

Securable Networks for Nonintrusive Sensor Fusion

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Abstract—Fault detection and diagnostics (FDD) and energy scorekeeping for power systems can be performed nonintrusively with current and voltage sensing at a utility panel. The key problem remains that some important electromechanical behavior, including vibration and acoustic signatures, cannot be easily detected in the power stream, and a small set of additional sensors may be necessary for automated analysis. A nonintrusive power monitor can serve as a central point for collating or “fusing” sensor data from remote sensors, providing a correlated picture of remote sensor data with power consumption. A local, physically secured intranet eases the cybersecurity challenge of a facility by avoiding conventional IoT solutions. This paper demonstrates a Wi-Fi-based implementation of an FDD intranet on the microgrids of several marine vessels. Connectivity tests presented in this work show that Wi-Fi is a viable link medium for an FDD intranet in shipboard environments. In addition, this work demonstrates the ability to track pump pressure, A/C compressor loading state, and fan imbalance using fused nonintrusive sensing. Cyclostationary signal processing techniques identified a faulty relief valve in a vacuum pump that evaded traditional analysis. Four sensor network strategies are presented for these scenarios. This work concludes that synchronized power and vibration data provide complementary fault detection ability.

Index Terms—Fault detection, power monitoring, vibration analysis, sensor fusion, wireless networks

I. INTRODUCTION

Internet of things (IoT) solutions have pervaded consumer and industrial markets, proliferating the application of computing and sensing for measurement and maintenance [1]–[3]. Networking solutions that rely on an external or third-party server expose communications to interception and security risks. These solutions also generally fail to collate and correlate sensor data to provide actionable information without resorting to additional networked processing, further exposing potentially sensitive information and conclusions. The internet client-server model has created an “arms race” of authentication and encryption in an attempt to secure data and decisions. This arms race is frequently a losing battle. There is another way.

For many industrial facilities and transportation systems, a self-contained client-server model can be physically secured at the target site. That is, physical access to data and processed information can be denied, even to trusted participants, who are not physically and verifiably proximate to the system and data. Computing power has reached a point where local systems are able to provide scientific computing without resorting to external computing devices. Even machine learning algorithms with computationally expensive training can produce systems that can evaluate inputs quickly and efficiently [4]. When adaptation for machine learning systems can be provided over reasonable time periods, local computing

may be entirely satisfactory for fault detection and diagnostics (FDD) in a mission critical facility.

For instrumentation and measurement challenges, a client-server model provides the convenience of a server that can collate data from a set of sensor node “clients.” For FDD applications for electromechanical systems, a nonintrusive load monitor (NILM) is in many ways an ideal “server” for coordinating data exchange and analysis. On its own, a NILM uses a single or limited set of voltage and current sensors to monitor the power consumption of electrical loads downstream of the metered point [5]. State-of-the-art NILM techniques enable individual load identification using machine learning and signal processing techniques [6]. Nonintrusive load monitoring has been demonstrated extensively for residential energy disaggregation [7], [8]. In addition, NILMs installed in industrial settings can perform automatic logging and watchstanding with knowledge of load operation and timing [9]. Industrial NILMs have been demonstrated to identify “soft” faults and presage impending “hard” faults that produce equipment failure by recognizing evolving power signatures for individual loads [10].

However, a challenge in industrial FDD with a NILM is that electrical power data is not always sufficient to diagnose certain faults. Additional measurements, such as vibration, temperature, and acoustic signatures, are required in these scenarios to reveal diagnostic indicators absent in the electrical data. A NILM can then correlate these measurements with the corresponding electrical events. Design requirements and challenges for FDD in an industrial setting through sensor fusion include the ability to securely collate sensor data without collecting more high-bandwidth data than necessary. An “FDD intranet” operated by the NILM facilitates this exchange and fusion of sensor data for fault detection and diagnostic analysis. This triggered data collection alleviates unnecessary data storage and also provides physical correlation between data streams for FDD analysis. The NILM is an ideal device for interacting with watchstanders or maintainers, as it can provide analysis and reports for addressing impending FDD problems before they become mission failures. Communication outside the facility is still possible, e.g., over the internet. However, these communications can involve only the level of detail and analysis considered to be both useful and secure. Perhaps most importantly, the FDD intranet can be physically secured to provide detailed information and analysis only to trusted operators physically present in a facility or system.

This paper demonstrates a new, wireless-enabled NILM implementation that coordinates both power monitoring and also data retrieval from distributed vibration sensors. Wireless

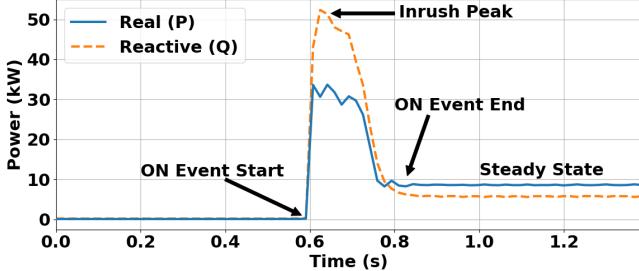


Fig. 1: CPP pump turn-on power transient acquired by a NILM.

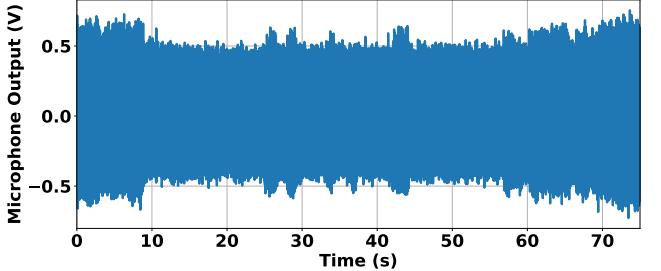
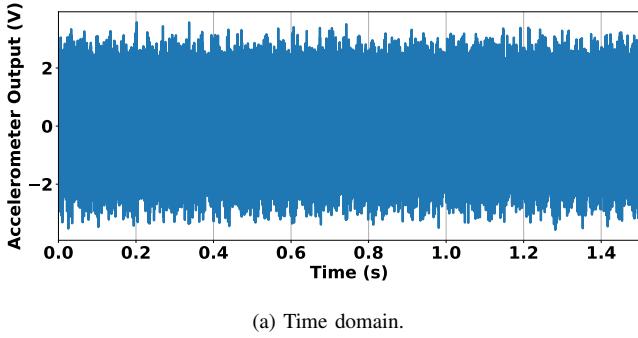
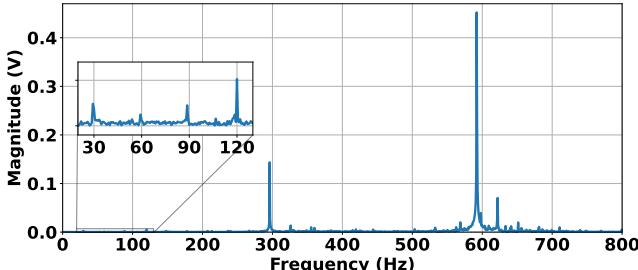


Fig. 3: CPP pump acoustic signature during changing propeller pitch.



(a) Time domain.



(b) Frequency domain.

Fig. 2: CPP pump steady-state vibration signature in time and frequency domains.

networks are configured using the custom NILM hardware to create shipboard diagnostic monitors that can only be accessed from inside the facility. The utility of the wireless intranet and multiple-sensor fault detection case studies are demonstrated with shipboard measurements taken on several US Coast Guard Cutters.

II. SENSOR HARDWARE

A NILM senses the voltage and current signals at a single point in a power system. Current and voltage waveforms are sampled (in this work at 8 kHz). A spectral envelope preprocessor is run using the digitized current and voltage waveforms [11], producing a stream of aggregate real power, reactive power, and higher-harmonic current consumption sampled at the utility frequency (60 Hz). A turn-on transient of both real and reactive fundamental power of an electromechanical load is shown in Fig. 1. A continuously-running event detector identifies transient events, from which features such as inrush

and steady-state power are extracted [6]. Using these features, the NILM classifies events to individual loads and identifies faulty behavior. Abrupt faults such as an open-circuited heating element are immediately obvious in the power stream [12]. Gradual variations of load power consumption over time can be tracked to identify “soft faults” that may eventually cause complete load failure. Finally, from the sequence of load events, the NILM can diagnose timing faults and errant duty cycles [13].

However, a pervasive challenge in NILM-based FDD is that many critical diagnostic measurements cannot be derived from the power stream. These include, but are not limited to, vibration, acoustic, and temperature data. Augmentation of nonintrusive power monitoring with sensor data such as light level and acoustics has been proposed and evaluated for load identification and energy estimation, which are common NILM applications [14], [15]. Fusion schemes of features such as submetered (rather than aggregate) current, acoustic, and vibration data have been demonstrated for diagnosing faults in induction motors [16], [17]. Sensor fusion theory encompasses several techniques to handle multiple sources of imperfect data. Some examples include Kalman filtering, Dempster-Schafer theory, and convolutional neural networks [18], [19]. However, in the interest of simplicity, this work uses heuristic-based techniques such as spectrum analysis. The fault and condition change detection discussed in this work could be extended to incorporate these techniques if desired.

As a case study to illustrate how sensor fusion can reveal electromechanical operation, consider the load in Fig. 1. This load is a controllable pitch propeller (CPP) pump in the engine room of a US Coast Guard Cutter, which provides hydraulic pressure for changing the pitch of the ship’s propeller. Aggregate power data shows recognizable turn-on transients, which the NILM can use to track load operational status. Fig. 2 shows vibration data in both time and frequency domains captured during steady-state load operation. At rated load, an induction machine drives the hydraulic gear pump at 1725 rpm. The shaft rotation creates peaks in the vibration frequency-domain plot at multiples of a little less than 30 Hz. Pump gear teeth meshing likely produces the large peaks located slightly below 300 and 600 Hz, multiples of the shaft frequency [20], [21]. These indicators are entirely absent in the power stream and provide insight on physical load behavior. Fig. 3 shows acoustic data from this load while the propeller’s pitch was

TABLE I: Comparison of this work’s contribution and previous NILM implementations.

	Previous NILM	Wi-Fi-Enabled NILM
Measurements	Electrical power only	Electrical power + vibration, acoustic, temperature, etc.
Multisensor analysis	Offline, <i>post-hoc</i>	Online, real-time
Identical loads	Cannot be distinguished	Can be distinguished with remote sensor data

modified, as indicated by the envelope of the signal. Steady-state signatures and spontaneous changes in operation are difficult to diagnose in aggregate power data, since the source of the behavior is inherently uncertain. These sensor data sources are thus complementary, and all three show a different and interesting side of the machine’s operation.

To measure these quantities and supplement the NILM’s power measurements, the sensor platform described in [22], [23] serves as an easily-installable distal sensor node. A block diagram of this device is shown in Fig. 4. The sensor platform acquires signals from up to four channels and supports sampling rates up to 128 kHz with 16- or 24-bit resolution. Each acquisition channel can measure arbitrary +/- 5 V signals or signals from Integrated Electronics Piezoelectric (IEPE) sensors. The IEPE standard provides high noise immunity and power and signal delivery on the same two wires. Since the IEPE interface is limited to ac signal transmission, companion hardware proposed in [23] extends IEPE to include dc and slowly varying quantities. The IEPE channels on the sensor platform can interface with any resistive or voltage-based sensor such as thermistors, strain gauges, and pressure sensors, as well as traditional IEPE devices such as microphones and accelerometers. The diverse set of compatible sensing elements provides a unique opportunity for diagnostics that complement electrical data observed by the NILM. Vibration analysis is particularly useful for electromechanical load diagnostics, as changes in mechanical health are often reflected in the vibration signature of the machine [22], [24].

The challenge that remains is that unless sensors are interlinked, tandem electromechanical diagnostic information is limited to being offline and *post-hoc*. Without synchronized and colocated data, there will be an inevitable delay between physically measurable indications of a fault and the actionable information for a watchstander to fix the fault. However, an intranet of sensors for FDD provides the ability to fuse sensor data and perform predictive, online analysis. Using a dashboard for human-computer interaction [9], the NILM makes this information actionable to watchstanders who can actually fix the fault as it happens. The novelty of this work is the demonstration of an enhanced NILM that can host a physically securable FDD intranet using wired or wireless channels for collating data from remote sensor nodes. Fig. 5 shows the upgraded NILM implementation capable of creating a Wi-Fi intranet and functioning as the server for the sensing network. Table I outlines a comparison of this new NILM implementation with previous implementations. Where necessary and desired, sensor nodes such as the one shown on the right in Fig. 5 are located remote from the

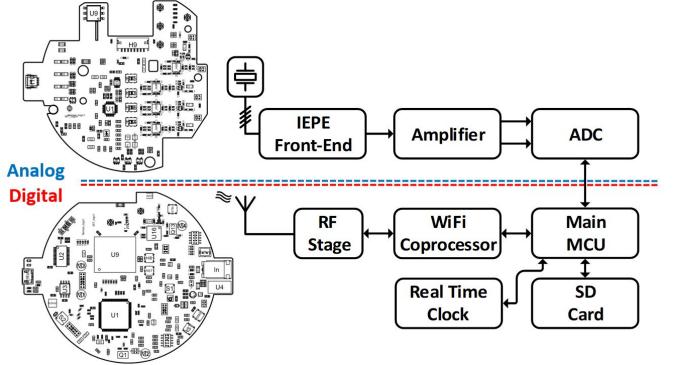


Fig. 4: Block diagram of the wireless sensor platform of [23].



Fig. 5: Wi-Fi-enabled NILM alongside wireless sensor platform.

NILM but in Wi-Fi communication range. Fig. 6 shows a block diagram of the system. Our experiments with this system use a commercial, off-the-shelf Wi-Fi router in the NILM to cover the key areas of a monitored space. Two 5 dBi Wi-Fi antennas mounted to the case provide spatial diversity to combat multipath fading from environments adverse to Wi-Fi transmission [25]. Broadcast power is limited so that usable signal strength is empirically verified to extend no farther than the desired internal secure areas on the ship. Although ships are used as a case study in this work, the proposed sensor network can be deployed to any number of systems. The key limitations are that a NILM is installed, a set of interesting loads and corresponding sensor types are identified, and a common channel for communication (e.g. Ethernet or Wi-Fi) is available.

III. PHYSICALLY SECURED NETWORK

The NILM can use either wired or wireless channels for creating a secured sensor network. However, wireless configurations allow for minimally invasive and easily changeable sensing solutions. Although many other wireless technologies exist, including Bluetooth and Zigbee, this work uses Wi-Fi as a link medium that is securable through encryption and can be implemented inexpensively with commercial, off-the-shelf hardware. To evaluate wireless transmission, point-to-point

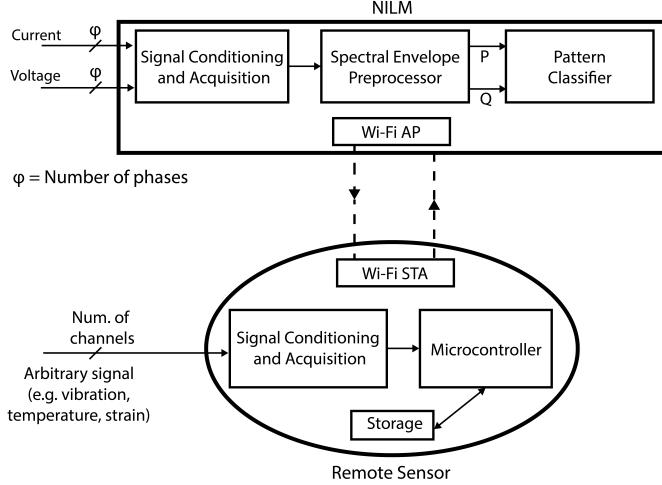


Fig. 6: Block diagram of NILM and wireless sensor platform operation.

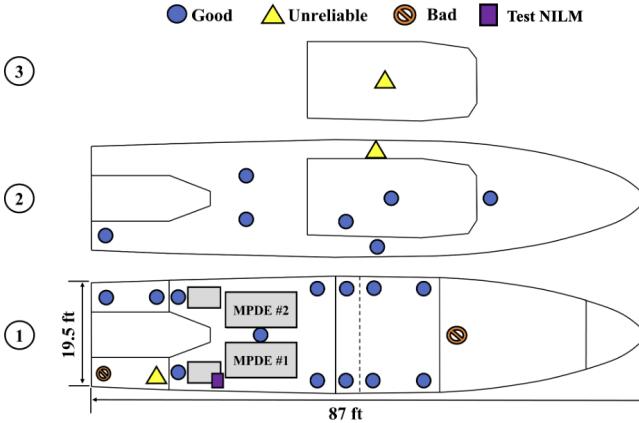


Fig. 7: Connectivity test results for USCGC MARLIN. The test NILM is shown with a purple rectangle, and the gray shapes show large shipboard equipment such as the main propulsion diesel engines (MPDEs).

radio communication can be modeled with the Friis transmission model [26]. The received power thus be calculated if the transmitting and receiving antenna gains, path distance, transmission frequency, and transmission power are known. However, this model does not include multipath effects, in which reflections cause a transmission to arrive along many paths with varying delays. These effects may be random and time-varying and are prevalent in industrial environments [27]. Therefore, in addition to being limited by distance and broadcast strength, wireless communication is often assumed to be ill-suited in industrial and shipboard environments [27]–[30]. Rather than create intricate transmission models, we evaluated the performance of Wi-Fi in shipboard environments empirically. Our experiments show that Wi-Fi is a viable communication channel for shipboard fault detection and diagnostics with multiple sensors.

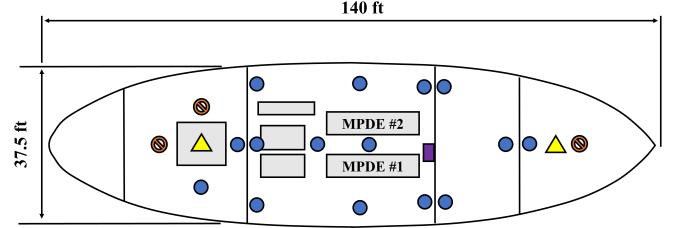


Fig. 8: Connectivity test results for USCGC THUNDER BAY.

A. Wi-Fi Evaluation

Wi-Fi was evaluated as a candidate channel for FDD intranet aboard three US Coast Guard Cutters (USCGCs) of various sizes and construction types. Connectivity was tested using the new wireless-enabled NILM (referred to as the “test NILM”) and remote sensor platform of Section II. In each connectivity test, the test NILM was placed near the utility panels to emulate a real installation. The test NILM created a Wi-Fi access point (AP), and the sensor platform connected to this access point as a client. Thus, the location of the AP was fixed during the test, such that the AP was located next to the utility panel. Evaluating the connection strength between the test NILM and the sensor platform as it was moved about a lattice of test points produced a “heatmap” of Wi-Fi connectivity for each environment.

The test NILM was used to run the following four tests for wireless connectivity: (1) maintain a Wi-Fi connection throughout testing without dropping packets, evaluated using the ping utility, (2) access the sensing device’s memory and list all files in storage, (3) direct the sensing device to capture a sample measurement of data, and (4) successfully download the sample measurement from the sensing device to the test NILM. Test points are labeled as “good” if they passed all four tests. Test points that passed one to three of these tests are labeled as “unreliable.” Test points that could not support a Wi-Fi connection are labeled “bad.”

Figures 7 to 10 show the heatmaps generated from the wireless tests conducted in the three shipboard environments. The “good” tests are represented by blue dots, the “unreliable” tests are represented by yellow triangles, and the “bad” tests are represented by orange slashed circles. Solid lines represent airtight and watertight bulkheads that span the entire width of the ship. Dashed lines denote bulkheads that are neither airtight nor watertight. Finally, the purple rectangle represents the location of the test NILM. Gray shapes indicate other significant equipment and obstructions such as main propulsion diesel engines (MPDEs), electrical generation equipment, and holding tanks.

The first of the three shipboard environments tested was USCGC MARLIN, a 87-foot coastal patrol boat. Fig. 7 shows testing results on three levels of the ship. The wireless range was sufficient to link almost all test points on the second level with the test NILM located on the first level. The second environment was USCGC THUNDER BAY, a 140-foot ice-breaking tug. As shown in Fig. 8, there was a strong wireless connection throughout the entire engine room. Additionally, the wireless connection was able to reach through the forward

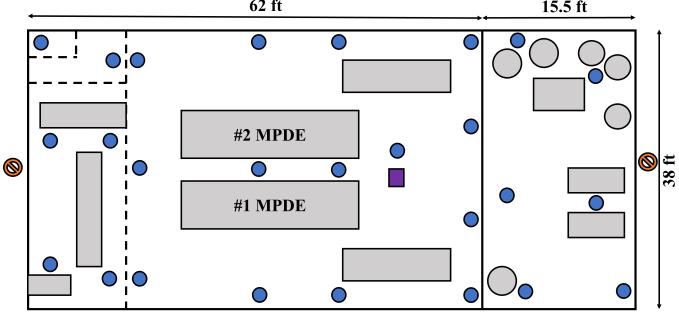


Fig. 9: Connectivity test results in upper engine room for USCGC SPENCER.

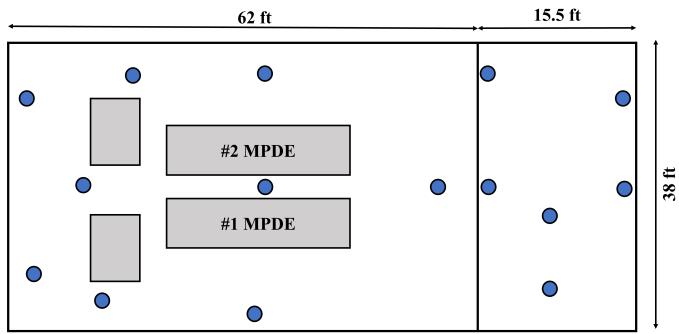


Fig. 10: Connectivity test results in lower engine room for USCGC SPENCER.

transverse bulkhead into the auxiliary machinery room. The final environment was USCGC SPENCER, a 270-foot medium endurance cutter. Fig. 9 and Fig. 10 show testing results for the upper and lower engine rooms, respectively. Both spaces supported a Wi-Fi connection between the test NILM and sensor platform. Each shipboard environment showed that Wi-Fi proved to be stable and reliable for the majority of the regions containing electromechanical loads of interest.

B. Data Transmission and Synthesis

Once a communication channel is acquired via Wi-Fi, either the NILM or the sensor platform initiates data transmission, depending on the use case. Choice of network protocol is an important design consideration, with the two prominent choices being the transmission control protocol (TCP) and user datagram protocol (UDP). For certain IoT and cyber-physical applications, UDP is attractive, since it prioritizes speed and simplicity in packet transmission, at the expense of reliability [3]. However, TCP is more suitable for the FDD intranet, since it guarantees reliability. The additional power and computation overhead of establishing a connection and verifying data integrity is more than outweighed by the assurance that data is received in order. This is especially significant for automatic fault detection and diagnostics, because a corrupted data transmission may cause a critical sensor measurement to be missed entirely. By using separate TCP ports and sockets for each remote sensor node, conflicts in sending and processing data can be avoided.

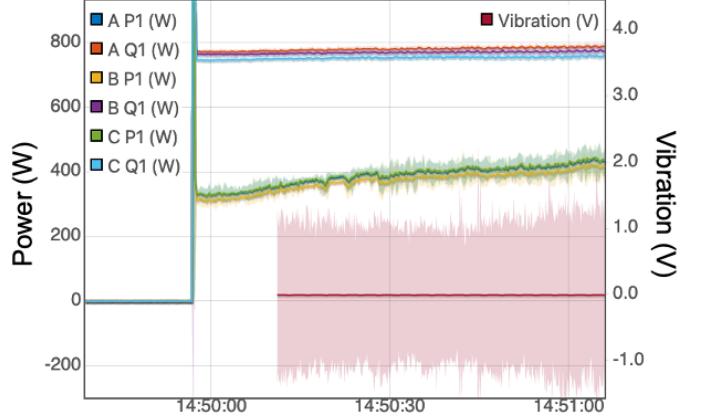


Fig. 11: Power and vibration data streams, captured synchronously with multiple sensors.

Data is processed with Joule [31], which models the data pipelines as a series of “modules” with streams of information passing between them, allowing for efficient, real-time measurement and signal processing. Joule modules are used to continuously run an event detector, feature extractor, and classifier on the power stream to identify load transient events. Once a load event is found, a separate Joule module establishes a TCP/IP socket with the wireless sensor platform of interest. The sensor takes a measurement for a user-configured duration and then sends the data back through the socket. Since timestamps from the remote sensor nodes are not guaranteed to be available or reliable, the NILM infers them to avoid clock drift and time misalignment. This is done via linear interpolation when data of a known duration is retrieved. Once data is received and timestamped, it is inserted into a time-series database [5] for further analysis.

A case study is shown here for a reciprocating A/C compressor. The NILM is configured to direct the sensor platform to capture two minutes of vibration data whenever the NILM detects a transient event in the power stream. Fig. 11 shows the resulting synchronized and colocated data from both power and vibration sensors, plotted with the Lumen data visualization app on the NILM [32]. Real and reactive fundamental power are plotted on the left axis for all three phases. Vibration is plotted on the right axis in red; due to the decimation performed by the data visualizer [5], the solid red line shows the average value (zero) and the lighter red region shows the envelope of the accelerometer measurements. With access to both of these data streams, the NILM can perform online analysis and provide actionable information for load diagnostics in real time.

C. Security

Strong, unbroken encryption is the keystone of modern network security. As such, the FDD network provides both encryption and authentication of network members using Wi-Fi Protected Access II (WPA2). However, the FDD network provides two additional security layers. First, the network is intentionally isolated from the public internet, in contrast to the IoT strategy. This “air-gapped” scheme denies many attack

vectors into the system by simply making it inaccessible to public channels. However, this shifts some of the security burden onto the process of moving data to and from the network. Care must be taken that any interactions with external computers, such as internet connection and removable media, are trusted.

Secondly, many environments relevant to FDD, such as ships, naturally attenuate wireless signal power at their boundaries. Carefully adjusting broadcast power of the NILM's access point to what is only necessary limits the network signals' ability to reach the outside world. As an example, consider the shipboard environments presented previously. The wireless signals broadcast from the two devices' radios permeate the bulkheads and hull of the ship only minimally, since the ship's steel hull acts as a Faraday cage that blocks electromagnetic fields. For a ship on open water, it would be difficult for an adversary to be in reception range without detection, without immensely powerful radio equipment. Finally, it is worth emphasizing again that these two additional layers do *not* take the place of up-to-date encryption and authentication practices, as a sufficiently determined and powerful adversary may find a way to communicate with the network.

D. Sensor Placement

When deploying a nonintrusive sensor network, there exists a trade-off between maintaining a low sensor count and obtaining actionable diagnostic information. The appropriate number of sensors is ultimately subject to the interests of the system operator. As a general guideline, however, loads that are known to contain behavior invisible in the power stream should be identified. Remote nodes with the appropriate sensor can then be installed and connected to the NILM. If the rest of the electromechanical behavior of interest can be identified by the NILM, this provides a reasonable balance of low sensor count and access to diagnostic information.

IV. SENSOR DEMONSTRATION

This section provides four case study scenarios in which fused nonintrusive sensor data streams are used in tandem to shed further light on load operation and diagnostics than power data alone provides. Centralized sensor fusion is achieved by first collating data on the NILM from multiple sensors (in these examples, power and vibration), and then generating diagnostic indicators from the sensor data streams. Scenarios A and B (in Section IV-A and Section IV-B) show a condition change apparent in the electrical power stream, and thus can be detected with a NILM implementation without remote sensors, although imperfectly. Condition changes in large machinery often do not create usable indicators in electrical power data [22], [33]. In addition, these indicators may be very small in remote sensor data such as vibration. Signal processing techniques that exploit the physical structure of the mechanical process can recover these small signals [34]. As confirmation, scenarios C and D (in Section IV-C and Section IV-D) show examples of these condition changes that are invisible to a NILM implementation without remote sensing, and the use of vibration analysis, including cyclostationary signal processing,

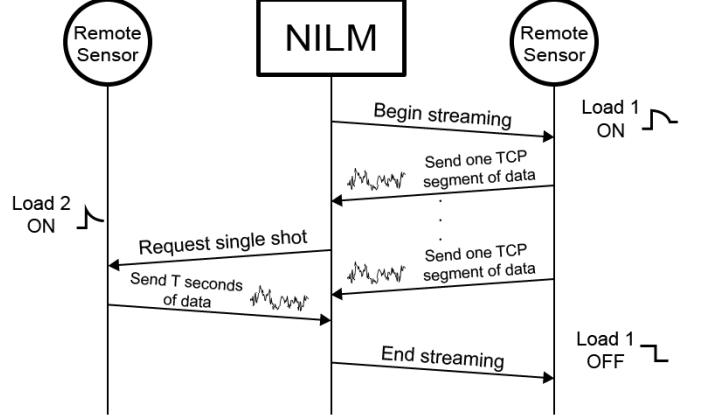


Fig. 12: FDD strategies described in Section IV-A and Section IV-B.

to detect them. Each of these four scenarios corresponds to a separate FDD network strategy for collating the sensor data and generating diagnostic indicators. These FDD network strategies and their parameters are coordinated by the NILM in software as Joule modules, as described in Section III-B. All experimental data was taken from equipment on USCGCs MARLIN, THUNDER BAY, and SPENCER, or equipment similar to that found on these ships. Vibration data was captured using Wilcoxon's model 728T single-axis 500 mV/g accelerometer [35].

The four FDD strategies are essentially: (1) continuously requesting remote sensor data for a load when the NILM detects that the load is running, (2) requesting only a small amount of remote sensor data for a load when the NILM detects that it turned on, (3) periodically requesting remote sensor data at a user-defined interval, and (4) continuously sending remote sensor data to the NILM whenever the remote sensor detects load operation. The first two strategies are useful for loads monitored by the NILM that turn on and off frequently. The third strategy is useful for loads that are almost always energized, since turn-on and -off events are not frequent enough to trigger sufficient data collection. The fourth strategy is useful for loads that are either not monitored by the NILM, or have turn-on transients that are difficult or impossible to identify in the power stream.

A. Bilge and Fire Pump

The most straightforward FDD network strategy involves using the NILM to track the operational state of a load outfitted with a remote sensor, as illustrated on the right side of Fig. 12. When the load is operating, the NILM continuously requests and downloads data from the remote sensor. The bilge and fire pump on USCGC MARLIN serves as an example of a fault for which this strategy is suitable. This centrifugal pump is designed to expel water from the bilge of the ship and supply water to the on-board firefighting system. The pump is driven by a 3-phase induction motor that is rated to operate at 57.4 rps. In the stable and normal region of operation, the slope of the induction motor steady-state torque-speed curve is negative. The torque developed by the motor

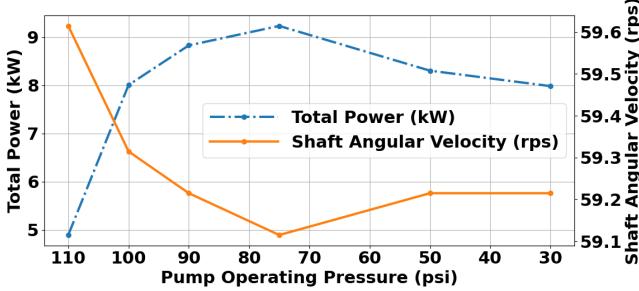


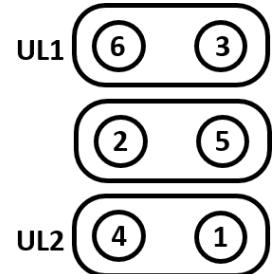
Fig. 13: Estimated power and shaft angular velocity for different operating pressures of the MARLIN bilge and fire pump.

and consequently the power consumed increase when rotor speed decreases. Power can therefore provide an indicator of shaft speed. Measurement of the shaft speed is also possible from vibration measurements [36]. Under normal operation the pump maintains a discharge pressure of approximately 110 psi. Changes in operating pressure maintained by the pump could be indicative of a variety of faults such as a blockage in the system or pump impeller wear. Both power and vibration measurements reflect changes in operating pressure of this load, as illustrated by the experiments presented in this section. In these experiments, the flow was adjusted with a controllable valve to simulate an increased demand of system. As the valve was adjusted, the outlet pressure of the pump varied from 110 to 30 psi. Power consumption and vibration were recorded using the installed NILM and an accelerometer connected to the wireless sensor platform, respectively. The accelerometer was affixed to the pump housing in a perpendicular orientation to the drive shaft.

Fig. 13 shows a plot of both the steady-state power consumption as measured by the NILM and shaft angular velocity (calculated from the discrete Fourier transform (DFT) of vibration data) across decreasing operating pressures. The steady-state power increases as the pressure changes from 110 to 75 psi, and then begins to slightly decrease as the pressure changes from 75 to 30 psi. The angular velocity of the bilge and fire pump's motor shaft decreases as the operating pressure changes from 110 to 75 psi, and then slightly increases as the pressure changes from 75 to 30 psi. This type of behavior is typical of normal operation of a backwards centrifugal pump [37]. Both curves have an inflection point at an operating pressure of 75 psi. This inflection identifies the point of operation where the pump is imparting the greatest work on the fluid, in terms of flow rate and pressure. Using these relationship curves, a change in operating pressure of the pump could be identified by either power or vibration data. Since this load turns on infrequently and is critical to shipboard operation, the proposed FDD network strategy produces two correlated indicators of faulty pump operation. In a practical NILM application, gradual changes in steady-state power may be difficult to resolve. Thus, tracking the operating pressure from the power consumption alone may be prone to errors. In addition to confirming changes in operating pressure detected in the power stream, vibration data can identify operating



(a) A/C compressor.



(b) Piston and unloader arrangement.

Fig. 14: A/C compressor and unloader arrangement onboard SPENCER.

pressure changes that were missed in the power stream. By fusing these two sensors, the NILM has access to a more complete diagnostic picture than power and vibration provide individually.

B. Air Conditioning Plant

Unlike the previous example, some loads require a minimal amount of remote sensor data to be collected for disaggregation and fault detection. For this FDD network strategy, the NILM requests a small window of data from the remote sensor whenever it detects a transient event of interest related to that load, as illustrated on the left side of Fig. 12. To demonstrate this, consider the air conditioning (A/C) plant on USCGC SPENCER, which consists of two refrigeration skids. Each skid contains two independent refrigeration loops with semi-hermetic compressors; one compressor is shown in Fig. 14a. The system is charged with R-134a refrigerant and cools a closed-loop chilled water system that circulates throughout the vessel. Each compressor has three piston pairs. A conceptual diagram of the pistons is shown in Fig. 14b. Solenoid-activated unloaders, referred to as UL1 and UL2, are installed on two of the piston pairs and allow for capacity control. The unloaders activate piston pairs based on cooling demand for efficient system operation [38]. The center piston pair does not have an unloader and is always activated. Activated pistons pull refrigerant through the suction ports and discharge compressed refrigerant to the high-pressure side of the system. In the following discussion, loaded operation refers to six activated pistons, partially loaded refers to four activated pistons, and unloaded refers to two activated pistons.

Fig. 15 presents a power stream of an A/C skid onboard SPENCER. The power stream depicts the turn-on event of a single compressor and subsequent loading events of the compressor. Upon startup, the compressor operates in an unloaded condition with only the center piston pair (2 and 5) activated. With an increase in loading, the real power consumption increases while reactive power remains nearly constant. As a result, loading the compressor increases the load's power factor. For instance, the step increase at approximately 2.5 minutes in Fig. 15 is a shift from unloaded to partially loaded operation, with the center and lower piston pairs (1, 2, 4, and 5) activated. The final step in real power is a shift from

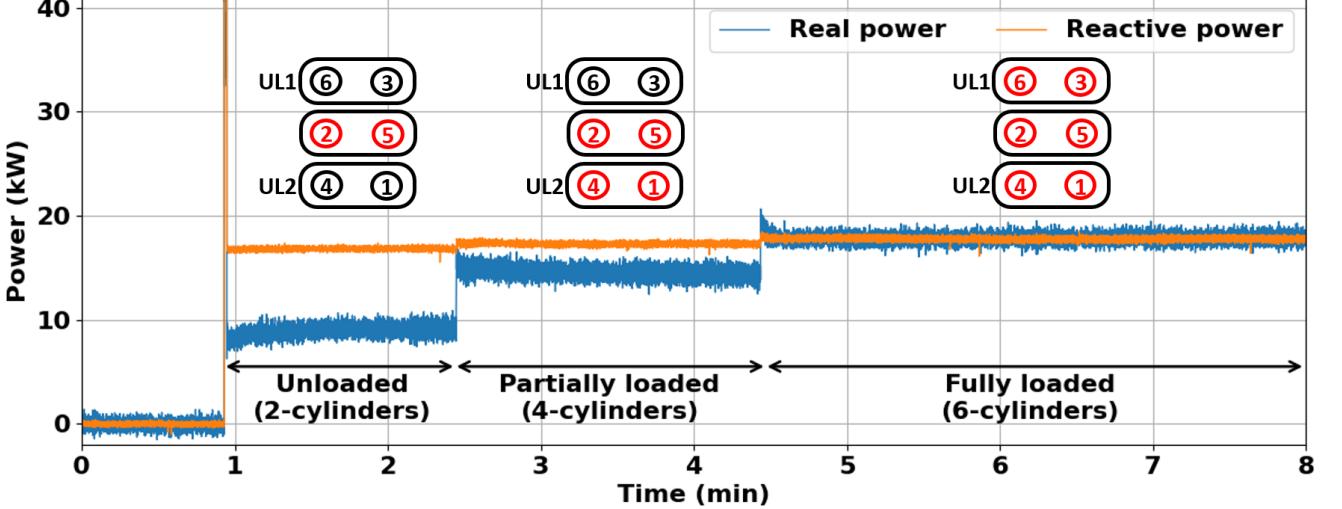


Fig. 15: SPENCER A/C compressor power stream.

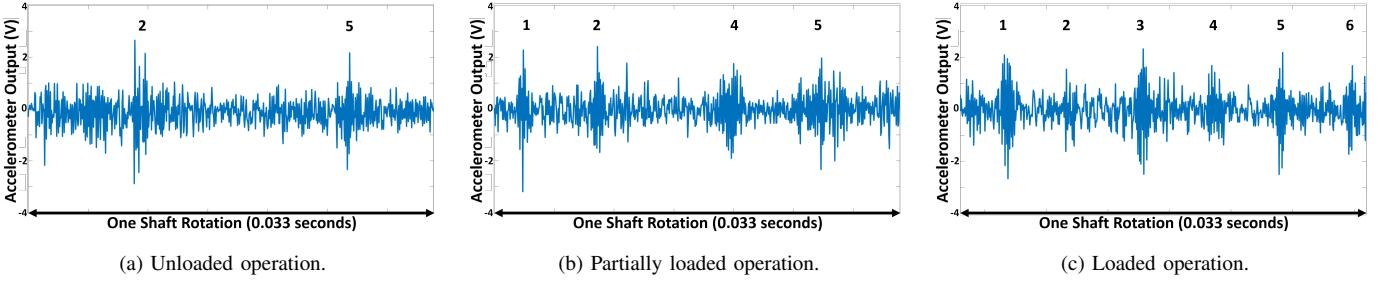


Fig. 16: SPENCER A/C compressor accelerometer time-domain plots of varying loading states. Impulsive events due to activated pistons are labeled.

partially loaded to fully loaded operation, with all piston pairs (1 through 6) activated. Table II presents the observed power factor in each loading state.

The A/C compressors are driven by grid-connected induction motors. The induction motor has 4 poles and a rated torque of 163 N·m while operating at 29.2 rps [39]. Fig. 16 shows time-domain vibration measurements for each loading condition. Impulsive events due to activated pistons are evident in each case. Low-frequency content in the vibration signature is associated with mechanical events that occur throughout shaft rotation, such as crank and piston movement. Higher-frequency content is likely a result of suction and discharge valve action, turbulent fluid flow, and excitation of natural structural frequencies of the compressor [40]. Vibration data was gathered using an accelerometer mounted to the discharge side of the compressor. At this location, measurements of 40 seconds in duration were taken at various loading conditions from eight compressors of the same model. In total, there were 32 loaded, 19 partially loaded, and 20 unloaded measurements. Based on the expected operating speed of 29.2 rps, the DFT is examined between 28.5 to 30 Hz. The location of the maximum value of the magnitude of the DFT in this range is an estimate of the shaft rotational frequency. The mean and standard deviation of the peak location for each loading

condition are shown in Table II. This demonstrates that the compressor shaft rotational frequency is inversely related to loading.

If both compressors on a skid are running, they will likely appear indistinguishable in the power stream. Thus, for healthy machines the NILM is unable to identify which compressor is responsible for a turn-on or loading transient. With access to the FDD network and one remote sensor, however, the NILM can track the loading condition of both compressors. Upon observing a compressor loading event, the NILM requests a small sample of vibration data from the remote sensor deployed to one of the compressors (referred to as the “monitored compressor”). From this measurement, the NILM estimates the shaft rotational frequency, and from that, the loading condition of the monitored compressor. If this compressor’s loading condition has not changed from what the NILM last observed, the NILM infers that the loading event occurred in the other compressor, and updates that compressor’s tracked state accordingly. Otherwise, the NILM updates the tracked state of the monitored compressor.

C. Crankcase Blower

In the third FDD network strategy, the NILM periodically requests data from the remote sensor at user-configured inter-

TABLE II: A/C power factor and shaft frequency for loading conditions.

Loading Condition	Power Factor	Shaft Rotational Freq., Hz ($\sigma_{F_{req}}$)
2 cylinders	0.477	29.74 (0.0229)
4 cylinders	0.642	29.49 (0.0254)
6 cylinders	0.708	29.29 (0.0407)

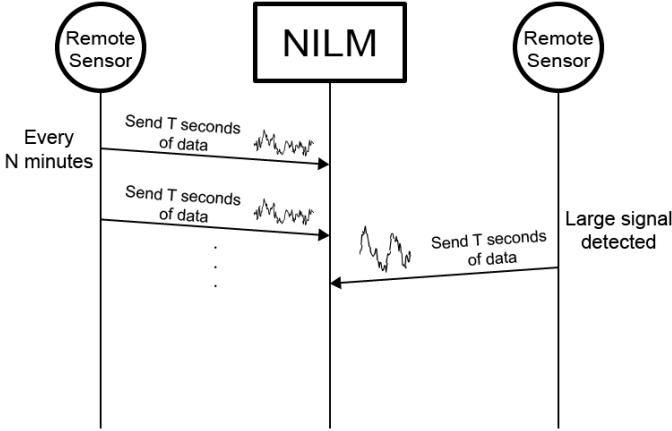


Fig. 17: FDD strategies described in Section IV-C and Section IV-D.

vals, as illustrated on the left side of Fig. 17. This strategy is motivated by imbalance condition faults, which are often invisible in the power stream but are apparent in vibration signatures. A controlled imbalance experiment using a centrifugal fan demonstrates this claim. Tests involved four conditions: a normal (balanced) condition and three imbalance conditions. The imbalance conditions were introduced with weights placed between blades of the fan's squirrel cage wheel. Ten power and vibration measurements of 30 seconds each were captured at each operating condition. The fan was operated at 19.2 rps for all experiments. For each test, average apparent power was computed over the 30-second measurement. Table III shows the average and standard deviation of these values for each condition. The magnitude of the DFT at the shaft rotational frequency is also shown, relative to the normal condition. The standard deviations of this frequency component were negligible. These results show that operating condition did not change apparent power. However, the magnitude of the DFT component at the shaft frequency and the operating condition are directly correlated. These results align with findings presented in [41] and demonstrate a fault condition that is readily apparent in vibration measurements, but nearly impossible to diagnose in power measurements.

Similar findings were made onboard USCGC THUNDER BAY with its main propulsion diesel engine (MPDE) crankcase blowers. These centrifugal fans draw air from the engine's crankcase to prevent the buildup of combustible gases. The #1 MPDE's blower is shown in Fig. 18. Each blower is driven by an induction motor operating at 57.5 rps and acts to maintain a vacuum in the crankcase. The blowers are fitted with filters to remove atomized oil from the air drawn from

TABLE III: Centrifugal fan power and vibration comparison.

Operating Condition	Eccentric Mass, g	Apparent Power, VA (σ_{AP})	Norm. Rotational Freq. Magnitude
Normal	0	838.8 (1.757)	1.000
Imbalance 1	1.085	840.7 (1.858)	1.141
Imbalance 2	2.156	839.5 (1.662)	1.369
Imbalance 3	3.398	839.9 (1.728)	1.500



Fig. 18: THUNDER BAY MPDE crankcase blower.

the crankcase. The mounting arrangement creates an overhang condition, similar to a cantilever beam, for the induction motor and squirrel cage wheel. With this configuration, minor manufacturing defects, deterioration, or debris buildup on the fan blades can result in imbalance and excessive amounts of vibration. The blower's mounting arrangement is illustrated in Fig. 19a. The mounting arrangement of the centrifugal fan used during the controlled imbalance experiment is shown in Fig. 19b. Both create an overhang condition.

The accelerometer measurements were first analyzed in the time domain and are shown in Fig. 20. It is apparent that there are significant differences in operation between the two blowers. The vibration signal envelope of the #1 blower is relatively uniform; the signal has an rms value of 0.596 V. The #2 blower displays a low-frequency oscillation at approximately 1.4 Hz and has a rms value of 0.278 V. Despite appearing drastically different, drawing firm conclusions from time-domain observations alone is difficult. Variations in mounting, misalignment, bearing faults, and increased looseness of linkages can excite natural frequencies of a machine, affecting its vibration signal envelope [42]. Analysis of the vibration signals in the frequency domain provides more useful insight. The magnitudes of the first six orders in the frequency domain for both blowers are shown in Fig. 21. The frequency content of the #1 blower is dominated by the first order. As shown during the controlled centrifugal fan experiment, this can indicate an imbalance condition in which an eccentric mass is oscillated once per shaft rotation [42]. The #1 blower is likely imbalanced due to an uneven buildup of soot and coagulated oil within the blower's rotating filter.

The steady-state apparent powers of the #1 and #2 blowers were approximately 646 VA and 786 VA, respectively. Without historical data, it is difficult to attribute the discrepancy in apparent power to a specific fault. Changes in power can be attributed to complex factors particular to the system,

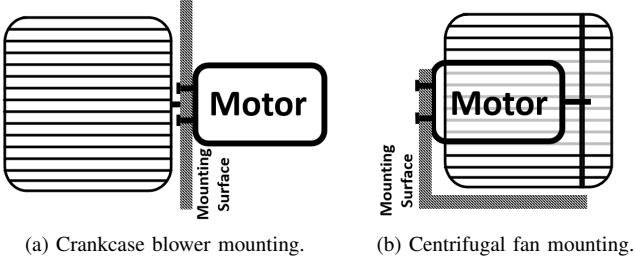


Fig. 19: Cantilever mounting arrangements.

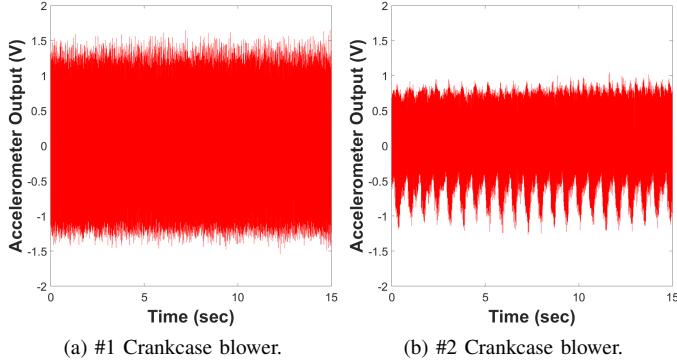


Fig. 20: Crankcase blower time-domain comparison.

such as restrictions and leaks [37]. However large first-order frequency content in vibration is a well-established indicator of imbalance [41], as corroborated by the controlled experiment. In practice, this type of load operates continuously, so turn-on and turn-off events will be sparse. With the proposed FDD network strategy, the NILM continually performs spectrum analysis on the periodically acquired vibration signals to generate diagnostics of imbalance conditions.

D. Sewage Vacuum Pumps

The final FDD network strategy presented addresses the case in which a load of interest does not draw power from a panel monitored by the NILM. For this strategy, the remote sensing device sends measurements to the NILM whenever it detects a signal exceeding a user-configured level, as illustrated on the right side of Fig. 17. A pair of positive displacement vacuum pumps onboard USCGC THUNDER BAY provide a case study. These pumps maintain vacuum in the sewage collection tank and do not draw power from the panel monitored by the NILM on the ship. The vacuum sewage pumps operate in a lead-lag fashion, in which the primary pump turns on when vacuum in the collection tank drops below 12 inHg and the secondary pump turns on when vacuum drops below 10 inHg [43]. Once the collection tank vacuum reaches 18 inHg, both pumps turn off and swap designations as primary and secondary pump, i.e., the primary pump becomes the secondary. These pumps are mounted on top of a small water tank that provides pump cooling and a fluid medium for the pumps to build vacuum via the Venturi effect.

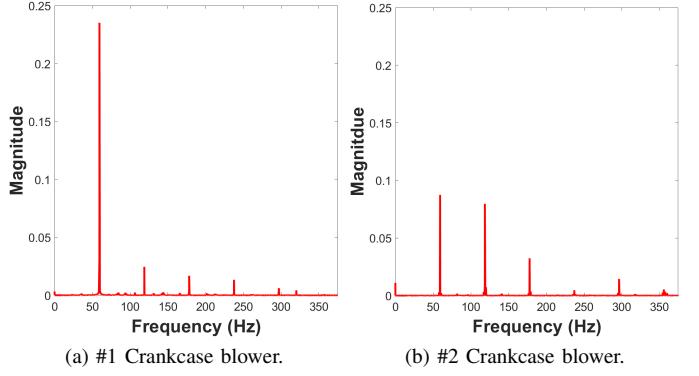


Fig. 21: Crankcase blower frequency-domain comparison.

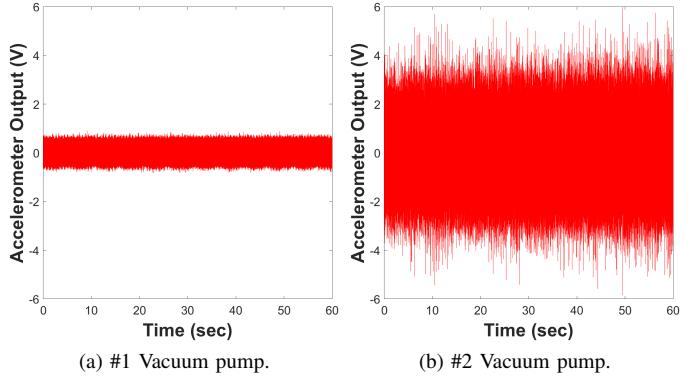


Fig. 22: Vacuum pump time-domain comparison (pre-repair).

The wireless sensor platform captured vibration data from both vacuum pumps using an accelerometer attached to each pump's motor housing. Fig. 22 shows the resulting time-domain measurements. The #2 pump exhibits a significantly higher rms value of vibration (1.013V) than the #1 pump (0.306 V). Common fault diagnostic wisdom states that an increase in a machine's vibration level indicates deteriorated operation or a fault. Indeed, faults involving imbalances, mounting, or bearings can increase vibration levels [42]. Without baseline measurements, one may be inclined to assume that the #2 pump is operating improperly since its vibration level is clearly larger than the #1 pump, which is supposed to be identical. The following demonstration of sophisticated signal processing techniques yields a surprising result: the #2 pump is healthy and #1 pump is the faulty one. By exploiting the cyclostationary nature of rotating machinery, these techniques offer this conclusion even without historical knowledge of the pump operating conditions.

Vibration measurements from rotating machinery are often modeled as realizations of cyclostationary random processes [34], [44], [45]. Cyclostationary random processes are characterized by periodic mean and autocorrelation functions [45]. Periodic vibrations of rotating machinery are due to shaft rotation, piston reciprocation, and other mechanical actions. In many systems, these periodic actions are associated with vibration content that is hard to model analytically such as friction, turbulent flow, and other physical factors. Vibrations

from these phenomena are more broadband in frequency and are often modeled as random, with periodic actions modulating the random content. Cyclostationary signal processing tools provide important insights, for example, estimates of the spectral correlation function, or if normalized, the spectral coherence function. These estimates can quantify the frequency of the periodic actions and the nature of the modulation. The mean envelope spectrum (MES) is calculated from the spectral coherence function. Lines in the spectral coherence map at a specific cyclic frequency correspond to relative peaks in the MES and indicate cyclostationarity [22], [33].

Detailed mathematical discussions and intuitive examples of cyclostationary analysis are presented in [22], [33]. Only the necessary definitions for the vacuum pump analysis are presented in this section. The spectral coherence function $\gamma_x^\alpha(f)$ is defined as

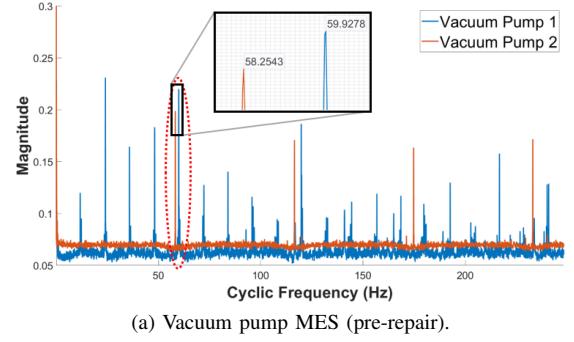
$$\gamma_x^\alpha(f) = \frac{\hat{S}_x^\alpha(f)}{\sqrt{\hat{S}_x^0(f - \frac{\alpha}{2})\hat{S}_x^0(f + \frac{\alpha}{2})}}, \quad (1)$$

where $\hat{S}_x^\alpha(f)$ is the spectral correlation function for a signal x , f is the carrier or center frequency, and α is cyclic frequency. For $\alpha = 0$, the spectral correlation function is equal to the traditional power spectral density (PSD). Eq. (1) shows that the spectral coherence is the spectral correlation function normalized by a function of values from the PSD. The MES $S_x^{<f>}(\alpha)$ over some range of carrier frequencies F is defined as

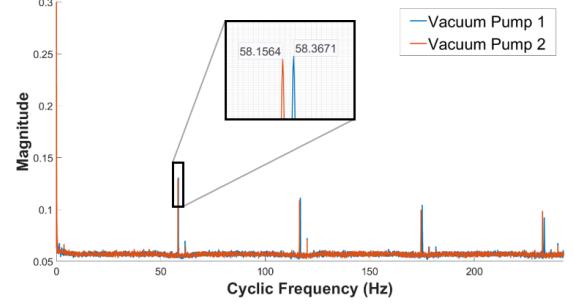
$$S_x^{<f>}(\alpha) = \frac{1}{|F|} \int_F |\gamma_x^\alpha(f)| df, \quad (2)$$

where F is chosen by the analyst and the upper bound of F is limited to one half of the sampling frequency (Nyquist frequency) [45]. Eq. (2) defines the relationship between the spectral coherence and the MES.

In the case of the sewage pump, shaft rotation is the main periodic action that modulates broadband content. The vacuum pump motors are rated to operate at 57.5 rps. Thus, relative peaks in the MES at cyclic frequencies around 57.5 Hz and its integer multiples are expected. Fig. 23a depicts the MES of both vacuum pumps as initially encountered on THUNDER BAY. The MES of the #1 pump has peaks at many cyclic frequencies unrelated to a reasonable shaft rotational frequency. The MES of the #2 pump has expected peaks at multiples of 58.25 Hz. Typically, MES values at cyclic frequencies that correspond to machine physics dominate the MES. When comparable in size to peaks without direct physical explanation, there is little modulation of broadband content and the system is likely not operating as intended. Additionally, for systems with negligible broadband frequency content, the normalization in Eq. (1) with small values of the PSD could give rise to artificially large values of the spectral coherence function. Abnormal operation of the #1 pump is further confirmed by investigation of the area around 59 rps circled in Fig. 23a. The MES peak of the #1 pump is at a noticeably higher cyclic frequency of 59.93 Hz. The shaft rotational frequency is very close to synchronous speed. This indicates the motor operates at very low slip and corresponds to a small load torque.



(a) Vacuum pump MES (pre-repair).



(b) Vacuum pump MES (post-repair).

Fig. 23: Vacuum pump MES comparison.



Fig. 24: Deteriorated vacuum relief valve.

The differences in the MES prompted further examination of the system. Upon inspection, the #1 pump was not maintaining its water prime from the seal tank. Loss of prime causes the pump housing to become air-bound and deteriorates the pump's ability to build vacuum. The source of the fault was finally identified as the deteriorated sealing surfaces of the vacuum relief valve. Fig. 24 shows the deteriorated valve and its sealing surfaces.

Fig. 23b shows the MES profile from measurements taken after cleaning the sealing surfaces and re-installing the valve. After repair, the MES of the two pumps are nearly identical and the additional MES peaks have vanished. The vibration of the #1 pump, shown in Fig. 25, increased to an rms value of 0.571 V. Though the #1 pump's vibration level increased, it is still notably less than the #2 pump's rms value of 1.105 V. This may be the result of differences in cumulative run-time, mounting condition, or impeller health, but further inspection is required to confirm these suspicions.

This fault demonstrates that degraded operation can present counterintuitive time-domain vibration signatures. Without the

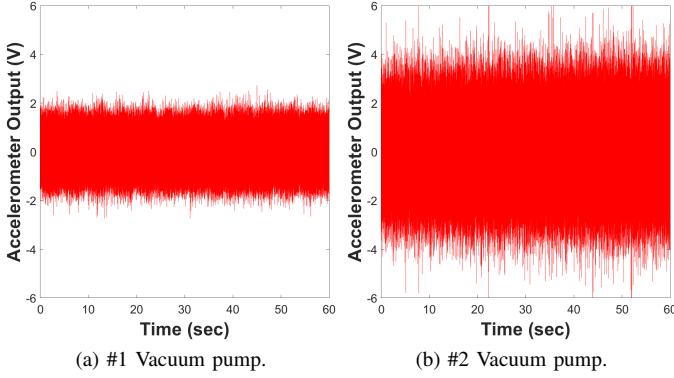


Fig. 25: Vacuum pump time-domain comparison (post-repair).

aid of power stream data, cyclostationary vibration analysis successfully diagnosed the faulty relief valve. To integrate this diagnosis into the FDD network, the wireless sensor platform should alert the NILM when there is sufficient vibration to be of interest. Since MES calculation is computationally expensive, the sensor platform sends data either continuously or periodically to the NILM, which uses its higher computing power to perform MES analysis for fault detection.

V. CONCLUSION

Conventional nonintrusive power monitoring allows for energy management and fault diagnostics with a low sensor count. This work demonstrates that these abilities can be augmented with minimally invasive sensors to integrate auxiliary measurements. In facilitating online analysis, a local intranet of distributed sensors offers many of the benefits of the Internet of things model while avoiding the inherent security issues of using a public channel. Wireless networks provide advantages such as ease of setup and scalability. Wi-Fi testing and equipment diagnostics aboard ships shows that this is a practical and flexible sensing solution for industrial sites. Four FDD network strategies for data acquisition are proposed, along with relevant case studies in condition monitoring.

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REFERENCES

- [1] X. Wang, S. Lu, W. Huang, Q. Wang, S. Zhang, and M. Xia, "Efficient data reduction at the edge of industrial internet of things for pmsm bearing fault diagnosis," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–12, 2021.
- [2] P. Ferrari, A. Flaminini, E. Sisinni, S. Rinaldi, D. Brandão, and M. S. Rocha, "Delay estimation of industrial iot applications based on messaging protocols," *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 9, pp. 2188–2199, 2018.
- [3] G. Mois, T. Sanislav, and S. C. Folea, "A cyber-physical system for environmental monitoring," *IEEE Transactions on Instrumentation and Measurement*, vol. 65, no. 6, pp. 1463–1471, 2016.
- [4] T. A. Putra and J.-S. Leu, "Multilevel neural network for reducing expected inference time," *IEEE Access*, vol. 7, pp. 174129–174138, 2019.
- [5] J. Paris, J. S. Donnal, and S. B. Leeb, "NilmDB: The non-intrusive load monitor database," *IEEE Transactions on Smart Grid*, vol. 5, no. 5, pp. 2459–2467, 2014.
- [6] 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. Industr. Inform.*, vol. 16, no. 2, pp. 992–1002, 2020.
- [7] R. Feng, W. Yuan, L. Ge, and S. Ji, "Nonintrusive load disaggregation for residential users based on alternating optimization and downsampling," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–12, 2021.
- [8] S. Ghosh, A. Chatterjee, and D. Chatterjee, "An improved load feature extraction technique for smart homes using fuzzy-based nilm," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–9, 2021.
- [9] 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 Transactions on Industrial Informatics*, vol. 15, no. 3, pp. 1405–1414, 2019.
- [10] S. B. Leeb, P. Lindahl, D. Green, T. Kane, J. Donnal, and S. Kidwell, "Power as predictor and protector," *Society of Naval Architects and Marine Engineers (SNAME) Marine Technology*, 2019.
- [11] J. Paris, J. S. Donnal, Z. Remscrim, S. B. Leeb, and S. R. Shaw, "The sinefit spectral envelope preprocessor," *IEEE Sensors Journal*, vol. 14, no. 12, pp. 4385–4394, 2014.
- [12] D. Green, T. Kane, S. Kidwell, P. Lindahl, J. Donnal, and S. Leeb, "NILM dashboard: Actionable feedback for condition-based maintenance," *IEEE Instrumentation Measurement Magazine*, vol. 23, no. 5, pp. 3–10, 2020.
- [13] 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 Journal*, vol. 18, no. 21, pp. 8986–8995, Nov 2018.
- [14] D. E. Phillips, R. Tan, M.-M. Moazzami, G. Xing, J. Chen, and D. K. Y. Yau, "Supero: A sensor system for unsupervised residential power usage monitoring," in *2013 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 2013, pp. 66–75.
- [15] Z. C. Tayisi, M. A. Guvensan, and T. Melodia, "Tinyears: Spying on house appliances with audio sensor nodes," in *Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, ser. BuildSys '10. New York, NY, USA: Association for Computing Machinery, 2010, p. 31–36.
- [16] A. Stief, J. R. Ottewill, J. Baranowski, and M. Orkisz, "A pca and two-stage bayesian sensor fusion approach for diagnosing electrical and mechanical faults in induction motors," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 12, pp. 9510–9520, 2019.
- [17] B.-S. Yang and K. J. Kim, "Application of dempster–shafer theory in fault diagnosis of induction motors using vibration and current signals," *Mechanical Systems and Signal Processing*, vol. 20, no. 2, pp. 403–420, 2006.
- [18] B. Khaleghi, A. Khamis, F. O. Karay, and S. N. Razavi, "Multisensor data fusion: A review of the state-of-the-art," *Information Fusion*, vol. 14, no. 1, pp. 28–44, 2013.
- [19] L. Jing, T. Wang, M. Zhao, and P. Wang, "An adaptive multi-sensor data fusion method based on deep convolutional neural networks for fault diagnosis of planetary gearbox," *Sensors*, vol. 17, no. 2, 2017.
- [20] H. Tian, "Dynamic pressure simulation of an external gear pump with relief chamber using a morphological approach," *IEEE Access*, vol. 6, pp. 77509–77518, 2018.
- [21] M. Kulpa, "A vibrational study of gear pumps and gear pump drives," Master's thesis, Rochester Institute of Technology, 1991.
- [22] L. Huchel, T. C. Krause, T. Lugowski, S. B. Leeb, and J. Helsen, "Chasing the cut: A measurement approach for machine tool condition monitoring," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–10, 2021.
- [23] L. Huchel, T. C. Krause, S. B. Leeb, and J. Helsen, "Stretched sensing strategies for IIEPE," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–10, 2021.
- [24] S. Fong, J. Harmouche, S. Narasimhan, and J. Antoni, "Mean shift clustering-based analysis of nonstationary vibration signals for machinery diagnostics," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 7, pp. 4056–4066, 2020.

- [25] S. Diggavi, "On achievable performance of spatial diversity fading channels," *IEEE Transactions on Information Theory*, vol. 47, no. 1, pp. 308–325, 2001.
- [26] H. Friis, "A note on a simple transmission formula," *Proceedings of the IRE*, vol. 34, no. 5, pp. 254–256, 1946.
- [27] M. Chen, K. Liu, J. Ma, and C. Liu, "Spatio-temporal fingerprint localization for shipboard wireless sensor networks," *IEEE Sensors Journal*, vol. 18, no. 24, pp. 10 125–10 133, 2018.
- [28] J. M. Batalla, "On analyzing video transmission over wireless WiFi and 5G c-band in harsh IIoT environments," *IEEE Access*, vol. 8, pp. 118 534–118 541, 2020.
- [29] H. Farhat, H. Kdouh, C. Brousseau, G. Zaharia, G. Grunfelder, and G. El Zein, "Radio wave propagation characterization between adjacent decks on board ships," in *2015 IEEE 82nd Vehicular Technology Conference (VTC2015-Fall)*, 2015, pp. 1–4.
- [30] X. Zeng, K. Liu, J. Ma, M. Chen, and M. Yu, "Reliability and delay trade-off analysis of unslotted IEEE 802.15.4 sensor network for shipboard environment," *IEEE Sensors Journal*, vol. 21, no. 2, pp. 2400–2411, 2021.
- [31] J. Donnal, "Joule: A real-time framework for decentralized sensor networks," *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 3615–3623, 2018.
- [32] J. S. Donnal, "Wattsworth: An open-source platform for decentralized sensor networks," *IEEE Internet of Things Journal*, vol. 7, no. 1, pp. 189–196, 2020.
- [33] L. Huchel, J. Helsen, P. A. Lindahl, and S. B. Leeb, "Diagnostics for periodically excited actuators," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 7, pp. 4145–4153, 2020.
- [34] J. Antoni, "Cyclostationarity by examples," *Mechanical Systems and Signal Processing*, vol. 23, no. 4, pp. 987 – 1036, 2009.
- [35] "Wilcoxon research - model 728t high sensitivity, low noise accelerometers," Accessed 2022. [Online]. Available: <https://buy.wilcoxon.com/>
- [36] C. Peeters, Q. Leclère, J. Antoni, P. Lindahl, J. Donnal, S. Leeb, and J. Helsen, "Review and comparison of tacholess instantaneous speed estimation methods on experimental vibration data," *Mechanical Systems and Signal Processing*, vol. 129, pp. 407–436, 2019.
- [37] J. W. O'Connell, D. H. Green, B. T. Mills, A. Moeller, S. Kidwell, K. Lee, L. Huchel, and S. B. Leeb, "Nonintrusive ventilation system diagnostics," *IEEE Sensors Journal*, vol. 21, no. 17, pp. 19 268–19 278, 2021.
- [38] Technical Manual 3910A-514-A: Air Conditioning System, accessed: 2021.
- [39] "Application data - 06d and 06e semi-hermetic reciprocating compressors," Accessed 2022. [Online]. Available: <https://www.shareddocs.com/hvac/docs/2002/Public/09/574-069.pdf>
- [40] J. N. Trout and J. R. Kolodzie, "Reciprocating compressor valve condition monitoring using image-based pattern recognition," *Annual Conference of the Prognostics and Health Management Society*, 2016.
- [41] G. Genta, *Dynamics of Rotating Systems*, 1st ed. Springer, 2005.
- [42] R. B. Randall, *Condition Based Monitoring - Industrial, Automotive, and Aerospace Applications*, 2nd ed. John Wiley & Sons Ltd, 2021.
- [43] Technical Drawing 101-WTGB-528-001: Sanitary and Deck Drains System Diagram, accessed: 2021.
- [44] W. A. Gardner, *Statistical Spectral Analysis: a Nonprobabilistic Theory*. Englewood Cliffs, NJ: Prentice-Hall, 1988.
- [45] ———, *Introduction to Random Processes with Applications to Signals and Systems*. New York: Macmillan, 1986.



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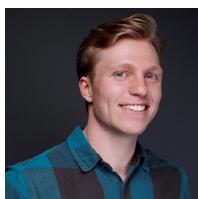
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