# Assessment of Impact of Modeling Simplifications for a Medium Voltage DC Shipboard Power System

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**In the paper, the response surface modeling approach is applied to study the effectiveness of different grounding schemes implemented for mitigation of single-line-to-ground faults in a simulation of a notional Medium Voltage DC shipboard power system. Multivariate adaptive regression splines (MARS) models are used for preliminary exploration of the functional relationships between the input parameters and response variables. Using the constructed MARS models, Sobol' total sensitivity indices were computed for the models to study possible differences in the sensitivities of the response variables for the different grounding schemes. For final analyses, and for response surface models for which the MARS models show significant prediction error, Gaussian process models are used to account for prediction variance.**

## Nomenclature

$V_{mid}$ = Zero potential at the midpoint between two high-impedance elements
$V_n$ = Voltage at the generator neutral point
$V_{dc}$ = DC bus line-to-line voltage

## I. Introduction

A commonly employed technique to reduce the computational burden associated with parametric studies involving computationally expensive simulations, such as electromagnetic transient simulations of power systems, is to create response surface (RS) models representing the behavior of the simulated system. Instead of directly carrying out the parametric studies on the detailed simulation model, the RS modeling approach aims to find the functional relationship between a set of input parameters and a set of output (response) variables representing the behavior of the simulated system. The parameter space can be systematically explored to efficiently characterize the functional relationship between the response variables and the input parameters, and the RS models obtained can be subsequently used for many different types of parametric studies, each requiring different sets of inputs for the analysis. A number of response surface modeling approaches, including Gaussian process models[1,2], multivariate adaptive regression splines (MARS)[3], and dimension-adaptive collocation methods[4] have been successfully used for analyzing the impact of parametric uncertainty on simulations of a notional all-electric shipboard power system[5,6]. In the present paper, the RS modeling approach is used to study the effectiveness of different grounding schemes implemented for mitigation of single-line-to-ground faults in a simulation of a notional MVDC shipboard power system. Traditionally, grounding schemes in a marine power system aim to reduce the potential for transient overvoltages, minimize the magnitude of current flowing in the hull, and allow for continuity of service, especially to mission critical loads[7].

When employing RS models for parametric studies, it is important to consider the inherent prediction uncertainty of the RS models, as the RS model is always only an approximation of the simulation upon which it is based. For

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cases in which the parameter space can be adequately sampled and the functional relationships between the parameters and the response are not too complicated, the uncertainty in the prediction of the RS model may be sufficiently small to be neglected in subsequent analyses. For such cases, models such as linear regression models, MARS models[3], or artificial neural networks may provide very simple and fast approximations for the simulation, neglecting prediction uncertainty. However, if cross-validation of the models reveals significant prediction errors, it is necessary to use RS models that can provide estimates of prediction uncertainty, and account for this prediction uncertainty in the subsequent analyses. For characterization of deterministic simulations, Gaussian process models are often suitable[1,2], as these models can correctly represent the prediction variance associated with data drawn from observations of deterministic systems. For the work presented herein, MARS models[8] are used for preliminary exploration of the functional relationships between the input parameters and response variables, as these models can be constructed very quickly for even large sets of data, and the models can be used to quickly generate large numbers of predictions. For final analyses, and for response surface models for which the MARS models show significant prediction error, more computationally intensive Gaussian process models[9] are used to account for prediction variance.

## II. Simulation Models

The general topology of a notional MVDC shipboard power system[10] under consideration is shown in Fig. 1.

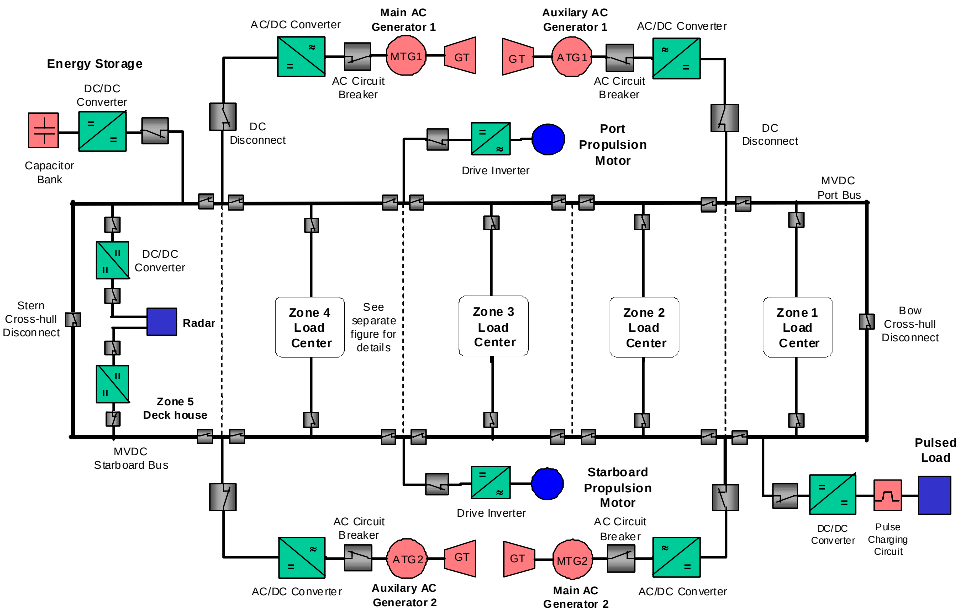

**Figure 1. Architecture of a notional MVDC shipboard power system.**

The system consists of two 36 MW main generators (MTG), and two 4 MW auxiliary generators (ATG), each connected through diode rectifiers to port and starboard longitudinal DC busses operating at 1 kV. The primary loads on the system are two 36.5 MW propulsion systems interfaced to the system through bi-directional pulse width modulation motor drives. For the research presented here, a simplified version of the general topology is considered (Fig. 2). Only one of the two auxiliary generators in Fig. 1 is taken into account. The generator is modeled as a voltage source behind a source inductance with a rated voltage of 4.16 kV. The source is connected to a diode rectifier which creates a DC bus operating at 5kV. A sine-triangle pulse width modulation DC-to-AC converter is then used to feed power into a resistive load. The resistive load is permitted to operate between 40kW and 4 MW. The cables located before the AC-to-DC converter and at the DC bus are modeled in a similar manner as suggested in Ref. 11. In order to properly reproduce issues related to grounding of shipboard power systems, stray capacitance to ground is modeled in several locations, including at the terminals of the generator and on the 5 kV DC bus. Here, "ground" is considered to be the ship hull. The power system model in Fig. 2 was implemented on PSCAD EMTDC[12]. This software is capable of handling very small time step sizes and therefore, offers high resolution time-domain transient waveforms. For the simulations considered herein, a time step size of 0.04 μs is used. As the simulation is only executed for a very short time interval, the effects of generator controls to regulate the DC bus voltage are neglected.

There are multiple options[13] for a high resistance grounding scheme for an AC/DC mixed system. In this study, three grounding schemes are analyzed: grounding at the DC midpoint ($V_{mid}$), grounding at the neutral point of the generator ($V_n$), and capacitive grounding (cables). In a capacitance grounded or ungrounded system there is no intentional connection between the system conductors and ground[14]. In each case, only a high impedance path to ground is provided in order to minimize the impact of single-line-to-ground faults in the system, minimizing disruption of service. In simulations, a change from one grounding scheme to another is achieved by closing or opening the three switches $S_A$, $S_{B,}$ and $S_C$ in Fig. 2. For example, if none of these switches are closed, then, the model is capacitive grounded. If only $S_A$ is closed, then the system is considered to be grounded at the generator. Finally, if $S_B$ and $S_C$ are closed, then the system is grounded at the DC midpoint.

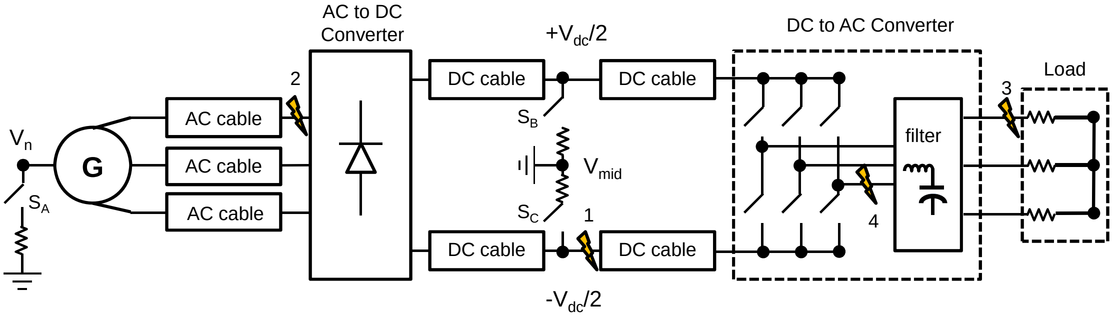

**Figure 2. Simplified shipboard power system. Fault locations are marked by (⚡) and physical interconnections of cables by (●). Other symbols are standard for power system diagrams.**

To compare the performance of the grounding schemes, single-line-to-ground faults are introduced into the system. Fault locations are shown in Fig. 2 and labeled in the following order: 1 - fault at the negative DC rail, 2 - fault at the AC terminals of the rectifier, 3 - fault at the load, and 4 - fault at the AC terminals of the DC/AC converter. Faults initiate transient phenomena and changes in the steady state voltages of the system with respect to ground. These steady state voltage offsets and their impact on the system are discussed in detail in Ref. 13. To illustrate the point, consider the results for one of the evaluations of the simulation, illustrated by Fig. 3. The figure shows the voltages with respect to ground of the positive and negative rails of the 5 kV DC bus for a fault applied to the negative rail (fault location 1) with the DC midpoint grounding scheme. Although the rail-to-rail voltage is maintained at approximately 5 kV throughout the event, and the loads are not affected, there is a shift in the rail voltages with respect to ground, which may stress the insulation between the conductors and the ship's hull. In addition to the steady-state shift in voltage, the overvoltage caused by the transient, and the related rate of rise of the voltage, may be severe. Further, the reversal in voltage polarity experienced by the negative rail may also cause significant stress to the insulation[15]. As the transients in the fault may depend significantly on uncertain parameters of the simulation, such as the stray capacitances to ground and the load power, it is important to study the simulation in the context of this parametric uncertainty, as well as in the context of a range of controllable parameters. However, due to the computational expense of evaluating such simulations with very small time-step sizes, it is important to make efficient use of evaluations of the simulation for such parametric studies.

## III. Methodology

The simulation models described above may contain hundreds of input parameters. Some of these parameters may represent design choices for the system, like the ground resistance, while others may represent uncertain environmental variables, like the load resistance. In this work, the impact of uncertainty in the value of eight parameters, as highlighted in Table 1, was evaluated. The table lists each of the considered parameters along with the range over which each of the parameters was varied. The stray capacitive coupling at the terminals of the generator was modeled based on the approach detailed by Ref. 16. Using this approach, half of the capacitance specified by $C_{src\text{-}gnd}$ was inserted between each phase and ground, and 1.5 times the value specified by $C_{src\text{-}gnd}$ was inserted between the neutral point and ground. Also, it should be noted that the switching frequency of the inverter,

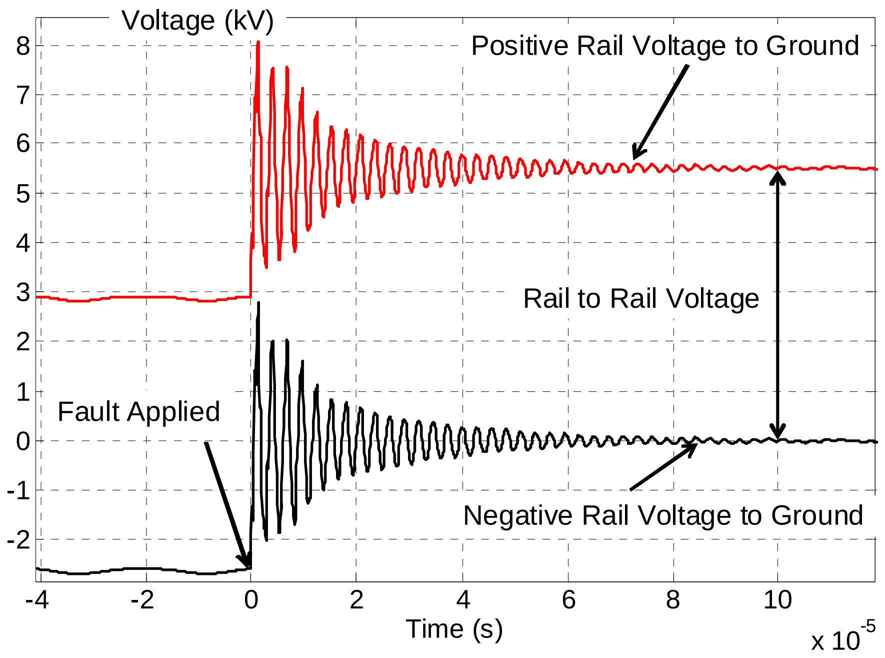

**Figure 3. Positive and Negative Rail Voltages with Respect to Ground for a Fault Applied at Location 1 (DC Midpoint Grounded).**

$f_s$, was not varied continuously over the given range as the other parameters, but was set at discreet values within the range satisfying the necessary criteria. In addition to the parameters in Table 1, a random time delay for the inception of the fault was added in order to consider the effect of the point-on-wave at which the fault was applied. Response variables, such as the DC rail-to-ground voltage at the point of inception ($V_{pre}$), were used to consider the impact of this random delay on the behavior of the system.

**Table 1 Simulation Parameters**

| **Parameter** | **Description** | **Minimum** | **Maximum** |
|---|---|---|---|
| $C_{DC}$ | Capacitance on the DC side of the rectifier (mF). | 5 | 20 |
| $R_{DC\text{-}gnd}$ | Resistance inserted between each positive rail and ground (kΩ). | 0.5 | 2.5 |
| $R_{src\text{-}gnd}$ | Resistance inserted between the source neutral and ground (kΩ). | 0.5 | 2.5 |
| $C_{src\text{-}gnd}$ | Stray capacitive coupling to ground at the terminals of the generator (nF). | 5.0 | 20.0 |
| $L_{src}$ | Source inductance (mH). | 0.229 | 1.0 |
| $C_{inv}$ | Capacitance on the DC side of the inverter (mF). | 6.0 | 15.0 |
| $f_s$ | Switching frequency of the inverter (Hz). | 540 | 3420 |
| $P_{load}$ | Load power (MW). | 0.4 | 4.0 |
| $C_{filt}$ | Inverter filter capacitance (mF) | 0.286 | 0.35 |

The response variables analyzed in the present paper are highlighted in Table 2. These response variables include the maximum voltage ($V_{max+}$) and maximum rate of change of the voltage ($V_{rate+}$) on the positive rail with respect to ground, as these are two of the key factors affecting insulation stress. Both of these quantities are normalized by the average rail-to-rail DC voltage prior to the fault ($V_{DC\text{-}avg}$). Also, it should be noted that in some cases (particularly for the midpoint DC grounded scheme), the voltage ripple ($V_{ripple}$) response variable does not reflect a true ripple, but, rather, the peak-peak difference between transients induced by switching. For each evaluation of the simulation, the actual time-domain waveforms were saved, so that additional response variables could be calculated as these are identified.

**Table 2 Response Variables**

| Parameter | Description |
|---|---|
| $V_{max+}$ | Maximum voltage on the positive DC rail with respect to ground (pu). |
| $V_{rate+}$ | Maximum rate of change of voltage on the positive DC rail to ground (pu/μs) |
| $V_{DC\text{-}avg}$ | Average value of rail-to-rail DC voltage prior to the fault (kV). |
| $V_{ripple}$ | Voltage ripple (peak-peak) on positive DC rail to ground (V). |
| $I_{max}$ | Peak fault current (A). |

The initial plan for characterization of the simulation was to begin with a small Latin hypercube sample (LHS) drawn from the parameter space, construct Guassian process models, and use prediction variance-based adaptive sampling to refine the models as in Refs. 5, 6. However, because the execution time of the simulation was less than expected (requiring only a few minutes per simulation run), a larger set of samples could be collected. With the simulation execution time smaller than expected, and the number of available samples higher than expected, the time required for constructing the Gaussian process models between selection of sample points, was expected to outweigh the efficiency afforded by this directed sampling approach. For this reason, a larger LHS of 350 points was initially chosen, with the intention of using augmentations to the LHS in order to collect additional points to improve the models, if necessary.

Because of its ability to quickly construct models from relatively large sets of data, MARS models were constructed using the "mda" package[8] for the R statistical software environment[17] for preliminary exploration of the data. These models could be quickly constructed and tested via cross-validation methods[18] to assess the prediction performance of the models. The models for which the prediction performance was reasonable could then be used for a number of preliminary investigative purposes. For example, the parameters included in the basis functions constructed by the MARS models could be used to provide some indication of the sensitivity of the response variables to the parameters. Because the MARS models can also be used to quickly generate predictions at a large set of points within the parameter space, these sensitivities could also be quickly analyzed quantitatively by calculating Sobol' sensitivity indices[19]. Such investigations into parameter sensitivity for a set of reasonably well understood response variables can be used to verify that the simulation is not behaving erroneously. These investigations can also help to ensure that the ranges for parameters have been suitably chosen. For final computations with RS models, and particularly for RS models for which prediction performance was poor, the plan was to use Gaussian process models, such as those implemented by the "tgp" and "mlegp" packages[9,20]. While these models comparatively require more computation time for construction and prediction, these models provide predictive distributions incorporating the inherent predictive uncertainty associated with the RS models. Thus, these models allow incorporation of the prediction uncertainty into subsequent parametric analyses, which can be important for cases in which the prediction variance is not negligibly small.

## IV. Results

As noted above, an initial sample of 350 executions of the simulation was obtained based on a LHS design for each of the three grounding schemes for faults applied at the negative DC rail (location 1 in Fig. 2). The initial inspection of the data was very useful in diagnosing problems with the approach, which were subsequently corrected. One of the initial questions to be answered from the first data set relates to the significance of the random time delay used to place the inception of the fault at different points on the voltage waveform. The initial MARS models constructed for the $V_{max+}$ response variable exhibited a marginal fit, with an apparently strong dependence on the time delay parameter. In an effort to simplify the functional relationship, the voltage at the point the fault was applied ($V_{pre}$) was calculated as an additional response variable and substituted for the time delay parameter in the model. The fit of the model improved significantly with this transformation, and the $V_{pre}$ parameter continued to be the most influential parameter in the model. This confirmed the importance of this parameter and, therefore, the need for the time delay in the model. Further inspection of the models revealed, however, a larger than expected range for this pre-fault voltage. Subsequently, a response variable for the average positive rail voltage prior to the fault ($V_{DC\text{-}avg}$) was computed, also revealing a larger than expected range for the DC bus voltage. A subsequent sensitivity analysis revealed a large portion of the parameter space in which anomalously high DC bus voltages were noticed. When the simulation was tested in this region of the parameter space, it was confirmed that, in such cases, the startup sequence of the simulation was leading to large over-voltages on the DC bus which decayed very slowly. Consequently, the simulation had not reached steady-state when the fault was applied, leading to incorrect results. Although the startup sequence seemed to have been satisfactory for the points in the parameter space at which the simulation was tested prior to running the LHS design, this sequence was not satisfactory over much of the parameter space. The startup sequence was corrected by choosing a ramp up time for the voltage source for which a correct initialization could be achieved in the most difficult area of the parameter space, and the simulation was again evaluated for the LHS design.

With the initial problems corrected, analysis of the data resumed using the MARS models. Based on cross-validation results using ten groups, it appeared that some of the models showed very little prediction error, while other models seemed to be of very little value for prediction. An example of one of the best fits is illustrated by Figure 4 showing the cross-validation predictions for response variable $V_{DC\text{-}avg}$ for the DC midpoint grounded case. Figure 5 illustrates the predictions for response variable $V_{max+}$ for the DC midpoint grounded case showing the model results with more significant prediction error, although still reasonable prediction.

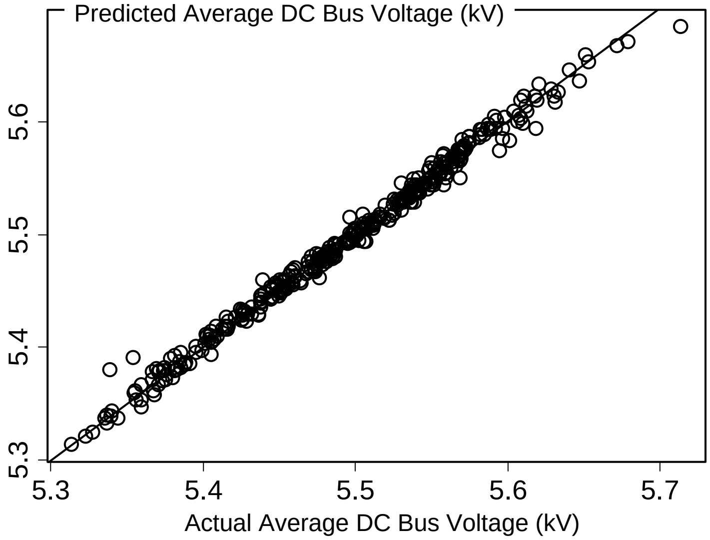

**Figure 4. Cross-validation prediction results for MARS models of response variable $V_{DC\text{-}avg}$ for the DC Midpoint grounding scheme.**

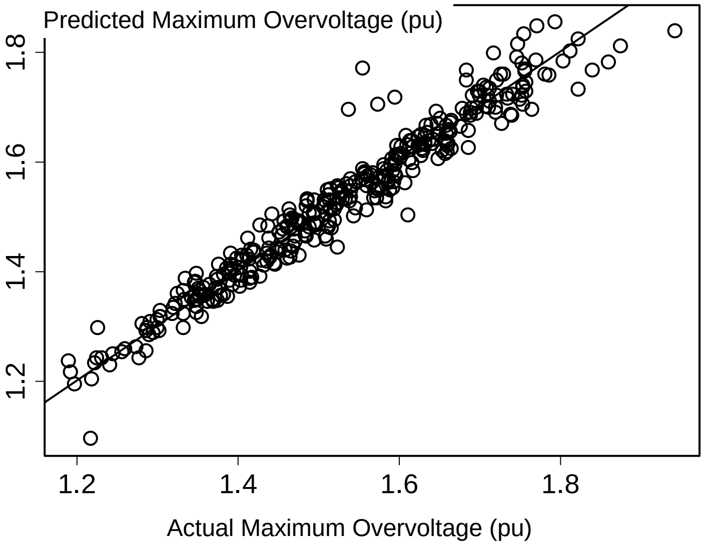

**Figure 5. Cross-validation prediction results for MARS models of response variable $V_{max+}$ for the DC Midpoint grounding scheme.**

Using the constructed MARS models, Sobol' total sensitivity indices[19] were computed for the models to study possible differences in the sensitivities of the response variables for the different grounding schemes. Sobol' indices provide information about the global influence of parameters through a general functional decomposition of the variance. A total sensitivity index value for a given RS model and parameter indicates the proportion of the variability in the RS model explained by that parameter or interactions involving the parameter. Because interaction effects are included for each parameter involving the given effect, the total sensitivity indices can sum to values greater than one. Nevertheless, these provide useful summary information for global sensitivity. Figure 6 illustrates the total sensitivity indices for the $V_{max+}$ response variable for each of the considered grounding schemes. Each of the simulation parameters are listed on the horizontal axis, with the associated sensitivity index for each given by the vertical axis. In this case, each of the responses is dominated by the $V_{pre}$ parameter, with a small contribution from the $P_{load}$ parameter. In contrast, Figure 7 illustrates the sensitivity indices for the $V_{ripple}$ response variable for each grounding case. For this case, there are notable differences in the parameters to which each response is most sensitive. In each case, the source inductance ($L_{src}$) and DC bus capacitance ($C_{DC}$) seem to play a significant role. The relative importance of other parameters varies significantly between grounding schemes. This may be partially affected by the significantly different ranges over which each of these response variables vary. However, these results will be further scrutinized and studied in future efforts.

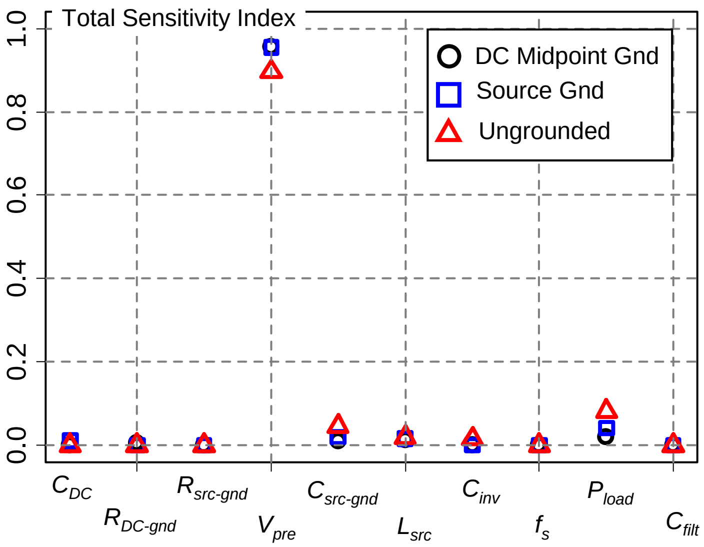

**Figure 6. Total sensitivity indices for MARS models of response variable $V_{max+}$.**

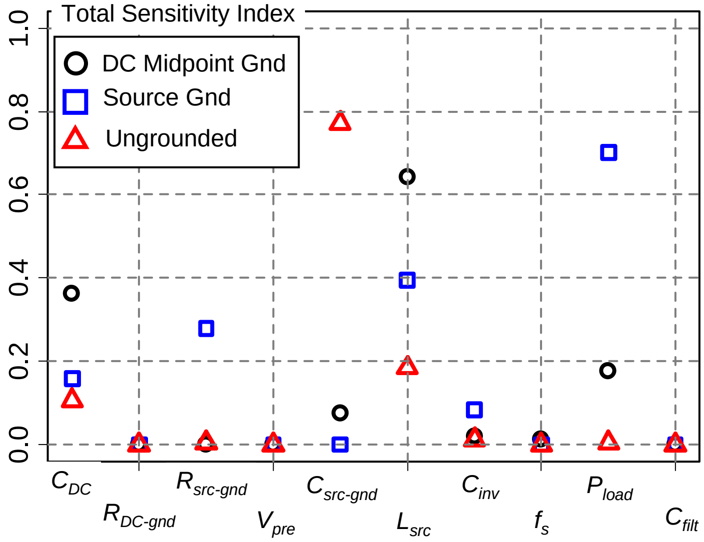

**Figure 7. Total sensitivity indices for MARS models of response variable $V_{ripple}$.**

For further analysis of the models, uncertainty analyses were carried out to study the general distributions of the response variables which could be expected for each grounding scheme. For these analyses, each of the input parameters was assumed to vary uniformly over its specified range. Ten thousand samples were drawn from these distributions and the MARS models were used to make predictions for each of the samples. Kernel density estimation was then used to construct approximate probability distributions for each of the responses from the model predictions, and the results were compared for each of the grounding schemes. Figure 8 illustrates a comparison of the distributions for the response variable $V_{max+}$ for each grounding scheme. As the figure shows, while the mean overvoltage for each grounding scheme was not significantly different, the variance in the distributions for the three schemes was quite different. Figure 9, similarly, shows the distributions for the $V_{ripple}$ response variable, illustrating very different distributions for each grounding scheme. From the analysis of the time-domain waveforms, the form of the variation of the positive rail voltage with respect to ground is quite different for each grounding scheme. Both the ungrounded and source grounded schemes seem to show pronounced 180 Hz oscillations (among other frequency components), while the primary disturbances for the DC midpoint grounded scheme appear to be quickly decaying transients associated with switching of the diodes. Once again, these issues will be scrutinized and studied in much greater detail in future efforts.

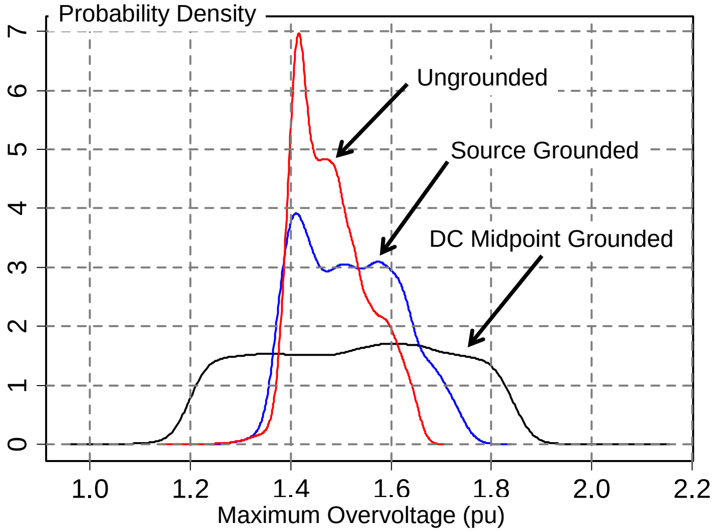

**Figure 8. Uncertainty analysis results for MARS models of response variable $V_{max+}$.**

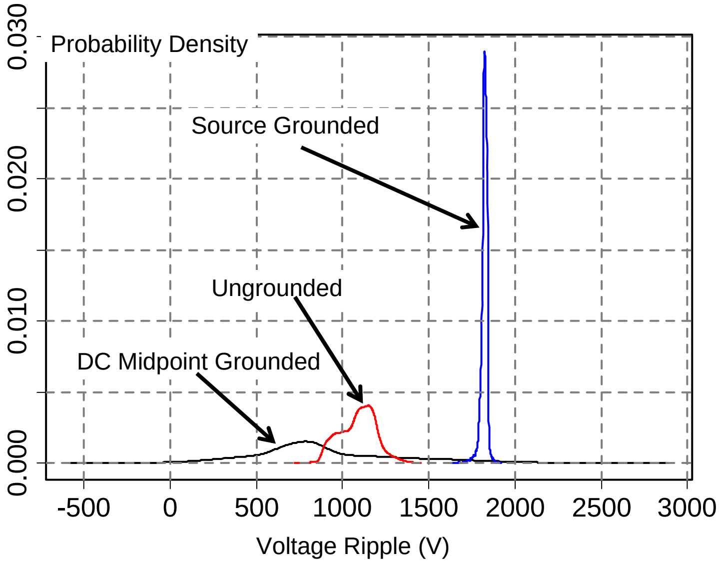

**Figure 9. Uncertainty analysis results for MARS models of response variable $V_{ripple}$.**

As noted above, while MARS models were used for most of the preliminary exploration of the data collected, more precise computations with the models may require the consideration of the RS model prediction uncertainty. This is particularly true for cases in which the prediction error of the RS models is more significant. For this reason, Gaussian process models were constructed for each of the response variables using the “mlegp” package[9]. Figure 10 illustrates the prediction results from cross-validation with the model constructed for response variable $V_{max+}$, showing the 95% confidence bounds for the cross-validation predictions. The overall prediction of the model is similar to that of the MARS model for which the cross validation prediction results are shown in Figure 5. As noted above, although the Gaussian process model requires more computation time for construction and prediction, the prediction variance information provided by the model can be important for many analyses.

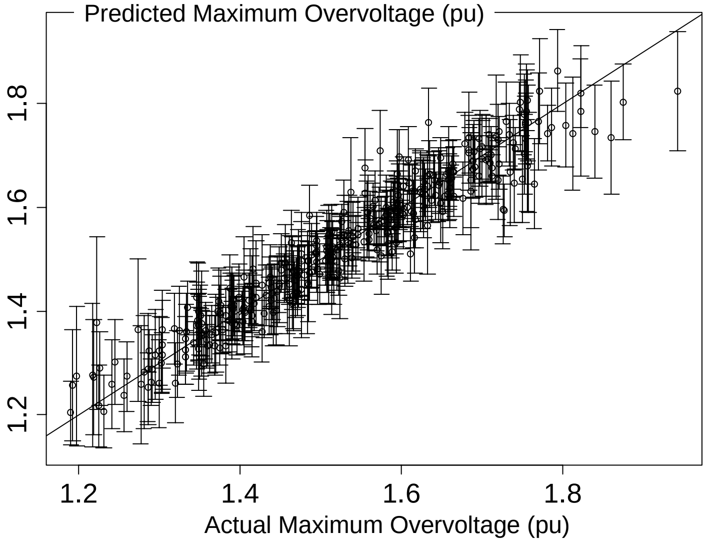

**Figure 10. Cross-validation prediction results for Gaussian process models of response variable $V_{max+}$ for the DC Midpoint grounding scheme.**

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## V. Conclusion

The application of RS modeling techniques to the study of high-resistance grounding schemes for MVDC shipboard power systems is described. Several response variables for characterization of the behavior of the system under four single-line-to-ground faults are identified. The originally intended approach to use Gaussian process models and variance-based adaptive sampling was altered due to the fact that the computational expense of the simulation was less than expected. Instead, a simple LHS design was used. Preliminary results are reported based on the initial exploration of the data using MARS models. However, it is important to note that the results presented herein are only representative of the system studied and the specific parameter values chosen, and are not necessarily reflective of a fully designed system. Thus, the emphasis of these results tends toward relative relationships between the parameters and the response variables, and not to the absolute magnitudes of the responses. Nevertheless, these results begin to lay the basis for more careful future analysis in order to glean meaningful and useful information from the simulation models and understand the driving forces and implications. It may be necessary, as well, to collect more samples for the existing cases in order to improve the prediction of some of the RS models. Additional work may be needed to expand the study to other fault types, other simulation parameters, other grounding schemes, and different system topologies. Such exploration of detailed transient simulations over a wide parameter space provides a valuable insight into the system behavior to properly understand issues associated with grounding and insulation for shipboard MVDC systems, for which experience with existing systems is rather limited.

## Acknowledgments

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