Characterization of the Transient Behavior of an AC/DC Conversion System for a Notional All-Electric Ship Simulation Using Sequential Experimental Design Methodology

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Abstract

Experimental design methodology is applied to the characterization of a transient simulation of the AC/DC conversion system of a notional all-electric ship in terms of parameters of the simulation. The process of constructing the surrogate models describing the behavior of the system during a load rejection transient scenario is presented and selected results from predictions from the surrogate models are presented.

1. INTRODUCTION

The use of large-scale transient simulations for modeling and design of the next generation of all electric ships is motivated, to a large extent, by the closely coupled nature of these shipboard power systems and the potential for interactions between the many components and subsystems of which they are composed. High fidelity simulation models may provide an avenue to study various options related to design and performance over a range of system designs and topologies that would otherwise be prohibitively expensive to explore. However, there are a number of challenges in the practical application of these simulation models to system analysis and design. The time domain waveforms produced by the simulations must be characterized in terms of useful system performance metrics, and the influence of system topologies and design parameters on these performance metrics must be characterized and understood. Additionally, uncertainty analyses are needed to assess the behavior of the systems in the presence of random environmental variables, as well as to assess the uncertainty of the model predictions due to imprecise knowledge of the system or system components. Further, it is important to simultaneously assess the impact of errors introduced through the simulation algorithm (e.g. assess the role of the time-step size in fixed time-step size transient simulations) and to ensure that the results are relatively insensitive to artificial parameters of the simulations. These issues are made particularly challenging by the need to simultaneously consider a large number of potentially influential factors in the simulation.

A generally accepted practice for carrying out the above analyses for computationally expensive simulations is to develop a surrogate model for the more detailed simulation, characterizing the input-output relationship with a relatively small number of simulation runs. General parametric studies of the system, including uncertainty analysis and design optimization, can then be carried out on the surrogate model, which can be evaluated with much less computational burden than the simulation. A number of approaches for representing such models have been proposed, ranging from simple polynomial models to numerous types of nonparametric models [1]-[5]. With all of these modeling approaches, the problem becomes one of efficiently sampling the parameter space in order to construct the surrogate model. Again, a number of criteria have been proposed for efficient sampling associated with different models ranging from the so-called alphabetic optimality criteria (e.g. D-, Q-optimality) of classical experimental designs, to uniform designs and maximum entropy designs that are often utilized for non parametric models [1]-[5]. Many of these approaches leverage knowledge of input parameter distributions or general complexity of the model in order to capture as much information as possible in a small set of samples. For any of these methods, however, it is difficult to adequately sample a high-dimensional parameter space. A number of factor screening techniques have been proposed for dealing with this problem, as well, each with its own set of underlying assumptions needed for success [6]. In [7], sequential experimental design methodology was employed in the characterization of the steady state behavior of the AC/DC conversion system of a notional all-electric warship. In this article, this approach is further applied to the characterization of the transient behavior of the system for a load rejection scenario.

2. SYSTEM DESCRIPTION

The work described herein is generally directed toward characterization and verification/validation of a large-scale electromagnetic transients simulation model of a notional all-electric warship, described in [8]. This time-domain simulation, distributed across nine racks of a real-time digital simulator [9], models numerous machines and converters, along with the hydrodynamics associated with the propulsion system with fixed time-step sizes on the order of 50 µs (subsystems with fast-switching converters utilize time-step sizes on the order of 2 µs). However, in order to gain insight into the behavior of this system, the work described herein, as well as that described in [7], focused on a flexible system of reduced size, composed primarily of the AC/DC conversion system, as illustrated in Figure 1. This reduced system models the 13.8 kV AC ring bus system as a single generator, utilizing a gas turbine engine model based on that described in [10]. The rated power of the generator is varied as a parameter of the simulation to reflect the impact of the ring bus configuration on the system behavior. In addition, the model includes a rectifier (PCM4) and two DC/DC buck converters (PCM1) supplying a single resistive load. Further, because it is necessary for the larger system to be split into multiple subsystems for implementation on the simulator described, the impacts of artificially splitting the system were also a point of focus. For this reason, the reduced system was implemented both as a single subsystem, as well as two subsystems split across the 1kV DC bus.

As noted above, this work focused on characterization of the system behavior for a transient scenario in which the DC load is abruptly reduced. The dynamics of the load change were modeled very simply as a single pole filter. For this scenario, 27 parameters of the simulation, given in Table I, were studied. These included environmental variables such as the load power and generator rms voltage, uncertain model variables such as the generator reactance values, along with a number of control variables. Additionally, parameters specific to the method of simulation such as the time-step size were also considered. Logarithmic transformations were used for a number of these variables in order to accommodate larger ranges for the parameter values. In order to avoid needlessly expending runs in regions of the parameter space where model break-down was expected, constraints were placed on some of the parameters. For example, the switching frequency for the buck converters was constrained as a function of the time-step size in order to avoid simulating excessively high switching frequencies for large time-step sizes.

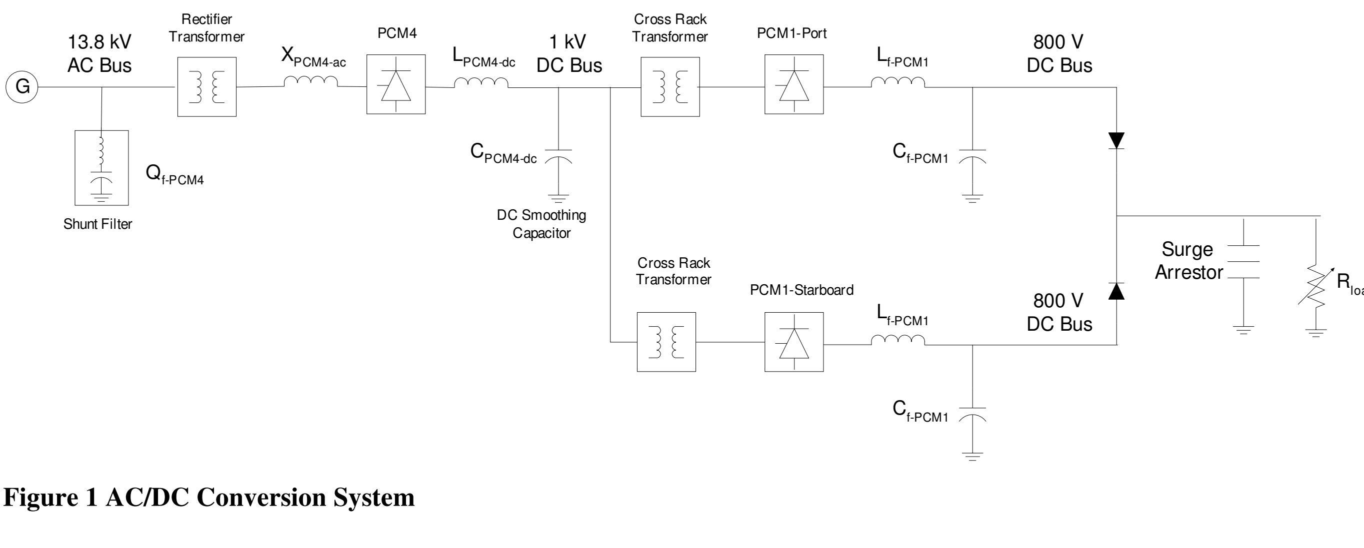

Figure 1 AC/DC Conversion System

TABLE I
MODEL PARAMETERS

Symbol	Description	Min	Max
P_{load}	Initial load power (MW).	0.1	3
$V_{rms\text{-}gen}$	RMS voltage on the AC bus (pu).	0.95	1.05
S_{gen}	Generator rated apparent power (MVA).	5	100
X_d'	Generator transient reactance (pu).	0.14	0.3
X_d''	Generator sub-transient reactance (pu).	0.081	0.13
$Q_{f\text{-}PCM4}$	Rectifier filter reactive power (MVAR).	0.01	2
$V_{hr\text{-}PCM4}$	Voltage head room for rectifier (pu).	0.05	0.25
$X_{PCM4\text{-}ac}$	Rectifier AC-side reactance (pu).	0.01	0.05
$f_{PCM4\text{-}dc}$	Rectifier DC-side filter resonant frequency (Hz).	100	1500
$C_{PCM4\text{-}dc}$	Rectifier DC-side filter capacitance (mF).	1	10
$\tau_{V\text{-}PCM4}$	Rectifier voltage measurement filter time constant (s).	0.01	1
$k_{p\text{-}PCM4}$	Rectifier PI controller proportional gain.	0.5	2
τ_{PCM4}	Rectifier PI controller time constant (s).	0.5	2
$L_{x\text{-}rack}$	Cross-rack transformer series inductance (μH).	0.1	10
$k_{f\text{-}PCM1}$	Ratio of buck converter filter resonant frequency to buck converter switching frequency.	0.18	0.75
$L_{f\text{-}PCM1}$	Buck converter filter inductance (mH).	1	50
$f_{s\text{-}PCM1}$	Buck converter switching frequency (Hz).	300	2000
$k_{p\text{-}PCM1}$	Buck converter PI controller proportional gain.	0.5	2
τ_{PCM1}	Buck converter PI controller time constant (s).	0.5	2
τ_{Load}	Time constant for load change (s).	0.01	0.001
H_{gen}	Generator inertia constant (MW*s/MVA)	3	5
$k_{p\text{-}lp}$	Low pressure turbine governor proportional gain.	2.81	7.9
τ_{lp}	Low pressure turbine governor time constant (s).	0.112	0.356
$k_{p\text{-}hp}$	High pressure turbine governor proportional gain.	0.63	6.3
τ_{hp}	High pressure turbine governor time constant (s).	0.079	0.79
$V_{d\text{-}SA}$	Surge arrestor discharge voltage (pu).	1.2	2.0
Δt	Time step size (μs).	15	150

For this scenario, a number of response variables were derived from the time domain waveforms produced by the simulation in order to characterize the system behavior. Summarized in Table II, these responses primarily focus on overvoltages on the various busses and the frequency deviations exhibited by the high-pressure and low-pressure turbines of the generator. The maximum current through the surge arrestor and the energy dissipated therein were also considered. Additionally, a number of diagnostic response variables were studied, in order to attempt to identify compromised fidelity of the model. All time-domain waveforms were retained, however, in order to facilitate the creation and analysis of new response variables for further characterization.

TABLE II
RESPONSE VARIABLES

Symbol	Description
$\Delta V_{AC\text{-}max}$	Maximum over-voltage on AC bus (pu).
$\Delta V_{1kv\text{-}max}$	Maximum over-voltage on 1 kV bus (pu).
$\Delta V_{load\text{-}max}$	Maximum over-voltage at the load (pu).
$I_{SA\text{-}max}$	Maximum instantaneous current through surge arrestor (kA).
E_{SA}	Energy dissipated in the surge arrestor during the transient event (kJ).
$\Delta\omega_{lp\text{-}max}$	Maximum frequency deviation of low pressure turbine (pu).
$\Delta\omega_{hp\text{-}max}$	Maximum frequency deviation of high pressure turbine (pu).

3. CONSTRUCTION OF SURROGATE MODELS

3.1. Methodology

The basic approach for characterization of the simulation is to simply run the simulation with a number of different combinations of parameter settings, calculate response variables for each one of these trials, and then construct a surrogate model for each response variable to capture the basic input-output relationships. The primary questions that arise relate to the number of runs needed, the placement of these runs (choice of parameter values), and the types of models to use for representation of the response variables. The sequential approach used in classical design of experiments seeks to address these questions by starting with a small number of runs and very simple models and, as necessary, progressively increasing the complexity of the design and models through a series of augmentations. By attempting to only expend the minimum number of simulation runs needed to characterize the process, the methodology is well suited to situations for which simulations are costly or time consuming. While this approach is not without its own set of limitations and requisite assumptions, the experimenter is afforded flexibility in configuring these assumptions for each experiment, allowing knowledge of the system to be leveraged in the process. Further, the experimenter is given the flexibility to test the validity of assumptions as the process progresses. Additionally, as these methods were primarily developed for physical experimentation, the ability to naturally extend the current work with a deterministic simulation to nondeterministic simulations and physical experiments (e.g. hardware-in-the-loop) also motivates the use of this approach.

The particular strategy for this work, with a moderate number of parameters, was to initially make use of highly fractionated two-level factorial designs [1] to fit a linear model of the form

$$y(\mathbf{x_0}) = \mathbf{x}_0^{\mathrm{T}}\mathbf{b} \qquad (1)$$

Here, y is the response variable (or some transformation thereof), **b** is a column vector of coefficients, and $\mathbf{x}_0$ is a column vector constructed from the parameter values specifying the point at which the response is to be predicted. The **b** coefficients can be estimated, from a set of observations, **y**, at a set of design points (parameter values), **X**, through least squares regression, for example, as

$$\hat{\mathbf{b}} = \left(\mathbf{X}^{\mathrm{T}}\mathbf{X}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{y} \qquad (2)$$

In general, **X** is some basis expansion of the parameters, which can include, for example, linear terms, interactive terms (between two or more parameters), and quadratic terms. In this case, the elements of $\mathbf{x}_0$ correspond to the basis expansion of the test points represented by the columns of **X**. A two-level, full factorial design is intended to estimate a model including linear and all interactive terms for all parameters by evaluating the simulation at each combination of two-level parameter values. These orthogonal designs seek to minimize the confidence intervals on coefficients of the model and model predictions. However, for a system of N parameters, this requires 2^N evaluations of the simulation, while estimating a number of terms that are not likely to be influential. Fractional factorial designs significantly reduce the number of runs required by systematically aliasing certain model effects. This allows the experimenter to leverage knowledge of the system, along with previous experimental results, to eliminate non-influential terms and infer which terms among aliased effects are truly influential. The design can be further augmented to break specific alias chains and identify an influential model term among a group of equally likely terms with which it is aliased. Such an approach is particularly effective if the model is dominated by terms associated with a small subset of the parameters involved.

If the linear-interactive models fit through these designs do not sufficiently model the response, higher order polynomial models can be constructed by augmenting the factorial designs. For example, central composite designs [1] can be constructed by augmenting factorial designs with center runs (for which all parameters are held at a midpoint value) and axial runs (for which each parameter is held at each of its extreme values while all other parameters are held at a midpoint value). Such designs can be used to fit quadratic models in order to model more nonlinear responses. Further augmentation designs to accommodate specific models of higher order can be generated using algorithmic designs that make use of one or more optimality criteria. In this way, models of arbitrary complexity can be constructed in a sequential fashion by targeting specific runs to estimate specific terms of models.

3.2. Experimentation

A Resolution III fractional factorial design [1], consisting of 32 runs, was used to gain an initial estimate of linear and interactive effects and to verify that the model behaved reasonably for the ranges of parameters chosen. Resolution III implies that linear terms are not aliased with each other, but they are aliased with interactive effects. For the factorial runs, the high and low values for each parameter were limited to 60% of the range for the respective parameter. In order to obtain a Resolution IV design and eliminate aliasing of two-way interactive effects with linear effects, a full fold-over augmentation was carried out, consisting of 32 additional runs. At this point, all 27 linear terms could be estimated, as well as 36 aliased interactive terms. From the estimated terms, along with knowledge of the alias structure and intuitive knowledge of the system, subsets of influential factors were identified for groups of response variables.

Because some two-way interactive effects involving the influential parameters were aliased with each other, an augmentation to the design was needed to properly estimate these effects. Typically, fold-over designs in terms of single parameters could be used, but this augmentation technique has the disadvantage that it may target unnecessary terms, while doubling the number of runs for each fold-over augmentation. For this reason, a D-optimal design augmentation [1] was used to estimate the two-way interactions for the subset of influential parameters. A D-optimal design seeks to minimize the confidence bounds on model coefficients by choosing the augmented runs in such a way to maximize the determinant of the matrix given by $\mathbf{X}^{\mathrm{T}}\mathbf{X}$. For this augmentation, generated using [11], 64 additional runs were expended in order to provide enough degrees of freedom for estimation of the model terms.

In order to test for nonlinearity and lack of fit, the design was further augmented to complete a central composite design. Five center runs were obtained to stabilize the prediction variance and provide some estimate of the "pure error" for the simulation. While the simulation is deterministic in the sense that the time domain waveforms are unchanged for runs of the same configuration of the system, the moment at which the load change is initiated may cause small variations in the response variables. Thus, for each run the load change is applied at a random time after the simulation is brought to steady state, introducing some variance in what is otherwise a deterministic model which would only exhibit variance in the form of lack of fit. This relatively inexpensive exercise (in terms of runs) can potentially expose such variance with the simulation if it exists. Additionally, 54 axial runs were generated to estimate pure quadratic terms for each of the parameters.

3.3. Model Fitting

The complete design, consisting of 187 runs (32 + 32 + 64 + 5 + 54) was used to construct quadratic models for several of the response variables. These models included linear terms for all factors, along with two-way interactive terms and quadratic terms for subsets of parameters of particular influence. As in [7], however, multicollinearity was introduced into the design through constraints placed on the parameters. Because multicollinearity can result in poor estimates of model coefficients with least squares regression, ridge regression was used to estimate the coefficients of the models by

$$\hat{\mathbf{b}}_{ridge} = \left(\mathbf{X}^{\mathrm{T}}\mathbf{X} + \lambda\mathbf{I}\right)^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{y}\,. \qquad (3)$$

Here, λ is a tuning parameter used to effectively place a penalty on the magnitude of the regression coefficients [12]. For these cases, the method of Hoerl and Kennard was used to choose λ [13].

Although all of the surrogate models developed could benefit from further development, some of the models seemed to fit well enough for general interpretive use. Models such as the over-voltage on the DC busses and the energy dissipated in the surge arrestor exhibited R^2 values and adjusted R^2 values around 0.8. Figure 2 shows the maximum over-voltage at the load predicted by the surrogate model versus the values given from the simulation.

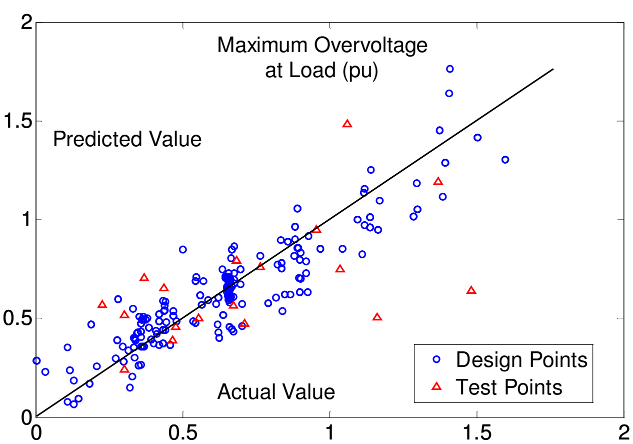

Figure 2 Comparison of surrogate model predictions to simulated values for the maximum over-voltage at the load

This model used 64 degrees of freedom, allowing 123 degrees of freedom to detect lack of fit. Additionally, the simulation was evaluated at 20 random test points in order to further test the predictions of the surrogate model. Although most of the test points were predicted reasonably well, several points were not predicted very accurately. Clearly, additional work is needed in order to obtain completely satisfactory models. This may include further experimentation, as well as the use of more flexible models.

4. UTILIZATION OF SURROGATE MODELS

Once satisfactory surrogate models have been constructed, a wide range of information can be obtained from these characterizations of the full simulation. Insight into the relative sensitivity of the simulation to parameters can be obtained by simple inspection of the magnitudes of model coefficients, or from more general metrics, such as the Sobol' indices [2], [3], [6]. Further, uncertainty propagation techniques can be applied directly to the surrogate models in order to obtain confidence bounds on the predictions of the simulation in the context of the uncertainty associated with parameters of the model. Such information is important to improving the fidelity of the simulation model and properly contextualizing the predictions of the simulation. The surrogate models and the information derived from these analyses are vital to the verification and validation of the simulation model.

Once the validity of the simulation model has been established, the surrogate models characterizing its behavior can be used in understanding the tradeoffs in the design of the system. An example using the surrogate models developed for the maximum over-voltage at the load and the energy dissipated in the surge arrestor is illustrated through Figure 3 and Figure 4. These figures illustrate the general trends exhibited by the simulation as the buck converter filter inductance and the discharge voltage for the surge arrestor are varied, while all other parameters are held constant. Figure 3 illustrates the reduction in the over-voltage associated with reduction of the filter inductor, as well as the reduction in the severity of the over-voltage provided by the surge arrestor. Figure 4, highlights the price that must be paid for this over-voltage reduction in terms of the energy that must be dissipated. By combining the predictions from a large number of such surrogate models, characterizing a wide range of steady state and transient scenarios, along with pertinent physical information, such as the size, weight, and cost of components, high fidelity simulation models may effectively lend themselves as useful design tools for large, closely coupled systems.

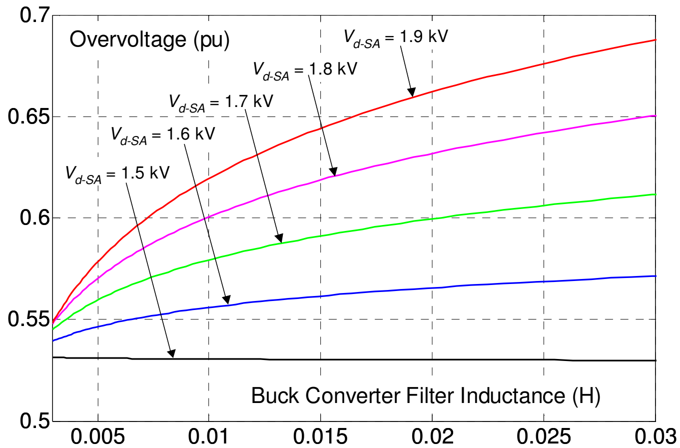

Figure 3 Predictions of the surrogate model for the maximum over-voltage at the load

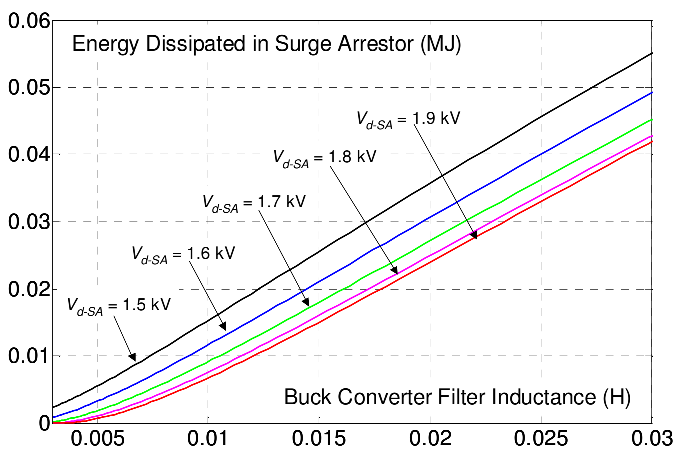

Figure 4 Predictions of the surrogate model for the energy dissipated in the surge arrestor

5. CONCLUSION

Herein, the behavior of a simulation model of the AC/DC conversion system of a notional all-electric warship has been described for a transient scenario in which the load was abruptly decreased. The system behavior was characterized through several response variables, modeled as functions of a moderate number of parameters, through a sequence of experimental designs and augmentations. While the process of constructing satisfactory models is ongoing, several points can be made from the experiences thus far.

- The sequential approach used for this work is particularly appealing because it attempts to make extremely efficient use of simulation runs by only resorting to more complicated designs and models as needed. Efficient use of runs is particularly important for transient power system simulations as typical PC based simulations may take several hours to execute [7], while the use of large scale parallel processor based simulators (as in this case) equivalently consumes significant resources in terms of the amount of time for which the simulator is occupied. Such considerations become even more important as the number of parameters increases for larger systems and the need arises to characterize the model for a number of scenarios.
- Although the models constructed are not yet satisfactory, a significant amount of information has been obtained with a relatively small number of simulation runs. It is important to note that even a two-level grid in 27 parameters would require over 10^8 simulation runs. Thus, although future work may require additional experimental runs, more complicated models, and/or forced reduction in the dimensionality of the problem, the information gathered may provide guidance in the choice of future actions needed to properly characterize the simulation.
- Although for this work control gains for the various control systems in the simulation were considered as parameters, the ranges chosen for these parameters limited the impact of potential tuning of the controls on the simulation. In reality, the controls should be tuned for each particular design setting, and this is clearly an area for which additional augmentation to the process is needed in order to properly characterize the behavior of a simulation model.

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