Machine Learning-based Load Monitoring, Fault Detection, and Network Reconfiguration in Next Generation Shipboard Power Systems

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Background and Research Objectives

- Rapid growing electricity consumption in modern navy ships.
- Complexity of energy management in Navy ships and growing interest in using unmanned surface vessels for long duration voyages.
- Potential risks of cyber/physical attacks to naval power systems.
- Utilizing future navy ships to assist the operation of power distribution grids, to enhance the reliability and resilience of power grids and the economic efficiency of the power networks.
- The overarching objective of this project is to:
  - Study the energy management and fault detection of the Navy power ship systems, by utilizing deep learning-based techniques to track the demand changes with real-time interactions and enhance the reliability and resilience of the Navy ships.
Research thrusts

**Research Thrust I: Monitoring and Tracking Navy Ships Electricity Demands**
- Load modeling and forecasting, and optimal unit dispatch
- Navy ship reliability enhancement

**Research Thrust II: Faults Detection, Isolation, and Service Restoration**
- Deep learning-based approaches
- Network reconfiguration
- Navy ship reliability and resilience enhancement

**Research Thrust III: Model Aggregation of Future Naval Power Ships and Power Grids**
- Co-optimization and scheduling
- Power grid reliability and resilience enhancement
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

**Generation**
Future SPS needs more generation capacity due to the constantly increasing demand.

**Energy Storage System**
Future SPS will leverage energy storage systems to improve the energy efficiency and response to pulsed loads.

**Pulsed Loads**
Some unique loads will be added to SPS (e.g., laser weapons), and these loads can make future SPS more complex.

**Integrated Power and Energy System**
Integrated power system provides electric power to the total ship (propulsion and ship service) with an integrated plant.

**Power Conversions**
Future SPS uses more power electronic-based converters to meet the vast variety range of electric demands.

**Ship to Grid Connection**
Future SPS will have more interaction with terrestrial power network to charge/discharge the energy storage system and help improve the grid operation and resilience.
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

Efficient Non-intrusive Load Monitoring

- Enormous number of sensors and components
- Onboard Supervisory
- Unique Loads
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

• **Steady-State Quantities Methods**
  - Use steady state quantities, such as active and reactive power in steady state.
  - Estimate the ON/OFF status and the power consumption of each component.
  - Voltage variations from external sources may cause overlap for different components in the P-Q plane.
  - The biggest concern on this type of method is the lack of ability to follow the transients.

• **Dynamic Performance Methods**
  - Focus more on dynamic performance, which is capable of following both steady state and transient load signals.
  - Use **signal processing methods** such as short-term Fourier transform (STFT) and discrete wavelet transform (DWT) approach for feature extraction.
  - Have the capability to **detect small load changes** through extracted features.
  - High computational burden for performing feature extraction and real-time signal disaggregation algorithms.
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

- A complete simulated dataset created that consists of power consumption of different devices on the **MVDC shipboard power system (SPS)**.
- **Wavelet transform** is used for feature extraction from aggregated current signals.
- different **deep learning-based models** for non-intrusive load monitoring (NILM) in the SPS. The models show high accuracies in detecting different devices based on an aggregated current signal.
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

- Online real-time Processing
- On/Off Status of each component in each zone

1. Real-time sampling
2. Data processing
3. DWT-CNN NILM
4. Load status Identification
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

- 200 Samples of Generator Current
- DWT: Current Sample
- Approx. Detail Coefficients
- Current sample
- Approx. 4 Detail 1 Detail 2 Detail 3 Detail 4
- Class 0-15
- Class 0-15
- Class 0-15
- Class 0-15

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Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

- A complete simulated dataset is created, consisting of power consumption of different devices with an MVDC shipboard power system (SPS).
- **Wavelet transform** is adopted for feature extraction from aggregated current signals.
- Different **deep learning-based models** have been developed for NILM in the SPS.

\[
Y^l_j = f \left( \sum_{s \in M_{j(l-1)}} \sum_{(u,v) \in K^{(l)}} W^s_{j,u,v} x^{(l-1)}_s (c + u, r + u) + b^{(l)}_j \right), \quad Y^l_i = \text{down} \left( Y^{(l-1)}_j \right), \quad o^l_j = f \left( \sum_{i=1}^{n} x^{(l-1)}_i w_j^{(l)} + b^{(l)}_j \right)
\]
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

1- Shipboard Power System

2- Sampling and Measurement

3- Feature Extraction using Discrete Wavelet Transform

4- Classification and NILM
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

### Accuracy of the NILM for the propulsion system (Percentage)

<table>
<thead>
<tr>
<th>Model</th>
<th>Training Accuracy</th>
<th>Testing Accuracy</th>
<th>Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelet-DNN</td>
<td>52.42</td>
<td>51.96</td>
<td>1.199</td>
</tr>
<tr>
<td>Wavelet-LSTM</td>
<td>82.3</td>
<td>78.96</td>
<td>0.455</td>
</tr>
<tr>
<td>Wavelet-CNN</td>
<td>90.08</td>
<td>89.23</td>
<td>0.241</td>
</tr>
</tbody>
</table>

### Accuracy of the NILM for the zonal components (Percentage)

<table>
<thead>
<tr>
<th>Model</th>
<th>Training Accuracy</th>
<th>Testing Accuracy</th>
<th>Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelet-DNN</td>
<td>54.38</td>
<td>54.19</td>
<td>1.66</td>
</tr>
<tr>
<td>Wavelet-LSTM</td>
<td>84.24</td>
<td>82.19</td>
<td>0.452</td>
</tr>
<tr>
<td>Wavelet-CNN</td>
<td>98.62</td>
<td>98.14</td>
<td>0.0437</td>
</tr>
</tbody>
</table>

\[
F1 = 2 \times \frac{precision \times recall}{precision + recall}
\]

\[
precision = \frac{TP}{TP + FP}, recall = \frac{TP}{TP + FN}
\]

<table>
<thead>
<tr>
<th>Metric</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1-score</td>
<td>99</td>
</tr>
<tr>
<td>Precision</td>
<td>98.5</td>
</tr>
<tr>
<td>Recall</td>
<td>99.6</td>
</tr>
</tbody>
</table>
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

Confusion matrix for zonal components

Confusion matrix for propulsion system
Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

Average Accuracy of WCNN NILM for each class

Average Accuracy of WCNN NILM for each class under extreme condition

- Generator Outage
- Line Outage
Conclusion

- Three deep learning-based models, including Wavelet-DNN, Wavelet-LSTM, and Wavelet-CNN, were developed for non-intrusive load monitoring in MVDC shipboard power systems.
- Discrete wavelet transform has a great capability to detect pulsed loads in aggregated current signals.
- The wavelet-CNN method can detect the On/Off status of components with 98% accuracy.
- The CNN model is more compatible with the wavelet output decomposition matrix than the DNN and RNN methods.
- The wavelet-CNN method has an acceptable accuracy and F1-score in detecting pulsed loads On status.

Outcomes

Research Thrust II: Faults Detection, Isolation and Service Restoration

SPS Model

Fault scenarios and simulations

Deep learning models

Output

- No fault
- Fault
  - Type (SLG, LLG, 3LG)
  - Location (Busbar number)
Research Thrust II: Faults Detection, Isolation and Service Restoration

Overcurrent protection

Distance protection

Current differential

Active impedance estimation

Traveling wave fault location

Wavelet analysis

Accuracy $\approx 85\%$, Fault Detection and Location

Accuracy $\approx 90\%$, Fault Detection and Location

Accuracy $\approx 96\%$, Fault Detection and Location

Accuracy $\approx 97\%$, Fault Detection and Location

Accuracy $\approx 97\%$, Fault Detection and Location

Accuracy $\approx 98\%$, Fault Detection, Classification and Location

Research Thrust II: Faults Detection, Isolation and Service Restoration

- Wavelet Transform-based Graph Neural Network (WGNN) for non-intrusive fault detection, classification, and location identification of SPS are designed and tested.
- A model of 4 Zone MVDC shipboard power system is used to investigate the effectiveness of the models.
- Fault scenarios are simulated at each zone. Then, WGNN model is trained and tested based on the voltages and currents signals.
- The results show that deep WGNN model can detect the faults, fault types, and fault locations very accurately and faster than conventional methods.
Research Thrust II: Faults Detection, Isolation and Service Restoration

Fault scenarios and sampling

Discrete Wavelet Transform

Learning Process

- Split the input data (X)
- Normalize the input features
- SMOTE process

Graph Conv. Layer (32)/ Act.:ReLU
Graph Conv. Layer (64)/ Act.:ReLU
Graph Conv. Layer (32)/ Act.:ReLU
Dense Layer (256)/ Act.:Softmax

Output Y (Fault/Non-fault and Location)

Graph Structure and Adjacency Matrix (A)
Research Thrust II: Faults Detection, Isolation and Service Restoration

- **Case I**: Intrusive fault detection
- **Case II**: Non-intrusive fault detection
- **Case III**: Non-intrusive fault detection with pulsation load

<table>
<thead>
<tr>
<th>Case</th>
<th>Training Accuracy</th>
<th>Training Loss</th>
<th>Testing Accuracy</th>
<th>Testing Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case I</td>
<td>99.99%</td>
<td>0.225e-4</td>
<td>99.99%</td>
<td>7.01e-4</td>
</tr>
<tr>
<td>Case II</td>
<td>97.26%</td>
<td>0.0851</td>
<td>97.70%</td>
<td>0.0392</td>
</tr>
<tr>
<td>Case III</td>
<td>94.44%</td>
<td>0.1392</td>
<td>95.23%</td>
<td>0.1180</td>
</tr>
</tbody>
</table>

**Case Training Accuracy Training Loss Testing Accuracy Testing Loss**

**Case I**
- Training Accuracy: 99.99%
- Training Loss: 0.225e-4
- Testing Accuracy: 99.99%
- Testing Loss: 7.01e-4

**Case II**
- Training Accuracy: 97.26%
- Training Loss: 0.0851
- Testing Accuracy: 97.70%
- Testing Loss: 0.0392

**Case III**
- Training Accuracy: 94.44%
- Training Loss: 0.1392
- Testing Accuracy: 95.23%
- Testing Loss: 0.1180
Research Thrust II: Faults Detection, Isolation and Service Restoration

### Performance Comparison

<table>
<thead>
<tr>
<th>Filter Bank in WGGN</th>
<th>Case I</th>
<th>Case II</th>
<th>Case III</th>
</tr>
</thead>
<tbody>
<tr>
<td>SNR (dB)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-5</td>
<td>82.1%</td>
<td>89.5%</td>
<td>95.1%</td>
</tr>
<tr>
<td>-2</td>
<td>84.5%</td>
<td>90.2%</td>
<td>95.2%</td>
</tr>
<tr>
<td>0</td>
<td>85.1%</td>
<td>89.8%</td>
<td>95.5%</td>
</tr>
<tr>
<td>2</td>
<td>85.2%</td>
<td>91.4%</td>
<td>95.6%</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Graphs

1. **Training and Validation Accuracy**
   - Case I
   - Case II
   - Case III

2. **Accuracy (%)**
   - Haar
   - Linear
   - Quadratic
   - Cubical

3. **Filter Bank in WGGN**
   - Harr
   - Linear
   - Quadratic
   - Cubical

4. **Cross-entropy**
   - Training and Validation Loss

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Spectral graph theory and graph signal processing form the basis for the graph convolution.

\[
L_G = I - D^{-\frac{1}{2}} AD^{-\frac{1}{2}}
\]

Normalized Laplacian and its eigen decomposition

\[
x *_g U = F^{-1}(F(x) \circ F(U)) = \Theta(\Theta^T x \circ \Theta^T U)
\]

Graph convolution of the graph signal \(x\) with a filter \(U\)

\[
x *_g U = \Theta U \Theta^T x
\]

First order approximated Chebyshev filter

\[
\Lambda = \text{diag}(e_0, e_1, e_2, \ldots, e_{n-1}),
\]

\[
\tilde{\lambda} = 2\lambda / \max(e_0, e_1, \ldots, e_{n-1}) - I
\]

\[
x *_g U = \alpha(I + D^{-\frac{1}{2}} AD^{-\frac{1}{2}}) x
\]

\[
K = 1, \quad \alpha_0 = -\alpha_1 = \alpha, \quad \max(e_0, e_1, \ldots, e_{n-1}) = 2
\]
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The node attributes of the graph and the adjacency matrix are normalized.

$$\tilde{X}_k = \frac{X_k - \bar{X}}{\max(X)}$$

(8)

Data Distribution

- Adjacency matrix
- Normalized Graph Laplacian ($L_G$)
- Renormalized adjacency

Architecture

- Input Layer 1, Feature Matrix $X$: (batch, n, f)
- GlobalSumPool()
- Graph Conv Layer (32), Activation: Softplus
- Graph Conv Layer (32), Activation: Softplus
- Graph Conv Layer (32), Activation: Softplus
- Dense Layer (512), Activation: elu
- Graph Conv Layer (32), Activation: elu
- Graph Conv Layer (32), Activation: elu
- Dense Layer (512), Activation: GlobalSumPool()
- Dense Layer (256), Activation: relu
- Output Y: (batch, n+1)

BUSBAR LOCATION

GlobalSumPool()
## Performance of the learning networks during Test phase

<table>
<thead>
<tr>
<th>Network</th>
<th>Categorical Accuracy</th>
<th>Categorical Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault Location</td>
<td>99.38%</td>
<td>0.027</td>
</tr>
<tr>
<td>Fault Type and Detection</td>
<td>99.75%</td>
<td>0.015</td>
</tr>
</tbody>
</table>

## Performance during Training

### Fault Type

<table>
<thead>
<tr>
<th>Model</th>
<th>Fault Detection</th>
<th>Fault Classification</th>
<th>Fault Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed GCN model</td>
<td>99.75%</td>
<td>99.75%</td>
<td>99.38%</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>97%</td>
<td>85%</td>
<td>-</td>
</tr>
<tr>
<td>K-nearest neighbors</td>
<td>90.4%</td>
<td>90.4%</td>
<td>-</td>
</tr>
<tr>
<td>Fully-connected DNN</td>
<td>-</td>
<td>99.58%</td>
<td>-</td>
</tr>
<tr>
<td>Differential Relay</td>
<td>96%</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
Research Thrust II: Faults Detection, Isolation and Service Restoration

- HIL simulation involves dedicated hardware, such as FPGA-based simulators, to achieve **high-speed** and **low-latency** real-time simulation.
- OPAL-RT systems are commonly used for **testing and validating** control systems in power systems.
- OPAL-RT real-time simulation has **high fidelity** and **low-latency** performance; thus, it can provide extremely **accurate** and **deterministic** simulation results in real-time.
Research Thrust II: Faults Detection, Isolation and Service Restoration

System modeling using Simulink MATLAB

Converting simulation to C language and implement on the HIL

Simulating the real time response of physical system

TCP/IP Communication

Sending the results to the monitoring console

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Research Thrust II: Faults Detection, Isolation and Service Restoration
Schematic of outage management in an example SPS network with main and auxiliary generators, and sectionalizing/tie switches.
The shipboard power system is simulated using Simulink Matlab.

The policy network consists of three main components:

1. A series of graph capsule network layers (GCAPS) which is used to compute the graph node embeddings for the SPS graph.

2. A feedforward network that is used to compute a feature vector, referred to as context embedding.

3. A Multi-Layered Perceptron (MLP) which takes the node embeddings from the GNN and the context embeddings from the feedforward network as input.

Node properties \( \gamma_i = [P_i^d, Q_i^d, P_i^g, Q_i^g, V_i] \)

Context \( [E_{supp}, V_{viol}, I^E] \)
Conclusion

- Wavelet Graph Neural Network (WGNN) was developed for fault detection, classification, and location identification in MVDC shipboard power systems.
- The fault detection methods can detect the faults with more than 99% and 97% accuracy in intrusive and non-intrusive modes, respectively.
- With a -5 dB signal-to-noise ratio, the models still have approximately 85% accuracy, while conventional methods can severely lose their accuracy.

Outcomes

- R. A. Jacob, S. Senemmar and J. Zhang, "Fault Diagnostics in Shipboard Power Systems using Graph Neural Networks," 2021 IEEE 13th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED), Dallas, TX, USA, 2021, pp. 316-321,
Questions