Load Modeling For Power System Requirement and Capability Assessment

Uzoma Orji, Bartholomew Sievenpiper, Katherine Gerhard, Steven B. Leeb, Norbert Doerry, *Member, IEEE*, James L. Kirtley, Jr., and Timothy McCoy, *Senior Member, IEEE*

***Abstract*—Load modeling is essential for designing and operating power systems. This paper presents an approach for load modeling on smaller power systems that could be "islanded," an approach that preserves the detail of a full differential equation simulation of relevant loads while requiring far less computation by employing behavioral models of important loads. Mixed domain models, e.g., stochastic, finite-state machine, and differential equation models, are employed to provide accuracy in a computationally tractable framework. Where simple load models may not be adequate, particularly for generation-constrained systems (in a paper by Sotiropoulos *et al.*), and full models are computationally unfavorable, this approach provides excellent results that enable "what-if" studies and flexible re-evaluation during power system design and operational assessment. Naval vessels, particularly warships with relatively large and increasing load power requirements, offer a unique laboratory for understanding isolated power grids. This paper examines the DDG-51 power distribution system as an example.**

***Index Terms*— Microgrids, power system dynamics, power systems analysis and computing, power systems planning, simulation.**

I. Introduction

POWER distribution systems need to meet requirements for sustained power delivery, transient response, and reliability and survivability in the face of unexpected electrical and mechanical disturbances. Distributed generation will raise new challenges for power system design and analysis. Local system impedances and harmonic content are likely to be more critical in determining system performance. Successful design and satisfactory analysis may require an understanding of load behavior more sophisticated than the relatively straightforward "name plate rating" and sizing models traditionally used for power system component sizing.

For power systems where a relatively small collection of loads may constitute a large fraction of the power consumption on the distribution system, comforting assumptions about aggregate load behavior, e.g., a "resistive model" for the load, may not be adequate. Unfortunately, detailed simulation of even a small collection of loads remains computationally time-consuming, approaching intractable for "what-if" scenarios involving repetitive analysis under different conditions [1]. A variety of techniques have been proposed for estimating load demand for assessing power system operation and stability; some recent examples can be found in [1]–[3]. Stochastic approaches to load modeling with varying degrees of time resolution are presented in [4]–[7]. An excellent summary is presented in [8] in the context of reliability assessment. Models that predict aggregate power demand using probabilistic models can provide relatively quick assessments of load flow under various conditions. Statistical techniques are widely used to solve "the short-term forecasting problem" for the utility [9]. However, particularly for smaller grids or isolated grids where detailed load dynamics effect grid operation, dynamic models of the loads are often required to design or assess operational performance [10]. These assessments are computationally expensive.

Computationally tractable approaches for forecasting or conducting "what-if" studies like those in [1]–[7] avoid consideration of detailed structure in the loads. A pumping station will be modeled as a time-varying power demand modeled in some way, rather than as a collection of motor-pumps each modeled individually in a computationally tractable way that is then aggregated. Generally, these methods estimate real power, or real and reactive power, based on time-series or other probabilistic metrics. For small power systems, or power systems that may "become small" when islanded, these load models may fail to take into account local correlations and dependencies inter-relating the operation of different loads. Full simulations can recover these details, but require adequate simulation models and extensive computation resources. These models are therefore less useful for the operator or designer of a local power distribution network that might be reconfigured or redesigned at the distribution level to optimize operating costs, maintenance, and peak consumption parameters.

This paper proposes a hybrid approach to load modeling that mixes stochastic and deterministic models to provide fine-grain predictions of load behavior, including details of in-rush, reactive power, and harmonic demand, while minimizing computation overhead and the burden of conducting "what-if" studies.

Here, multi-layered, flexible models for loads permit fast "what-if" studies that can reflect different stages of operation of loads on a small power system, and with proper accounting of the effects of time of day, weather, and other exogenous variables. This type of modeling is essential for assessing the demands of cold-load pick-up (turning on a collection of loads) with realistic sequencing. This type of modeling (employing flexible, computationally efficient load models with

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U. Orji, S. B. Leeb, and J. Kirtley, Jr. are with the Electrical Engineering and Computer Science Department, Massachusetts Institute of Technology, Cambridge, MA 02139 USA.

B. Sievenpiper is with the United States Navy, Pearl Harbor, HI 96860 USA.

K. Gerhard is with the United States Navy, Norfolk, VA 23505 USA.

N. Doerry is with the United States Navy NAVSEA, Washington, DC 20376 USA.

T. J. McCoy resides in Crofton, MD 21114 USA.

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hierarchical behavior and operating characteristics) permits estimation of electrically realistic load demand waveforms. This approach accounts for exogenous inputs like time of day, weather, and load condition, and permits easy experimentation with hypothetical reconfiguration.

Our approach uses behavioral modeling like that used in [11] for load models, but vastly updated to take advantage of modern computational tools for probabilistic and finite state modeling. We demonstrate this approach using the DDG-51 Naval power system as an example. This paper begins with a look at current design practice, and considers computationally reasonable enhancements employing behavioral load modeling to improve the fidelity and predictive power for design studies. The analysis and the computational tools described here are intended not only for the analysis of shipboard power systems but as a potential framework for understanding small or islanded power systems in general.

II. Electric Plant Load Analysis (EPLA)

Current design practice for USN shipboard electrical plants reflects good practice for designing any traditional power distribution network for a multi-megawatt scale. One approach for plant sizing commonly employed involves electric power load analysis (EPLA), summarized in the data design sheet (DDS) 310-1 [12]. EPLA is used to determine component sizing in the electrical distribution system for everything from generating capacity to breaker and cable sizing. EPLA does not really address transient requirements, does not provide an orderly or structured approach for conducting speculative studies, and does not particularly address quality of electrical service [13], [14].

EPLA begins with a list of all loads installed on-board the ship and uses one of three methods for calculating demand power.

1) Load Factor Analysis: The load factor represents the long-term average operating power level as a fraction of the component's rated load for a given operating condition. A load factor is calculated by estimating the fraction of the operating time (FOP) that a system will be functioning in a particular operating condition and the average power the component will draw when in operation (P_{avg}). The load factor (LF) is the product of these values:

$$LF = FOP \cdot P_{avg}. \tag{1}$$

For each load, the load factors are tabulated and then used to compute a calculated electrical demand for various operating conditions. The calculated load power P_{calc} is the product of the load factor LF and the rated load power P_{rated} as shown in (2):

$$P_{calc} = LF \cdot P_{Rated}. \tag{2}$$

Expected load on-board the ship is calculated by summing the expected load of all components on-board the ship. Tabulated estimates for specific load centers or switchboards can be performed in a similar manner to aid in sizing these portions of the electrical distribution system.

2) Stochastic Load Analysis: Stochastic load analysis is an alternative method provided in DDS 310-1 for estimating the demand power on-board a ship in the design process. This method assumes that a probability distribution function (PDF) and an associated cumulative distribution (CDF) for electrical loading can be determined or estimated for each load. The DDS 310-1 [12] describes the uniform, triangular and discrete distributions as the three most common distributions to characterize the stochastic behavior of the components.

A simulation process, e.g., Monte Carlo simulation, completes the total overall loading profile. The total load is then a summation of the loading of each component. This simulation is then run for a large sample group to determine relevant output statistics.

For each loading condition of the ship, there will not only be an estimated mean value for the load, but a standard deviation. Understanding the range of expected loading provides improved information for sizing the electrical distribution. This type of stochastic EPLA will exhibit potential variations with different simulation runs. However, these variations do not necessarily reflect actual correlations in power demand that may occur on the ship power system.

3) Modeling and Simulation: Direct modeling and simulation is the most computationally complex of the three methods for performing an EPLA. This approach requires physics and mathematical modeling of the loads and their interactions with other ship systems. Transient simulation is especially time consuming. Detailed simulation may be demanded when loads are large relative to generation capacity, when loads have abnormal characteristics, or when the loads cannot be modeled by the means discussed above [12].

We propose a hybrid approach to power systems modeling that avoids excessive computational burden while producing power consumption profiles that reflect accurate time-series behavior of load demand. This approach blends stochastic modeling and time series data to produce estimates. We assemble a power system simulation with a three step process. The first step in modeling is defining high level operational requirements and conditions for the system. For a ship, for example, this would include information like seasonal weather and rigging conditions, e.g., cruising versus general quarters operation. Analagous inputs for other power systems are immediate, e.g., outdoor temperature and time of day for an office park. Next, ship systems and subsystems are modeled with a variety of computationally speedy models, e.g., finite-state machines or probabilistic models or combinations, which best capture the system behavior in light of the high level inputs. This modeling level produces a multi-level or quantized power profile for each load. Finally, approximate time-series data for a variety of power system variables can be quickly created using the quantized power profiles to "modulate" stored time-series data for each load. The time-series data can be collected in the field or produced with focused simulations for specific loads as needed (as opposed to trying to simulate the entire ship power system). Modeling can therefore be conducted with a selectable degree of likely fidelity, that is, with a selectable level of detail in estimated consumption characteristics.

Behavioral modeling allows a user to define system responses to global inputs and uses both deterministic and stochastic models to predict component electrical demand within the system. Unlike a direct differential equation modeling and simulation approach, behavioral modeling is not based on differential equations governing load electrical properties. Instead, behavioral modeling uses rules, time series data, and statistical characterization to develop realistic load profiles over time.

For situations where the power system exists and operating data is available, measurements can be folded into the behavioral models to ease the effort of *a priori* modeling and to improve accuracy. However, it is equally possible to use the behavioral approach to model a power system before it is ever constructed. Here, the approach is illustrated using extensive data from the DDG-51 power system to demonstrate the modeling framework and its ability to produce data at varying levels of detail for a power system.

III. Behavioral Modeling for DDG-51 Systems

Operational data was gathered for the power system and loads on DDG-51 class destroyers. This included raw operational data, e.g. log books, which was gathered from visits to the fleet concentration areas of San Diego, CA, Norfolk, VA, and Pearl Harbor, HI. Data from the machinery control message acquisition system (MCMAS) was acquired from the Navy's Ships Systems Engineering Station (SSES). The MCMAS program contains a record of the configuration of the ship's systems over time, which provided a basis for understanding and profiling equipment behavior [15].

The DDG-51 program office also provided documents that were critical in the development of the concepts discussed later in this paper. These documents included baseline data for the DDG-51 class, such as the EPLA and electric plant schematics, but also included a report produced as part of the new construction process for the DDG-111 (USS SPRUANCE) [16], [17]. This study logged power readings for hundreds of components on the ship and showed the steady state and transient behavior.

Fig. 1 shows an overview of the multi-ring power system employed on a DDG-51. The "nodes" in the ring bus are monitored and guarded by multi-function monitors (MFM) that endeavor to provide zonal electrical distribution (ZEDS) and the ability to isolate different ring elements during a fault. The ship's power system is organized as a collection of power buses, shown as "straight line" buses in Fig. 1. Conventional radial panel distribution networks, not shown in the figure, are connected to the six switchboards shown, three along the top and three along the bottom of the diagram. Switchboards are associated with each power buss, like the 1SA switchboard shown in the lower right corner of Fig. 1. Power is fed to each buss using a ring network that connects the entire ship and that can be fed from the three generation buses (shown in the center of Fig. 1. The eleven MFM's guard the inlet and outlet power connections of the ring network at each buss. A high-speed information network connects the MFM's, which operate in concert to isolate faulted sections of the ring buss, leaving healthy sections available for continued operation. One, two, or three gas-turbine powered generators can feed electrical energy to the network from the bus-ties in the center of the diagram.

The behavioral approach for modeling power systems is illustrated by focusing on an examination of the behavior of the 1SA switchboard.

A. Behavioral Modeling

In behavioral modeling of the power system, subsystem and component behaviors are decoupled from electrical responses. An example of how a component power simulation is implemented is illustrated in Fig. 2, which depicts a notional system component or electrical load. The load is described by a model sensitive to global inputs like ship operating speed, time, and relevant independent or dependent random variables. In this example shown in Fig. 2, the top trace shows a square wave of simulated operating state for a component. The load has two possible operating states in this particular example, on and off. The center trace shows a transient electrical response for the load (note the time scale change) that could be acquired through measurement, simulation, or estimation. Modulating the component state (top trace) with appropriate copies of the transient power (middle trace) produces the bottom trace, a quick and accurate emulation of the behavior of the load on the power system.

This approach is attractive in that a very limited duration simulation or time series of measured data, e.g., the middle trace in Fig. 2, can stand in place of a much longer duration and computationally expensive simulation. There are also a variety of caveats. A simple approach assumes a "stiff" system voltage, in which case the emulated power trace (bottom trace in Fig. 2) may reasonably well represent observed system behavior. A more realistic emulation would account for voltage variations on the system by tracking system currents and anticipated or known system line impedances, resulting in a scaling factor for system voltage. This scaling factor can be applied to the transient power trace of the transient (middle waveform) used to assemble the emulated power trace. For reasonable disturbances, linear scale factors are often adequate for achieving acceptable fidelity in the emulation trace. Also, the behavioral simulator can proceed assuming that some scale function is to be applied, and use a *posteriori* check to make sure that assumptions made in the behavioral simulation are reasonable.

The following sections consider the information a designer must assemble to create a behavioral model.

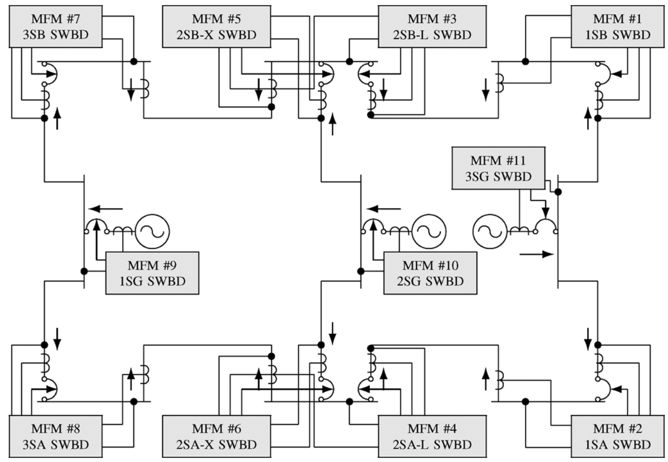

Fig. 1. ZEDS Electrical Distribution (adapted from [18]).

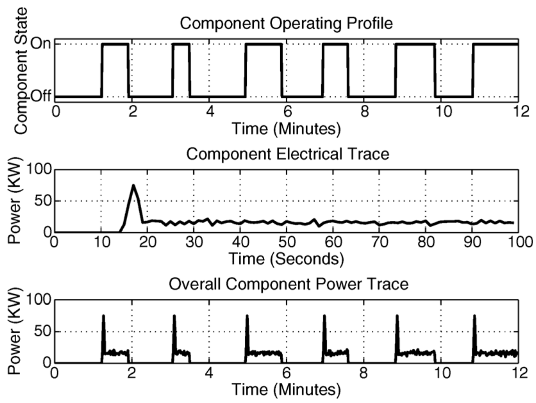

Fig. 2. Creating a power trace (see text).

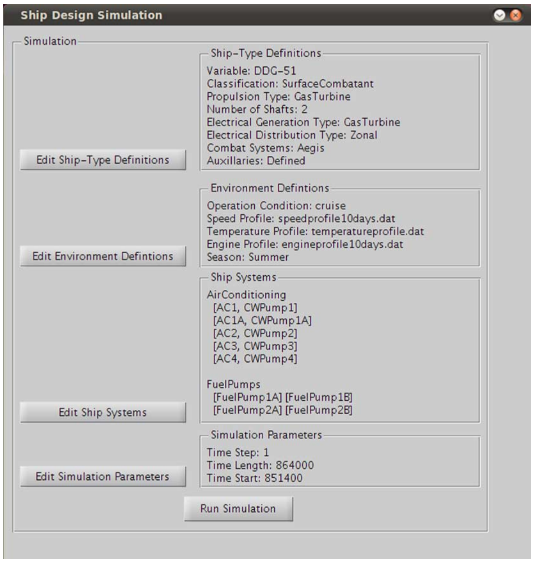

Fig. 3. Graphical main interface screen.

B. Global Inputs

Global inputs are external parameters that drive the behaviors of systems within the ship. The global inputs evaluated in the DDG-51 example include propulsion plant operating mode, ship speed, time, season, and ambient temperature. For demonstration purposes here, the data used was actual operating information for a deployed DDG Flight IIA ship.

In the behavioral simulation tool, which runs on a personal computer in the MATLAB environment using an object oriented programming model, the designer is presented with an opening screen shown in Fig. 3.

Three selection buttons are provided on the main screen: one for modifying the ship inputs, one for the environment inputs, and one for model parameters. The ship inputs include ship classification (surface combatant for a DDG-51), propulsion type (gas turbine) and electrical distribution type (gas turbine). The environment inputs include the operating conditions of the ship. For the study presented here, the DDG-51 was in the cruise condition. The speed-time profile of the ship, engine configuration, and temperature were provided as input data files to the simulation. These files could be real data where available, or hypothetical data representing to-be-studied operating conditions. For example, a "what-if" study might vary how often the ship might use both propulsion shafts versus only one. We have conducted "what-if" studies with the simulator, and also compared these simulations with real fleet data, as will be shown in the following sections.

Next, a designer would proceed to define electromechanical components and systems on the ship or power system.

C. Modeling Ship System & Subsystem Behaviors

Models for the ship systems and subsystems provide waveforms like the top trace shown in Fig. 2. The power system is modeled as a collection of components relevant for different tasks, allowing the power system designer to logically organize loads by function. A functional task on the ship, for example, cooling, heating, or providing fire-fighting water, is modeled by loads organized as systems that contain subsystems and components. The interrelations between the system, subsystem, and component levels can be entered graphically in our simulator. Each system handles a specific function within the entire ship. In this case, the air conditioning system is a collection of five identical subsystems consisting of two components in each subsystem, a compressor and a chilled water pump. With the systems, subsystems, and components organized, each level can be modeled with specific behaviors. Systems may be operated at different times and under different environmental conditions, e.g., hot weather for the cooling systems. Subsystems within the system may, for example, operate on a rotating time schedule to distribute wear and maintenance. Components within the subsystem may vary their power consumption according to more or less detailed models as desired to reflect electrical waveform characteristics likely to be observed on the power system.

When a new system is entered using the graphical interface, the user is effectively creating a new system object that is responsible for generating operational data like the top waveform in Fig. 2. For the DDG-51, six types of system models were identified that reasonably well represent all of the behaviors of loads on the ship:

1) Single-State: The single-state condition refers to a system or subsystem that maintains a single configuration in a given ship state, that is, a "base" load that is always "on". Examples of such systems include ventilation fans, some radars, or communication equipment that runs continuously during ship operation.

2) Cycle Type: A system with cycle-type characteristics is a "two-state" load that behaves periodically, but independent of the time of day. These systems have stochastic on/off cycling behavior. For example, a lube oil purifier runs periodically at a set interval to clean circulating oil. A user can define stochastic models that govern the length of time the system remains in the "on" or "off" states. These behaviors can be characterized speculatively by a designer, or, for existing loads, determined using methods developed for stochastic modeling in Section IV.

3) Finite State Machine: A more general load behavior can be defined by a finite state machine (FSM), which allows the prediction of load demand based on probability of transitioning between various states. For the FSM type, the user specifies a transition probability matrix which governs how the model transitions from state to state.

4) Level-Type: The level-type system is directly dependent on the state of a specific input. In this case the system may be on whenever a specified condition is met, and secured during all other conditions. An example of this is the fuel service system, in which a pump for a specific plant will be energized whenever one of the two gas turbine motors (GTMs) is operating. In this case, the subsystem is dependent on the "level" state of the corresponding GTMs shown graphically in Fig. 4. For a DDG-51, the GTM configuration is dependent on the ship speed as certain speeds require certain plant configurations as specified in the current NAVSEA design standards.

5) Time Dependent: The time-dependent system depends on the time variable of the model to drive the cycling performance of the system. These systems tend to operate in a predictable manner over the course of a day, or periodically over the course of several days. For example, food service equipment in the galley is operated during meal hours, and sparsely during other times of day.

6) Random Subset: For reliability and operational robustness, a ship or other power system may contain a multiplicity of loads for redundancy. That is, not all loads are operated at all

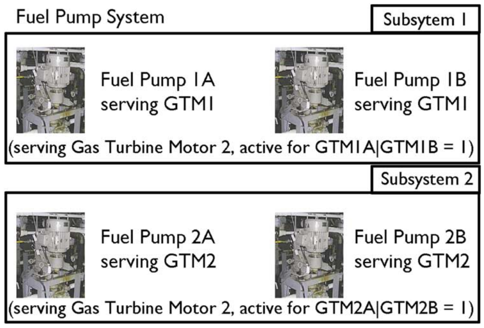

Fig. 4. Fuel service system model.

times, and more of a type of load may be present than is generally needed. For example, a DDG-51 includes 6 fire pumps, two in each of the three electrical zones. Only two pumps operate nominally at any instant in time under normal operation, one pump in one zone, one pump in another. These and similar loads are modeled using a "random subset" method. A random subset of two of the six is chosen to operate at appropriate simulation instants based on operating procedure rules included with the model, e.g., no more than one pump operating in one electrical zone under normal conditions. HVAC plants on the DDG-51 are also well modeled in this way and a more detailed description of the AC system will be discussed in Section V-A.

D. Load Electrical Modeling

The designer defines all subordinate components within each subsystem. Component models provide waveforms like the middle trace shown in Fig. 2.

For example, within the "Fuel Pump" subsystems shown in Fig. 4, the designer defines "best available" electrical waveform behavior for each fuel pump, e.g., for "Fuel Pump 1A." The user identifies each component as a master or slave. A slave component has the operational profile of its subsystem. When the subsystem is active, the component is always on, and the component model provides a waveform like the middle trace in Fig. 2 that directly scales the subsystem operating waveform. Alternatively, a master component is on when its subsystem is active, but has its own operational profile that also modifies or defines the top trace in Fig. 2, described by a stochastic model that is defined by the user.

Four separate methods of implementing a component response were found relevant for DDG-51 loads: constant, finger-print, finite state machine, user-defined. Each of these methods provides a unique means of developing a power trace.

1) Constant: When no other information is available and no further speculation is desirable, a component or load may be modeled by traditional means, e.g., a load factor, which could be derived from nameplate data and a guess or known utilization duty cycle.

2) Fingerprint: The fingerprint method assumes that the component power trace consists of three phases: a transient turn-on phase, a steady-state phase, and a transient turn-off phase. Essentially, the designer provides a piece-wise linear model of the anticipated or known electrical waveform. Each electrical phase is individually defined within the model. This method is most useful for components such as motors that exhibit regular behavior, and is most applicable when the operating profile for a component is readily available.

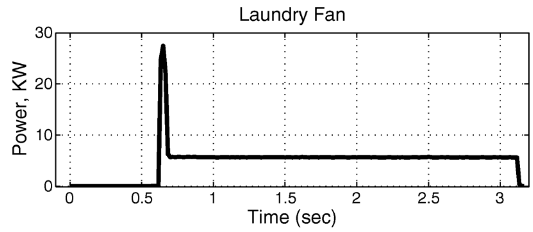

Fig. 5. Example electrical operating data [17].

An example is shown in Fig. 5.

3) FSM: The finite state model is similar to that described in the fingerprint model, but requires a more complex series of inputs. This model corresponds to a potentially multi-level power consuming load, whose behavior further modulates or scales the subsystem operating trace. For components described by an FSM, the user must define the stochastic model for each state and a transition probability matrix like those discussed in Section III-C-3.

4) User Defined: "User Defined" component modeling works for input-dependent systems. In this case, one of the input variables for the model drives the electrical profile of the load. When using this method, the user defines the interrelations between global inputs to the model and component electrical response. The air conditioning plants in the DDG-51 are modeled with a user-defined component behavior. The air conditioning loads are determined by multiple factors. The first piece of information required is the fingerprint power trace of the compressor components. Furthermore, the global input temperature affects the total load as diurnal variations occur. A detailed discussion on the AC plants is found Section V-A.

IV. Stochastic Models

Stochastic models are used to describe processes with distribution functions that are known or can be estimated. These models are important for both subsystem and also component level models, as both, for example, might use an FSM model with stochastic transitions. Reference [19] uses normal distributions to model the uncertainty of daily power peak loads in a system. Reference [20] proposes the use of normal, log-normal and beta distributions to model high voltage loads and [21] advocates that load distribution is a combination of normal, log-normal and Poisson distributions.

For loads in the DDG-51 power system model, useful stochastic distributions included constant (deterministic), uniform, normal and exponential. While these distributions were sufficient for modeling the loads surveyed in the development of this framework, other distributions could be used, e.g., log-normal, Poisson, and Beta.

A. Constant

The constant method represents a distribution that defaults to deterministic. In this model the user defines a value of a, which is related to the random variable X_c by

$$\mathbf{P}(X_c = a) = 1. \tag{3}$$

B. Uniform

A random variable X_U has a uniform distribution, $f_{X_U}(x)$, if the PDF is constant within the interval a and b. In this case, the

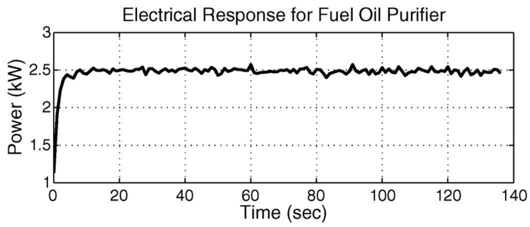

Fig. 6. Electrical response of a fuel oil purifier.

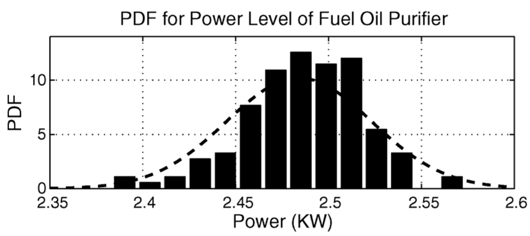

Fig. 7. Histogram of the steady-state region in the electrical response of a fuel oil purifier.

user defines the values of a and b, and the distribution is shown in (4):

$$f_{X_U}(x) = \frac{1}{b-a}, \quad \text{for } a \leq x \leq b. \tag{4}$$

C. Normal

When a random variable X_N has a normal distribution the user must input the mean, μ, and standard deviation, σ. The system will then cycle with a frequency dictated by these values according to the distribution shown in (5). Care must be used in implementing this distribution, to ensure the probability does not return negative time values:

$$f_{X_N}(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}. \tag{5}$$

For component power traces created using the fingerprint method, The steady-state portion of the electric consumption might be modeled, for example, with normal distribution. Consider the actual transient electrical response of a fuel oil purifier in Fig. 6.

A normal distribution describes the behavior of the steady-state region as there is an underlying mean with some variation around the mean. The histogram of the steady-state region is shown in Fig. 7 and the underlying normal distribution is prevalent.

To estimate the mean μ and standard deviation σ, N points of the steady-state region are extracted. With N observations $(x_1, x_2, \ldots, x_N)$ and the maximum likelihood method to estimate parameters [22], the estimates of the mean and variance of the underlying normal distribution are

$$\hat{\mu}_N = \frac{1}{N} \sum_{i=1}^{N} x_i, \tag{6}$$

$$\hat{\sigma}_N = \frac{1}{N} \sum_{i=1}^{N} (x_i - \hat{\mu})^2. \tag{7}$$

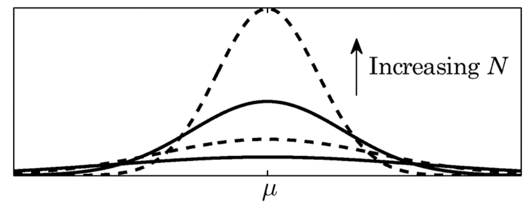

Fig. 8. Example normal distribution for several values of N. Standard deviation decreases as N increases.

D. Exponential

A random variable X_E has an exponential distribution $f_{X_E}(x)$ when the PDF is defined as shown in (8):

$$f_{X_E}(x) = \lambda e^{-\lambda x}, \quad \text{for } x \geq 0 \tag{8}$$

for $\lambda > 0$. When the exponential distribution is used, the user must input the variable λ, which is the rate parameter for the function. The choice of this value will determine how quickly the exponential function decays away, and will therefore influence the width of the distribution of cycle time.

The exponential random variable is widely used in to describe the interarrival times in a stochastic process. With N observations of the interarrival times, a maximum likelihood estimate $\hat{\lambda}_N$ can be calculated as

$$\hat{\lambda}_N = \frac{N}{\sum\limits_{i=1}^{N} x_i}. \tag{9}$$

E. Consistency

In statistics, a consistent estimator is one whose sequence of estimates becomes more concentrated around the true value of the parameter as the number of data points uses increases.

The estimators in (6), (7), and (9) are consistent estimators. The $\hat{\mu}_N$ estimator of μ, the mean of the normal distribution in (6), is itself a normal distribution with a mean of μ and a standard deviation of σ^2/N. As more data points are collected, N increases and the standard deviation of $\hat{\mu}_N$ tends to 0.

Fig. 8 illustrates how the standard deviation decreases as N increases and most of the distribution is centered around the mean.

Mathematically, the estimator $\hat{\mu}_N$ is consistent if

$$\lim_{N \to \infty} \mathbf{P}\left(|\hat{\mu}_N - \mu| \geq \epsilon\right) = 0 \tag{10}$$

for any fixed $\epsilon > 0$. As more data are collected to update the value of the estimator, the higher the probability that it is close to the true value of the parameter. The estimators in (7) and (9) can be proven consistent through a similar exercise [22].

Even with a collection of data, such as those from [16], [17], there may not be enough sample points to reliably trust the estimated value of the parameters. For the DDG-51 simulation presented here, these surveys provided a foundation in which to develop the framework and estimate parameters to fit the underlying distribution. However, confidence in these values could be improved if more field observations are available.

V. Behavioral Model Output and Results

When the power system global inputs, systems, and components have been defined and the time parameters set, the simulation can run using the user-defined models. After the simulation is complete, the GUI allows the user to plot power traces of individual components and, for example, of the entire 1SA switchboard. The examples below show the results of simulating components with the framework.

A. AC Plants

The chilled-water air conditioning (AC) plants on-board the DDG-51 operate by refrigerating a chilled water loop and rejecting heat to seawater. The chilled water is then piped throughout the ship to provide air conditioning and electronic equipment cooling. There are 5 AC plants on-board the DDG-51 class, labeled 1, 1A, 2, 3, and 4.

An average distribution of the plants over the time period for the operation of a single AC plant was developed by examining several weeks of data from MCMAS. This distribution is shown in Fig. 9.

The PDF inherently contains two separate pieces of design information required by DDS 310-1, the plant configuration and operating distribution. The plant configuration can be inferred by the amount of time spent with no power, which occurs approximately 40% of the time. In the normal operating configuration 3 of 5 AC plants are operating on-board the ship, so this corroborates expectations. The other piece of information available from this PDF is the running distribution of power. With this known distribution, a triangular or normal distribution could be fit to the data set for the purpose of stochastic modeling.

A plot of the total load consumed by all AC compressors is shown as a time series in Fig. 10. It is important to note the long tail to the right hand side of the graph (loading seen at approximately 190 kW) that does not exist in Fig. 9 for the average AC plant. This tail is representative of the overlap time that exists when switching between AC plants, yielding a temporary condition where 4 AC plants are in operation. From this time series, it is evident that the loading profile has a couple of notable features. The first is that the transient periods of switching AC plants yield power spikes periodically, as discussed previously. The second is that the AC plant loading is heavily diurnal; over each one-day period there exists a minimum that occurs in the early portion of the morning and a maximum that occurs in the afternoon.

The diurnal behavior presents an additional difficulty for a stochastic model. To examine the temporal effects, the data was sorted such that individual profiles were obtained for each 2-hour block of time over the course of a day: 0000-0200, 0200-0400, etc. Fig. 11 summarizes observed operating data that can be used as a general summary of behavior for a single AC plant. The top trace shows the average power in kW drawn over the course of a 24-hour time period. The bottom trace shows the standard deviation in this consumed power, a variation of just under 2 kW. Given this observed data, the AC plant subsystem, a single AC plant, is sufficiently well characterized to permit good estimation and "what-if" studies for the entire installation of 5 AC plants on-board ship under a variety of real or speculative operating scenarios.

The AC system loading changes with the day-to-day variations in ambient temperatures. During the time period of analysis the vessel is operating in a single location performing a continuing presence in anti-piracy operations. This singular mission profile allowed the investigation the effects of ambient temperature. By plotting the daily high, low, and mean temperatures seen in cities near the ship's operating location in the Gulf of Aden, the weak effects of the temperature can be seen in Fig. 12.

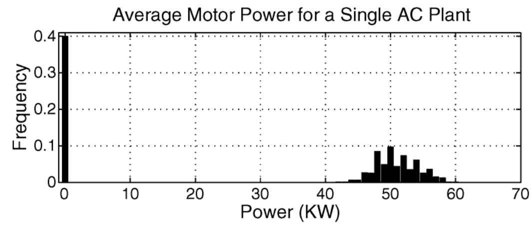

Fig. 9. AC compressor PDF.

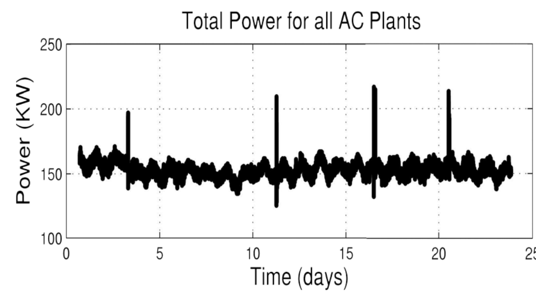

Fig. 10. Time series of AC plant cumulative load.

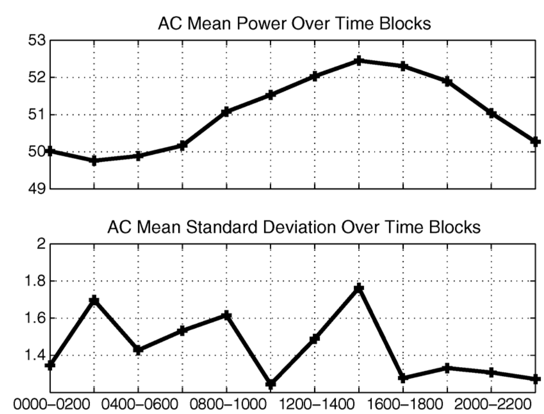

Fig. 11. AC compressor power mean (kW) and standard deviation (kW).

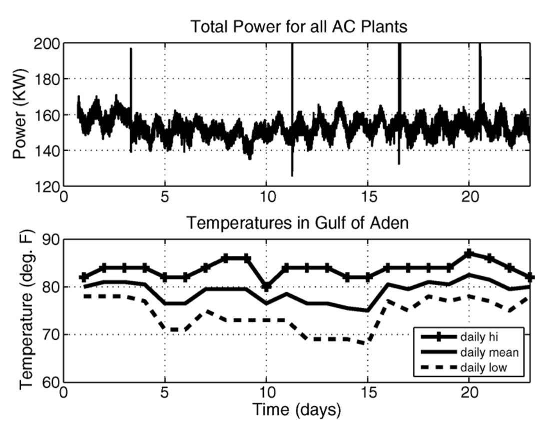

Fig. 12. Total ship compressor loading and temperature variation.

Examining this data, it was noted that there was an additional correlation between the mean value for temperature and the total load placed on the AC compressors. By allowing the

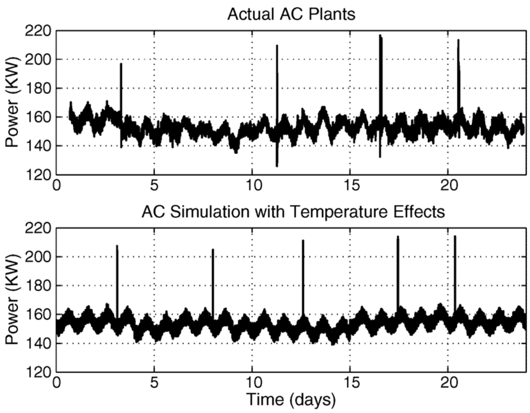

Fig. 13. Comparison of AC load simulation and actual profile.

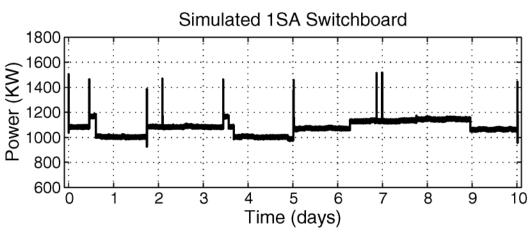

Fig. 14. 1SA simulation (10 days).

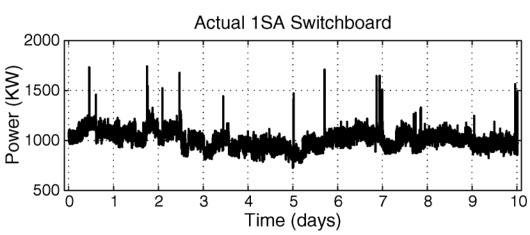

Fig. 15. 1SA actual load (10 days).

mean shown in Fig. 11 to drift slightly with the variation in temperature a more accurate behavioral model could be developed.

The results for the AC plant total compressor simulated and actual loading are presented in Fig. 13. These results show the strong correlation level between simulation and fleet data that can be created using the behavioral modeling.

The large spikes in the profile represent the operating condition where 4 compressors are on line in the intermediate state of switching AC plants. The simulation performs this randomly with similar periodicity to that seen in the fleet, but it would not be expected to line up at corresponding times.

B. 1SA

Once all individual systems, subsystems, and components applicable to the 1SA switchboard were defined the simulation was run. The most important aspect of the simulation for the calculation of an EPLA is the overall loading, since this will be the primary result used for the sizing of electrical distribution equipment.

The output profile for the 1SA switchboard is shown for a ten-day simulation is shown below in Fig. 14, while the actual loading on the 1SA switchboard during this time period is shown in Fig. 15.

While the simulation does not perfectly recreate the 1SA switchboard, it captures many features that exist within the system. Power transients associated with starting loads are captured, and much of the behavior over time is included. Since power transients have an impact on the sizing of generators, breakers, and cabling this behavioral model could allow designers to rely less on large margins and instead optimize the plant for expected load conditions. These results, using a relatively small subset of fleet data, demonstrate that the method can deliver high fidelity results and could enhance the ship design process. Overall, the simulation for the 1SA switchboard is bound within the same general region (800–1200 kW), indicating a good data fit for this simulation.

The randomness of the system models dictates that no two simulations will be the same, and that the different power levels seen in Fig. 14 will change for each run. Behaviors linked to inputs (such as GTM stops and starts) would be the same for every simulation. By running the simulation many times a long term statistical description of ship behavior could be created, similar to the process for a Monte Carlo method.

An additional benefit of using the program is that the individual results for a selected system could be analyzed if desired. This would provide the ability to use model results to inform selection of components, or could be used for the purposes of model validation.

VI. Discussion

The framework described in this paper provides a flexible solution to the increasingly complex problem of conducting "what-if" studies for a proposed or existing power system design. The approach presented here offers a blend or family of load mathematical models that are computationally efficient, provide detailed electrical load behavior, and admit the incorporation or effect of arbitrary exogenous variables like temperature, insolation, and human usage or behavior. Here, the focus was on an "islanded" power system, specifically, the distribution network of a DDG-51 destroyer. The emulation described in this paper can be used to reproduce the behavior of the ship and power system under a variety of different operating scenarios. The emulation can be used to provide base data for other studies, including fuel consumption surveys, damage assessments, and sensitivity analyses to determine the reliability of metrics like EPLA load factors. It is an invaluable tool for focusing design decisions and operating analysis for further study by more time-consuming methods like time-domain simulation of differential equation models. This approach can be extended to other "small" power systems like microgrids, or regions of a power system that can be considered from a local perspective where substantial renewables and distributed generation may be present.

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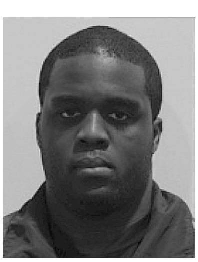

Uzoma Orji received the Ph.D. degree from the Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Cambridge, MA, USA, in 2013.

Bartholomew Sievenpiper received the Naval Engineer degree and the Master's degree in mechanical engineering from Massachusetts Institute of Technology, Cambridge, MA, USA, in 2013.

He currently serves as an officer and active duty engineer in the United States Navy, Pearl Harbor, HI, USA.

Katherine Gerhard received the Naval Engineer degree and the Master's degree in engineering and management from Massachusetts Institute of Technology, Cambridge, MA, USA, in 2013.

She currently serves as an officer and active duty engineer in the United States Navy, Norfolk, VA, USA.

Steven B. Leeb received the Ph.D. degree from the Massachusetts Institute of Technology (MIT), Cambridge, MA, USA, in 1993.

He has been a member on the MIT faculty in the Department of Electrical Engineering and Computer Science since 1993. He also holds a joint appointment in MIT’s Department of Mechanical Engineering. He is concerned with the development of signal processing algorithms for energy and real-time control applications.

Norbert Doerry (M'92) is a 1983 graduate of the United States Naval Academy and a 1991 graduate of Massachusetts Institute of Technology (MIT), Cambridge, MA, USA.

He is presently the Senior Scientist in the NAVSEA SEA 05 Technology Office. He retired in 2009 as a Captain in the United States Navy with 26 years of commissioned service, 23 years as an Engineering Duty Officer. In his final billet, he served for nearly six years as the Technical Director for Surface Ship Design. He has published over 25 technical papers

Dr. Doerry is the 2008 recipient of the ASNE Gold Medal. He is a member of ASNE, SNAME, and the Naval Institute.

James L. Kirtley, Jr. is Professor of Electrical Engineering at the Massachusetts Institute of Technology, Cambridge, MA, USA. He has also worked for General Electric, Large Steam Turbine Generator Department, as an Electrical Engineer for Satcon Technology Corporation as Vice President and General Manager of the Tech Center and as Chief Scientist, and was Gastdozent at the Swiss Federal Institute of Technology. He is a specialist in electric machinery and power systems.

Timothy McCoy (SM'03) has served as Director of the Electric Ship’s Office (PMS-320) within the Program Executive Office for Ships. In this role, he was responsible for developing electric power and propulsion systems for the United States Navy’s fleet. Prior to entering government service, he worked in industry as R&D Director and President of a defense contractor. Previously, he served on active duty in the United States Navy.

Dr. McCoy is a registered Professional Engineer and is a member of ASNE, IMarEST, and SNAME.