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Behavioral Modeling for Microgrid Simulation

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ABSTRACT Trends in power system simulation that demand computationally-intensive, physics-based models may impede the acquisition of useful results for applications like condition-based maintenance, electrical plant load analysis (EPLA), and the scheduling and tasking of finite generation and distribution resources. A tool that can quickly evaluate many scenarios, as opposed to intense, high fidelity modeling of a single operating scenario, may best serve these applications. This paper presents a behavioral simulator that can quickly emulate the operation of a relatively large collection of electrical loads, providing ''what-if'' evaluations of various operating scenarios and conditions for more complete exploration of a design or plant operating envelope. The presented simulator can provide time-series data of power system operation under loading conditions and usage assumptions of interest. Comparisons to field data collected from a microgrid on-board a 270-foot (82 meter) US Coast Guard medium-endurance cutter demonstrate the utility of this tool and approach.

INDEX TERMS Load modeling, power system planning, power system simulation.

I. EFFICIENT EMULATION

Applying the remarkable gift of vast computational capability in an endless drive for increased simulation fidelity with the physical world may offer diminishing returns in many design and analysis efforts. For a power system, high fidelity simulations might be irreplaceable for fault studies, analysis of the effects of non-linear loads, or the subtle impacts of changing environmental conditions, e.g., in temperature or humidity, on electromechanical performance [1]–[3]. However, particularly for analyses focused on ''what-if'' studies (which may explore many possible operating scenarios and conditions), current trends in power system simulation that demand computationally-intensive, physically-based models may impede the acquisition of useful results [4], [5].

There are two main approaches for load modeling in power system simulation: physically-based modeling and measurement-based modeling. Physically-based, or component-based modeling, uses physics and mathematical descriptions to characterize a load. For example, HVAC systems can be physically-modeled based on thermodynamic principles [6]. Physics modeling is always an effort, and accurate parameter identification is essential [5], [6]. Alternatively, with measurement-based modeling, in which data acquisition equipment is used to measure actual load behaviors, accurate load characteristics can be obtained quickly from a physical example, when available [7]. Curve-fitting techniques in sophisticated forms, e.g., artificial neural networks, have been applied for measurement-based modeling and the efficient representation of complex nonlinear systems [8]. However, it is challenging to obtain data over a wide range of operating conditions for use in measurement-based modeling [5], [9]. There has also been interest in using residential user behavior for predicting energy use patterns and demand [9]–[11]. In [12], both user behavior and individual load component models are used together for residential power system modeling.

Power system design and analysis, especially for isolated, microgrid, and generation-constrained systems, requires flexible evaluation of ''what-if'' scenarios to design adequate capability and to explore options for condition-based maintenance [13], electrical plant load analysis (EPLA [14]), and

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the scheduling and tasking of limited generation and distribution resources [15]. ''What-if'' scenarios can reflect different stages of operation of loads, while also accounting for load dependencies and the effects of exogenous variables such as time of day, weather, or human behavior [4]. For example, a ''what-if'' study on a ship might vary the number of propulsion shafts energized at a time. A tool that can quickly evaluate many scenarios, as opposed to intense, high-fidelity modeling of a single operating scenario, may best serve these applications. Behavioral modeling of electrical loads [16] may provide sufficient fidelity to provide datasets and enable rapid exploration of a range of scenarios. Behavioral modeling combines rules about load behavior, time series data, and stochastic modeling to develop realistic load profiles and evaluate electrical demand within the system [4].

This paper introduces the Shipboard Power Simulator (SPS), a software tool configured as a behavioral simulator that can quickly emulate the operation of a relatively large collection of electrical loads on a microgrid, providing ''what-if'' evaluations to support more complete exploration of a design space or plant operating envelope, and is further detailed in [17]. A wide variety of approaches have been adopted for time-domain simulation of microgrid and shipboard power systems, as described in [18] and its associated references. The complexity of detailed time-domain simulation for power systems has pushed these simulation studies to hardware-in-the-loop and custom processors [18]. These approaches are expensive, customized to particular problems or power systems, and remain computationally burdensome and time-consuming. In studies that require quick analysis of many scenarios to understand energy consumption and aggregate dynamics, a behavioral simulation can provide speedy results without the computational burden of detailed time-domain or hardware-in-the-loop simulation. This paper introduces a behavioral simulator unlike other time-domain simulation approaches for power systems. The SPS tool can provide estimated load demand and EPLA load factors for a load across multiple mission sets. By providing an accurate picture of likely power demand, the data is invaluable when designing marine microgrids and assessing power system operation.

In situations where the power system voltage is relatively ''stiff,'' the interactions between loads on the system are relatively minimized. In this case, individual observations of loads can serve to represent the load behavior, reasonably decoupled from the direct operation of other loads. The SPS exploits this assumption to simulate the overall ship or microgrid energy requirements as a function of different ship or grid missions. The intent of the SPS is not necessarily to reproduce the exact instant-to-instant behavior of measured data from an overall observation of a power system, although the simulator can be configured to do so. Rather, the goal of the SPS is to produce detailed time-series snapshots of power system operation under loading conditions and usage assumptions of interest. The resulting waveforms can be used to evaluate typical likely demand profiles on the grid. The SPS output waveforms can also be used to test monitoring schemes for condition-based maintenance by including exemplar waveforms for pathological conditions inserted randomly or on other schedules into the simulation. Furthermore, the SPS outputs can be used to confirm the starting assumption that the grid will behave as a relatively stiff, decoupled collection of loads. Output waveforms that would challenge this assumption, i.e., overload the grid capability, can be checked to confirm when the SPS assumptions are trustworthy.

Behavioral emulation of loads in the SPS begins by describing a load as a power consumer represented by a finite state machine (FSM) [17]. Temporal transitions in the FSM power demand model can follow a fixed logical sequence in time, or transition between states randomly, or in concert with the states of other systems or parent systems on the microgrid, or in response to environmental conditions like temperature. Proper modeling of the ship (microgrid) operational dependencies becomes more important than the precise mathematical description, e.g., differential or difference equations, for a load. Load power and load transients are modeled by stored waveform segments that represent power demand in each state and in the transitions between states. The waveform segments can be acquired from field data if examples of the loads or microgrid system already exist, e.g., using a Nonintrusive Load Monitor (NILM) [13]. Alternatively, a waveform segment can be entered as a ''best guess'' from ''name plate rating'' information, or based on observations of a similar load, or from a detailed load simulation conducted once, thus limiting the computational expense to a small set of expensive simulations with outputs that can be re-used. This paper presents comparisons of SPS results with field data collected from the power system on-board a 270-foot (82 meter) US Coast Guard medium endurance cutter, SPENCER (WMEC 905). The SPS is evaluated against ship data from SPENCER to demonstrate it's ability to accurately model ship behavior for various ''what-if'' scenarios, such as ship operational status, or ''mission,'' and a load operating in a degraded condition.

II. MARINE MICROGRIDS

The structure of the SPS behavioral modeling rules reflects the top-down design of a microgrid power system. An engineering ''V'' [19] diagram illustrates the correspondence between power system design and SPS modeling. The left side of Fig. 1 visually illustrates the microgrid power system design, beginning at the top with mission requirements and operating environment, then engineering systems, and, finally, engineering electrical loads. Mission capabilities for the microgrid, or ship in this case, drive the deployment of necessary ship systems. For example, requirements for speed and survivability may drive the number of propulsion shafts installed on a ship. Each shaft requires necessary supporting subsystems or electrical loads to provide compressed air, lubrication pumping, fuel pumping, and so on, each of which places demands on the ship electrical system. Each supporting subsystem includes electrical loads like motors, resistive

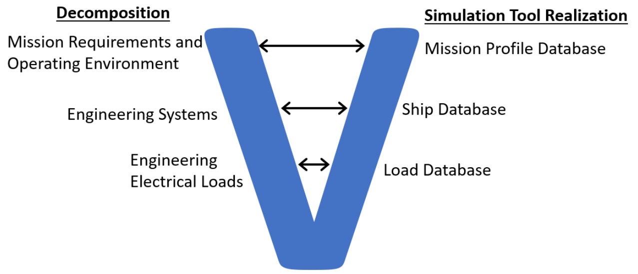


FIGURE 1. **Systems engineering "V" process reflected in Shipboard Power Simulator (SPS) architecture.**

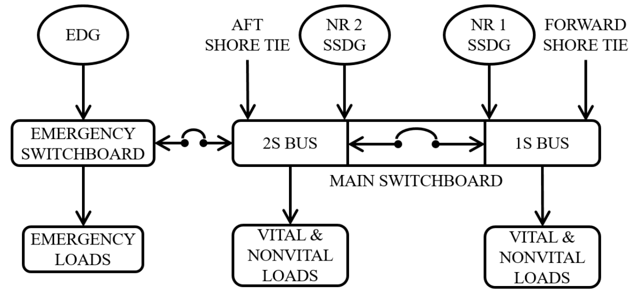


FIGURE 2. **Schematic of radial ac electrical distribution onboard USCGC SPENCER.**

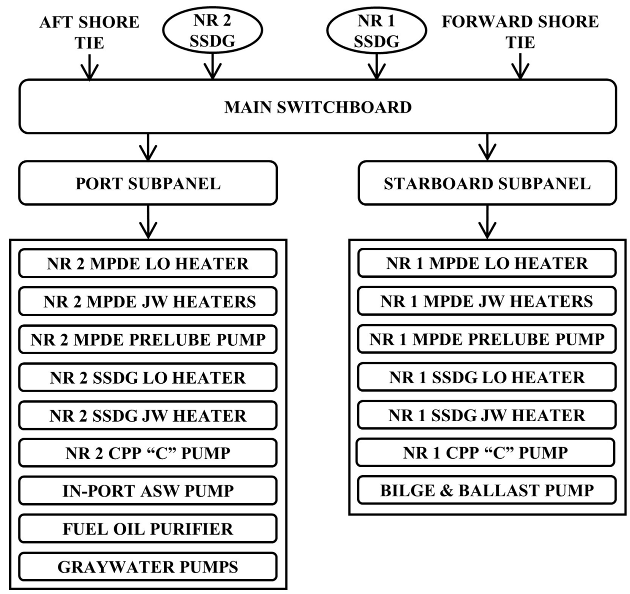


FIGURE 3. **Partial schematic of radial ac electrical distribution onboard USCGC SPENCER, with details on the PORT and STBD subpanels.**

heaters, and electronic controls. These loads operate at a specified voltage (e.g., 120V, 208V, or 440V ac) and present two or more "states" of operation (e.g., "off" and "on"), with specified power consumption levels. Connections may be line-to-line, three phase, and so forth.

High-level global parameters, such as the ship's mission, the operating environment, or other factors further discussed in Section III of this paper, create requirements for specific systems on ships, and cause these systems to energize or secure at any point in time. US Coast Guard (USCG) and US Navy (USN) ships designate specific operational status, or "mission," to indicate operating environment and ship system configuration. In the USCG, for example, "Alpha," "Bravo," and "Charlie" mission statuses respectively indicate that the ship is underway, or in-port and ready to get underway if the need arises, or in-port and not expected to get underway for an extended period of time. Each mission calls for certain systems to be energized, and systems will be progressively brought from secured status into standby and, eventually, online, or vice-versa, as the ship transitions between missions. Furthermore, environmental factors can also cause systems to be energized or secured, such as HVAC loads during changing weather.

The engineering systems serve the different requirements of ship missions. For example, the shafting systems translate energy from the main engines into propulsion thrust. Shafting systems, energized when the main engines are online, include a variety of subsystems with pumps and other electrical devices to support propulsion. Other example ship systems include seawater cooling, electrical generation, HVAC, weapons systems, and communications.

Finally each ship system consists of various electrical loads. Because the electrical loads are part of ship systems, their behavioral model can be determined by the operation of the system. Here, it is assumed that the ship microgrid is wired to provide radial ac electrical distribution. This is a common electrical distribution architecture used by the USCG and USN. For example, Fig. 2 shows a depiction of the electrical distribution of USCG cutter (USCGC) SPENCER. A variety of sources can energize the 440 VAC, 60 Hz main switchboard, depending on if the ship is at sea or in-port. When at sea, power is provided by two ship-service diesel generator (SSDG) sets, while in-port power is provided by either an aft or forward tie to shore power. These generator sets, along with the main propulsion diesel engines (MPDE) propelling the ship, are located in the ship's engine room [20]. The SSDG and MPDE require auxiliary equipment, e.g., fluid pumps and heaters, to maintain operational readiness when in standby mode. Two electrical subpanels, port and starboard, which power these loads along with several other engine room loads critical for ship operation, are depicted in Fig. 3.

III. BEHAVIORAL MODELING

The SPS is written in C ++, and applies a "bottom-up" approach [10], [21] for defining the hierarchical structure of a behavioral microgrid simulation, shown in the right side of Fig. 1. Beginning with individual loads, FSM power demand models for each load are stored in the SPS Load Database. Next, information about the radial panel wiring in the ship, system response to global inputs, and the load-to-system relationships are all stored in the Ship Database. Finally, the operating profile and missions that the ship carries out during the simulated time are stored in the Mission Profile Database. With these three databases properly configured, the SPS assembles operating power waveforms for any collection of ship missions of interest.

A. LOAD DATABASE

The FSM model for each load captures the power demand behavior of the load. Each state in the model represents a unique steady-state power level. Each transition between states is associated with a transient change in power demand. For example, Fig. 4 shows a portion of the SPS Load Design Wizard page displaying the FSM model of a Controllable Pitch Propeller (CPP) pump. The real and reactive power waveforms for all three phases for this load, as observed on USCGC SPENCER, are shown in Fig. 5. The power traces are segmented into three sections, the "Off-On" transient, "On" steady-state, and the "On-Off" transient. When first activated, an in-rush current causes a large peak in power demand, creating the "Off-On" transient. Once the CPP pump finishes its transition to the "On" state, the "On," or steady-state behavior, is repeated or concatenated in the behavioral simulator until the load switches to the "Off" state. In steady state, the pump is observed to consume approximately 2500 W and 1700 VAR per phase for real and reactive power, respectively.

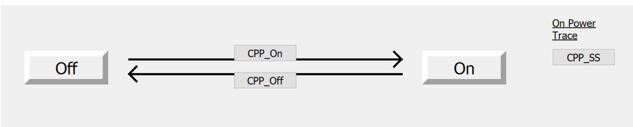


FIGURE 4. Finite State Machine (FSM) model of a CPP pump.

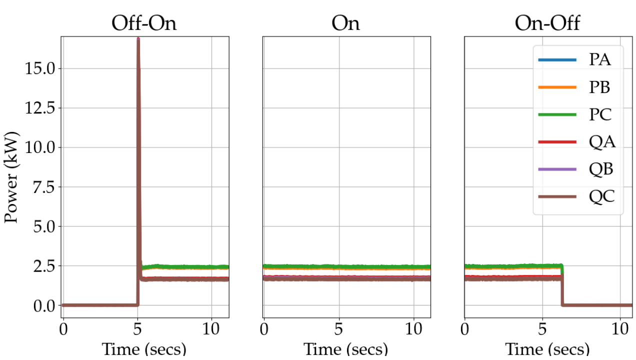


FIGURE 5. Power waveforms for the CPP pump.

Critical information for the SPS regarding each load is stored in a Load Database that comprises four tables: Loads Table, Power Traces Table, Uploaded Data Table, and the Operations Table. The "Loads Table" stores basic characteristics for each load, including the load name, the voltage required for operation, how the load is connected electrically (e.g, 3-phase), as well as the FSM model of the load and its parent system, if applicable. The "Power Trace Table" stores the power waveforms for steady-state and transient behavior at a 10 Hz sample rate. The power waveforms can be from field data, e.g. collected with a NILM, or they can be entered as a graphical approximation of an expected power curve, or the data can be provided from other sources including a detailed, one-time simulation of the load. The "Uploaded Data Table" serves as an index that identifies data in the Power Trace Table, e.g., as real or reactive power or harmonic content, and with electrical phase for each waveform. The "Operations Table" is another indexing table that connects a previously designed FSM operation with its specific power trace.

B. SHIP DATABASE

Moving up a conceptual level in the simulator organization, a "system" defines a collection of loads that work together to provide a service to the ship. For example, a "starboard shafting system" consists of Number (NR) 1 CPP Pump, 1A Lubrication Oil Service Pump (LOSP), and 1B LOSP. All three of these loads would energize in response to any mission that demanded propulsion from the starboard shaft, and therefore required the use of the starboard shafting system.

One or more state-change variables define the operational behavior of a system. On a ship, sometimes operation is "automatically" triggered depending on conditions on or around the ship, and other times the operation occurs "manually," e.g., based on an operator's demand. Examples of state-change variables that might automatically trigger a system to operate include simulated or operational variables like crew size, time of day, day of week, ambient temperature, seawater temperature, mission, and ship speed. Changes to these parameters can prompt responses from the systems and associated loads based upon pre-defined rules of operation. In contrast, manually activated systems may not operate on a crisp schedule or in tight coordination with ship mission. These manually activated systems might, for example, include pumps for graywater disposal on the ship. These pumps run essentially randomly distributed around other events, e.g., crew needs. In the SPS tool, a stochastic state variable might command the operation of these "manual" loads.

The Ship Database in the SPS stores the structure of the electrical panel system and load connections on the ship, and the relationship between each load on the power grid and its associated system. The individual load behavior, e.g., the FSM describing the load's power demands, have already been defined and stored in the Load Database. When a user of SPS "connects" a load to the ship power system modeled in a particular ship simulation, the Ship Database stores the electrical interconnection or panel location of the load on the ship, and also stores the specific ship system associated with the load. For example, the NR 1 CPP pump might have been defined previously in the Load Database as being part of a "shafting system." The Ship Database stores the data that pairs the NR 1 CPP pump with the specific shafting system on the ship, in this case, "starboard shaft."

The Ship Database also stores the associations or state-change variables that will trigger the operation of each system. Note that the Load Database defines load behavior specific to each load, and the Ship Database stores load connections and system memberships associated with a particular ship. This distinction permits a single Load Database, e.g., for a broad class of USCG or USN surface ships, to serve as basic data for assembling simulations of many different ships, each with a distinct Ship Database, while reusing the same basic loads where appropriate.

More specifically, the Ship Database comprises five tables: Ship Electrical Network Table, Component Details Table, Panel Details Table, Load Interactions Table, and Mission Assumptions Table. The ''Ship Electrical Network Table'' stores the structure of the ship's electrical distribution system. This table records the breakers, panels, transformers, and interconnections that make up the electrical network. The ''Component Details Table'' stores specifics on components like panels in the network, including defining characteristics like voltages, connected phases, feeder conduit size, transformer type, transformer grounding, and transformer sequencing for each component. The ''Panel Details Table'' stores the specific details for a particular instance of a load on the network and a tag indicating its defining example in the Load Database. For example, a load defined in the Panel Details Table as ''NR 1 CPP Pump'' may be a specific instance of a load class ''CPP Pump'' found in the Load Database. The specific instance ''NR 1 CPP Pump'' is now an example of the class with a particular connection to specific power system phases, a defined location on the grid, and a membership in a parent system like ''starboard shafting.'' The ''Load Interactions Table'' records the system membership for each particular load, e.g., NR 1 CPP Pump to the ''starboard shaft system.'' This table stores the specific state variables and associated changes that influence the operations of each load. For example, if a load changes state with the ship's missions, the Load Interactions Table would have a record of what transient operations a load would experience when a particular mission starts and ends. State change variables may be deterministic with mission changes, or stochastic as a function of time or crew size or other environmental variables. The SPS can model a load as responding to a logical combination of state change variables. For example, a heater might respond to the logical AND of a deterministic variable indicating that a system is in standby and a stochastic variable modeling thermostatic cycling. Finally, the ''Mission Assumption Table'' records ship operating rules including, for example, the speed, generator configuration, and engine configuration for different missions.

C. MISSION PROFILE DATABASE

The highest level of data abstraction in the SPS, the Mission Profile Database, records a log of state-change variables that reflect the record of a real or imagined deployment of the ship and its microgrid. For example, every ship maintains logs that record the ship's speed, ambient temperature, seawater temperature, crew size, date, present mission, engineering plant line-up, and time. State-change variables affect the behavior of the electrical loads. Data stored in the Mission Profile Database reflects the environment and events the ship will experience during a simulation. Changing entries in the log stored in the Mission Profile Database will create endlessly varied simulations that assemble and emulate the behavior of collections of loads on the ship.

IV. CONFIGURING AND RUNNING A SIMULATION

The user interface of the SPS eases the data input effort to quickly produce valuable results for ''what-if'' scenario analysis. This section demonstrates configuring the SPS to simulate part of the USCGC SPENCER, with the radial electrical distribution system and loads shown in Fig. 3. Configuring the SPS proceeds with the same ''bottom-up'' approach used to describe the SPS database structure. First, the Loads Page allows the user to add, edit, delete, or preview all loads within the Load Database. The Load Design Wizard Page, shown in part in Fig. 4, is used to design or modify the transient and steady-state behavior of a load.

Next, the Ship Design Page, shown in Fig. 6, configures the Ship Database. A user is given a ''tree widget'' to enter the structure of the radial electrical network, from the generator breakers to the power panels. Fig. 6 illustrates how the user has designed the electrical network for the USCGC SPENCER, with two monitored panels connected to the Main Switchboard. Specific loads, shown in Fig. 3, are entered as connections to specific panels. The user defines operations for the ship-specific state-change variables using the Load Class Interaction Designer pictured in the lower left corner of Fig. 6. For example, a particular mission type known as ''Alpha Restricted Maneuvering Doctrine'' (Alpha-RMD) places a premium on the ships ability to move nimbly. In this case, both NR 1 and NR 2 CPP pumps are operated to provide the greatest likelihood of retaining propeller pitch control, and these pumps change state when entering or leaving the Alpha-RMD mission. When Alpha-RMD is entered, both CPP pumps energize, and when Alpha-RMD ends, both CPP pumps secure. The user defines the engineering configurations and speeds at which this ship conducts various missions, using the Mission Assumptions table.

To load the Mission Profile Database, the user enters mission logs on the Simulation Inputs Page. The user may choose to manually enter the input variables such as mission and ambient temperature, or may upload a Mission Profile CSV data file produced elsewhere, e.g., in a spreadsheet tool. Fig. 7 shows a cropped image of the Simulation Inputs Page after the user has uploaded a Mission Profile data file for a 15-day cruise.

Finally, the Reports Page allows the user to choose the loads, phases and types of power to be simulated. Any panel or breaker downstream of the selected breaker, or panel, is automatically included in the simulation. The user may further elect to export the results to a text file.

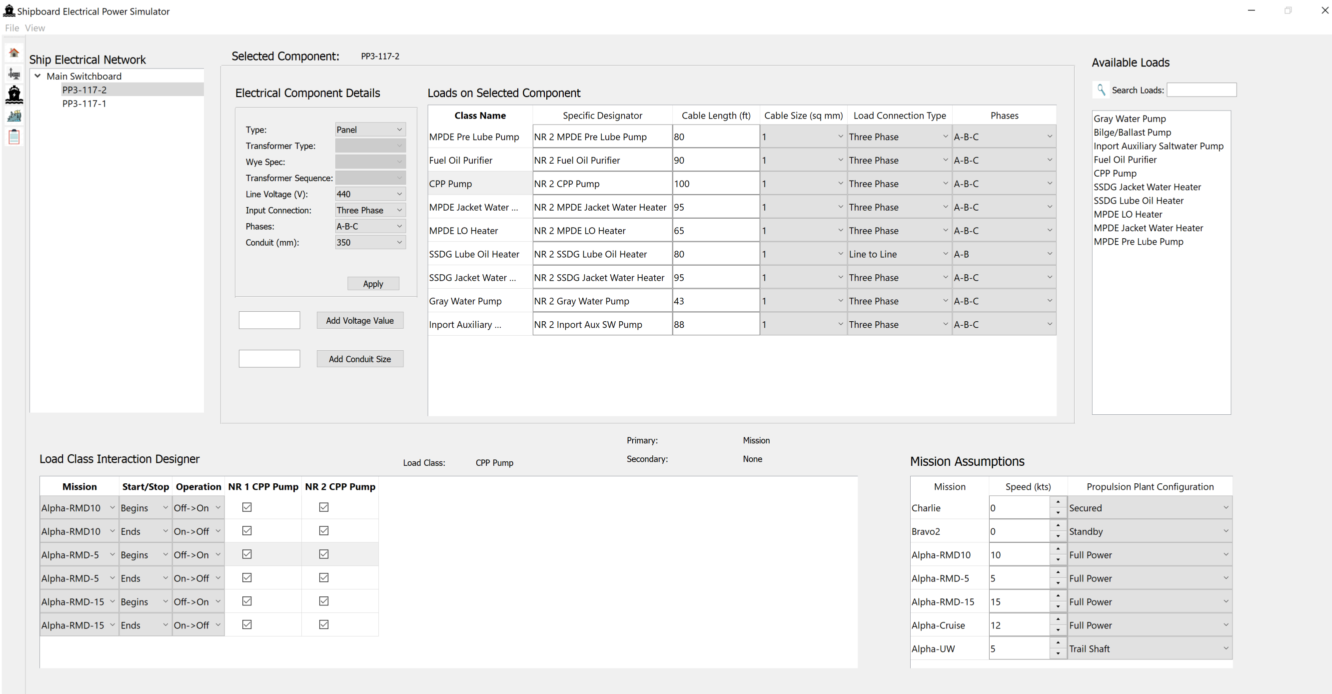


FIGURE 6. Ship Design Page.

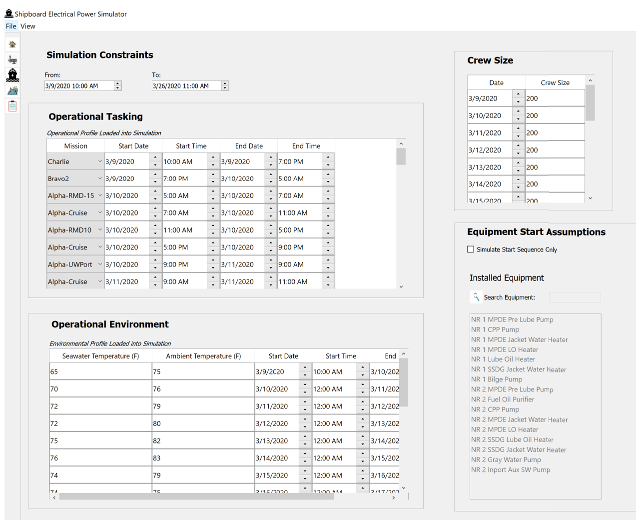


FIGURE 7. Simulation Inputs Page.

Fig. 8 illustrates the SPS algorithm to collect data from the Mission Profile Database, identify the operation of relevant ship systems from the Ship Database, and assemble the power waveforms for relevant operating loads from the Load Database to produce simulation waveforms for the emulated cruise. Simulation begins by searching through missions within the Mission Profile Database to create a set of online, standby, and secured main engines and shafts for each mission. The algorithm also logs the speed for each mission recorded in the Ship Database. Once all the missions have been processed, the SPS algorithm searches through the other inputs in the Mission Profile Database such as seawater temperature or crew size, and logs the start and stop time for any changes. These changes define instants when a load may change state.

Next, the user selects a collection of loads of interest. The Ship Database is queried to identify phases associated with each load. For each phase that supplies power to the load, the SPS queries the Ship Database for the load's state-change variables and searches for changes in these variables in the Mission Profile Database. For all state changes from the Mission Profile Database, the program uses the start and stop times associated with the change to develop a list of possible state changes for the load. Each of these times are checked against the user defined state change variables in the Ship Database for the load. The start and stop times are computed for the load based on the state changes, which includes both the deterministic changes, such as mission inputs, as well as stochastic changes, e.g., time, or crew size. The state changes could also be a logical AND of a deterministic and stochastic variable. For each state change, the SPS retrieves the name of the operation, such as "Off-On," from the Ship Database.

For each state change, the SPS takes the time and operation name, looks up the power waveform in the Load Database, and adds it to the total time series for the phases connected to the load. In between state-changes, such as after an "Off-On," the SPS will retrieve the steady state, or "On" state waveform from the Load Database and will repeat the waveform until the next state-change, in this case the "On-Off" state change. This process repeats until all

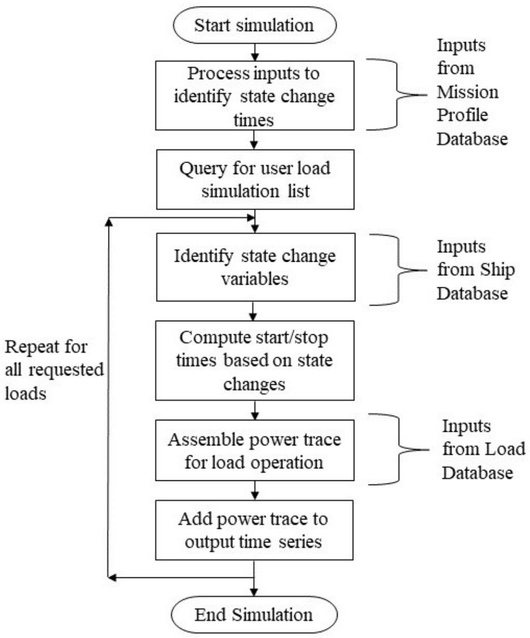


FIGURE 8. Simulation Algorithm Process.

requested phases, loads, and power types have been analyzed across the entire mission profile. The aggregate power is the summation of the power trace of each individual load. The next section demonstrates the utility of this approach by comparing SPS simulations to underway data recorded on a cruise of USCGC SPENCER.

V. COMPARISON TO FIELD DATA

Nonintrusive Load Monitor (NILM) systems are installed upstream of two 440V sub-panels in the main engine room of USCGC SPENCER. These monitors have proven to be reliable tools for collecting data for condition-based maintenance, fault detection, and energy scorekeeping [20], [22]. This NILM data provides insight into the load traces and behavior of equipment essential to the cutter's operational capability while underway. Fig. 3 lists the electrical loads on each of these two panels, port and starboard. This section discusses the observed load behaviors onboard USCGC SPENCER and describes how such behaviors were modeled in the SPS tool, allowing for a comparison of the real ship data with the SPS simulation output data.

A. MAIN PROPULSION DIESEL ENGINE LOAD BEHAVIOR

A collection of loads service each of the main propulsion diesel engines (port and starboard). The main propulsion diesel engine (MPDE) pre-lube pump is a motor-driven centrifugal pump that operates upon shutdown of the main diesel engines. The state-change variable for the pre-lube pump is "mission," as the mission determines whether certain main engines are online, in standby, or secured. The MPDE lube-oil (LO) heater works in tandem with the pre-lube pump to maintain desired lube-oil viscosity and temperature. These heaters secure upon engine start, and return to an automatic cycling mode when the engine secures. To model the heater behavior in the simulator, a logical combination of two state-change variables is used to trigger a change in the simulated heater load state. A "primary" state-change variable tracks with the pre-lube pump and is activated whenever the associated MPDE is put in standby. The "secondary" state-change variable is a "random" event that models the automatic thermal cycling when the heater is operating. The simulator effectively models the heater operation with a logical AND operation of these two state-change variables, the primary variable tracking the MDPE state and the secondary variable tracking the random cycling. The heater energizes and secures at random times to reproduce the thermostatic behavior of the actual heater whenever the simulated MDPE enters a standby state. Finally, the MPDE jacket water (JW) heater consists of two 3-phase immersion heating elements sitting between the cylinders on either side of the engine block. These elements are modeled with the same approach used for the LO heater.

B. SHIP SERVICE DIESEL GENERATOR LOAD BEHAVIOR

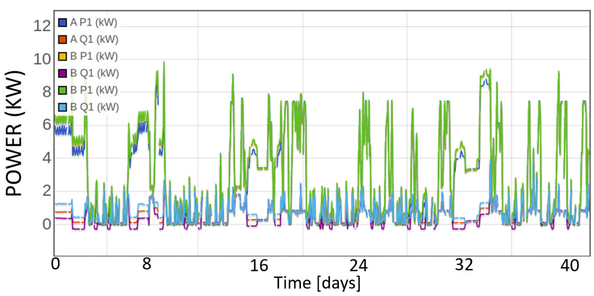
The Ship Service Diesel Generators (SSDG) are also served by a collection of support loads. Similar to the MPDE LO heater, the SSDG LO heater keeps engine lubricating oil temperature within a set range while the engine is secured. The SSDG LO heater is a line-to-line single-phase load. The heater secures when the SSDG is brought online and the temperature rapidly increases above the upper set point. The ship mission also drives the generator configuration, similar to the MPDE behavior. The primary state-change variable for this load is "mission" and the load will only activate if the associated generator is put in standby. The secondary or "random" state-change variable models the thermostatic cycling. The SSDG JW heater serves the same purpose as the MPDE JW heater and was modeled similarly.

C. ADDITIONAL ENGINE ROOM LOAD BEHAVIOR

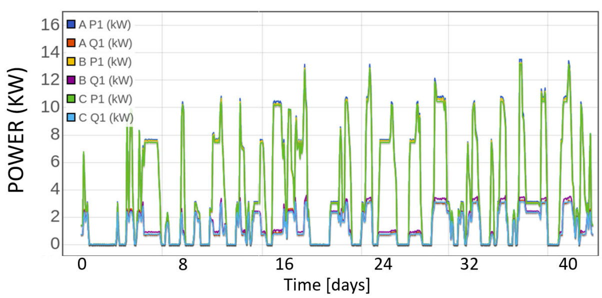
The Controllable Pitch Propeller (CPP) pump is energized when Alpha-RMD has been set. The primary state-change variable is "mission." The two graywater pumps are identical, motor-driven centrifugal pumps that alternate runs to empty the graywater tanks when a high level is reached. The graywater pumps' behavior was modeled through the use of the random option for the state-change variable. The fuel oil purifier (FOP) is run underway to clean the diesel oil before use in the MPDE or in the SSDG. Thus, it runs more frequently if the quality of fuel onboard is poor. Because the FOP is the only modeled load that is dependent on the fuel quality, this behavior was modeled using the "random" state-change variable. The in-port auxiliary saltwater (ASW) pump provides cooling water at the pier. This pump was modeled with "mission" as its state-change variable, as it only turns on when in port, and secures upon leaving port. The bilge and ballast pump is a motor-driven centrifugal pump used for taking on or discharging ballast water for stability purposes and also for emptying the cutter bilges of excess water. The bilge and ballast pump was modeled as a two-state, random occurrence.

VI. SIMULATION RESULTS AND TESTING

The Shipboard Power Simulator was put through an extensive testing process to evaluate the simulator's ability to accurately model ship behavior and estimated load demand. Unlike detailed time-domain simulation approaches which are often on the seconds timescale and require hardware-in-the-loop and computationally burdensome algorithms [18], [23], [24], the SPS provides quick analysis of energy consumption and overall demand profiles for entire ship missions and cruises. First, the simulator was challenged to reproduce various ship missions, with testing culminating in a 41-day simulation shown in Fig. 9b, which spanned multiple missions, speeds, and temperatures. This is compared to 41-days of an observed cruise on USCGC SPENCER, from December 28, 2016 to February 7, 2017, shown in Fig. 9a. The purpose of the behavioral simulation, of course, is not to reproduce exact instant-to-instant details of the ships power demands. Rather, the simulator reproduces the overall quality of the ship energy requirements as a function of different mission tasking. Comparing the observed power in Fig. 9a and the simulation output in Fig. 9b, both show similar aggregate power levels, indicating the SPS was able to model behavior well.



(a) SPENCER power streams as observed with NILM.



(b) Simulation power streams from the SPS.

FIGURE 9. 41-day aggregate power streams for the port sub-panel.

Further, to test the SPS's ability to accurately model ship behavior during various "what-if" scenarios, the SPS was used to simulate different ship missions. The simulated power streams are used to analyze individual load operation,

TABLE 1. Charlie duty cycle results.

Equipment	NILM (2016)	NILM (2019)	SPS
Additional engine room loads			
Graywater Pump	0.003	0.007	0.009
In-Port ASW Pump	1.0	1.0	0.999
MPDE keep-warm system			
NR 2 JW Heater	1.0	0.989	0.999
NR 1 JW Heater	1.0	0	0.999
SSDG keep-warm system			
NR 2 JW Heater	0.417	0.424	0.483
NR 1 JW Heater	0.387	0.580	0.459
NR 2 LO Heater	1.0	1.0	0.999
NR 1 LO Heater	0.556	0.377	0.481

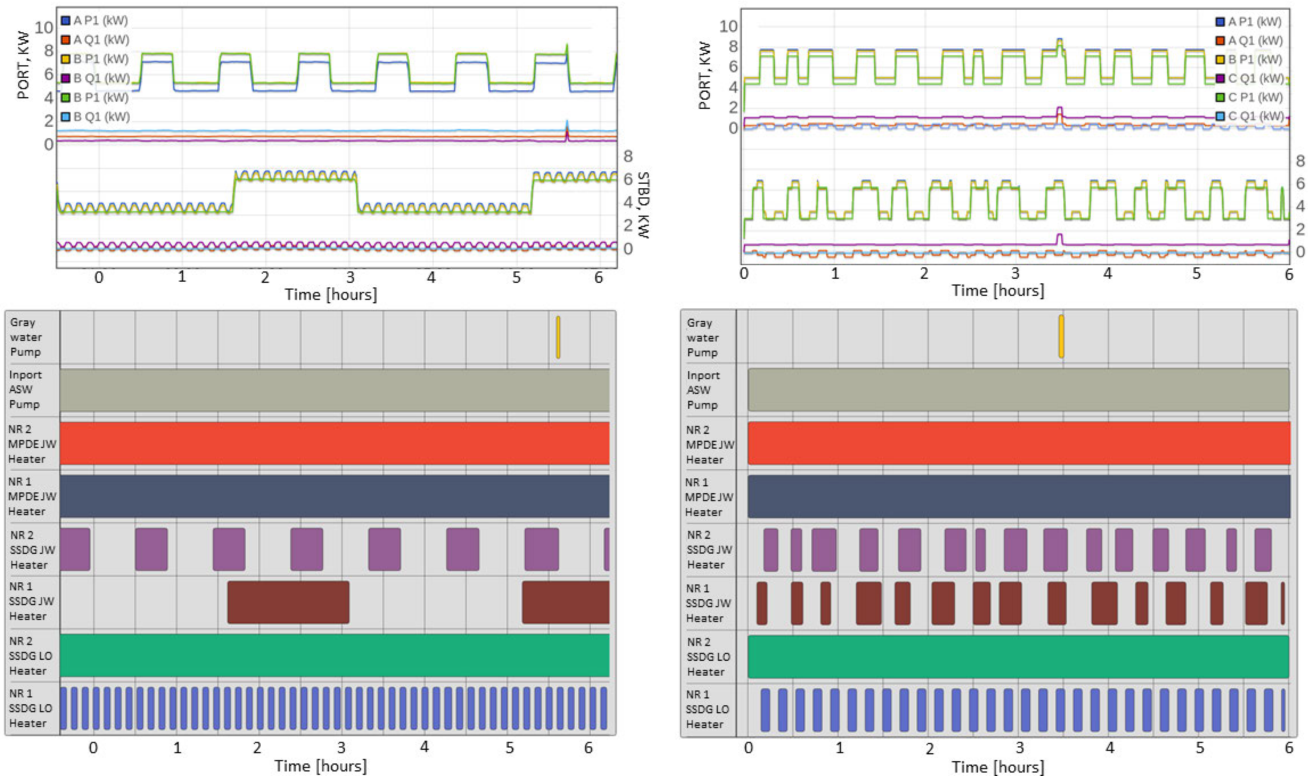
by employing signal processing and pattern recognition algorithms to associate the power waveforms with the operating schedule of specific loads. The NILM algorithms can identify load operation in both field and simulated data because the SPS uses real "slices" of power observations to assemble simulated waveforms. Loads are identified by first using a change of mean detector to detect "on" and "off" events [25]. The power stream can then be examined to calculate a set of features. For the simulation data, the "on" and "off" events are characterized using a correlation algorithm. The correlation algorithm matches the shape of the input data to known exemplars [26]. Consider two sampled waveforms f and g, where f is an observation or input signal and g is a load exemplar or example waveform. The correlation metric, C, is

$$C = 1 - \left| \frac{(f - \bar{f}) \cdot (g - \bar{g})}{|g - \bar{g}|^2} \right| \tag{1}$$

where $\bar{f}$ and $\bar{g}$ are the mean of f and g, respectively, and are subtracted from the original signals, f and g in order to remove the DC offsets. When C approaches zero, this indicates that the exemplar and observation match in both shape and amplitude. When an event is detected, C is calculated for each load using a fingerprint exemplar, and the event is classified as the load with the minimum C value. For SPENCER, the loads are classified using the load identification algorithm in [25].

A. CHARLIE STATUS

The first ship mission simulated was Charlie status, in which the cutter is moored at a pier and not expected to get underway for an extended period of time. Results are presented for a six hour window of ship operations, with plots in Fig. 10 showing three-phase aggregate power time-series streams as well as a NILM Dashboard "Timeline View" of individual loads [13]. The dashboard shows individual load operation with colored bars to indicate periods a load is energized. The six hour SPS emulation of Charlie status for the eight active ship loads in this mission required only 35 seconds to complete on a 1.8 Ghz i7-8565 CPU.



(a) SPENCER power streams and detected events as observed with NILM.

(b) Simulation power streams and detected events from the SPS.

FIGURE 10. Charlie status. Power streams are displayed above. NILM Dashboard Timeline View is displayed below, where colored blocks indicate periods where a load is energized.

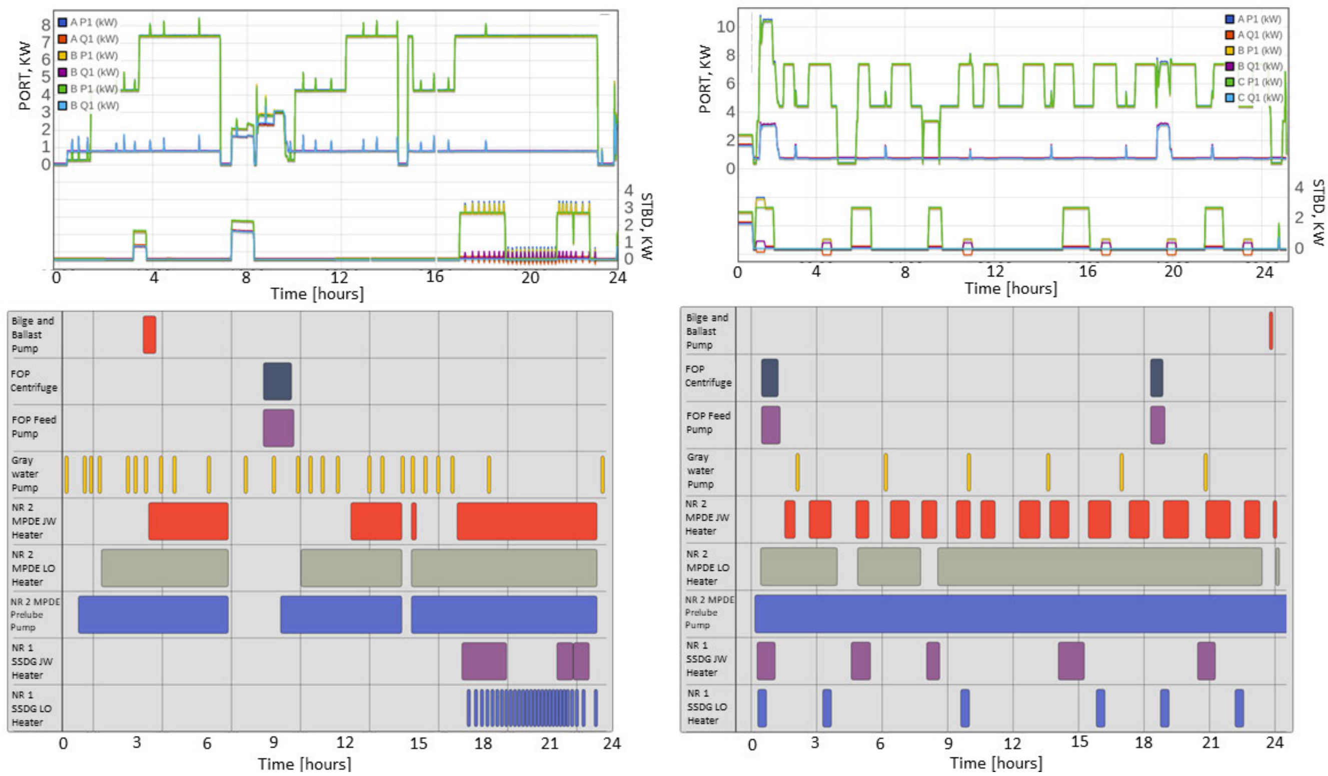
The duty cycle, D, for each load is expressed as,

$$D = \frac{T_{ON}}{T}, \tag{2}$$

where T_{ON} is the total time a load is energized during time period T. Observed duty cycles from two observed ship periods (December 29, 2016 and July 12, 2019) and simulated duty cycles for the respective loads are compared in Table 1. Fig. 10 shows the 2016 observed power streams and simulated power streams for the port and starboard power panels as well as the detected events during this 6-hour Charlie status. The duty cycles for all loads agree well for the simulated data and both data observations, with the exception of the NR 1 MPDE JW heater. The NR 1 MPDE JW heater is not operating in the 2019 observation window due to a fault condition in which the heaters were operating in a degraded state with reduced power consumption or not operating at all [27]. The MPDE JW heaters were kept in healthy condition in the simulation. For both the observed data and the simulation data the main propulsion diesel engines are secured and kept warm using only the jacket water heaters. The graywater is cycling, and the in-port ASW pump is on, as expected while in-port. The ship is receiving power from a shore tie connection, but a minimum of one SSDG must be kept in standby. As observed on SPENCER, and modeled in the simulator, both SSDGs are in standby, with support heaters for both generators cycling. The observed NR 1 and NR 2 SSDG LO heaters exhibited different behavior, due to the NR 2 SSDG LO heater on the ship operating in degraded condition. This was modeled in the simulator, showing its ability to model this "what-if" scenario, in which both SSDG LO heaters correctly respond to the primary state change variable "mission" and activate when the associated generator is but in standby, but have different behavior based on the secondary state change variable representing thermostatic cycling.

B. ALPHA-NORMAL STATUS

The next ship mission simulated was Alpha-Normal status, in which the cutter is underway in open waters. Observed duty cycles from two observed 1-day ship periods (January 26-27, 2017 and September 18-19, 2019), and simulated duty cycles for the respective loads are compared in Table 2. Fig. 11 shows the 2017 observed power streams and simulated power streams for the port and starboard power panels as well as the detected load events during this 1-day Alpha-Normal status. The SPS completed this simulation for nine active ship loads in 17 seconds on the i7 CPU. Again, the duty cycles for all loads agree well for the simulated data and both data observations, except for the NR 2 MPDE JW heater which is not operating in the 2019 observation window due to the same MPDE JW heater fault condition observed in Charlie status. In this operational status, once



(a) SPENCER power streams and detected events as observed with NILM.

(b) Simulation power streams and detected events from the SPS.

FIGURE 11. Alpha-Normal status. Power streams are displayed above. NILM Dashboard Timeline View is displayed below, where colored blocks indicate periods where a load is energized.

TABLE 2. Alpha-normal duty cycle results.

Equipment	NILM (2017)	NILM (2019)	SPS
Additional engine room loads			
Bilge and Ballast	0.025	0	0.002
FOP Centrifuge	0.055	0.024	0.055
FOP Feed Pump	0.060	0.029	0.063
Graywater Pumps	0.020	0.013	0.011
MPDE keep-warm system			
NR 2 JW Heater	0.526	0	0.491
NR 2 LO Heater	0.796	0.734	0.885
NR 2 Prelube Pump	0.878	0.814	0.993
SSDG keep-warm system			
NR 1 JW Heater	0.150	0.209	0.180
NR 1 LO Heater	0.042	0.092	0.099

the cutter leaves restricted waters and enters the open ocean, the ship is configured for the Alpha-Normal condition and the CPP pumps are secured. One engine and one generator are secured and placed in standby status to save fuel, indicated by the associated heaters and pumps cycling. In this case, NR 2 MPDE and NR 1 SSDG are placed in standby in both the observed and simulated data. Additionally, the fuel oil purifier may be online to move fuel to appropriate tanks and the bilge and ballast pump may be online while moving ballast water. Similar to Charlie status, the graywater pump is seen cycling.

C. EPLA VALIDATION

Electrical Plant Load Analysis (EPLA) load factors are often called for in the design of marine microgrids. These load factors summarize power demand by providing an estimate of average load [4], [14]. The SPS tool can provide a wealth of data for calculating EPLA load factors for a load across multiple mission sets, providing an accurate picture of likely power demand. The load factor [4] is expressed as:

$$LF = \frac{P_{avg}}{P_{rated}}, \quad P_{avg} = \frac{1}{T}\int_0^T P(t)dt, \tag{3}$$

where P_{rated} is the rated power, P_{avg} is the long term average power the component will draw when in operation, T is the total time period of interest, and $P(t)$ is the power draw of the load at time, t. For the two-state loads common on the example power panel, $P(t)$ is constant (P_{ss}) during the "on" state, as in Fig. 5. For these two-state loads, the average power can be expressed as,

$$P_{avg} = \frac{\sum_{i=1}^{N}(T_{ON,i} \times P_{ss,i})}{T}, \tag{4}$$

where i is an individual load cycle. There are N full or partial load cycles in the time window, in which a full load cycle consists of an "on" followed by an "off," and a partial load cycle is when either the detected "on" or "off" (or both) of the full load cycle is outside of the time window of

TABLE 3. EPLA load factor results.

	In-port		Underway	
	NILM	SPS	NILM	SPS
Additional engine room loads				
Bilge & Ballast Pump	0	0	0.008	0.001
NR 2 CPP "C" Pump	0.099	0.121	0.064	0.064
NR 1 CPP "C" Pump	0.094	0.125	0.066	0.064
FOP Centrifuge	0	0	0.031	0.053
FOP Feed Pump	0	0	0.019	0.028
Graywater Pumps	0.015	0.011	0.020	0.016
In-Port ASW Pump	0.472	0.540	0	0
Main propulsion diesel engine (MPDE) keep-warm system				
NR 2 JW Heater	0.958	1.01	0.376	0.344
NR 1 JW Heater	0.950	1.01	0.268	0.247
NR 2 LO Heater	0.099	0.106	0.594	0.609
NR 1 LO Heater	0.093	0.108	0.294	0.247
NR 2 Prelube Pump	0.093	0.111	0.614	0.688
NR 1 Prelube Pump	0.098	0.095	0.292	0.305
Ship service diesel generator (SSDG) keep-warm system				
NR 2 JW Heater	0.391	0.468	0.017	0.010
NR 1 JW Heater	0.480	0.436	0.147	0.124
NR 2 LO Heater	0.903	0.934	0.208	0.285
NR 1 LO Heater	0.462	0.434	0.039	0.066

interest. $T_{ON,i}$ is the duration of each individual load cycle (or portion thereof that is within $t = 0 \ldots T$), and $P_{ss,i}$ is the steady-state power draw for each individual load cycle. The variable P_{ss} is calculated as the change in total apparent power, defined as the difference between the median values over Δt_M length windows, where here $\Delta t_M = 0.5$ seconds, before and after the "on" to "off" event. Table 3 lists the load factor for each load, comparing the simulated data with NILM data from USCGC SPENCER for two periods, in-port and underway, compiled from data from Fig. 9a. For in-port data, several standard configurations during Charlie and Bravo status from SPENCER were compiled into a 1-day in-port period. For underway data, several standard Alpha-RMD and Alpha-Normal missions from SPENCER were compiled to create a standard 3-day underway period. The SPS required approximately 64 seconds and 151 seconds of simulation time on the i7 computer for seventeen loads over the full emulated 1-day in-port period and 3-day underway period, respectively.

D. AVERAGE POWER VALIDATION

The duty cycle results and EPLA load results show that the simulator can accurately model individual load behavior. Although the SPS is not meant to give an instant-to-instant replication of the observed data, it does give an accurate overall picture of power demand and load profiles. Thus, the average power is calculated for each of the above simulated missions to compare the actual observed ship data with the SPS simulated output. The average power for each load from Eq. (4) is summed, to give the overall power demand from both the port and starboard subpanels. Table 4 shows the average power for the previously described missions (i.e., Charlie, Alpha-Normal, in-port, and underway), as well as the percentage difference. The 2016 and 2017 data from Table 1 and Table 2 is used for the Charlie and Alpha-Normal NILM observations, respectively.

TABLE 4. Average power.

Mission	NILM Avg. Power	Simulation Avg. Power	Percent Difference
Charlie	29.82 kVA	32.01 kVA	7.33%
Alpha-Normal	19.42 kVA	19.45 kVA	0.16%
In-port	33.66 kVA	35.85 kVA	6.81 %
Underway	21.48 kVA	20.83 kVA	-3.02 %

VII. CONCLUSION

The duty cycle, EPLA load factors, and average power results computed from the SPS emulations provide fantastic estimates in comparison to actual observations on-board a ship. The data provided by the SPS for the demonstrations presented in the tables was available in minutes or less. Of course, simulation through behavioral modeling is not expected to slavishly reproduce field waveforms. For example, the NILM Dashboard plots of observed and simulated Charlie status show clear differences between the exact time instants of operation for the SSDG JW heaters. However, they do reflect similar duty cycles of the field systems using only seconds of computation to emulate a six hour operating window. Longer, multi-day missions were also emulated, providing accurate power demand estimates compared to field data. The behavioral approach offers spectacular possibilities for quickly evaluating the energy demands and overall performance of microgrid loads over many operating scenarios. Furthermore, the output of the simulator can be provided as base data for other studies, such as focusing design choices for electric distribution systems or sensitivity analysis to determine the reliability of metrics such as EPLA load factors [4]. Additional model input parameters can be utilized for further studies. For example, using the quality of fuel as an input parameter would enable studies of the effect of fuel-quality on certain load profiles, such as the FOP. The focus of this paper was a USCG medium endurance cutter, but this modeling approach can be applied to other small power systems or power systems that can be "islanded" in general, such as a system with substantial renewable energy and distributed resources. In this regard, future testing of the SPS simulator includes simulating other types of microgrids and distribution systems, such as a ring bus zonal electrical distribution system, often used by the US Navy, or providing energy demand scenarios to aid in the facilitation of renewable energy sources to a grid.

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REFERENCES

[1] J. V. Milanovic, K. Yamashita, S. Martinez Villanueva, S. Z. Djokic, and L. M. Korunovic, "International industry practice on power system load modeling," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3038–3046, Aug. 2013.

[2] S. Shao, M. Pipattanasomporn, and S. Rahman, "Development of physical-based demand response-enabled residential load models," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 607–614, May 2013.

[3] T. I. Bo, A. R. Dahl, T. A. Johansen, E. Mathiesen, M. R. Miyazaki, E. Pedersen, R. Skjetne, A. J. Sorensen, L. Thorat, and K. K. Yum, ''Marine vessel and power plant system simulator,'' *IEEE Access*, vol. 3, pp. 2065–2079, 2015.
[4] U. Orji, B. Sievenpiper, K. Gerhard, S. B. Leeb, N. Doerry, J. L. Kirtley, and T. McCoy, ''Load modeling for power system requirement and capability assessment,'' *IEEE Trans. Power Syst.*, vol. 30, no. 3, pp. 1415–1423, May 2015.
[5] A. Arif, Z. Wang, J. Wang, B. Mather, H. Bashualdo, and D. Zhao, ''Load modeling—A review,'' *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 5986–5999, May 2017.
[6] F. Scotton, L. Huang, S. A. Ahmadi, and B. Wahlberg, ''Physics-based modeling and identification for HVAC systems?'' in *Proc. Eur. Control Conf. (ECC)*, Jul. 2013, pp. 1404–1409.
[7] B.-K. Choi and H.-D. Chiang, ''Multiple solutions and plateau phenomenon in measurement-based load model development: Issues and suggestions,'' *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 824–831, May 2009.
[8] Q. Ai, D. Gu, and C. Chen, ''New load modeling approaches based on field tests for fast transient stability calculations,'' *IEEE Trans. Power Syst.*, vol. 21, no. 4, pp. 1864–1873, Nov. 2006.
[9] L. Bottaccioli, S. Di Cataldo, A. Acquaviva, and E. Patti, ''Realistic multi-scale modeling of household electricity behaviors,'' *IEEE Access*, vol. 7, pp. 2467–2489, 2019.
[10] A. Capasso, W. Grattieri, R. Lamedica, and A. Prudenzi, ''A bottom-up approach to residential load modeling,'' *IEEE Trans. Power Syst.*, vol. 9, no. 2, pp. 957–964, May 1994.
[11] J. Widén and E. Wäckelgård, ''A high-resolution stochastic model of domestic activity patterns and electricity demand,'' *Appl. Energy*, vol. 87, no. 6, pp. 1880–1892, Jun. 2010.
[12] A. J. Collin, G. Tsagarakis, A. E. Kiprakis, and S. McLaughlin, ''Development of low-voltage load models for the residential load sector,'' *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2180–2188, Sep. 2014.
[13] A. Aboulian, D. H. Green, J. F. Switzer, T. J. Kane, G. V. Bredariol, P. Lindahl, J. S. Donnal, and S. B. Leeb, ''NILM dashboard: A power system monitor for electromechanical equipment diagnostics,'' *IEEE Trans. Ind. Informat.*, vol. 15, no. 3, pp. 1405–1414, Mar. 2019.
[14] N. Doerry, ''Electric power load analysis,'' *Nav. Eng. J.*, vol. 124, no. 4, pp. 45–48, Dec. 2012.
[15] H.-M. Chin, C.-L. Su, and C.-H. Liao, ''Estimating power pump loads and sizing generators for ship electrical load analysis,'' *IEEE Trans. Ind. Appl.*, vol. 52, no. 6, pp. 4619–4627, Nov. 2016.
[16] S. B. Leeb, J. L. Kirtley, D. S. Woodruff, and M. S. LeVan, ''Building-level power network analysis,'' *IEEE Comput. Appl. Power*, vol. 5, no. 1, pp. 30–34, Jan. 1992.
[17] T. Deeter, ''Creating a shipboard power simulation tool using electrical load behavior modeling,'' M.S. thesis, Massachusetts Inst. Technol., Cambridge, MA, USA, 2020.
[18] K. Schoder, H. Ravindra, M. Stanovich, J. Langston, I. Leonard, and M. Steurer, ''Shipboard power system baseline modeling and evaluation,'' in *Proc. IEEE Electric Ship Technol. Symp. (ESTS)*, Aug. 2019, pp. 536–541.
[19] D. D. Walden, G. J. Roedler, K. J. Forsberg, R. D. Hamelin, and T. M. Shortell, *Systems Engineering Handbook: A Guide for System Life Cycle Processes and Activities*. Hoboken, NJ, USA: Wiley, 2015.
[20] P. A. Lindahl, D. H. Green, G. Bredariol, A. Aboulian, J. S. Donnal, and S. B. Leeb, ''Shipboard fault detection through nonintrusive load monitoring: A case study,'' *IEEE Sensors J.*, vol. 18, no. 21, pp. 8986–8995, Nov. 2018.
[21] L. Chuan and A. Ukil, ''Modeling and validation of electrical load profiling in residential buildings in singapore,'' *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2800–2809, Sep. 2015.
[22] T. Kane, ''The NILM dashboard: Shipboard automatic watchstanding and real-time fault detection using non-intrusive load monitoring,'' M.S. thesis, Massachusetts Inst. Technol., Cambridge, MA, USA, 2019.
[23] C. S. Edrington, G. Ozkan, B. Papari, D. E. Gonsoulin, D. Perkins, T. V. Vu, and H. Vahedi, ''Distributed energy management for ship power systems with distributed energy storage,'' *J. Mar. Eng. Technol.*, vol. 19, pp. 31–44, Jan. 2020.
[24] F. D'Agostino, D. Kaza, M. Martelli, G.-P. Schiapparelli, F. Silvestro, and C. Soldano, ''Development of a multiphysics real-time simulator for model-based design of a DC shipboard microgrid,'' *Energies*, vol. 13, no. 14, p. 3580, Jul. 2020.
[25] D. H. Green, S. R. Shaw, P. Lindahl, T. J. Kane, J. S. Donnal, and S. B. Leeb, ''A multiscale framework for nonintrusive load identification,'' *IEEE Trans. Ind. Informat.*, vol. 16, no. 2, pp. 992–1002, Feb. 2020.
[26] J. Paris, J. S. Donnal, and S. B. Leeb, ''NilmDB: The non-intrusive load monitor database,'' *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2459–2467, Sep. 2014.
[27] D. Green, P. Lindahl, S. Leeb, T. Kane, S. Kidwell, and J. Donnal, ''Dashboard: Nonintrusive electromechanical fault detection and diagnostics,'' in *Proc. IEEE AUTOTESTCON*, Aug. 2019, pp. 1–9.

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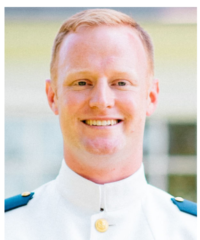

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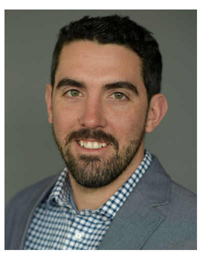

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