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Modeling Failure of Electrical Transformers due to Effects of a HEMP Event

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ABSTRACT

Understanding the effect of a high-altitude electromagnetic pulse (HEMP) on the equipment in the United States electrical power grid is important to national security. A present challenge to this understanding is evaluating the vulnerability of transformers to a HEMP. Evaluating vulnerability by direct testing is cost-prohibitive, due to the wide variation in transformers, their high cost, and the large number of tests required to establish vulnerability with confidence. Alternatively, material and component testing can be performed to quantify a model for transformer failure, and the model can be used to assess vulnerability of a wide variety of transformers.

This project develops a model of the probability of equipment failure due to effects of a HEMP. Potential failure modes are catalogued, and a model structure is presented which can be quantified by the results of small-scale coupon tests.

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ACRONYMS AND DEFINITIONS

Abbreviation	Definition
HEMP	High-altitude Electromagnetic Pulse
BIL	Basic Impulse Level
GIC	Geomagnetically Induced Current
HFWM	High Frequency Winding Model
CDF	Cumulative Distribution Function

1. INTRODUCTION

This work develops a methodology for constructing a failure model for a power transformer when exposed to the insult of a High-altitude Electromagnetic Pulse (HEMP) event. The methodology is designed to be general so available data can be extrapolated to create failure models for a wide range of types and classes of power transformers.

A HEMP event can be delineated into three different phases based on timescale: E1, E2, and E3. The E1 phase has a rise time of about 2.5 nanoseconds and is defined as the portion of the HEMP wave that occurs within the first microsecond. The E1 phase of a HEMP exhibits very high frequency content (up to 100 MHz) and could cause significant damage to power transformers. The HEMP couples to high voltage transmission lines and creates a voltage pulse that can induce significant electric field stresses. These stresses can potentially cause dielectric failure of several different transformer components.

The E2 phase of the HEMP creates voltage pulses that corresponds to timescales beyond one microsecond, which are similar to lightning strikes, thus their effects are better understood and can be mitigated by existing practices such as Basic Impulse Level (BIL) design criteria and the use of lightning surge arrestors (which are not fast enough to mitigate E1 pulses).

Finally, the E3 phase occurs over times on the order of seconds to minutes. During this phase, the HEMP could induce a quasi-DC voltage into the transmission lines that is highly unlikely to lead to dielectric failure of transformer components. However, where transformer winding configurations allow, the resulting DC currents could magnetically saturate the transformer core and induce physical or functional failure from heating effects.

A framework to estimate the failure probability of power transformers from experimental data will help researchers develop failure models for a variety of transformer configurations. These models can inform researchers and planners to assess electrical grid vulnerability and resilience to HEMP events.

As follow-on research, this process is anticipated to be applied to a limited set of HEMP test results for power transformers.

2. FAILURE MODES

A HEMP event can cause failure of a transformer in a variety of modes involving different components and mechanisms. A failure model should account for all potential failure modes. Here, we describe several failure modes and the relevant mechanisms.

Due to a HEMP event a transformer can fail if either the transformer's components physically fail or if the transformer's proper function is interrupted, termed a functional failure. Generally, a transformer has several different component failure modes involving different components: windings, bushings, tap changers, cores, tanks, protection systems, and cooling systems. A mechanism common to many physical failure modes, and of particular concern during the E1 phase of a HEMP event, is dielectric failure of an insulating material which could involve several of the transformer components, such as windings, bushings, and protection systems [1]. Another failure mechanism of concern during the E3 phase of a HEMP event involves geomagnetically induced currents (GICs) which can cause local resistive heating and failure of components. Failure modes associated with E2 were not considered to be likely and were not included as part of this model.

2.1. Dielectric Failure

There are essentially two dielectric failure modes for a transformer: flashover of insulators in a weak dielectric environment (including surface tracking, also termed called electrical creep), and dielectric breakdown of insulating materials. An example of a weak dielectric environment in a transformer is an oil with a higher moisture content, which would have a lower insulating dielectric strength, or oil with dissolved gases, which tend to decrease the insulation breakdown strength. Generally, flashover occurs through these weak dielectric environments at much lower stresses than in a non-degraded dielectric material. However, it has been shown that impurities within dielectric material have less of a detrimental effect on breakdown strength when the voltage stress applied is pulsed rather than continuous [2].

Dielectric breakdown can also occur in non-degraded insulating materials, such as oil-paper insulation, oil and air. Breakdown occurs if the voltage across the insulation is large enough to cause the material to become electrically conductive. The dielectric breakdown strength of the material can change with environmental conditions such as pressure and temperature, and with the duration of the imposed voltage stress. In addition to insulating materials, dielectric failure can occur external to components which currents flow around an insulating device, for example, electrical creep along a bushing's external surface, from high voltage to ground.

The model that we describe in the next section focuses on dielectric failure of insulation materials within a transformer, to illustrate how a general failure model could be quantified from experimental data.

2.2. Geomagnetically Induced Currents

The E3 component of a HEMP creates a quasi-DC (DC) voltage potential along transmission lines that potentially drives GICs in transformers. This voltage potential can occur in circuits where a DC voltage exists (caused by E3 or GMD coupling) and where direct current can travel in a closed loop, such as in transmission lines between transformers using grounded Y neutral connections. DC voltages in circuits which cannot form GICs are generally not harmful and will not cause transformer saturation. GICs can result in both physical and functional failure of the transformer. Although GIC is less likely to be caused by HEMP than by geomagnetic disturbances (GMD), physical failure results if GICs cause localized heating in transformers which can subsequently lead to component failure. GICs increase core flux density which can saturate the core and result in magnetic flux leakage. Leakage flux can link with components inside the transformer that are not intended to carry current, causing unintended circulating currents and heating.

GICs can also result in the dielectric failure of transformer materials. For example, GIC-caused temperature increase may cause bubbles to form in insulating oil, leading to dielectric failure across the weak dielectric environment. This phenomenon was studied for the transformers in the continental U.S. electric grid. However, it was determined that only a small number of geographically dispersed transformers would be at potential risk of thermal damage from GICs resulting from a HEMP [3].

GICs can also induce functional failure by causing voltage collapse. Core saturation causes increased reactive draw, which may lead to voltage suppression near the transformer. This could occur because of an increase in the consumption of reactive power. Voltage collapse can propagate and result in large-scale system outages for extended periods of time. However, several anticipatory actions, diagnostic tools, and mitigations are employed to reduce the impact of voltage collapse in transformers [4]. Functional failure is temporary in the sense that after the GICs cease, the transformer can recover to a functional state. Another functional failure is the potential misoperation of protective relays caused by harmonic voltages. These harmonics are created from transformer saturation in the presence of GICs. Again, when the GICs cease, the harmonics return to their previous level, and no longer interfere with protective relay operation.

3. FAILURE PROBABILITY MODELS

Given the occurrence of a HEMP, the possible states of a transformer can be described as normal (*N*), physical failure (*A*) and functional failure (*B*). The probability of physical failure of the transformer can be described formally as $P(A|H, C)$ where *H* is a vector representing properties of the HEMP E1[1] event such as the peak voltage pulse at the transformer terminals, and *C* is a vector representing physical properties of the transformer such as insulating material thickness. Given that no physical failure occurs, the probability of a functional failure can be analogously denoted by $P(B \mid H,C)$. The probability of transformer normal operation given a HEMP event is then given by

$$P(N \mid H,C) = 1 - P(A \mid H,C) - (1 - P(A \mid H,C))P(B \mid H,C) \quad (1)$$

A physical failure of the transformer (state *A*) occurs when one or more physical components of the transformer fails. Enumerating the components and their associated failure modes with the index $i = 1,\ldots$, we can denote the probability events for the failure of these components as A_1, A_2,…. The relationship between $P(A \mid H, C)$ and $P(A_1|H, C)$, $P(A_2|H, C)$, … depends on the relationships among the component failure events A_1, A_2, … In the simple case where the component failure events are judged to be independent, and transformer failure results if one or more components fail, the transformer failure probability is calculated from the equation

$$P(A \mid H,C) = 1 - \prod_i (1 - P(A_i|H, C)) \quad (2)$$

The failure probability model in Eq. (1) and (2) illustrates a general approach to model construction by encompassing a broad range of pathways for physical or functional failure of a transformer. Application of this approach and quantification of the model requires development of details for each failure mode and component. The following sections focus on one failure mode and component: dielectric failure of an insulating component.

3.1. Connection between Transformer Physics and the Failure Model

As discussed in the previous section, we can assume that the component failures are conditionally independent given the properties of the E1 phase of a HEMP event and the transformer properties. In the case of dielectric failure of an insulating component, say A_1, the probability of failure $P(A_1|H, C)$ is more naturally expressed in terms of electric field $E_{A,1}$ on the dielectric which derives from the properties of the HEMP event. Translating the external event parameters *H* to an electric field $E_{A,1}$ requires use of physics models and is dependent on the material properties and arrangement of various components within the transformer. The models that translate the HEMP event properties *H* and transformer characteristics *C* to the electric field on the dielectric $E_{A,1}$ can be abstractly represented as a function $E_{A,1} = f(H,C)$. Propagation of uncertainty in *f*, *H* or *C* can result in a probability distribution for $E_{A,1}$ Then

$$P(A_1 \mid H,C) = \int_{minE_{A,1}}^{maxE_{A,1}} P(A_1|E_{A,1},C)P(E_{A,1}|H,C)dE_{A,1} \quad (3)$$

[1] A HEMP E3 event is unlikely to cause physical failure (A) of a transformer and is therefore omitted. However, if GICs from a GMD event were considered in this analysis, such characteristics would be represented in the vector H.

quantifies the probability of failure of component A_1 given a HEMP event H, transformer characteristics C, and the translation of external effects to the electric field that is represented by the function f.

A physics-based model of the dielectric failure of a component composed of insulating material due to the E1 phase of a HEMP begins with the voltage time-series of the transformer terminals $V_{couple}(t)$ due to this event. This voltage insult then causes a voltage response in the transformer windings $V_{winding}(l,t)$, where l describes a location on the winding. This voltage response can be computed using a High Frequency Winding Model (HFWM) that is a function of the insult and the transformer properties:

$$V_{winding}(l,t) = HFWM(V_{couple}(t),C) \tag{4}$$

Sandia is considering development of a HFWM to estimate the voltage response for V_{couple} disturbances on fast timescales (up to 100MHz). These timescales are much faster than typical winding models that are required for studying the resilience of transformers to lightning strikes. For failure studies, a set of different transformer parameterizations and HEMP characteristics that yield V_{couple} will be selected and the resulting $V_{winding}$ computed.

The voltage response, $V_{winding}$, causes an electric field, $E(x,t)$, within the transformer. Here x is a vector location within the transformer. The electric field can be expressed as

$$E(x,t) = \frac{\partial}{\partial x} V(x,t, V_{winding}, C) \tag{5}$$

where $V(\cdot)$ is potential through the transformer and C contains the dielectric constants for the components at different locations within the transformer $\kappa(x)$. Computing the electric fields due to the winding voltage response is typically done using finite element methods. These electric fields are the dielectric stresses on the different insulating dielectric components within the transformer. These stresses can cause dielectric breakdown when the material loses its insulating properties and starts conducting electricity, causing significant damage to components. This breakdown is likely to occur when the dielectric stress $E(x,t)$ at some location x and time t exceeds the dielectric strength of the material at that location, $E_{bd}(x)$. Because the breakdown is stochastic, a probabilistic model is developed for the breakdown probability given the dielectric stress and strength based upon experiments.

These transformer physics models that either exist or are in development could be integrated into the failure model to compute the dielectric stress on the transformer as a function of properties of the E1 phase of the HEMP and of the transformer. The failure probability of the individual components can then be computed, which is modeled in terms of the dielectric stress they experience, not the properties of the E1 phase of the HEMP event. Future work may integrate uncertainty into these physics models and quantify the resulting uncertainty of the dielectric stress; however, for this current study it is assumed that the dielectric stress map is given and is accurate.

3.2. Uncertainty Quantification

The model for the probability of failure $P(A_1|H, C)$ expresses the probability of failure conditional on characteristics of the HEMP event and of the transformer, represented abstractly by vectors characteristics $E_{A,1}$, including for example the peak voltage V_{EMP} the HEMP (V) and the ramp rate R_{EMP} of the HEMP (V/s). Depending on the model f that computes $E_{A,1}$, other characteristics of the HEMP event may be pertinent.

The vector C describes transformer characteristics that either affect the translation of the HEMP to $E_{A,1}$, or the likelihood of dielectric failure given an electric field $E_{A,1}$. Elements of C quantify details of the transformer's design and construction; examples are the thickness of the insulating material or the closest distance between conductors separated by the insulating material. Other elements of C may quantify susceptibility of the insulating material to dielectric failure, including pressure in the transformer, water and air content within the insulating material, and transformer age.

Electrical breakdown of a dielectric material in an electric field manifests as an abrupt rise in current through the material. Whether breakdown occurs, or not, is inherently uncertain even when all aspects of the electric field and material are carefully determined. Physically, dielectric failure in a solid dielectric material can be thought of as beginning with an electron with enough energy to initiate the breakdown current [5]. The presence, or absence, of the "initiating electron" is inherently uncertain. Furthermore, some aspects of the insulating material are impractical to quantify, for example, presence and nature of defects, material heterogeneity, presence and nature of interfaces between insulating material components, and presence and extent of contaminants. These aspects may be represented by lumped or averaged quantities in the parameter vector C or may simply be treated as part of the inherent uncertainty quantified by the conditional probability of failure.

3.3. Conditional Failure Probability

Given vectors C the conditional probability of failure $P(A_1|H,C)$ of a dielectric material is quantified through testing. A test matrix is assumed to encompasses ranges of appropriate variables (e.g., different voltage/ramp rate combinations, the appropriate range of pressure, different internal geometries, and different oil water content). Elements of experimental design should be used to efficiently estimate $P(A_1|H,C)$ without undue expense and complexity.

3.4. Estimating Failure Probability Through a Surrogate Model

Consider for example the dielectric failure of an oil paper insulation, denoted by A_1. To model the probability associated with A_1 using experimental data, a transformation is needed that maps continuous values measured in the experiments into a probability space bounded by $[0,1]$. Let η_i be some outcome of the experimental results $\eta_k = g(H_k, C_k)$, where H_k is a vector of HEMP properties and C_k is a vector of physical properties, each determined through the experimental design; the subscript k refers to the k-th experiment.

For convenience denote the probability of dielectric failure of the oil paper insulation, $P(A_1 \mid H,C)$ in the i-th experiment as π_i. Any cumulative distribution function (CDF) of a continuous probability density provides a one-to-one transformation that maps real values into $[0,1]$. For a choice of CDF F, let $\pi_i = F(\eta_i)$. Now an inverse transformation of the CDF gives $\eta_i = F^{-1}(\pi_i)$ and allows a function of the failure probability to be modeled as the function of the experimental results. The function of the failure probability $F^{-1}(\cdot)$ is called the link function. Three common choices of F are the CDFs corresponding to the normal, the logistic, and the extreme value CDFs [6].

Logit (Logistic CDF)	Probit (Normal CDF)	Complementary Log-Log (Extreme Value CDF)
$\ln\left(\frac{\pi_i}{1-\pi_i}\right)$	$\Phi^{-1}(\pi_i)$ [2]	$ln(-\ln(1-\pi_i))$

Using the normal or logistic CDF is known as probit and logistic regression, respectively. They tend to produce similar predictions because the transformations used in each method are almost linear combinations of each other for moderate values of π_i (in between 0.1 and 0.9). Despite similar predictions, their respective coefficients have different meanings, so care should be taken when comparing coefficients across models. If the extreme value distribution is used, then a complementary log-log link function is used. This type of modeling will give similar values as the probit model for small values of π_i but the transformation tends to infinity much slower than the probit or logistic models, as π_i tends to 1. This can be useful when modeling probabilities that are either thought to be very large or very small [6].

One of the most intuitive choices is to represent η_i as a linear function of the predictors:

$$\eta_i = \beta_0 + \sum_{j=1}^{p} x_{ij}\beta_j$$

where:

- p is the number of experimental conditions
- x_{ij} is one of the p experimental conditions from H and C for the i-th experiment
- β_j is the regression coefficient for the j-th experimental condition.

This choice of η_i is typically used in logistic, probit, and cumulative log-log regression. However, an underlying assumption for this model choice is that each predictor has a linear relationship with the link function of the failure probability. Physical processes can violate this assumption in practice. Transformations of the model covariates may be necessary in order to (approximately) satisfy the linearity condition. Physical processes covariates can also be correlated and have an interaction effect; these types of effects can also be investigated and added to the linear model η_i.

Modeling a function of the probability of failure by a linear function falls under the category of generalized linear models. Based on experimental data, the generalized linear model allows us to compute $P(A_1)$ if the coefficients associated to the predictor variables are estimated via a statistical approach such as *maximum likelihood estimation* or *Bayesian estimation.* In either estimation procedure, the joint distribution of the experimental results must be specified. For each experiment $i = 1,...n$ the joint distribution is:

$$f(y\,|\,\beta) = \prod_{i=1}^{n} P_i(A_1)^{y_i} * \left(1 - P_i(A_1)\right)^{1-y_i}$$

[2] $\Phi(\cdot)$ denotes the CDF for the standard normal distribution.

Where:

- $P_i(A_1)$ is as specified above through $F(\eta_i)$
- $y_i = \begin{cases} 1, & \text{Dielectric failure occurs on the ith trial} \\ 0, & \text{Otherwise} \end{cases}$

For maximum likelihood, the experimental results are treated as fixed and the coefficients or parameters $\beta_0, \beta_1, \ldots \beta_p$ are unknown. Therefore, the maximum likelihood estimate is given by the combination of parameters that maximizes the likelihood function as obtained from the probability of dielectric failure. This maximization requires some numerical optimization approach such as the *Newton-Raphson* method. For example, with the statistical software *R*, the optimization can be achieved with the *glm* function which provides a *fitted model.* The fitted values of the logistic regression are the estimates of the class probabilities in this case: dielectric failure or non-dielectric failure. It is worth noting that there is a potential that the model may not reach convergence due to a variety of reasons: having a large number ratio of predictors to cases, multicollinearity, sparseness or separation, which occurs when a predictor is majorly associated with only one of the two possible outcomes.

A second approach to estimate the logistic regression is to consider *Bayesian Statistics.* In addition to the likelihood function, for Bayesian methods, prior distributions are placed on the unknown parameters and then a posterior distribution for the parameters is derived via *Bayes theorem* where

$Posterior \propto Prior * Likelihood$

The likelihood function would have the same specification as above, except now coefficients $\beta_0, \beta_1, \ldots, \beta_6$ would be treated as random variables. The posterior distribution provides a representation of the uncertainty of the parameters given the experimental data and can be summarized with *point estimates, quantiles or credible intervals* [6]. For logistic regression, it is usual to assign a prior distribution where the parameters or regression coefficients follow some Gaussian distribution. In this case, the corresponding posterior distribution does not have an analytic closed which makes the posterior difficult to calculate specially when the number of coefficients is large [6]. However, the posterior distribution can be approximated using stochastic simulation methods such as *Markov Chain Monte Carlo (MCMC)* which can be implemented with open source software such as *R, OpenBugs, Jags* or *Stan.* One attractive feature of the Bayesian approach is that the parameter or coefficient uncertainties given by the posterior distribution can be propagated to other levels of the regression model and particularly, to provide uncertainty estimates to the probability of dielectric failure. From the maximum likelihood perspective, the alternative to obtain such uncertainties would be to rely on *bootstrap* methods. On the other hand, when the sample size or the number of coefficients is large, full simulation with *MCMC* can be very slow, so an alternative would be to consider approximate methods that arise from Bayesian inference and Machine learning such as *variational Bayesian methods.*

Some of the limitations of the generalized linear model have been addressed previously; the assumption that the link function of the failure probability is linear with the predictors can be difficult to satisfy, even after considering transformations of the covariates. There are many non-model-based alternatives that have less restrictive assumptions such as classification trees, k-nearest neighbors, and support vector machines [7]. Typically, these methods are classifiers but there are ways to model probabilities with them with potential tradeoffs of interpretability and model inference methods.

4. SUMMARY AND CONCLUSIONS

In this report, the methodology for constructing a failure model for a power transformer when exposed to the insult of a High-altitude Electromagnetic Pulse (HEMP) event has been developed. The methodology was designed to be general so available data can be extrapolated to create failure models for a wide range of types and classes of power transformers. Multiple failure modes were explicitly evaluated, including dielectric failure of an insulating material during the E1 phase of a HEMP event and GICs during the E3 phase. A framework to estimate the failure probability of power transformers from experimental data was outlined to help researchers develop failure models for a variety of transformer configurations. These models can inform researchers and planners to assess electrical grid vulnerability and resilience to HEMP events.

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