Sensitivity Analysis of the Shipboard Integrated Power System

Pradya Prempraneerach, Franz S. Hover, Michael S. Triantafyllou, Timothy J. McCoy, Chryssostomos Chryssostomidis, and George E. Karniadakis

Abstract

Stochastic sensitivity analysis is a valuable tool in ranking inputs and in investigating the degree of interaction of its components. In this paper, we present stochastic simulation results for a shipboard integrated power system and study its sensitivity. Specifically, we apply sensitivity analysis to two high-fidelity models of shipboard subsystems, investigating open- and closed-loop control of the propulsion system. The results show that different inputs are most important for the open- and closed-loop control, with sensitivities that change dramatically in time as they reflect the transition from the fast electrical scales to slower mechanical scales. We also demonstrate how sensitivity analysis can be used to establish the robustness of the AC drive.

Introduction

The integrated power system (IPS) is a complex and central feature of the All-Electric Ship (AES) architecture. Many input parameters of this system are uncertain and the vessel can undergo substantial environmental disturbances and time-varying loads due to unpredictable sea states. These facts pose immense challenges in all stages of design. To date, however, there have been no studies that account for stochastic variation in large-scale shipboard power systems, from either an analytical or a computational perspective.

With a large number of components in the AES, it is important for the IPS designer to prioritize the design parameters as well as to recognize parameters’ interactions for improving the system performance and avoiding a cascaded failure. Sensitivity analysis can help to identify efficiently the most influential and coupled parameters under many stochastic variations using only independent evaluations. Then, the unimportant parameters can be neglected from further system designs by fixing them at their nominal values to accelerate experimental studies.

The two main classes of sensitivity analysis are local and global approaches. A partial derivative is mainly used as a sensitivity index in the local approach (Hockenberry 2000; Rabitz, Kramer, and Dacol 1983); thus, this approach cannot provide accurate information when parametric uncertainties occur within a wide range. With regard to the global approach, the Morris method (Morris 1991; Campolongo et al. 2005; Saltelli, Chan, and Scott 2000, Saltelli et al. 2004) is based on One-At-a-Time (OAT) screening and can deal with system with many uncertain parameters. This method has been widely used for to both complex functions and ordinary differential equations (ODEs) because of its model independence, efficiency, and implementation simplicity. However, the Morris method provides only a qualitative ranking of parameters, which prevents the designer from...
enhancing the system robustness and reliability quantitatively. Several other global sensitivity analysis techniques, such as the iterated fractional factorial design (Saltelli, Andres, and Homma 1995) and the variance-based sensitivity measure (Campolongo et al. 2005, Saltelli, Chan, and Scott 2000, Saltelli et al. 2004), have been introduced in the literature; nevertheless, their time-consuming characteristics overcome their advantages when the system consists of hundreds or thousands of parameters.

In this paper, we first review concepts of the Morris method and a new Monte Carlo Sampling method in section 2. In section 3, we investigate the performance of these sensitivity analysis methods using a nonlinear function with stochastic parameters. Finally, in section 4, the parametric sensitivity and machine interactions are studied for AC open- and closed-loop propulsion motors powered by a prime mover and a synchronous generator. We show that the sensitivity analysis can help quantify the robustness of the AC drive.

**Sensitivity Analysis Methods**

Practically, when the system has hundreds or thousands of input parameters \([x_1, \ldots, x_d]\), it is almost impossible to fully investigate all combinations of input parameters. Therefore, parameter screening is needed to examine which inputs have the most effect on the output and to rank those inputs accordingly, so that the smallest number of further experiments or calculations can focus only on the sensitive set of parameters. To investigate the OAT global sensitivity, the first-order or elementary effect of \(i\) input on \(j\) output \((EE_j^i)\) is defined as the approximated gradient, when only the \(i\) input deviates from its nominal value with \(\Delta\) magnitude. To avoid averaging out the effects from the \(i\) input in the \((EE_j^i)\) computation, we use the absolute difference of the \(j\)th output (Campolongo et al. 2005), as shown below:

\[
EE_j^i = \frac{|y_j(x_1, \ldots, x_i + \Delta, \ldots, x_d) - y_j|}{\Delta}
\]  

(1)

where \(x_i\), with \(i = 1, \ldots, d\) is contained within a domain of variation in \(d\) parametric and inputs’ dimensions. For \(y_j\) outputs with \(j = 1, \ldots, n\), we need a total of \(n \times d\) computations of \((EE_j^i)\).

Using the local gradient computation, when \(\partial y_j/\partial x_i\) is equal to (1) zero, (2) a non-zero constant, or (3) a non-constant function of input parameter(s), the effects of \(x_i\) on \(y_j\) are (1) negligible, (2) linear and additive, or (3) nonlinear and coupled, respectively. The numerically approximated gradient can capture all the above effects, called the elementary effect. If all \(x_i\) except \(x_i\) are fixed at their nominal values, the \((EE_j^i)\) can only rank the input parameter according to the elementary effect without specifying

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**TABLE 1: The Values of \(b\) Coefficients for the Modified Morris Functions**

<table>
<thead>
<tr>
<th>(b) coefficients for (n = 6) inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>(b_0 = 1,)</td>
</tr>
<tr>
<td>(b_i = 20, \text{ for } i = 1, 2, 3)</td>
</tr>
<tr>
<td>(b_{ij} = -15, \text{ for } i, j = 1, 2)</td>
</tr>
<tr>
<td>(b_{ijk} = -10, \text{ for } i, j, k = 1)</td>
</tr>
</tbody>
</table>
any influence of the interaction among inputs. By randomizing all values of \( x \) in computing \( (EE_j^i) \), the interaction effects can be discovered from the variation of the \( (EE_j^i) \) distribution.

With this concept in mind, we next present the gradient-based methods—Morris and Monte Carlo sampling methods—and then compare their accuracy and efficiency against one another.

**MORRIS METHOD**

The Morris method considers the OAT \( (EE_j^i) \) to identify the significant first-order and interaction effects of input parameters with only a few evaluations of \( (EE_j^i) \). The basic methodology of this approach is to randomly select an initial condition on the grid points and construct a randomized trajectory along this grid structure in a high-dimensional input space for \( r \) trials. Thus, the mean and standard deviation of \( (EE_j^i) \) represent the elementary effect of \( i \)th input and interaction of other inputs with the \( i \)th input.

Originally, all input parameters in the Morris method (Morris 1991) are assumed to be independent uniformly distributed; nevertheless, the normal distribution can be applicable to parameters in this method as well (Campolongo et al. 2005). The Morris method becomes more efficient when \( d/\frac{n}{p} \approx \log n \) (Morris 1991). The procedure to construct the OAT randomized trajectory is described next. First, each input dimension of the \( d \)-dimensional hypercube is divided into a \( p \)-level grid, \([0, 1/p-1), 2/(p-1), \ldots, 1]\), such that the initial condition, \( x^* \), can be randomly assigned to one of these grid points. According to Morris, the value of \( \Delta \) is set as \( p/2(p-1) \) using an even \( p \) value and \( p > 2 \) such that \( \Delta \) optimally covers the \( d \)-dimensional \( p \)-level random space with an equal probability. It is clear that the randomized trajectory is contained within the range of input variation.

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**Figure 3:** For the Modified Morris Function with Six Inputs and \( w_i \in [0, 1] \): the Mean and Standard Deviation of \( EE_i \) from the Morris Method with \( p = 16 \) and \( r = 8,000-10,000 \) (Left), from the MC Sampling with \( \Delta = 1/2 \) and \( N = 8,000-10,000 \) (Right)

**Figure 4:** For the Modified Morris Function with Six Inputs and \( w_i \in [0, 1] \): the Convergence Characteristics, Plotted Versus the Computational Time, for RMS(\( \varepsilon_{\text{mean}} \)) (Upper) and RMS(\( \varepsilon_{\text{var}} \)) (Lower) Using the Morris, MC, and QMC Sampling Methods
The total computational cost consists of two parts: generating the randomized trajectory with cost on the order of $\mathcal{O}(r \times d)$ and evaluating the $EE_i$ for one output using the randomized trajectories with cost on the order of $\mathcal{O}(r \times (d + 1))$. Note that, as we increase the $p$-level in this $d$-dimensional space, the value of $\Delta$ approaches $1/2$. This minimum $\Delta = 1/2$ seems to constrain the randomized trajectory on the boundary more often than in the interior of the input domain.

The Morris method was first developed for ranking the sensitivity of a multi-input function. To extend the capability of the Morris method for solving ODEs, we can view the computation of the elementary effect at each time step as a random perturbation in each input dimension. This formula only generates feasible paths within the input domain. The last step is to construct $r$ trials of this randomized $B^*$ matrix such that the $r$ random trajectories can be obtained from the row difference of $B^*$, called the $\Delta B^*$ matrix. To distinguish between the row difference of $B$, $\Delta B$, and the row difference of $B^*$, $\Delta B^*$, we show one of the $r$ trajectories from $\Delta B$ and $\Delta B^*$ for $p = 4$ in Figure 1.
**Monte Carlo Sampling Method**

Instead of computing the statistics of the $EE_i$ from the randomized trajectories on the $p$-level grid as in the Morris method, Monte Carlo (MC) and Quasi-Monte Carlo (QMC) sampling methods can be used to randomly generate the $N$ initial conditions in the $d$-dimensional inputs, and then the elementary effect in each direction can be computed at these $N$ random initial points. Similar to the Morris method, the mean of each $i$ elementary effect or $E[EE_i]$ can be directly used to rank input parameters. In addition, $\sigma[EE_i]$ can specify the respective influences of inputs' interaction and nonlinearity on the output.

To demonstrate this methodology, Figure 2 shows nine realizations of random initial conditions and directions in the $EE_i$ computation with fixed $\Delta$ in a three-dimensional input space. The total evaluation of output for $d$ elementary effects is on the order of $\mathcal{O}(N \times (d + 1))$ for the $d$ parameters and inputs. Therefore, the accuracy of $E[EE_i]$ and $\sigma[EE_i]$ depends on the convergence characteristic of the Monte Carlo method, approximately $1/\sqrt{N}$ and $1/N$ for pseudo- and quasi-random sampling techniques Press et al. (1992), respectively. This rate of convergence is independent of the parameter dimension, which is attractive for metamodels. The main advantages of this approach over the Morris method are that the approximated gradient computation is not restricted only on the $p$-level grid structure. Thus, the method inherits the high dimensionality of Monte Carlo methods.

Applying this technique to analyze the sensitivity of ODEs requires solving $N$ problems. At each time step, we perturb the system inputs one at a time with a fixed $\Delta$. Similar to a maximum limit of the $\Delta$ magnitude in the Morris method, which equals 1/2 for an input range between $[0, 1]$, we assign the $\Delta$ magnitude to be half of the parameter-variation range. If $\Delta$ is greater than 1/2 of the input range, the distribution of $EE_i$ might be misleading due to the possible strong nonlinearity present in the system, and the value of $x_i \pm \Delta$ in $EE_i$ computation can exceed the input domain. However, if the value of $x_i \pm \Delta$ is outside the input domain, the sign of $x_i \pm \Delta$ must be reversed.

**Comparison of the Two Sensitivity Analyses: Modified Morris’s Function**

To evaluate the convergence performance of these sensitivity algorithms, we systematically test the parametric sensitivity and interaction of the system for a function with six input parameters, modified from Morris’s original function (Morris 1991). All numerical computations are performed with Microsoft C++ compiler on an Intel Pentium 4 3.0 GHz processor. This function with six inputs is modified from the original test function with 20 inputs in the Morris paper (Morris 1991). This modified Morris function is suitable for testing the effectiveness of

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**TABLE 3: Parameters of the Synchronous Generator (a-l), the Induction Machines (m-s), the Power Converter (y-ee), and the RC Bus (t-x) with $V_{\text{base}} = 450$ V**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stator resistance</td>
<td>$r_s$</td>
<td></td>
</tr>
<tr>
<td>Stator flux leakage reactance</td>
<td>$X_{sh}$</td>
<td></td>
</tr>
<tr>
<td>d-Axis mutual flux reactance</td>
<td>$X_{md}$</td>
<td></td>
</tr>
<tr>
<td>q-Axis mutual flux reactance</td>
<td>$X_{mq}$</td>
<td></td>
</tr>
<tr>
<td>Rotor field winding resistance</td>
<td>$r_{fd}$</td>
<td></td>
</tr>
<tr>
<td>Field winding’s flux leakage reactance</td>
<td>$X_{fd}$</td>
<td></td>
</tr>
<tr>
<td>d-Axis rotor damper winding resistance</td>
<td>$r_{dd}$</td>
<td></td>
</tr>
<tr>
<td>d-Axis damper winding’s flux leakage reactance</td>
<td>$X_{dd}$</td>
<td></td>
</tr>
<tr>
<td>q-Axis rotor damper winding resistance</td>
<td>$r_{qd}$</td>
<td></td>
</tr>
<tr>
<td>q-Axis damper winding’s flux leakage reactance</td>
<td>$X_{qd}$</td>
<td></td>
</tr>
<tr>
<td>Rotor resistance</td>
<td>$r_{r2}$</td>
<td></td>
</tr>
<tr>
<td>Stator flux leakage reactance</td>
<td>$X_{sh2}$</td>
<td></td>
</tr>
<tr>
<td>Mutual flux reactance</td>
<td>$X_{md2}$</td>
<td></td>
</tr>
<tr>
<td>Rotor flux leakage reactance</td>
<td>$r_{fr}$</td>
<td></td>
</tr>
<tr>
<td>RC bus capacitor</td>
<td>$C$</td>
<td></td>
</tr>
<tr>
<td>RC bus resistance</td>
<td>$R$</td>
<td></td>
</tr>
<tr>
<td>Harmonic filter capacitor</td>
<td>$C_f$</td>
<td></td>
</tr>
<tr>
<td>Harmonic filter resistance</td>
<td>$R_f$</td>
<td></td>
</tr>
<tr>
<td>Harmonic filter inductor</td>
<td>$L_f$</td>
<td></td>
</tr>
<tr>
<td>Inductance of voltage source</td>
<td>$L$</td>
<td></td>
</tr>
<tr>
<td>Resistance of rectifier</td>
<td>$r_{dc}$</td>
<td></td>
</tr>
<tr>
<td>Inductance of rectifier</td>
<td>$L_{dc}$</td>
<td></td>
</tr>
<tr>
<td>Capacitance of rectifier</td>
<td>$C_{dc}$</td>
<td></td>
</tr>
<tr>
<td>Inductance of DC-link filter</td>
<td>$L_k$</td>
<td></td>
</tr>
<tr>
<td>Resistance of DC-link filter</td>
<td>$R_k$</td>
<td></td>
</tr>
<tr>
<td>Capacitance of DC-link filter</td>
<td>$C_k$</td>
<td></td>
</tr>
</tbody>
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algorithms to rank both inputs' sensitivity and interaction, when all inputs have strong coupling among them. The modified Morris function and parameters are given in the equation below:

\[
y = \beta_0 + \sum_i^n \beta_i w_i + \sum_{i < j} \beta_{ij} w_i w_j \\
+ \sum_{i < j < k} \beta_{ijk} w_i w_j w_k
\]  

(4)

where \(w\) are uniform random variables \(\in [0, 1]\).

The values of the \(\beta\) coefficients are given in Table 1. The rest of \(\beta_i\) and \(\beta_{ij}\) are assigned zero-mean unit-variance random numbers, associated with the normal distribution. The other coefficients of \(\beta_{ijk}\) are set to be zero. For the case when \(w_i \in [0, 1]\), the Morris method with \(p = 16\) or \(\Delta = 8/15\) and MC sampling method with \(\Delta = 1/2\) can classify the sensitivity of inputs according to \(E[EE_j]\) and \(\sigma[EE_j]\) into three distinct groups: (1,2,3), (4), and (5,6), as shown in Figure 3. The quantitative results from these three techniques agree with one another. The second group of inputs, (4), exhibits only a strong elementary effect with a minor interaction with the other inputs. In contrast, the first group, (1,2,3), shows a strong coupling and a small sensitivity on the output. Lastly, the (5,6) group has a small effect on the output.

Moreover, to compare the convergence characteristics of all these sensitivity techniques, we need to define an absolute difference between estimated and reference solutions of \(E[EE_j]\) and \(\sigma[EE_j]\) for each input, normalized by the absolute reference solutions. The reference solutions must have a higher accuracy than the estimated solutions. With \(d\) multiple inputs, the RMS values of the normalized difference are defined as:

\[
\epsilon_{i, mean}^j = \frac{|E[EE_j] - E[EE_j, ref]|}{E[EE_j, ref]} \quad (5)
\]

\[
\text{RMS}(\epsilon_{mean}) = \sqrt{\frac{1}{d} \sum_{i=1}^{d} (\epsilon_{i, mean}^j)^2} \quad (6)
\]

Similarly, the \(RMS(\epsilon_{var})\) is obtained by substituting \(E[EE_j]\) with \(\sigma[EE_j]\) in the above formula. The results from the Morris method with \(r = 5 \times 10^5\) and MC and quasi-MC (QMC) sampling with \(N = 10^6\) are used as reference solutions in \(RMS(\epsilon_{mean})\) and \(RMS(\epsilon_{var})\) computations. For the convergence comparison, the Morris and MC sampling methods perform similarly as shown in Figure 4. But the sensitivity indices of the QMC sampling method...
converge much faster than the Morris and MC sampling methods by at least one order of magnitude.

**Results and Discussion of Shipboard IPS**

We next apply these sensitivity algorithms to a large-scale multi-rate dynamical system, the AC power distribution and propulsion system PC (Krause and Associates 2003), in the shipboard IPS. Two models considered in this section are the propulsion systems with and without an AC drive connected to an AC power generation unit. The robustness of the AC drive using the constant-slip current control can be examined from a comparison of the sensitivity indices between open- and closed-loop control of the propulsion system. The state variables and parameters of all subcomponents are given in Tables 2 and 3; (see also Prempraneerach 2007; PC Krause and Associates 2003) for more details.

**AC POWER DISTRIBUTION WITH AN OPEN-LOOP PROPULSION SYSTEM**

The sensitive parameters of this system can be distinguished according to two different time scales associated with the electrical and mechanical time constants of the synchronous generator and the induction motor. The one-line diagram of this system is shown in Figure 5. This system consists of the 59 kW Synchronous Machine (SM), the IEEE-type 2 exciter/voltage regulator (IEEE Committee Report 1968) the 50-hp Induction Machine (IM), and the three-phase RC bus with a harmonic filter. There are a total of 24 uncertain parameters in Table 2 (12 in the SM and exciter/voltage regulator, 7 in the IM, and 5 in the RC bus connecting between the SM and IM) and 25 state variables in Table 3. We assume all 24 uncertain parameters to be independent uniform random variables with ±30% variation from their nominal values.

The mechanical torque load is modeled as proportional to the motor speed squared with the $s_{\text{load}}$ coefficient, which is similar to a propeller load. In this simulation, SM is assumed to initially operate in its steady state at a rated speed and voltage, and then the IM is suddenly turned on at time 0 seconds (Prempraneerach 2007). Thus, the start-up transient dynamics of the IM must be taken into account. With this particular proportional torque load, the electrical transient responses die out within the first second, while the responses of the mechanical subcomponents approach the steady state within 6 seconds.

To study the parametric sensitivity for all state variables, we use only the QMC sampling methods with $\Delta = 1$ to perform the sensitivity analysis for $t \in [0, 1]$ and $t \in [0, 12.4]$ seconds, where the electrical and mechanical time constants dominate, respectively. The normalized sensitivity time traces of the $a$-phase harmonic filter’s current, $I_a$, and the IM’s rotor speed, $\omega_r$, up to 1 second are shown in Figure 6 for the 10 parameters most sensitive to these two variables. The motor speed, $\omega_r$, is only slightly sensitive to both electrical and mechanical parameters within this time range compared with the electrical state in Figure 6. On the other hand, the fast electrical transient of $I_a$ sensitivity strongly dominates during the IM’s start-up.
Sensitivity Analysis of the Shipboard Integrated Power System

acceleration as can be seen from its peak sensitivity indices; however, the $I_a$ sensitivity indices approach small steady-state values quickly.

In a large system with many outputs, to compare $EE_i^j$ of different output quantities, we must normalize $EE_i^j$ with the nominal value of $x_i$ over the maximum magnitude of $y_j$. To summarize the parametric sensitivity analysis over a specified time interval, we define an average sensitivity as $ES_{2,(i,j)}$ using the $L_2$ norm, i.e.,

$$ES_{2,(j,i)} = ||E[EE_j^i]||_2$$ (7)

The average sensitivity indices are summarized in the $ES_{2,(i,j)}$ plot (see Figure 7) over a specified time interval. The $ES_{2,(i,j)}$ reveals that the three-phase currents ($I_a, I_b, I_c$) of the harmonic filter in the RC bus are the most sensitive variables among 25 state variables and they are highly sensitive to $C_f$ and $L_f$ because the harmonic filter is tuned to reduce high harmonic frequency and the RC bus is subjected to a large high-frequency start-up current of the IM. Moreover, most state variables are sensitive to the IM’s parameters, which implies a direct interdependency among the SM, IM, and RC bus.

For $t \in [0, 12.4]$ where the mechanical time constant is dominant, the normalized sensitivity trajectories of the $I_a$ and $\omega_r$ in Figure 8 to the 10 most sensitive parameters exhibit significantly higher sensitivity than those for $t \in [0, 1]$ (seconds) in Figure 6. We can see that $C_p$, $r'_{r_2}$, and $J$ have the strongest influence on the $I_a$. The sensitivity of $I_a$ to $r'_{r_2}$ and $J$, particularly after 2 seconds, directly confirms interactions between the RC bus and IM. The sensitivity time traces of $\omega_r$ to $r'_{r_2}$ and $J$ and to $r_{fd}$ are consequently 7 and 17 times larger than that in the short time frame, and then approach a zero steady-state value within three times the mechanical time constant. Moreover, the IM’s rotor speed also becomes more sensitive to the load coefficient, $\alpha_{load}$, after 2 seconds. This phenomenon implies that each parameter can have a strong influence at a different time scale.

From the $ES_{2,(i,j)}$ plots in Figure 9, only three parameters—$r_{ld}$ of the SM and $r'_{r_2}$ and $J$ of the IM—have distinct impacts on all state variables in this longer time frame. The reasons why these three parameters are more sensitive than other parameters are: (1) the rotor inertia directly governs the mechanical time constant, (2) the rotor resistance of IM has a direct influence on the generated rotor flux and motor operation, and (3) the rotor field winding of SM, which is
connected to the voltage feedback from the exciter/voltage regulator, can amplify the propagation of uncertainties. Therefore, a small variation in $r_{fd}$ of the SM can lead to a large fluctuation in the bus voltage.

**AC POWER DISTRIBUTION WITH AC PROPULSION DRIVES**

Instead of the free acceleration of the induction machine as in the previous case, a power converter and constant-slip current control (Krause 2002) are incorporated into the propulsion system to control the electromagnetic torque of the induction machine, as shown in Figure 10. This system has 30 state variables and 31 uncertain parameters (see Table 3), which include 7 additional parameters: $(I_{dc}, R_{dc}, L_{dc}, C_{dc})$ of the six-pulse full-wave rectifier and $(R_L, L_L, C_L)$ of the DC-link filter. Parameters’ variations are assumed to be within ±30% from their nominal values such that the sensitivity results can be compared with those of the open-loop propulsion system.

Again, we assume that the generator initially operates at its rated speed in its steady-state
condition and then at 0 seconds the closed-loop propulsion drive is suddenly connected to the RC bus. The torque command to the controller is kept constant at 2 Nm.

Using the QMC sampling method with $\Delta = 1$ to perform the sensitivity analysis, Figure 11 shows the normalized sensitivity trajectories of the IM’s $\omega_r$ and the RC bus’s $I_d$ to seven parameters of the induction machine and three parameters of the RC bus. $I_d$ is very sensitive to both $C$ of the RC bus and to $C_f$ of the harmonic filter. The controller draws more power to produce a constant torque of the IM, while the exciter/voltage regulator attempts to maintain the bus voltage at a rated voltage; thus, a small change in the bus’s and harmonic filter’s capacitors, governing the bus voltage, has a significant impact on the entire system. The interaction of $C$ and $C_f$ with state variables is strong during the start-up transient of this system and then becomes weaker, approaching 0.05 and 1, respectively, as the electrical transient dies out within 0.2 seconds. Furthermore, only $J$ and $x_{load}$ have a strong influence on the normalized sensitivity trajectories of the induction machine’s $\omega_r$, while other parameters have a negligible effect. The constant-slip current controller makes the propulsion system sensitive only to its mechanical component; thus, the performance of the closed-loop propulsion is much better than that of the open-loop propulsion in terms of the sensitivity to the electrical components of the machines. These characteristics confirm that the controller becomes very active.

When the simulation time is lengthened to 1.62 seconds, where the mechanical time constant dominates, the sensitivity trajectories of $I_d$ to $C_f$ are still much larger than other parameters as they approach steady-state oscillation, as shown in Figure 12. Nevertheless, the sensitivity index of $C$ on $I_d$ diminishes very quickly as time approaches 0.4 seconds. For the sensitivity of $\omega_n$, both $J$ and $x_{load}$, exhibiting the same order of the sensitivity magnitude, become even more dominant than other parameters, as shown in Figure 12. Also, the sensitivity index of $\omega_r$ to $X_{m12}$, governing the interaction between stator and rotor windings of the IM, gradually increases as the time reaches 1.62 seconds. These characteristics show that the constant-slip controller controls the induction motor exclusively.
well and the controller’s action increases sensitivity to the mutual reactance, which is directly used in the maximum torque per current calculation of the constant-slip controller.

To make a comparison on electrical and mechanical time scales, the overall view can be examined from the $E_{S_2, (j, i)}$ plots. In Figure 13, when the electrical time constant is dominant, most of the IM state variables are sensitive to its electrical and mechanical parameters, including $X_m$, $r_2$, $J$, and $a_{load}$. However, when the mechanical time constant is dominant, the IM’s states are sensitive only to two mechanical parameters, $J$ and $a_{load}$, with a large average gradient magnitude. Notice that the IM’s parameters only affect its own states. This again implies that the controller is very active to compensate for any variation of the IM’s parameters. Figure 14 shows the average sensitivity indices of all state variables to only the power converter parameters. Only currents are sensitive to both capacitors and inductors of the rectifier and the DC-link filter ($L_c$, $C_{dc}$, $L_L$, $C_L$) when both electrical and mechanical time constants dominate. However, in a short time frame, the currents of the power converter are more sensitive because the controller needs to compensate for a large torque error during the IM’s acceleration. Only the state variables of the RC bus and the power converter are sensitive to the power converter’s parameters, which implies that the controller can separate the interaction between the generator and the induction motor.

**Summary**

Sensitivity analysis techniques, based on stochastic simulation results, can assist the designer to identify the most influential parameters in nonlinear functions and systems of ODEs, particularly the large-scale, multi-rate dynamical system such as the the shipboard IPS. For the same computational cost, the QMC sampling method is much more efficient in providing the accurate sensitivity indices than the Morris and MC sampling methods. The sensitivity analysis of the AC power distribution and the propulsion systems with and without an AC drive shows that this system without any controller has very strong interdependency among machines. For this IPS with the constant-slip current control, the controller can isolate the interaction between the generator and the propulsion system.
Acknowledgments

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References


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