Fast Shipboard Electric Power Systems Simulation: Applications of Behavioral Modeling

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***Abstract*—Mission requirements and electrification trends are pushing new platforms toward more complex electric power distribution networks, often featuring integrated electric and hybrid propulsion architectures. As a result, shipboard electric plant modeling has never been more important. Behavioral modeling offers a fast approach to achieve concept-level microgrid simulation, which may be used for design, diagnostic, and sustainment tasks. Transient and steady-state data captured at the component level allow entire microgrids to be modeled at a fraction of the computing cost of traditional numerical techniques. The software suite presented here offers a scalable platform, intuitive graphical user interface, and efficient solving algorithm to rapidly produce large quantities of statistically accurate results. The simulator's utility is demonstrated across a ship's life cycle through examples supporting set-based design, developing synthetic training data for machine learning-based diagnostic models, and providing sustainment support to platforms facing obsolescence.**

***Index Terms*—Behavior modeling, electric propulsion, nonintrusive load monitoring, machine learning, diagnostics**

I. Trends and Challenges in Shipboard Electrification

Ship electrification dates back nearly 150 years, when in 1880 the S.S. *Columbia* set sail with an electric microgrid to provide passengers and crew with light. Thirty-three years later the U.S.S. *Jupiter* became the first U.S. naval ship to make use of turbo-electric propulsion. While gas turbines and direct-drive diesel engines became popular in the majority of subsequent propulsion systems, the capacity and complexity of shipboard microgrids has steadily increased in recent years. Technological improvements and flexible plant configurations offered by integrated propulsion systems (IPS) can decrease light loading operations, reducing diesel engine maintenance and increasing fuel economy. Defensive systems and radar platforms demand increasing amounts of power, fueling a demand for higher voltages and more generation capacity. General trends in component electrification and control drive a broader trend of higher electric consumption onboard.

The effects of these trends ripple across all aspects of the naval system life cycle. In the design stage, engineers face an ever-growing complexity of their design space. This enables greater platform optimization, but simultaneously plagues them with an increase in computation demands for the necessary modeling efforts. Design techniques such as set-based design offer methods to mitigate emergent design failures that lead to significant late-stage rework [1]. In practice, designers carry all feasible combinations of the design space through increasing levels of analysis fidelity. Successful implementation of this technique prevents premature removal of possibly optimal design choices, but requires significant early-stage work to evaluate each combination until feasibility constraints narrow the design space. As designers advance through progressive stages of evaluation, the computational demand for analysis increases, inhibiting the ability for designers to scale their process to numerous combinations.

Increased design complexity exacerbates the challenges of maintaining operational readiness. Government assets with funding and personnel constraints already struggle to remain operationally available. As unmanned ships begin to see widespread naval and industry use, they will demand even more accurate diagnostic systems. Utility monitoring, and in particular nonintrusive load monitoring, offers the ability to detect anomalies and ongoing faults by observing patterns in aggregate power streams [2]. Data-driven techniques also show promise for diagnostics at the component and subsystem level [3]. However, both depend on the availability of quality, actionable data for training or tuning a diagnostic system. The acquisition of this data is traditionally very costly, requiring numerical methods to solve the underlying circuit models, physical data collection, or a land-based physical system model [3], [4].

Lastly, ship maintenance is a significant component of a ship's life cycle cost. As ships adopt electronic equipment susceptible to a quickly innovating industry, the challenges faced by engineering leadership and sustainment personnel compound as the likelihood of component obsolescence grows. The U.S. Coast Guard's In-Service Vessel Sustainment program is an example of this significant effort [5]. It is focused on life-extension and sustainment for the medium endurance cutter and icebreaking fleet, with a 2025 budget of $148 million – nearly 10% of the total budget allocated towards vessel procurement, construction, and maintenance [6]. Projects without high-cost digital models can face difficulty in replacing obsolete components while mitigating the risk of unforeseen integration issues.

Behavioral techniques in power system modeling offer a

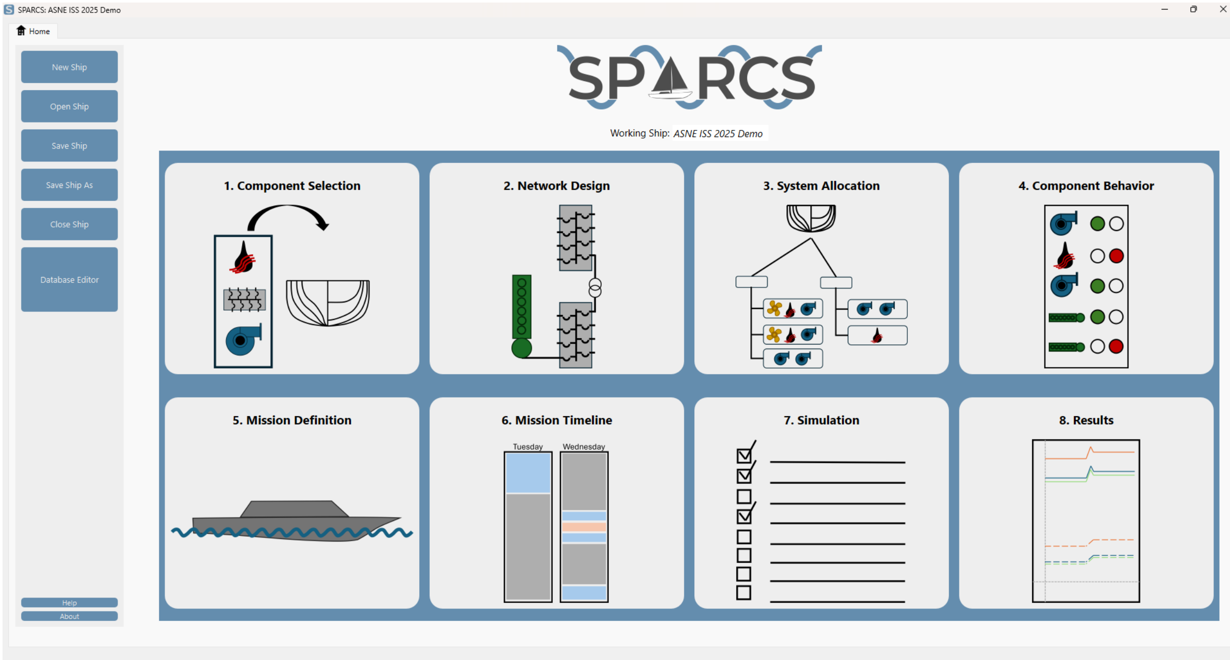

Fig. 1: The start screen of SPARCS. The user builds and simulates their ship model through an intuitive eight step process in a graphical environment.

possible solution to the challenges above by providing a fast method for simulating complex electric networks. Behavioral simulation avoids the use of complex mathematical models for a load, trading some degree of simulation fidelity for a reasonable, computationally fast approximation of load and power system behavior using waveform-level models of a load. Instead of solving circuit models from first principles, behavioral techniques use stateless operation models to reduce computational demands. We present SPARCS (Shipboard Parallelized Analytics with Rapid Configuration Simulator), a new open-source simulation package leveraging behavioral techniques and a graphical interface (shown in Figure 1) for solving the power tracking problem for shipboard microgrids.

II. SPARCS

Traditional modeling efforts for ship electric plants are performed at various levels of fidelity. In concept design, a bookkeeping exercise is performed to understand power generation requirements across a concept of operations (CONOPS). This exercise is then expanded to solving the load flow problem with simplified one-line diagrams of the power network. Operational areas of concern are identified for higher-fidelity modeling, at which point a numerical circuit solver simulates transient behavior.

Solving the load flow problem can quickly become a tedious and time-consuming task, hobbling the search through a proposed or existing design space when considering new designs or new methods of operation for existing systems. Load flow statistics provide insight for design- and performance-related metrics. Although these are valuable at all stages of design, load flow is typically performed with methods that do not scale well with increasing ship complexity or a large variety of designs. SPARCS offers an integrated approach to the power system simulation problem, allowing the user to define component operation across a range of CONOPs and quickly solve a given electrical network.

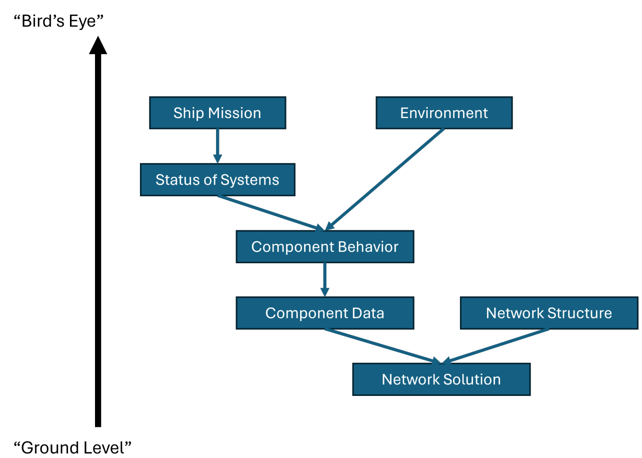

Fig. 2: SPARCS's approach to modeling a shipboard power network.

In contrast to conventional simulation approaches, SPARCS does not seek to replicate the true dynamics of a system under a timeline of external conditions and controls. It instead emulates power system behavior that may probabilistically occur. This is advantageous as it inherently captures the range of expected operating conditions, and extreme events that

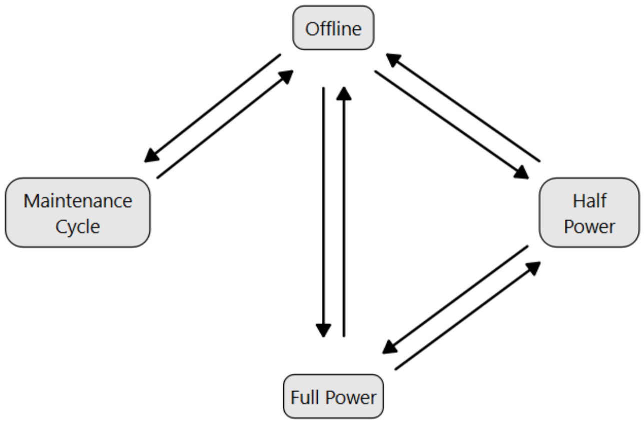

Fig. 3: The state machine available to a sample load in SPARCS. It is defined to allow unrestricted operation between Offline, Half Power, and Full Power, but entering a Maintenance Cycle must begin from the Offline state.

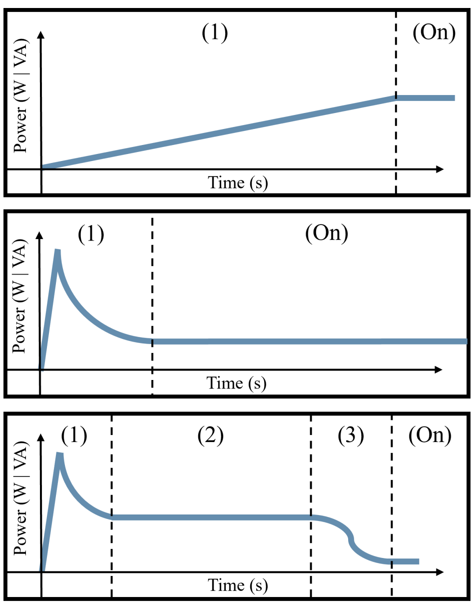

Fig. 4: Transient templates offered by the Load Wizard. (top) linear ramp; (middle) inrush; (bottom) constant power acceleration.

could occur. Instead of iterating through permutations of initial conditions and external factors to extract extreme events, each component can be defined with a probabilistic range of it exhibiting such a behavior.

A typical use case of SPARCS will involve running deterministic simulations in which the behavior of components is sampled from their prescribed probability distribution. As SPARCS solves the network through time, it builds a nominal solution that could feasibly occur. By executing many of these deterministic simulations, a Monte Carlo analysis could be performed.

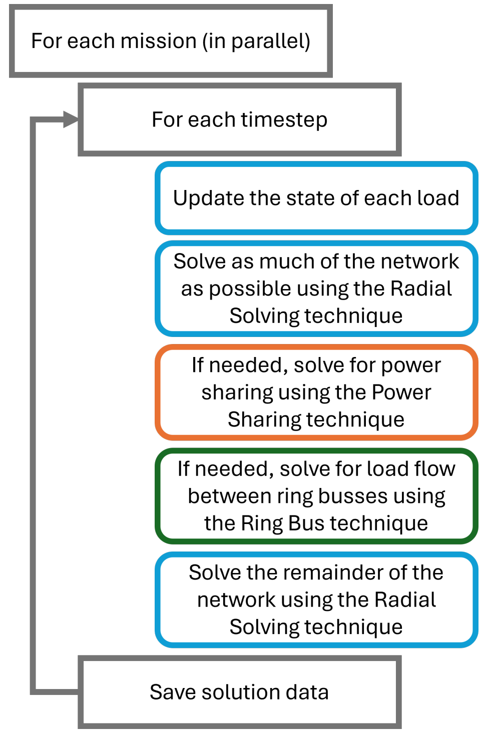

Fig. 5: The high-level solving algorithm of SPARCS.

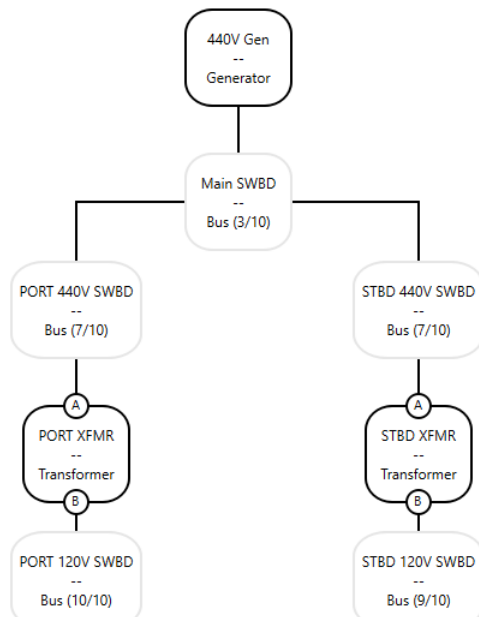

Fig. 6: One-line diagram of the sample ship's electric plant.

A. Operational Modeling Framework

The highest level of abstraction for a ship's CONOP comes from the mission and environmental conditions it will operate in, as illustrated in Figure 2. For example, a ship may be tasked with traveling to a designated location at a specified speed (the mission), while facing head winds and mild seas

CONOP	Base Load (kW)	Expected Variable Load (kW)	**Expected Total Load (kW)**	μ_{CONOP} T (minutes)	D (%)	No. of Online Loads
Underway Efficient	300	910	**1210**	240	0.46	25
General Quarters	600	1125	**1725**	180	0.56	25
Loiter	200	367	**567**	360	0.20	24
RMD	300	693	**993**	60	0.36	25
In Port on Ship Power	60	95	**155**	720	0.05	15

TABLE I: Load characteristics for different mission profiles

CONOP	λ_{Online} (minutes)	$\lambda_{Offline}$ (minutes)
Underway Efficient	70	163
General Quarters	94	63
Loiter	24	213
In Port on Ship Power	92	825
RMD	26	39

TABLE II: Sample Poisson distribution parameters for a single load with nominal power 100 kW and power factor 0.98.

Generation Design Set #	**Generator Capacity (kW)** **Gen 1**	**Gen 2**	**Gen 3**	**Gen 4**	**Gen 5**
Set 1	600	2000	2000	0	0
Set 2	800	2000	2000	0	0
Set 3	600	600	1500	1500	0
Set 4	600	600	1500	2000	0
Set 5	600	600	600	800	800
Set 6	600	600	600	800	1500
Set 7	600	600	600	800	2000
Set 8	600	600	800	800	800
Set 9	600	600	800	800	1500
Set 10	600	600	800	800	2000

TABLE III: Generation sets defined for the sample design case. Each design set has up to five generators comprised of 600 kW, 800 kW, 1500 kW, and 2000 kW generators.

(the local environment).

A ship's components can be grouped into systems [7], [8]. For example, a commercial cargo vessel may have systems including "Propulsion," "Navigation," and "Cargo Handling." These systems are defined such that their member components behave in a similar manner for any given mission. For instance, the "Cargo Handling" system may have three operational statuses: "Offloading," "Onloading," and "Standby." By grouping components in such a manner, missions can describe the status of each system, rather than the status of each individual component. As the complexity of the microgrid increases, this allows for a decoupling between the definition of ship-level behavior (missions), system-level behavior (system statuses), and load-level behavior.

Finally, the operating state of each component is determined by the status of the system(s) it belongs to (e.g., "Offloading" status of the "Cargo Handling" system) and the ship's environment. A series of *IF, THEN* statements define a component's behavior by establishing its state based on the environment and its system's statuses. For example: *IF* the "Cargo Handling" system is "Offloading," *THEN* the gantry crane's hydraulic pump is cycling with a 50% duty cycle. *OTHERWISE* the pump is offline. The environment variables are primarily intended to capture the influence of the external conditions on the ship. For instance, a variable such as the sea state significant wave height may drive variations in the duty cycle for a bilge pump. These parameters can also be used to capture operational nuances, such as the order of cycling generators.

B. Component States and Data Management

Loads and generators may have many steady-state operating conditions. These can be modeled as a finite state machine (FSM), shown in Figure 3. These steady states are separated by state transitions or "transients," represented by the arrows in Figure 3. Each steady state and transient is defined by a set of real and reactive power traces for each relevant phase (e.g., A, B, C) and harmonic (e.g., 1st, 3rd, 5th, 7th). These traces may be defined by data captured from detailed modeling efforts (e.g., a numerical model of a pump's inrush current), from data acquisition systems onboard existing ships, or through SPARCS's "Load Wizard" feature. The Load Wizard characterizes transients as parameterizations of transient templates, as shown in Figure 4.

SPARCS assumes that every load power trace is independent of the operation of other equipment on the power system. While the user may choose to upload traces for different states which represent the power stream under specific operational cases, the power traces are not modified in the simulation stage. This independence across components allows the simulation to be solved in parallel across multiple CPU cores. On modern computing hardware, this results in a drastic speedup compared to a non-parallel, serialized approach.

C. Solving Techniques

SPARCS uses three primary techniques to solve the power system simulation problem: Radial Propagation, Power Sharing, and Ring Bus algorithms. These methods are applied sequentially for each time step as shown in Figure 5. The order of this process ensures that as much of the network is solved as possible before using more time-intensive solving algorithms.

The Radial Propagation algorithm applies conservation of power across every node in the system where every input and output power value is known except for one. This is performed for as many nodes as possible until there are no more nodes with only one unknown input or output power value. If multiple generators are online in the network, the Power

Fig. 7: Sample results during the General Quarters mission. The phase A real power trace is shown at the port transformer (red), port 440 Volt switchboard (blue), and the generation probe points (green).

Sharing algorithm distributes power proportionally between each of the generators based on their maximum continuous rating (MCR). Finally, if a ring exists in the network, the Ring Bus algorithm solves a linear system to emulate the remaining power system.

Losses across components (cables, transformers, and converters) in the Radial Propagation algorithm are modeled for each harmonic and phase according to the following equation:

$$S_{\phi,out} = S_{\phi,in} + \left(\frac{S_{\phi,in}}{V_{ref}}\right)^2 Z_{comp.} \tag{1}$$

Here, S_ϕ is the complex power spectral envelope on phase ϕ, V_{ref} is the root-mean-square reference voltage of the component, and $Z_{comp.}$ is the equivalent impedance of the component. Although the voltage is assumed to be stiff across the power system, this provides an estimate of distribution losses provided they are small.

III. Vessel Design

Behavioral modeling offers a method to emulate power system behavior in a quick and scalable manner. Solutions to late-stage design considerations can become available at the same time as a concept-level electric power load analysis (EPLA), reducing the likelihood of encountering unforeseen emergent design failures. From the behavioral emulation, key design parameters can be obtained, such as:

- Generator light loading
- Fuel consumption
- Component runtime and maintenance schedules
- Damage case redundancy
- Component size, weight, power, and cost (SWaP-C)
- Harmonic distortion
- Thermal signatures
- Electromagnetic interference (EMI)

SPARCS is especially useful for estimating these design parameters because of its ability to consider not only average loading events, but the volatility of the loading. In early design stages, loads are traditionally associated with a constant load factor for each CONOP, but variability is often not considered. This is analogous to designing a ship for the motions induced by a significant wave height of a storm, but not considering the low-probability, extreme amplitudes that may occur. The capability of SPARCS to use randomized behavior allows it to produce sample instances of time-series data, which can capture these extreme events.

A. Design Demonstration

To demonstrate its usefulness in assessing load volatility, a sample concept design is presented and the time spent light-loaded is estimated. Loading mechanically injected diesel engines below their nominal ratings can lead to incomplete combustion cycles, increasing maintenance frequency, diminishing fuel economy, and potentially causing engine failure [9]. While light loading plays a major role in ship availability throughout its life, it is often neglected until the later stages of design, if it is considered at all.

Figure 6 shows the radial network of an example concept ship. This network contains two 440 V buses, each with a 120 V distribution sub-panel. The parameters describing each load's duty cycle and period were randomly sampled from a CONOP-specific distribution, representing the case where data from a similar existing class of ship is known. Alternatively,

Generation Design Set #	% of Time Light-Loaded below 25% (SPARCS Results || Avg. Loading) Underway Efficient		General Quarters		Loiter		RMD		In Port on Ship Power	
Set 1	0.00	0	0.02	0	0.50	1	0.69	1	0.71	1
Set 2	0.00	0	0.03	0	0.52	1	0.69	1	0.78	1
Set 3	0.00	0	0.00	0	0.51	1	0.62	1	0.58	1
Set 4	0.00	0	0.02	0	0.50	1	0.62	1	0.75	1
Set 5	0.00	0	0.00	0	0.41	0	0.62	1	0.32	0
Set 6	0.00	0	0.00	0	0.44	1	0.62	1	0.55	1
Set 7	0.00	0	0.02	0	0.50	1	0.62	1	0.71	1
Set 8	0.00	0	0.00	0	0.41	0	0.62	1	0.38	0
Set 9	0.00	0	0.00	0	0.41	0	0.62	1	0.61	1
Set 10	0.00	0	0.03	0	0.41	0	0.62	1	0.78	1

Generation Design Set #	% of Time Light-Loaded below 40% (SPARCS Results || Avg. Loading) Underway Efficient		General Quarters		Loiter		RMD		In Port on Ship Power	
Set 1	0.23	0	0.61	1	0.74	1	0.88	1	1.00	1
Set 2	0.31	0	0.71	1	0.77	1	0.88	1	1.00	1
Set 3	0.27	0	0.36	0	0.75	1	0.68	1	1.00	1
Set 4	0.23	0	0.67	1	0.74	1	0.68	1	1.00	1
Set 5	0.23	0	0.09	0	0.67	1	0.68	1	0.91	1
Set 6	0.12	0	0.32	0	0.69	1	0.68	1	1.00	1
Set 7	0.23	0	0.61	1	0.74	1	0.68	1	1.00	1
Set 8	0.15	0	0.14	0	0.67	1	0.68	1	0.95	1
Set 9	0.12	0	0.41	0	0.67	1	0.68	1	1.00	1
Set 10	0.23	0	0.71	1	0.67	1	0.68	1	1.00	1

TABLE IV: Percentage of operational time spent with a generator loaded below 25% and 40% of its nominal rating. For each CONOP, the percentage of time light-loaded calculated with SPARCS through a probabilistic simulation is on the left, and with average loading is on the right.

operator experience and intuition could be used to estimate these distribution parameters, or the duty cycle and period on a per-load basis.

The distribution panels and 440 V buses hold 25 variable loads and a constant base load for each CONOP, described by Table I. The magnitude of the variable load's nominal rating is sampled from an exponential distribution with a mean of 75 kW, with the power factor randomly sampled from a uniform distribution between 0.80 and 1.00. During simulation, the online and offline cycle times of each load are sampled randomly from two Poisson distributions described by λ_{Online} and $\lambda_{Offline}$. Poisson distributions are common representations of independent stochastic cycle times. They are characterized by λ, the expected value of the inter-arrival time of the process.

$$\lambda_{Online} = T_{i,CONOP}\ D_{i,CONOP} \tag{2}$$

$$\lambda_{Offline} = T_{i,CONOP}\ (1 - D_{i,CONOP}) \tag{3}$$

It is further assumed that the duty cycle (D) and period (T) for all of the variable loads on the ship can be described by a Gaussian distribution where the standard deviation (σ_{CONOP}) is equal to one third of the mean (μ_{CONOP}) with 99.7% accuracy, given no value can be below 0. From these two distributions, $D_{i,CONOP}$ and $T_{i,CONOP}$ can be randomly sampled for each load i. Equations 2 and 3 can then be used to determine λ_{Online} and $\lambda_{Offline}$ for each load. The result is 25 loads which follow a behavior similar to the sample load in Table II.

From the known distributions of online and offline cycle times for each load, SPARCS generated a time-domain solution to the network. Cycle periods for each load were sampled from the user-defined distributions for each component. In this case, 1 week's worth of data sampled at 10 Hz was generated for each of the five missions (5 weeks total), requiring a total of 19.86 minutes of processing time on a 13th Gen Intel i7-13700 2.10 GHz processor. This CPU has 16 cores, each with a maximum clock frequency of 4.50-5.10 GHz. A sample of the solution power trace from the general quarters operation is shown in Figure 7.

Note that there is only one generator block in the SPARCS one-line diagram. This permits the user to quickly find the total power provided by any configuration of online generators. If the generators onboard a ship are already known, this makes iteration through different online combinations straightforward. Alternatively, in a set-based design environment, there may be many generation sets under consideration. In this sample case, 10 combinations of generators are considered. Each generation set has the capacity to sustain the worst-case loading scenario with one generator in repair, and is comprised of a combination of 600 kW, 800 kW, 1500 kW, and 2000 kW diesel generators. These are summarized in Table III.

With the simulation complete, a percentage of time that the ship's generation is light-loaded can be calculated for each CONOP and generator set. Two light loading thresholds are defined at 40% (light load) and 25% (extreme light load) [10]. The results are presented in Table IV. In the general quarters and RMD (restricted maneuvering doctrine) CONOPs,

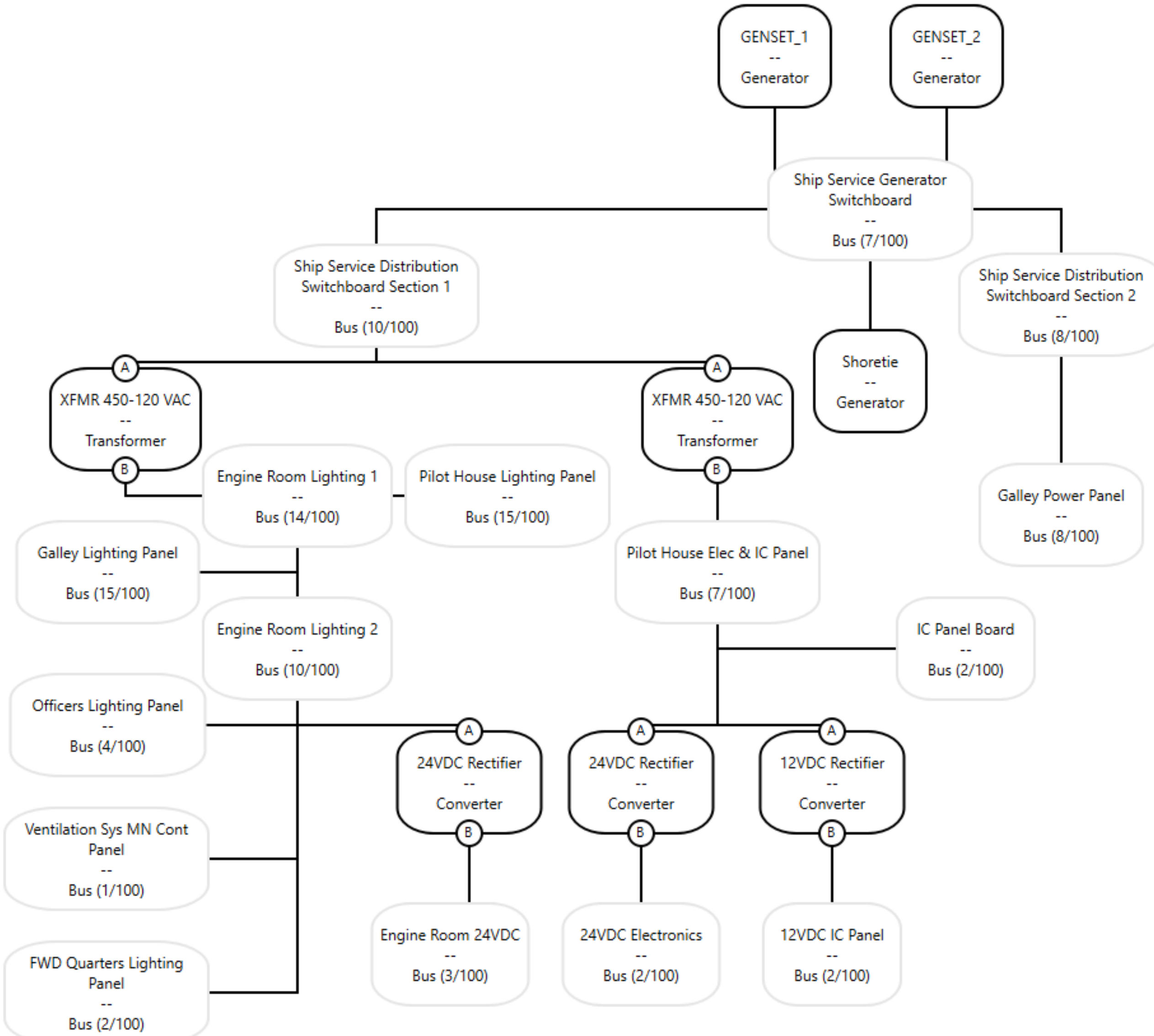

Fig. 8: One-line diagram in SPARCS for the 87-ft Marine Protector class patrol boat model.

all generators are placed online. When the ship is in port under its own power it is permitted to run on one generator, but otherwise there must be at least two generators online. With these constraints, the generation online is determined as the smallest capacity possible while still being capable of maintaining sufficient capacity for peak loading events in that CONOP.

Table IV compares the SPARCS-based estimate of light loading to an estimate made using average component loading (the load factor). The load factor-based assessment results in a binary YES (1) or NO (0). It is evident that the simulation produces a spectrum of results, and captures cases of light loading not identified by the load factor-based method. This provides the designer with more insight into the challenges faced by each generation set. However, it is important to recognize that the data output is only as good as the data input. In other words, the simulation is sensitive to the distribution parameters estimated by the designer. A false sense of accuracy can be implied by higher fidelity results.

IV. Data-Driven Diagnostics

Whether it is an analog pressure gauge on a steam turbine inlet or an aggregate current sensor on an electrical distribution panel, data availability increases an operator's awareness of their system. The primary challenge becomes making sense of otherwise meaningless data.

There are two general methods for approaching this task. First, physics-based approaches attempt to make interpretable connections between the data and the physical system being sensed [11], [12]. For instance, vibration on an induction motor should be expected to peak in magnitude around an integer multiple of the mechanical shaft speed. If this peak occurs closer to the electrical frequency (i.e., motor slip is small) then

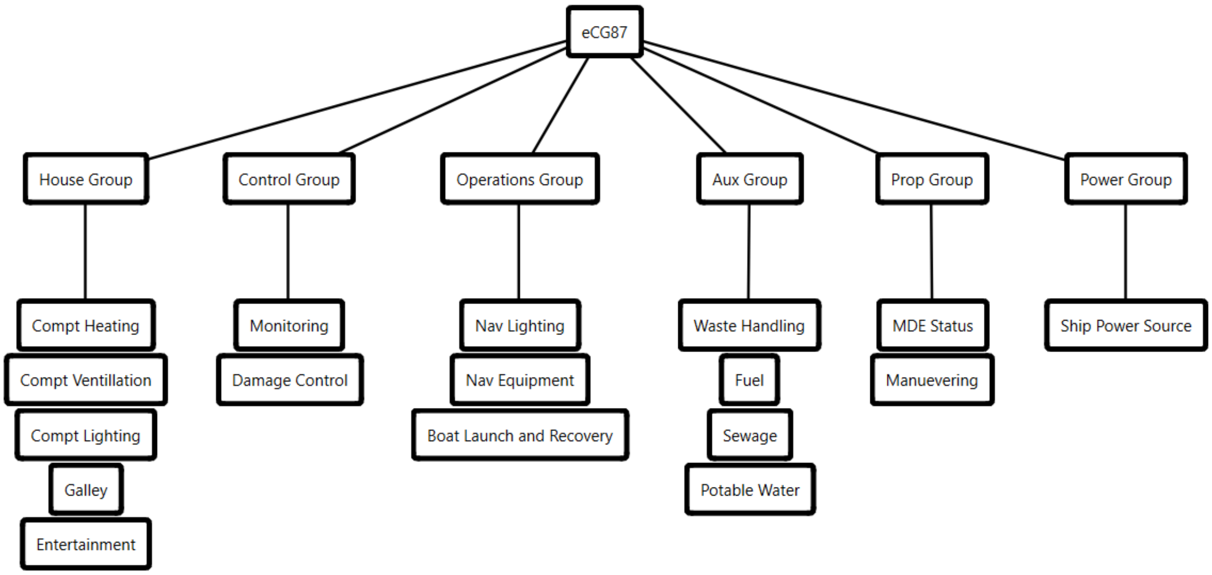

Fig. 9: System hierarchy defined in SPARCS for the 87-ft patrol boat model.

it may indicate that the motor is abnormally light-loaded [13]. Secondly, machine learning (ML) holds significant promise for identifying trends in data which are a result of specific operating modes and failures. These models have the potential to draw connections between data patterns to classify faults [4] and predict timeline to failures [3].

Neither approach is perfect on its own. A challenge both approaches face is the the inability to draw contextual awareness of the equipment that is online and operating at any given time. Understanding what *should* be happening at a given moment makes anomaly detection easier, and can help match the correct physical model to the system.

Section III established that the cumulative loading of a ship under different mission profiles can be characterized as a stochastic process. By understanding and replicating each of these stochastic events, system-level synthetic data can be generated to help train ML models which can classify the ships current operational status. A demonstration of simulating a ship's operating mode using SPARCS is presented here for an 87-ft USCG Marine Protector class patrol boat.

A. U.S. Coast Guard Cutter Sturgeon

The U.S. Coast Guard's Protector-Class cutter is 87 feet in length, has a crew of 10 to 12, and primarily conducts near coast law enforcement missions such as fisheries protection, search and rescue, and counter drug enforcement. The relative size of this ship limits its range, so missions are typically limited to 1 or 2 days before refueling and reprovisioning is necessary. The ship was modeled with a radial power distribution system and 78 defined loads. USCGC *Sturgeon*, a Marine Protector Class cutter stationed in Boston, MA, served as the reference for developing the simulation model. NILMs were installed on this ship's port and starboard electrical panels, as shown in Figure 10. Equipment behavior cycles representative of USCGC *Sturgeon* were generated from previously collected NILM data, referenced from ship engineering logs, and otherwise estimated from similar ships and mariner intuition. The SPARCS one-line diagram and system hierarchy are presented in Figures 8 and 9.

SPARCS's ability to replicate real-ship distributions at the system-level is tested by building a behavior profile for each of the components on the ship. Each load was prescribed a behavior profile for 17 different missions observed on the USCGC *Sturgeon* during a 26-day sample period over the summer and winter months. These missions constituted variations of "in port" and "underway," which are presented in Figure 11. The figure displays the July collection period, with the port and starboard power traces for phase A plotted above a mission timeline. These power traces were recorded from the NILM systems installed on the *Sturgeon's* main starboard and port electrical panels, shown in Figure 8 as Section 1 and Section 2, respectively.

All 26 days of the collection period were simulated in a total of 19.9 minutes at a sample rate of 1/10Hz. An advantage of SPARCS is that all data generated by the program is automatically labeled with a timeline of the operating state of each component and the ship's mission, making machine learning tasks much more streamlined.

Two high-level classifications are presented in Table V: summer vs. winter operation, and in-port vs. underway. From the table, it is clear that both capture similar mean loading over the mission durations. This can be visually confirmed in Figure 11, and with higher fidelity in Figures 12 and 13. The SPARCS traces are not intended to precisely match their corresponding NILM traces, as SPARCS generates a probabilistic time series sampled from the cycling behavior of each load.

Fig. 10: The two NILMs installed on the USCGC *Sturgeon*.

	NILM (W)	SPARCS (W)	% Difference
Total	10,074	10,094	0.64%
Underway	10,674	10,777	0.96%
In Port	10,025	10,042	0.18%
Winter	10,506	10,439	0.64%
Summer	9,737	9,840	1.05%

TABLE V: USCGC *Sturgeon* vs. SPARCS average combined loading on phase A of the port and starboard panels during the 26-day sample period. Accuracy in emulating summer vs. winter operations and in port vs. underway are presented.

There are notably periods, such as around July 7 18:00 and July 13 00:00, where there is behavior captured in the NILM data that is not represented in the SPARCS data. This is largely due to the fidelity of operational logs that were available during the SPARCS setup. These periods could have experienced equipment malfunctions, maintenance, or other mission-specific actions not modeled in SPARCS. However, despite these anomalies, the system-level aggregate trends were accurately captured by SPARCS.

Additional discrepancies between the NILM data and SPARCS results are likely due to the aggregation of loads in the SPARCS model. By aggregating, a small collection of loads can be prescribed the same behavior to reduce solving and set up time. For loads which have a constant behavior the loss in accuracy is minimal. However, for loads which cycle frequently and independently of others within the group, this leads to the representation of the group as a single, large load. Aggregation can also be useful or unavoidable when the amount of known information about a subsection of the network is small. While building the 87-ft Patrol Boat SPARCS model, some panels (e.g., the 24V DC Electronics panel) were aggregated due to a lack of information on their load-specific behavior.

V. Vessel Life Cycle Sustainment

The rapid trends which bring about improvements to electrical components and enable electrified ships also complicate their ship's life cycle sustainment. This life can span decades, with 10-year design cycles and 40-year service durations common. In this time component obsolescence is likely. The original manufacturers may no longer be in business, or the base technology may have advanced so much that supporting the specific product may not make sense as a manufacturer.

The ability to quickly assess the implications of replacing a component is demonstrated with a simple case using the same Marine Protector class USCG patrol boat model developed in Section IV. This case considers the scenario where the ship's galley refrigerator is considered for replacement by a newer model, which features higher efficiency and lower overall power draw. Both the original and replacement fridges are single phase and connected line-to-line on the delta B/C phases of the existing network. This causes an imbalance in the loading of the three phases, which may be problematic.

The original version draws 425 W of real power and 245 VAR of reactive power per phase across phases B/C. A replacement is considered that draws 25% of the original load. All other interface properties and cycling behaviors are held constant.

To evaluate this impact on generator-level phase balance, the operations observed in Section IV-A are again considered. Operations where the ship's service generators are in use are simulated for a 1-week period at a 1 Hz sample rate, requiring a total simulation time of 54.96 minutes for 56 days of data. The distribution of time spent unbalanced above certain thresholds was then calculated, where phase imbalance is defined by the following equation:

$$\text{Imbalance} = \frac{S_{\phi,max} - S_{\phi,min}}{\frac{S_A+S_B+S_C}{3}}, \tag{4}$$

where S_ϕ is the apparent power on phase ϕ.

	Original	Replacement
Mooring/Anchoring (Winter)	0%	0%
Mooring/Anchoring (Summer)	65%	69%
RMD (Winter)	0%	0%
RMD (Summer)	86%	94%
Underway Efficient (Winter)	0%	0%
Underway Efficient (Summer)	85%	92%
UW Eff. $\geq$ 3nm Offshore (Winter)	0%	0%
UW Eff. $\geq$ 3nm Offshore (Summer)	47%	53%

TABLE VI: Time spent with greater than 25% load imbalance compared between the original and replacement galley fridge.

The results of the imbalance assessment are presented in Table VI. The results for the original component align well with empirical data from the USCGC *Sturgeon*. While the replacement load is more efficient and decreases the overall loading on the electric plant, it increases the proportion of unbalanced time significantly. This is especially true during the summer months and when generator jacket water heaters are not used as much. These two heaters are also single phase loads, and are connected across phases C/A, and A/B. During the missions where they are not in use at the same time as the galley fridge, generator imbalance is presumably higher.

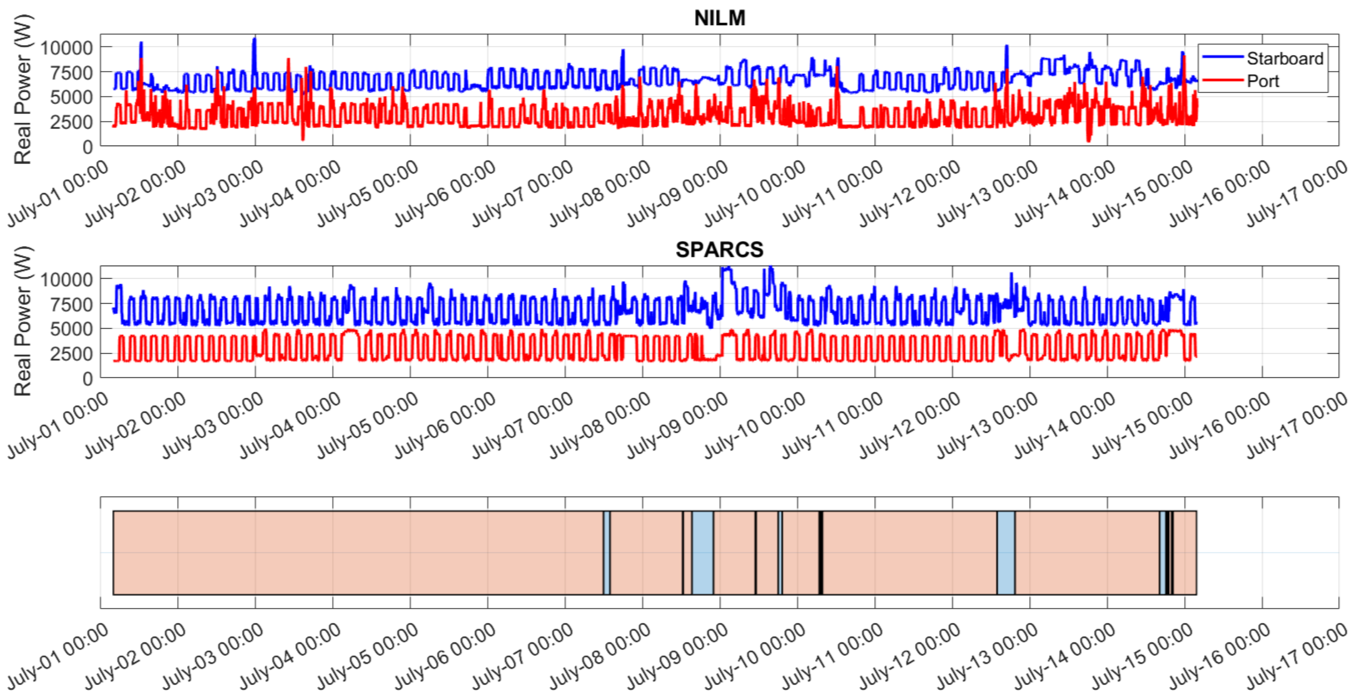

Fig. 11: Sample phase A real power data collected on the NILMs installed on the USCGC *Sturgeon*, compared to SPARCS-generated data for the same period in July. Known periods of underway (blue) vs. in port (red) time are plotted below the power traces.

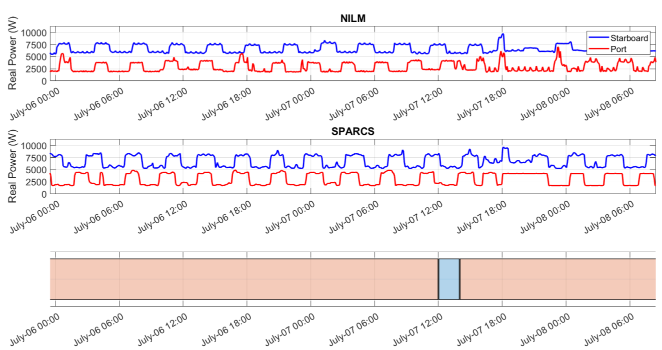

Fig. 12: Sample phase A real power data collected on the NILMs installed on the USCGC *Sturgeon*, compared to SPARCS-generated data for the same period in July. Known periods where the cutter is underway (blue) and in port (red) are plotted below the power traces. The most prominent cycling loading on both panels are main diesel engine jacket water heaters, online when the engines are not in use.

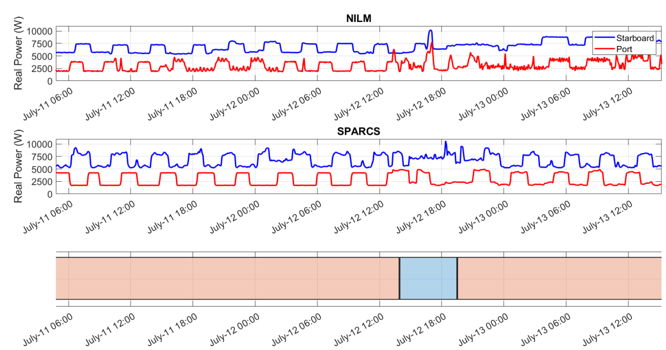

Fig. 13: Sample phase A real power data collected on the NILMs installed on the USCGC *Sturgeon*, compared to SPARCS-generated data for the same period in July. Known periods where the cutter is underway (blue) and in port (red) are plotted below the power traces.

To mitigate this issue, the sustainment engineer might locate other single-phase loads on the ship which are connected across phases C/A or A/B. On the Marine Protector class, these are primarily navigation and lighting loads which are consistently on. By connecting these loads across phases B/C instead, the phase loading can be rebalanced.

This analysis could also be performed with average loading metrics for each of the operations. However, this method would result in a binary "yes" or "no," and may miss cases of concern. This is the same problem that was identified in Section III, in which light loading identification was missed for many cases where a significant proportion of the operation was light-loaded.

VI. Future Opportunities

SPARCS is presented as the foundation of a software environment which can serve ship designers, owners, and operators across a variety of tasks. Its current state serves as a method for extracting data streams from a simulated network at desired probe points, which can be post-processed by the user to extract variables of interest. Many improvements to the software environment can come in the form of post-processors. Automated methods for estimating operating metrics can be implemented, enabling a rapid and seamless process of estimation entirely within SPARCS.

Beyond post-processing, SPARCS presents the foundation for fault analysis within the network. As the network's impedance characteristics are contained within the simulation, the ability to model ground faults could be implemented. This would be helpful at all stages of the ship's life cycle: from ensuring the proper rating of breakers during design, to locating faults during operation.

With a representation of the ship's impedance network already developed by the user, electric network stability analysis can also be explored by future work. The ability to iterate quickly across the ship's CONOP would allow SPARCS to serve as a fast method for assessing network stability in the early stages of design.

Finally, common mode currents are of a large concern for electrified ships, and especially those with large inverter-driven motors. The behavioral techniques implemented in this paper can be explored for their potential application in the common mode problem too.

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