inherent problem with FIR and MTBF measures is that they assume event intensity is constant over time which is usually an invalid assumption in industrial application where one encounters infant mortality early in life and wear out later in life of a system. MTBF is often used as a summary measure, but if you compare those summary measures across populations with different exposure amounts the results provide flawed, biased comparisons.

A better measure than field incident rate is defined as Average Field Two-year Recorded Event Rate (AFTRER). This measure gauges the number of events that occur within the first two years of service. The two-year time interval was selected because it captures the standard warranty period; approximately 12 percent of events occurred after two years from the date of shipment. This is rational since all of the units in the data set are less than 13 years old and most events occur within the warranty or burn-in period (typically less than 24 months).

$$AFTRER\,(\%) = \frac{\sum(No.of\ \ Events) - \sum(No.of\ \ Events\,Occuring\ After\,Two\,Years\ of\ \ Age)}{\sum Number\ of\ Units\ Manufactured}$$

From the raw data, it is observed that most events occur with the first year of shipment. This is intuitive for new shipments, but for older units one may expect more incidents to occur after the first year of shipment. This can be partially explained because these are technician or customer reported events (i.e., there is no way to track unreported events). It is also important to keep in mind that these units are designed based on an IEEE/IEC 30 year useful like and the oldest unit in the population is 13 years old. It will be interesting to analyze these data for the same population in 30 years.

Table 20. Product Family, Model Matrix

Class (Product Family)	Models	No. Events	No. Events Occurring after Two Years of Age	No. Units	FIR (percent)	AFTRER (percent)
1	A, J, M, O, X, Z	268	0	2257	11.87	11.87
2	B, E, F, I, N, Q, Y	1361	21	7410	18.37	18.08
3	C, K, P, S, V	964	13	3956	24.37	24.04
4	D, G, U	490	2	1222	40.10	39.93
5	L, T, W	650	9	1443	45.05	44.42

Figure 6 is a MCF plot for each class. Note that rates (slopes) stabilize after approximately three years and that this stabilized rate appears to be highly dependent on the early rate (e.g., the FIR in the first three years of service).

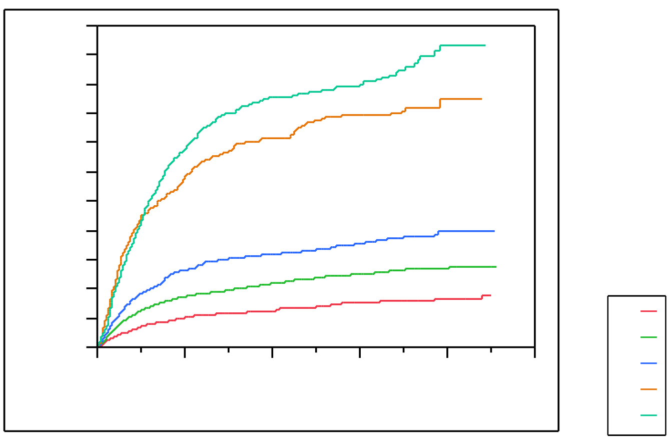

Figure 6. MCF Expected Number of Recurrences over time (by breaker class 1-5)

It should be noted that the metrics calculated in this work are a factor of service or warranty related issues and do not indicate the magnitude or the cost of failure. As network architecture and systems get more complicated the number of incidents increase. The data include user induced mis-operations; therefore the metrics are not a true representation of circuit breaker performance, but rather an estimation of time between events for specific models or classes.

A third question relates to production year impact. For instance, what if model K were sliced and separated into various production years? Model K is a popular model in terms of the size of the installed base (i.e., there are a large number of this model in the field) and model K has performed well in the field. Because there is a large amount of data the MCF confidence intervals are narrow. Model M is part of the same family as models J, X and Z which are rarely produced models.

To answer this question, the events that occur were divided by the total number of units shipped from each given year. Table 21 and Figure 7 contain the results from this analysis. The number of incidents reported by year (e.g., 4 incidents for 1997 shipped models) is divided by the total number of units shipped per year, e.g., 23 units in 1997, to determine a FIR measure. AFTRER is also provided although it is observed that only 2001 and 2003 had incidents which occurred past two years of service.

Table 21. Events per year and FIR for model K population shipped in a given year

Model K				
Year	Events by year manufactured	Number of Units Shipped by year	FIR	AFTRER
1997	4	23	17.4%	17.4%
1998	13	93	14.0%	14.0%
1999	26	86	30.2%	30.2%
2000	61	121	50.4%	50.4%
2001	99	214	46.3%	**43.9%**
2002	92	284	32.4%	32.4%
2003	29	159	18.2%	**17.6%**
2004	29	116	25.0%	25.0%
2005	32	90	35.6%	35.6%
2006	18	101	17.8%	17.8%
2007	15	55	27.3%	27.3%
2008	15	73	20.5%	20.5%
2009	4	78	5.1%	5.1%

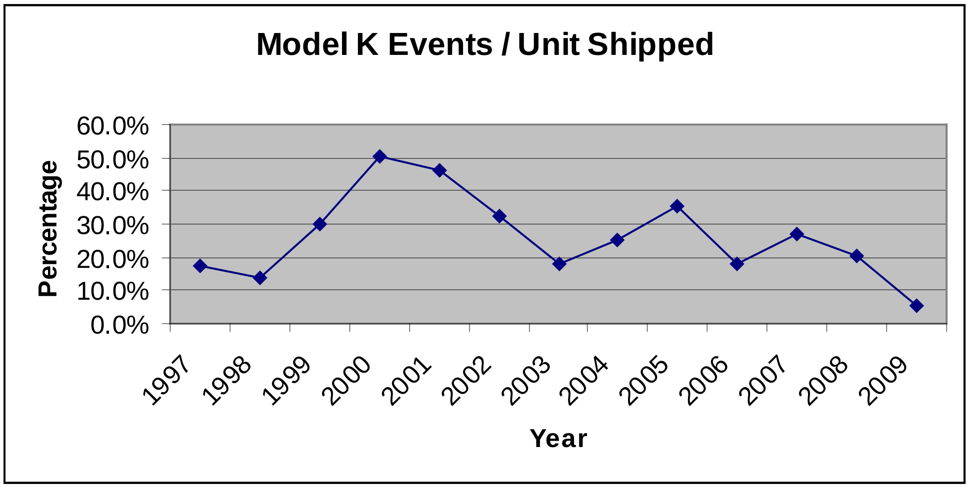

Figure 7. Field incident rate (FIR) for Model K (1997-2009)

To validate these results, the MCF for each model K production year was generated as shown in Figure 8. The likelihood of encountering an event as a function of time is highest in units produced during the 2000 and 2001 production years. Note that values during the period 2008 to 2009 are biased because they have not been in service for more than two years. The MCF plots closely correspond to the FIR and AFTRER calculations for this specific example.

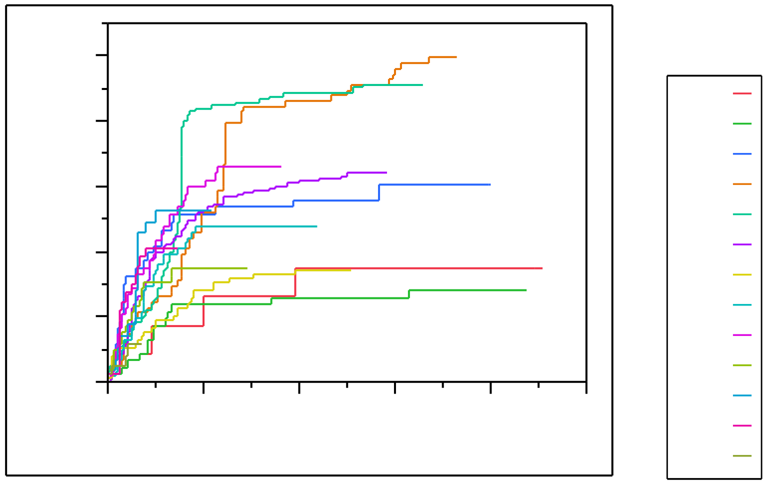

Figure 8. Model K MCF by year

To put the number of events in perspective, the estimated average number of years from start to service event is 6.94 years and the average number of years from start to warranty event is 1.66 years. Typically warranty events would be minor repairs.

V. Conclusions and Future Work

In this paper, various maintenance techniques have been reviewed and an insightful recurrent data analysis for circuit breaker population data is provided. This type of information is very useful in establishing predictive maintenance programs across a large network or fleet of equipment as it aids in identifying poor performing classes and units.

The cost of events was not included in our analyses. If the actual repair costs were available for each event the MCF could be computed to report the mean cumulative cost per unit for different types of events (e.g., minor vs. major events). This could be accomplished by either determining actual costs from field service records or estimating the costs of each incident type by using a typical or average repair cost depending on the type of repair.

Recurrent event data analysis could be used to determine the MCF for fleet equipment fleets to provide a snapshot into actual performance of circuit breakers or transformers on a specific electrical network. Event rates depend on explanatory variables and if such explanatory variables were in the database, a better, more predictive model could be used. For instance, 1000 operations under low loading conditions could be equivalent to a relatively small number of high-fault interruptions in terms of maintenance and time to next event estimation (see Table 15). This would allow for prediction of failure events for specific units based on operating conditions and could also allow for comparison and benchmarking across electric utilities. As more utilities install circuit breaker condition monitors, more data sets will provide this type of analysis. (Hong et al., 2009) note similar future work to improve predictions of remaining life for individual transformers.

As noted in section II, there remains much work to be done in terms of the installation and retro-fitting of breakers with conditions monitors. The methods outlined above could be extended to condition monitoring data once such information is readily accessible.

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VII. Authors' Biographies & Acknowledgements

Daniel Bumblauskas is an Assistant Teaching Professor of Management at the University of Missouri – Columbia and has been employed-by or affiliated with ABB Inc. since 2003. His most recent role with ABB was as a Group North American Account and Marketing Manager for the Power Products Division Transformer Business Unit. Prior to this Dan was with ABB High Voltage Products circuit breaker service and ABB utility front end sales organizations. Before joining ABB, Dan was with the sears.com web center team as a communication and product specialist. Dan is a Ph D candidate in the department of Industrial and Manufacturing Systems Engineering at Iowa State University, Ames, Iowa, where he has been conferred B.S. and M.S. degrees in Industrial Engineering. Dan is also a masters degree candidate at Harvard University, Cambridge, Massachusetts, in general management. Dan is a senior member of IIE, a member of IEEE, and has received numerous academic awards and honors.

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Douglas D. Gemmill is an Associate Professor of Industrial Engineering at Iowa State University. He received a B.S. in mathematics and an M.S. in industrial engineering from Iowa State University. He received his Ph.D. in industrial engineering from the University of Wisconsin - Madison. His professional interests include simulation modeling, systems engineering, applied operations research and the modeling, design, and performance analysis of complex systems. He is Director of Graduate Education for Iowa State's masters in systems engineering program. He is a member of the International Council on Systems Engineering, American Society of Engineering Education, and a senior member of the Institute of Industrial Engineers. He has also spent over 25 years as an officer in the United States Air Force, both active duty and as a reservist.

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CHAPTER 4. SMART MAINTENANCE DECISION SUPPORT SYSTEMS (SMDSS): APPLICATION OF AN ANALYTICAL HIERARCHY PROCESS (AHP) MODEL INTEGRATED WITH A MAKRETING INFORMATION SYSTEM (MKIS)

A paper submitted to *MIS Quarterly*

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Abstract

This paper investigates the prioritization of maintenance for a fleet of electrical equipment, specifically circuit breakers, in an electric power system. The most common failure modes are documented in terms of events taking a breaker offline. These factors (parameters) are established based on industry data, defined, and compared to those considered in previous studies. Saaty's Analytical Hierarchy Process (AHP) is used to prioritize the order in which maintenance is performed on a fleet of SF_6 gas filled circuit breakers. An example of a small circuit breaker fleet is used to establish maintenance priority for breakers in the sample network. The AHP model is integrated with a Marketing Information System (MkIS) for use in engineered-to-order product manufacturing sector. The combined system is defined as a Smart Maintenance Decision Support System (SMDSS).

The SMDSS has been developed using conventional maintenance modeling and decision support system algorithms and is integrated with an MkIS to provide maintenance service offerings (quotations) for maintenance solution output. The SMDSS input consists of output from two analytical models: a dependent component model (DCM) and a circuit breaker fleet prioritization maintenance AHP model. To validate the system, the model outputs are reviewed and a sample quotation is provided based on the logic of the combined application.

Keywords: Circuit breaker, Electrical power system maintenance, Intelligent maintenance decision system, expert system

Smart Maintenance Decision Support System (SMDSS): Application of an Analytical Hierarchy Process (AHP) Model Integrated with a Marketing Information System (MkIS)

I. INTRODUCTION

This paper develops the framework for a *Smart Maintenance Decision Support System* (SMDSS) and expands upon previous work in the area of systems and requirements engineering as it relates to intelligent maintenance decision systems, decision support systems (DSS), and marketing information systems (MkIS). This particular application is for a system to quote high voltage circuit breaker parts and services for modeled maintenance actions. The maintenance outcomes are based upon previous work in modeling dependent component systems (DCM) and new work examining fleet prioritization by applying the analytical hierarchy process (AHP) algorithm. This work examines the integration of various systems with two analytical decision models developed and applied to the circuit breaker maintenance problem.

Business systems, such as the proposed SMDSS, are very useful in the preparation and tracking of documentation such as quotations, purchase orders, and invoices which have become critically important since the Sarbanes-Oxley Act of 2002. The motivation for this work is the prospect of a system able to *predict* the recommended maintenance action(s) to be performed on a piece of equipment and provide real-time pricing information and service availability. There is a desire in industry to establish maintenance programs for equipment fleets such as small power and distribution transformers, circuit breakers, industrial manufacturing equipment, etc. Maintenance decision making in power system planning is of extreme importance to energy providers and users; the assets making up the U.S. power system are valued at roughly $300B USD per (McCalley et al., 2006). Most of the previous work in this area has focused on isolated single component parallel systems, i.e., a transformer or a breaker, and not on dependent series network systems with multiple components and integrated system architectures.

II. BACKGROUND

The research questions to be answered are (1) how to prioritize which breakers to perform maintenance upon and (2) how to develop a system in which a user could input usage parameters for inter-connected pieces of equipment and receive a comprehensive proposal for service to fulfill the recommendations generated by an analytical model. This includes how to analyze and parametrically assess common equipment failure modes. This system can make use of remote condition monitoring information eliminating the need for a user to manually enter usage parameters. For example, a typical 'technical sales' process to establish a proposal for equipment maintenance may be as follows (time scale is in weeks or months):

1. Owner (e.g., utility, industrial entity, building manager, etc.) needs to decide on maintenance program for equipment
2. Contact manufacturer or service provider for maintenance recommendation
    a. Conduct on-site service inspection(s)

b. Remote assessment of equipment

3. Manufacturer or service provider report's findings
4. Owner prepares specification
5. Specification solicited to vendors for proposals
6. Vendors establish requirements to prepare proposal
7. Vendors submit proposals for parts and service
8. Owner reviews proposal

An alternative system could be defined as follows (time scale is now in days):

1. Owner to decide on maintenance program for equipment
2. Owner inputs parameters in analytical model for multiple units
    a. Or uploaded from remote condition monitors
3. Proposal is generated
4. Owner reviews proposal

The contribution of this work is in establishing parameters to be monitored, applying a method to establish maintenance prioritization, and creating a framework for an SMDSS. The traditional output from a typical analytical maintenance model may be to perform preventative maintenance (PM) on unit X or replace unit Y. The SMDSS would expand this by utilizing the model recommendations to populate a work scope specification, generate a set of requirements, and produce a proposal to fulfill such requirements. The system makes use of the equipment owner's inputs and generates the end deliverable; the quotation.

There is limited publicly available information related to maintenance and marketing information systems for highly engineered products in global organizations. This is partially because many systems are 'homegrown' and developed internally or are purchased from third party software vendors typically as part of an ERP module (e.g., SAP). Detailed requirements and specifications for such systems generally do not exist in a disclosed form. One exception to this is the U.S. Army Business Transformation Knowledge Center (U.S. Army, 2010).

A review was conducted of related work within ABB Inc. and other organizations. Research on marketing information systems (MkIS) gained notoriety in the mid-to-late 1990's and tapered off when many of the 'dot-com' start-ups began to collapse in the late 90's and early 2000's. A more recent review showed that many of the MkIS modules installed over this time period have already been replaced by customer relationship management (CRM) systems (Wilson and McDonald, 2003). There are various types of CRM systems typically tailored to the needs of the specific organization. The type of MkIS or CRM systems of interest can be classified as those used for "collection and analysis of customer data (its internal use) rather than as a builder of relationships with customers (its external role) (Valos et al., 2007)."

The specific type of MkIS or CRM of interest in this research is the creation of a marketing expert system (ES) which utilizes knowledge and decision making of field experts to drive marketing decisions and their corresponding support systems (Wagner and Zubey, 2006). Issues exist in developing marketing expert systems including "…the understanding of the features of marketing planning, the identification of users' requirements, knowledge elicitation and representation, the integration of ESs and DSSs [Decision Support System], and the user interface design," and often time such issues create a need to develop "hybrid systems" such as the SMDSS/MkIS framework (Duan and Burrell, 1997). It has been reported that as much as 70 percent of these projects "fail to meet their objectives," which further illustrates the uniqueness and complexity exhibited in creating such systems (Wilson and McDonald, 2002). As recently as 2008, it was acknowledged that there has been very little research in the area of electric grid related market information systems related to the purchase and sale of electricity (Brunner et al., 2008). The same holds true for the maintenance of the equipment which comprises the electrical grid.

Most of the maintenance literature in the field of industrial and systems engineering is related to the development of Markov Decision Process (MDP) models and not further development of systems around such analytical models. There are sources that support the assertion that maintenance programs can make use of analytical models to form decision actions [systems]. In electrical engineering applications, much of the literature is focused on computer based facilities preventative maintenance programs in particular industries and not on SMDSS type systems for the electrical equipment industry. Some early examples include maintenance systems for a cement plant (Ehinger, 1984), nuclear generation plants (Kozusko, 1986), and gas insulated substations [Yamagiwa, 1991; Utsumi, 1993). More recent literature (2007-2009) focuses on the use of sensors to help assist with preventive maintenance programs (Ramamurthy, 2007). The primary difference between these studies is that they are ***preventive*** in nature as opposed to the proposed SMDSS which is ***predictive*** in nature by utilizing an analytical model.

The primary literature which exists related to maintenance decision systems are classified under the research umbrella of Decision Support Systems (DSS). This all encompassing area of study includes fields such as facilities management, manufacturing, finance, and marketing. In the area of computer maintenance, there is a field known as Maintenance Assistance Capability for Software (MACS) which attempts to use maintenance decision logic for software applications (Georges, 1992; Desclaux, 1992). In systems engineering, the terminology 'knowledge management' is often used for systems which would be able to assist in providing some form of intellectual capital which in the case of an SMDSS would be the ability to predict maintenance decision actions (Rasovska, 2008).

As recently as 2004, it has been noted that there are significant deficiencies in the ability of common ERP software platforms to incorporate maintenance planning tools, such as the proposed SMDSS (Fernandez, 2003). In 2005, researchers proposed that a system, such as an SMDSS, should be developed to aid in maintenance decision making (Noori and Salimi, 2005). In 2000, researchers attempted to outline some common approaches and methods to develop integrated marketing management support systems (MMSS) (Wierenga and Van Bruggen, 2000). There has been much academic and commercial interest in the development of an SMDSS system for large engineered-to-order equipment manufacturers.

The lack of publicly available literature dedicated to ERP marketing and maintenance modules, the complexity of developing such highly integrated systems, and the need for maintenance models and software applications in the electric power industry indicate that there is a need for an SMDSS system. In the case of the electric power industry there are a wide variety of commercially available software packages with various functional capabilities. A review of commercially available software packages showed that SMDSS functionality does not exist in these applications.

II.A. Commercial Software Packages

An analysis was conducted to compare and contrast the SMDSS system to commercially available products. The most common terminologies in the industry for commercial software packages are Energy Management Systems (EMS) and Distribution Management Systems (DMS). EMS and DMS systems typically include a maintenance tracking application that contains nameplate data and critical operating conditions and events for circuit breakers on a power system. Some of the systems reviewed include IBM Maximo, Cascade, ABB Asset Sentry, Passport by Indus, and Power Delivery IQ. The findings from this review were that analytical models and methods such as dependent component modeling, AHP modeling, and recurrent event data analysis, could be used as modules in such systems to provide a modeled predictive maintenance solution. Such modules do not exist today; systems like IBM Maximo and Cascade act as ERP systems and are typically used for work order management (e.g., parts, labor, and equipment allocations), scheduling, and accounting business functions. Maintenance activities are primarily limited to data warehousing of preventative maintenance data and some condition monitoring data. There is very little to no non-operational maintenance data and a goal of future work for such systems is to incorporate condition-based maintenance modules in the software packages (IBM, 2007).

Condition monitors provide real-time data capture of circuit breaker operating parameters and have gained notoriety over the past decade. The ABB Circuit Breaker Sentential (CBS), CBS Mini, and CBS Lite all provide on-line diagnostic condition monitoring which can be used to collect data on various parameters. The area of monitoring has been well researched by Dr. Kezunovic's research team at Texas A&M's Power Systems Engineering Research Center (PSERC). For example, Cooper Power System's Cannon Technologies has a Visual Asset Monitoring System used to collect and send data to remote users (Cooper Industries, 2010). They provide real-time monitoring of some circuit breaker parameters but do not provide maintenance decision actions, predictive maintenance recommendations, dependent component interactions, or service proposals for such activities. Another example, TJ/H_2b Analytical Services, Inc. provides laboratory and consulting services for condition-based maintenance programs (TJ/H2b Analytical Services, 2010). The area of interest for this research is with regard to SF_6 gas testing and services. They will review oil and gas samples and internal inspection data. Based on this information they will provide recommended maintenance suggestions, as will most any circuit breaker manufacturer, but they do not consider predictive solutions, dependent component interactions or automated service proposals. A final example, DigitalGrid, Inc. provides power line carrier (PLC) installations for network protectors and transformers which transmit and receive condition data (Digital Grid, 2010). Having completed many installations at utilities across North America, they do not have any circuit breaker monitor installations.

III. SYSTEM COMPONENTS

A layered mapping of the SMDSS framework of integrated systems is proposed. The layered system consists of the dependent component model (DCM), an analytical hierarchy process model (AHP), an expert system (ES) or knowledge base, a full cost model (FCM) and a marketing information system (MkIS). This unique layered system has the following structure:

Layered system (SMDSS) = DCM + AHP + MkIS + ES + FCM

The system process map can be summarized as follows:

- DCM provides output in terms of a maintenance decision policy [actions] for a specific unit of interest
- AHP provides output in terms of a maintenance priority for fleet of breakers
- DCM and AHP generate requirements for the ES and FCM
- ES utilizes a keyword search of database for bill-of-material (BOM), equipment and labor requirements
- BOM part numbers from ES are loaded to the MkIS quote system
- BOM equipment and labor from FCM are loaded to the MkIS quote system
- MkIS output is a maintenance quotation based on the DCM and AHP

Today this is primarily a manual process with some automated improvements having been made. This smart maintenance decision support system (SMDSS) is a novel concept which could be incorporated into commercial products (e.g., Maximo, Cascade, ABB Asset Sentry) to provide a predictive maintenance program for equipment. This could also be scaled to include industrial factory equipment.

III.A. Dependent Component Model (DCM)

Much reliability and maintenance research focuses on maintenance decision making for discrete components, such as a single piece of equipment, or system wide resource allocation, such as operations and maintenance (O&M) scheduling or budgeting. In system network architectures, components are often linked together which creates the potential for series component dependency. Dependent components are two or more items which are connected in a network, whereby the condition of one or more items can impact the performance, or condition, of other dependent component(s). While these dependency considerations are mentioned in some existing literature, there are notable gaps in the models that attempt to incorporate such considerations. In order to address this, an analytical model has been developed to help provide maintenance decision actions for dependent components. This topic is explored in greater depth in previous work (Bumblauskas and Ryan, 2010).

Since component dependency has not been comprehensively studied, the majority of work related to providing products and services has also been focused on discrete, individual, components. In order to provide more comprehensive maintenance service a solution must consider a network as a group of inter-connected pieces of equipment which interact with one another. This type of systems based approach has not been implemented in maintenance programs for industrial equipment which must be extensively maintained in order to operate electrical generation sites and industrial facilities. Service providers give quotations for parts and field service to keep such equipment in good working condition. However, such systems rely on human experts and manual preparation of documents and bid materials. While there has been research related to capturing human expert knowledge in a computer application or system, there has not been research in the automatic generation of service proposals from predictive maintenance decision models for dependent component networks.

The user inputs required for the DCM are historical failure event data, failure probabilities, repair times, and repair costs. After running the DCM algorithms, the primary output of interest for the SMDSS is the optimal decision policy for the dependent component system which includes actions such as no action, minor maintenance, major maintenance, or replacement decisions. This recommended maintenance action policy is used to generate the required parts bill-of-material, labor, and equipment requirements.

III.B. Parameter Selection

An analysis of breaker population data provides insight to allow for the identification of the most common failure mode parameters, i.e., those parameters which should be closely monitored. Usage parameters for breakers and transformers are the key component to analyzing equipment condition or developing any sort of maintenance service model. For a circuit breaker, such considerations include the insulation [gas] purity, any faults experienced, operating currents, etc. while for a transformer the degradation of the cellulose insulating paper, fluid purity, temperature rise conditions, etc. are important. (Natti et al., 2005) defined these parameters of interest as the mechanism, contacts, and oil condition and (Velasquez et al., 2007) recommended monitoring the parameters listed in Table 22.

Table 22. Circuit Breaker Parameters of Interest by (Velasquez et al., 2007)

mechanism, interrupter	Number of operations
Interrupter	Contact wear Based on accumulated interruption energy and number of operations
mechanism	Mechanism state
external devices	Line voltage (voltage transformer)
external devices	Load current (current transformer)
external devices	Switch open or closed (aux. contacts) Determine operating time from aux. contacts

Using industry population data [24, 27], eight criteria were selected based on the number of incidents reported. These are the most frequent causes of field incidents and were evaluated using a Pareto analysis of the population data. The data was collected from industry field service databases and reviewed by subject matter experts. The parameters to be monitored are given in Table 23. The parameters are not represented in any particular order (i.e., tank / casting is not necessarily the fourth most common failure mode) and would be weighted by an electric utility based on their experience with their specific fleet of equipment. Here pw_n denotes the parameter weight given to each factor.

Table 23. Parameters to be monitored (*pw*)

Eight Factors / Criteria		pw_n
1	cabinet	pw_1
2	mechanism	pw_2
3	external devices / field assembly	pw_3
4	tank / casting	pw_4
5	interrupter	pw_5
6	bushing	pw_6
7	tool kits	pw_7
8	Frame / Support	pw_8

By focusing on the parameters in Table 24, the objective of establishing parameters to monitor for a predictive maintenance program has now been defined. These parameters are then utilized in the next step of the model which is the fleet prioritization maintenance model.

III.C. Fleet Prioritization Model using AHP

In reviewing prioritization algorithms used in industrial applications, the most prevalently referenced method is the Analytical Hierarchy Process (AHP) developed by Dr. Thomas Saaty (Saaty, 1983). This prioritization method is applied in the following sections to a fleet of circuit breakers. Most of the case studies using AHP have been applied to generators and fuzzy AHP methods seem to be the most commonly applied (Srividya et al., 2007). While there is some work in the area of AHP in power plant maintenance, none deal directly with circuit breaker or transformer maintenance. The AHP algorithm was selected as the basis for this case application since it is the most commonly used prioritization method for electrical equipment maintenance applications, such as generators.

The goal of the AHP model is to determine the optimal maintenance and asset utilization priority for a set of alternatives, in this case a fleet of circuit breakers. Using valuations from an industry subject matter expert, a comparative judgment or pairwise comparison matrix was generated as shown in Table 24. For example, when comparing the importance of mechanism (element 2) to tank (element 4) a value of 5.0 was given indicating that the mechanism (element 2) has priority over the tank (element 4). Note that the matrix as established in this paper is subjective; a more objective weighting could be accomplished using remote condition monitoring history data to help value the importance of each factor compared to one another. Here we are calculating a priority vector (PV) to establish the weighting or priority of each parameter. A consistency ratio (CR) measures whether or not the assignment of values during the pairwise comparison is consistent. CR should be less than or equal to 0.2 (Saaty, 1983). It may take several iterations to pass this consistency test due to the subjective nature of the valuation process. We also assume that the elements are independent.

Table 24. Comparative Judgment (CJ) Matrix

	1	2	3	4	5	6	7	8	RP	PV
1. Cabinet	1.00	3.00	3.00	5.00	7.00	7.00	7.00	9.00	4.39	0.364
2. Mechanism	0.33	1.00	1.00	5.00	5.00	5.00	7.00	9.00	2.68	0.221
3. E.D. / F.A.	0.33	1.00	1.00	3.00	5.00	3.00	5.00	5.00	2.10	0.174
4. Tank	0.20	0.20	0.33	1.00	3.00	3.00	3.00	5.00	1.08	0.089
5. Interrupter	0.14	0.20	0.20	0.33	1.00	1.00	3.00	3.00	0.60	0.050
6. Bushing	0.14	0.20	0.33	0.33	1.00	1.00	1.00	3.00	0.56	0.046
7. Tool Kits	0.14	0.14	0.20	0.33	0.33	1.00	1.00	1.00	0.38	0.032
8. Frame	0.11	0.11	0.20	0.20	0.33	0.33	1.00	1.00	0.29	0.024
sum	2.41	5.85	6.27	15.20	22.67	21.33	28.00	36.00	12.08	1.000
(sum)(PV)	0.875	1.297	1.088	1.354	1.129	0.987	0.886	0.874	8.490	λ_{max}
									0.070	CI
									0.050	CR

Next, element matrices are established for each of the eight parameters being compared. For example, element one is the cabinet and the question to be asked is which cabinet is in the worst condition in the fleet being considered. In this example, we consider a three breaker network Table 25 illustrates the element matrix development process. This element matrix would need to be processed each time the breaker fleet changes in scope or scale, a state degradation occurs, or a new quotation is required.

Table 25. Element Matrix for Cabinet

Parameter 1	Cabinet - which one is in worst condition?					
	B1	B2	B3	RP	PV_n	
Breaker 1	1.000	5.000	7.000	3.271	0.731	PV_1
Breaker 2	0.200	1.000	3.000	0.843	0.188	PV_2
Breaker 3	0.143	0.333	1.000	0.362	0.081	PV_3
sum	1.343	6.333	11.000	4.477	1	
(sum)(PV)	0.981	1.193	0.891	3.065	λ_{max}	
				0.032	CI	
				0.056	CR	

The priority vector (PV) denotes the score for each breaker for the element of interest, e.g., cabinet. The same procedure is followed for all identified parameters in Table 23 and next a principle of composition of priorities is calculated as shown in Table 26. As with the element matrix in Table 25, this matrix is subject to dynamic changes based on the network or system architecture being analyzed.

Table 26. Principle of Composition of Priorities

	1	2	3	4	5	6	7	8	weighted average
PV of Table 24	0.364	0.221	0.174	0.089	0.050	0.046	0.032	0.024	
Breaker 1	0.731	0.567	0.672	0.785	0.685	0.087	0.105	0.053	0.621
Breaker 2	0.188	0.323	0.257	0.149	0.234	0.149	0.258	0.257	0.231
Breaker 3	0.081	0.110	0.070	0.066	0.080	0.764	0.637	0.690	0.148

Based on this AHP algorithm, it is recommended that maintenance first be performed on breaker 1, followed by breaker 2, and finally breaker 3.

III.D. MkIS System

In previous research work, the requirements and specifications for a marketing information system (MkIS) developed for a highly engineered parts and service organization were accurately defined and a software program was developed for use in industry (Bumblauskas, 2006). This was done using the problem frames modeling language developed by (Jackson, 1995). The developed framework and specification for high voltage products parts and service module for the ABB Common Configurator Platform (CCP) is used as a marketing information system (MkIS) to track negotiations and quote projects. Since the completion of this research component, process flow logic for the parts and a service quotation system were developed and requirement checklists were created. A requirements checklist is shown in Table 27.

Table 27. Requirements Checklist

Description	Example
Type of service	Replacement parts, commissioning, installation, repair, upgrade, etc.
Request for quotation (RFQ) process	Sales / distribution channel flow
Customer inputs	Serial number(s), part ID(s), condition monitor data, etc.
Factory user inputs	Cost model entries for labor, equipment, and parts
Configuration inputs	Work scope and bill-of-materials
System outputs	Quote letter, parts lists, drawings
System exchange logic	ERP system, quote system, order system, quality system
Breaker service classifications	Materials only, technical assistance/oversight, turnkey service, etc.

A product catalog consisting of nearly 40,000 line items was created to populate a parts database for use by the CCP system and is in use today. A final quotation letter was developed based on user feedback. The ABB CCP parts configurator module allows the customer or user to enter part numbers and retrieve item specific information from a database. The SMDSS tool will make use of the existing parts catalog for material requirements and the existing full cost model for labor and equipment requirements.

III.E. Expert System

A typical expert system makes use of logic by programming around a knowledge base or the experience of subject matter experts. In the case of the circuit breaker expert system, an information repository was built for maintenance decision making to include instruction books, spare part lists, drawings, bills of material, common field repairs, etc. as provided by industry consultants. This system can be utilized to locate various requirements based on the breaker serial number. This system has already been developed but is not being fully utilized in the manual quotation process and is not being utilized at all in the automated quotation process.

III.F. Full Cost Model (FCM)

The full cost model is a proprietary ABB Inc. tool used to establish costs for items such as labor, equipment, materials, permitting, insurance, etc. It can be populated by elements from the aforementioned expert systems to provide a comprehensive bill of material, cost, and quotation price for field services. This tool utilizes input cost considerations and provides a financial calculation based upon the requirements and risk involved in the project. The user can then determine the fiscal impact of the project.

IV. SMART MAINTENANCE DECISION SUPPORY SYSTEM (SMDSS)

The SMDSS makes use of the output from the analytical models to develop a proposal for maintenance service. The SMDSS starts by utilizing the user data as input to the dependent component model which provides a predictive maintenance plan. The recommended maintenance plan populates the Marketing Management Support System (MMSS) (Wierenga and Van Bruggen, 2000) which in this case is the ABB Common Configurator Platform (CCP) and ABB Business Intelligence Portal (BIP) applications. The CCP application's built-in configurators generate a parts and service proposal based on the maintenance plan. The methodology and initial results are detailed below. Figure 9 shows an example of the SMDSS framework.

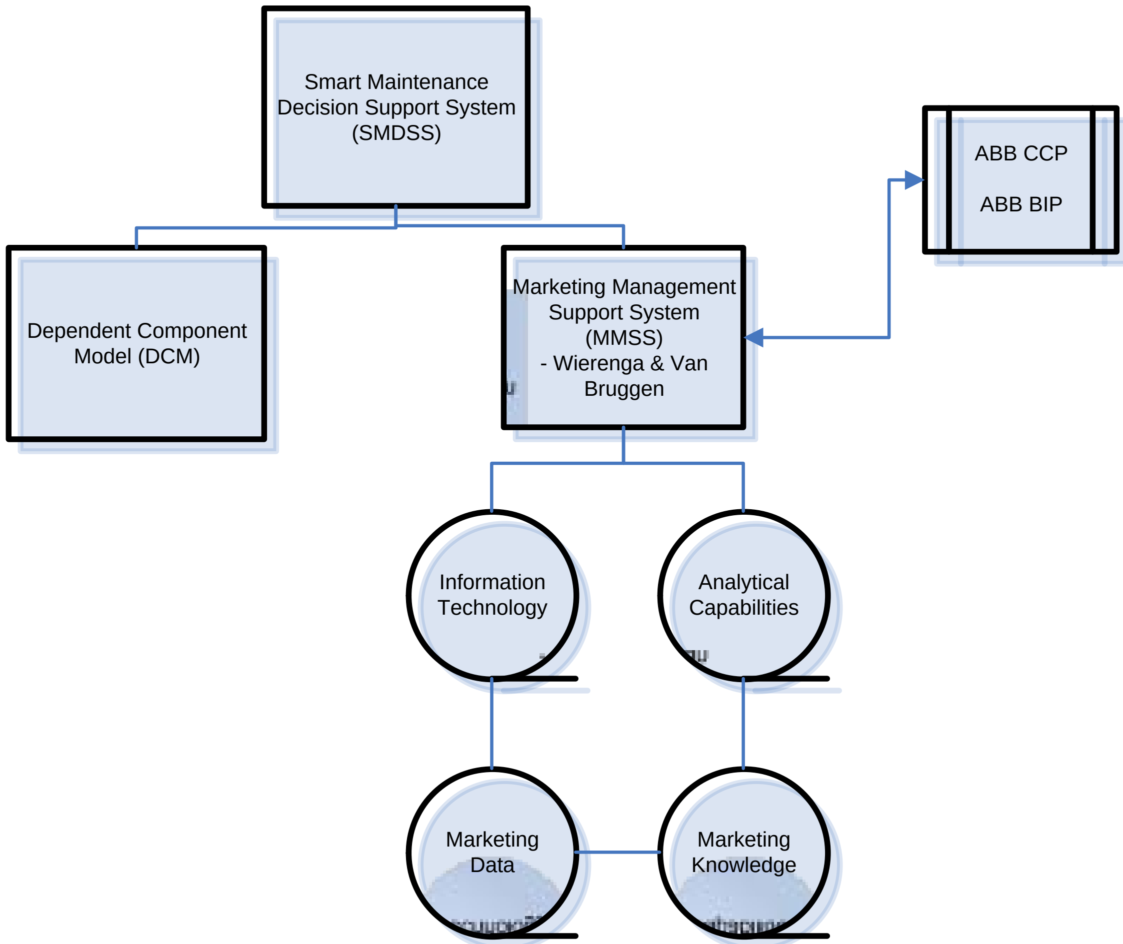

Figure 9. Schematic of SMDSS

IV.A. Methodology

In order to accomplish the desired research objectives, a framework is defined to integrate (1) the analytical dependent component model (DCM) which provides an optimal maintenance decision policy for a component in an electrical power system with (2) the fleet prioritization model which evaluates the order in which to perform maintenance on a breaker fleet and (3) a marketing information system (MkIS) to provide pricing for products and services that fulfill the recommended maintenance actions output by the models. For example, if a certain maintenance action is provided as output by the DCM, a quotation could be generated by the MkIS for the recommended parts and services. From this quotation, additional marketing and accounting functions can also be administered. This type of work is very practical and relevant to wide array of organizations and industries.

The first analytical maintenance decision model was developed for circuit breaker maintenance actions with optimal decision policies based on user input data and a dependent component, in this case a transformer. By using the output from the analytical dependent component model (DCM) and using the MkIS a user can generate a bill-of-material for parts, estimate field service labor & equipment, establish a field service schedule & outage duration plan, and provide a quotation for such services. The marketing information system (MkIS) is the ABB CCP application which is used to quote parts and field services.

The SMDSS utilizes input data from user input or remote monitoring communication protocol for analysis by the system. The data is evaluated using an algorithm to determine the optimal maintenance decision policy using the analytical maintenance decision models to provide predictive recommendations for maintenance. Using this recommendation, the SMDSS accesses an ERP bill of material (BOM) for the equipment and a database which contains parts, labor, and equipment content. The maintenance solution has pre-defined requirements for labor, equipment, and materials. The output will be in the form of a quotation which is generated using these pre-defined requirements. Figure 10 is a flow chart for this process.

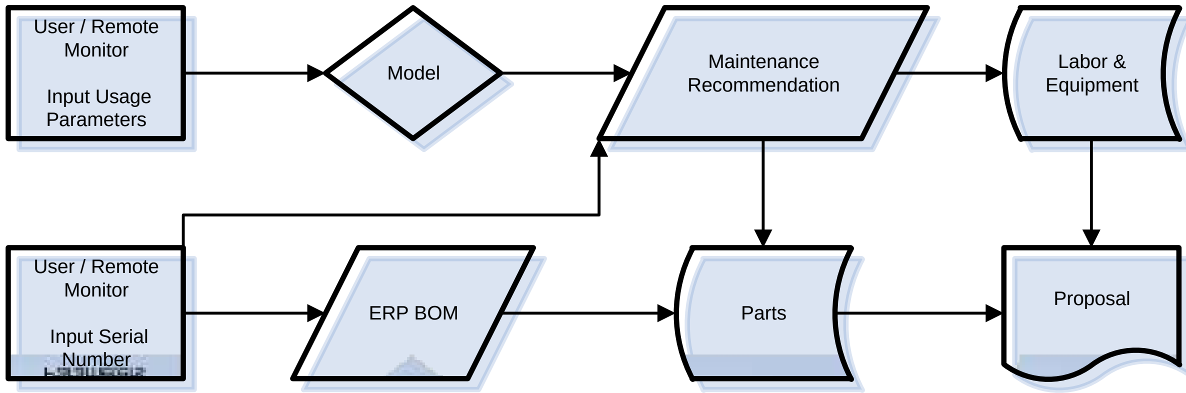

Figure 10. SMDSS Process Flowchart

Using the quotation system specified in previous research, and later implemented, a proposal would be generated in a format similar to the quotation letter shown in Appendix A.

IV.B. SMDSS Process

Here is a general example of how these systems can be integrated to form a commercially viable predictive circuit breaker unit and fleet assessment maintenance program:

1) breaker owner completes data sheet(s) – i.e., user inputs
2) assemble maintenance history files (paper or electronic system such as IBM Maximo or Cascade)
3) assemble one line electrical diagrams (to establish dependency)
4) run the dependent component model (DCM)

5) run the predictive circuit breaker fleet algorithm (using an analytical hierarchy process, AHP)
6) run the MkIS / SMDSS program

The DCM and AHP models would be processed (run) once to get the prioritization results for the SMDSS. The AHP model would need to be re-processed (re-run) each time a new quotation is required. Deliverables from each step are as follows:

(A) From Step (4) = recommended predictive maintenance policy [actions] by unit

(B) From Step (5) = maintenance priority across a fleet of breakers [breakers 1, 2… n]

(C) From Step (6) = comprehensive service quotation for the maintenance recommendations and program based on (A) & (B)

This information would be manually entered or automatically transferred between systems using software applications. All three elements utilize actual or projected cost figures in the models and analyses. Previous work has tended to negate or underestimate such costs.

VI.C. IDEF0 Model and Diagrams

To better illustrate the inputs, outputs, and interactions amongst the various systems, the National Institute of Standards and Technology (NIST) Integration Definition for Function Modeling (IDEF0) was utilized to develop model diagrams (NIST, 1993). Figure

11 is the IDEF0 process boxes for the single top level process (A-0), input sub models (A-1), and support sub models (A-2).

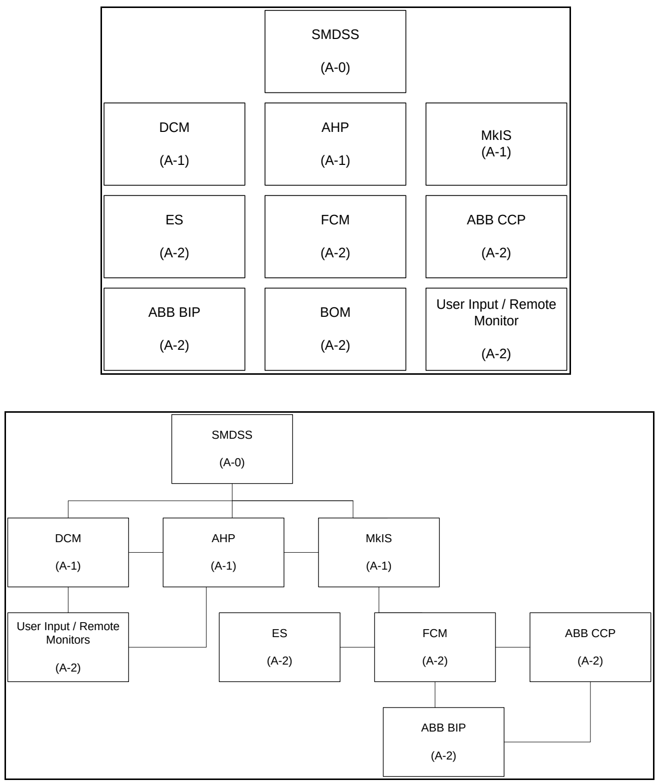

Figure 11. IDEF0 Process Boxes and Basic Tree Structure

Next, we define the inputs, outputs, controls and resources related to each process in levels A-0 and A-1. We do not define these elements for level A-2 since these support systems are only used for information acquisition.

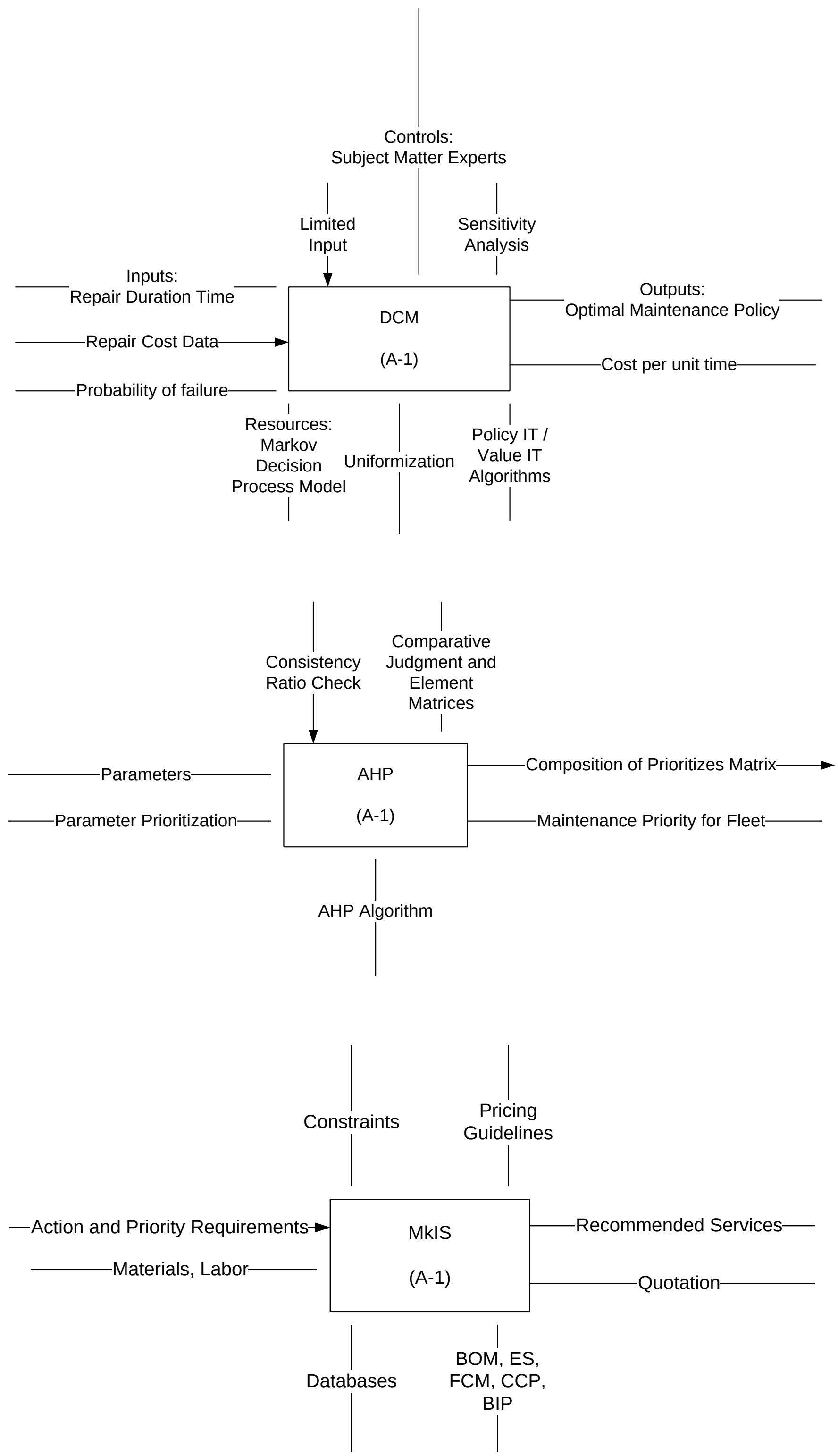

Figure 12. IDEF0 Process Description Diagrams

The final step is to develop the structure for the combined processes as shown in Figure 13.

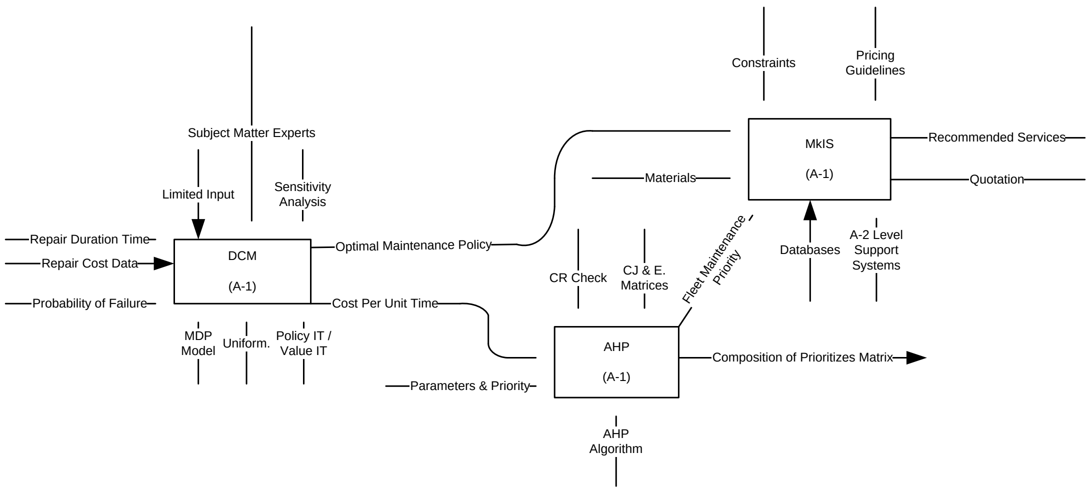

Figure 13. IDEF0 Combined Process Tree Structure (Level A-1)

IV.D. Example

The first step in the process is for a user to enter usage parameters into the dependent component model. Table 28 shows the required user inputs for the dependent component model.

Table 28. User inputs for the dependent component model

Repair Duration Times (λ)	Mean time to perform minor repair Mean time to perform major /overhaul repair Mean time to replace a unit Energization failure rate
Costs for State and Actions *c(s,a)*	Cost to perform minor repair (various conditions) Cost to perform major repair (various conditions) Cost to perform maintenance Cost (savings) of no action

After entering this information, the model makes use of data transformation or uniformization to convert the continuous-time inputs to discrete time for solution by established methods (Puterman, 2005). A detailed description of this model formulation can be found in (Bumblauskas and Ryan, 2010) and the sample output showing the optimal maintenance decision policy, i.e., which action to perform from each state for the model is show in Table 29.

Table 29. Dependent component model outputs

States	Actions
Transformer Down *Circuit Breaker Failed*	*Minor Maintenance of Breaker*
Transformer Up *Circuit Breaker Failed*	*Replacement of Breaker*
Transformer Up *Circuit Breaker Poor Condition*	*Replacement of Breaker*
Transformer Up *Circuit Breaker Good Condition*	*No Action*
Transformer Up *Circuit Breaker Excellent Condition*	*No Action*

Based on the user inputs, it is suggested that the user perform minor repairs if the transformer is out of service and the circuit breaker has failed, perform a replacement if the transformer is in service and the circuit breaker has failed or is in poor condition, and to perform no action if the breaker is in service and in good or excellent condition. Suppose that the scenario being faced by the user is that the breaker has failed while the transformer is out of service; in this case the user is interested in performing a minor repair of the breaker.

Because the user has a fleet of such breakers, the user is also interested how to prioritize the recommended minor maintenance action for a set of three breakers. To do this, the user inputs maintenance conditions related to each of the parameters shown in Table 23. The user enters the comparative judgment values (Table 24) based on the condition of the fleet to be assessed. In the AHP model used in the SMDSS, the entry values are constrained to values of 1, 3, 5, 7, and 9 as defined in (Bumblauskas et al., 2010). The output takes on the form of Table 26 which provides the recommended maintenance priority for the network. Based on the recommended maintenance action (Table 29) and the recommended maintenance priority (Table 26), we know which unit ID to quote service (breaker 1) and what service to perform (minor maintenance) which is used as the input to the SMDSS. By searching the FCM and ES (BOM), we are able to extract the elements required for the MkIS to quote the model recommended service. The actual quotation tool is the ABB CCP application.

V. VERIFICATION AND VALIDATION

In the future, we will need to work with electric utilities to further validate the SMDSS system. In the case of the DCM, the optimal maintenance policy of the dependent component system is compared to an isolated system (breaker only) and a non-optimal maintenance policy to validate the results. The outcome is an optimized set of maintenance decision actions for the system which are predicted by the model algorithm. The AHP model prioritization can be further verified by comparing the algorithm predicted order to the actual field conditions of the units being considered (worst comprehensive rating of pw_n). For example, in the case described in this paper, one expects to find in the field that the breaker in the worst condition is breaker 1, making it the highest maintenance priority.

In order to verify the SMDSS framework, the output of the system has been reviewed for accuracy. This includes a review of the inputs, outputs, and information to be acquired form support subsystems (FCM, ES) as detailed in the IDEF0 process diagrams. The end deliverable from the system is a quotation for field service which includes materials (parts), equipment, and labor (see Appendix A). Further validation of the SMDSS can be accomplished by using a typical industry example to confirm a quotation for service can be generated using the SMDSS method. The automated system is not entirely in place as this project has not been funded as a business process improvement or corporate research initiative as of publication (see future work). The output of the model is a valid set of maintenance actions, a valid prioritization or maintenance order, and a set of material and labor requirements to fulfill the model recommendations.

VI. CONCLUSION AND FUTURE WORK

Predictive maintenance modeling, as defined above, for circuit breakers is a new field; providing a methodology for establishing a predictive maintenance program and recommendations and considerations for remote monitoring. There is a difference between traditional predictive maintenance and modeled or simulated predictive maintenance. The objective of both is to identify the most critical units to spend time and maintenance monies on. The traditional method focuses on condition monitoring data and statistical trending while the latter is based on a prediction or simulation based on expected potential future failure. The AHP method in this paper can be used to prioritize which units resources should be expended on (time and money). This can be accomplished by utilizing AHP and/or some additional logic.

While many organizations have developed ‘home-grown’ prioritization schedules, this method provides a formalized framework for power circuit breakers. A primary contribution is the evaluation of defined parameters as discussed in Section III.B. Future work includes applying this method and algorithm to a larger fleet and scaling this to other industrial equipment. In the AHP example, three units were prioritized since three phase service and ring-bus topology are the most prevalently used network architectures in North America. In some cases, the networks being considered are larger than three units, including industrial manufacturing operations interested in prioritizing maintenance actions across a plant or shop. Additional resources such as capital investment and labor hours to fully implement the SMDSS framework are required for comprehensive verification of the completely automated system (see section V.A. regarding funding).

The scenario in which the dependent component model (DCM) could be implemented in consultation with an electric utility is as follows. Each power component is typically managed by subject matter expert. By using a coordinated outage maintenance approach such as DCM, activities can be considered at the same time (e.g., buswork, transformer, breaker, etc.). These activities could be categorized into subsets based on whether they are planned or unplanned, severity, contingency planning, spare inventory, etc. Triggers for maintenance action by scope could be based on the PERT scenarios used in the DCM.

One area that could be further explored is the use of artificial intelligence (AI) to provide decision making maintenance recommendations. This type of human computer interaction is an area of rapid development and much current research.

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APPENDIX A. SAMPLE QUOTATION

ABB

COMMERCIAL AND TECHNICAL TENDER

ABB Power Technologies

Prepared for:

Eaton

,nc

Prepared by:

Dan Bumblauskas

Date: 06 May 2009

Eaton reference no.
ABB reference no. 09Q650677

In response to your inquiry, I am pleased to present, for your consideration, an offer for the following equipment.

Customer Name:
Eaton

Telephone:	ABB Tender ID	Date	Validity	Your Reference Number
Contact Person:	09Q650677	06 May 2009	07 Jul 2009	

Item	Qty	Product Type	Price Each (USD)	Item Total
10	1	962A54204 1200|BALL VALVE||11 Leadtime is 9 working weeks.	116	
20	1	109A17701 1200|DESICCANT BAG (molecular sieve) Leadtime is 9 working weeks.	109	

Grand Total Sales Price: 224 USD

Other terms and conditions are per ABB General Terms and Conditions of Sale (ABBGTC073101).

We thank you for your inquiry and quote in accordance with the attached appendixes.
We hope that the offer is to your full satisfaction and we remain

Best regards,
Dan Bumblauskas

Authors' Biographies

Daniel Bumblauskas is an Assistant Teaching Professor of Management at the University of Missouri – Columbia and has been employed-by or affiliated with ABB Inc. since 2003. His most recent role with ABB was as a Group North American Account and Marketing Manager for the Power Products Division Transformer Business Unit. Prior to this Dan was with ABB High Voltage Products circuit breaker service and ABB utility front end sales organizations. Before joining ABB, Dan was with the sears.com web center team as a communication and product specialist. Dan is a Ph D student in the department of Industrial and Manufacturing Systems Engineering at Iowa State University, Ames, Iowa, where he has been conferred B.S. and M.S. degrees in Industrial Engineering. Dan is also a masters degree candidate at Harvard University, Cambridge, Massachusetts, in general management. Dan is a senior member of IIE, a member of IEEE, and chair of the ASEE Student Constituent Committee.

Douglas D. Gemmill is an Associate Professor of Industrial Engineering at Iowa State University. He received a B.S. in mathematics and an M.S. in industrial engineering from Iowa State University. He received his Ph.D. in industrial engineering from the University of Wisconsin - Madison. His professional interests include simulation modeling, systems engineering, applied operations research and the modeling, design, and performance analysis of complex systems. He is Director of Graduate Education for Iowa State's masters in systems engineering program. He is a member of the International Council on Systems Engineering, American Society of Engineering Education, and a senior member of the Institute of Industrial Engineers. He has also spent over 25 years as an officer in the United States Air Force, both active duty and as a reservist.

CHAPTER 5. GENERAL CONCLUSIONS

This work provides a methodology to provide predictive maintenance recommendations and service quotations for the electrical equipment. As noted in the introduction, the four primary contributions of this dissertation are (1) a dependent component transformer / circuit breaker model to provide a maintenance decision policy [actions] which can be increased in scope to contain other components and scaled to other applications, (2) a recurrent data analysis for production population data, (3) a maintenance prioritization model which can be used for planning predictive maintenance rather than via traditional time or condition based programs, and (4) a system to integrate this data output into a maintenance service quotation.

The results are a predictive set of maintenance actions for an individual circuit breaker, an analysis of breaker population data, examples of frequently asked questions which can be answered using recurrent data analysis, a breaker prioritization for a subset of breakers, and an integrated network architecture making use of modeling results.

The final deliverable or end product of this research is the framework herein referred to as a *Smart Maintenance Decision Support System* (SMDSS). This system is very useful and can be used in a module in existing enterprise computer systems or as a stand-alone software application.

This documented system provides steps to effectively *predict* the recommended maintenance action(s) on a piece of equipment, provide prioritization of units within a fleet, and provide quotation information in such a manner that it has substantial value to business and industry. The DCM model provides an optimized solution minimizing average total cost and the AHP model provides a prioritization solution based on reliability subject to budget and time constraints. The potential commercial viability of such a system is high and is already being discussed with multiple organizations. These methods are not widely used in industry and have not been popularized. The next step will be to develop a commercial software package for use in industry or to conduct consulting services utilizing the models above for clients.

BIBLIOGRAPHY

See each chapter of this document for relevant works cited.

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BIOGRAPHICAL SKETCH

Daniel Bumblauskas is an Assistant Teaching Professor of Management at the University of Missouri – Columbia Robert J. Trulaske, Sr. College of Business and has been employed-by or affliated with ABB Inc. since 2003. His most recent role with ABB was as a Group North American Account and Marketing Manager for the Power Products Division Transformer Business Unit (2006-2010). Prior to this Dan was with ABB High Voltage Products circuit breaker service and ABB utility front end sales organizations. Before joining ABB, Dan was with the sears.com web center team as a communication and product specialist. Dan is a Ph D candidate in the department of Industrial and Manufacturing Systems Engineering at Iowa State University, Ames, Iowa, where he has been conferred B.S. and M.S. degrees in Industrial Engineering. Dan is also a masters degree candidate at Harvard University, Cambridge, Massachusetts, in general management. Dan is a senior member of IIE, a member of IEEE, and chair of the ASEE Student Constituent Committee.