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





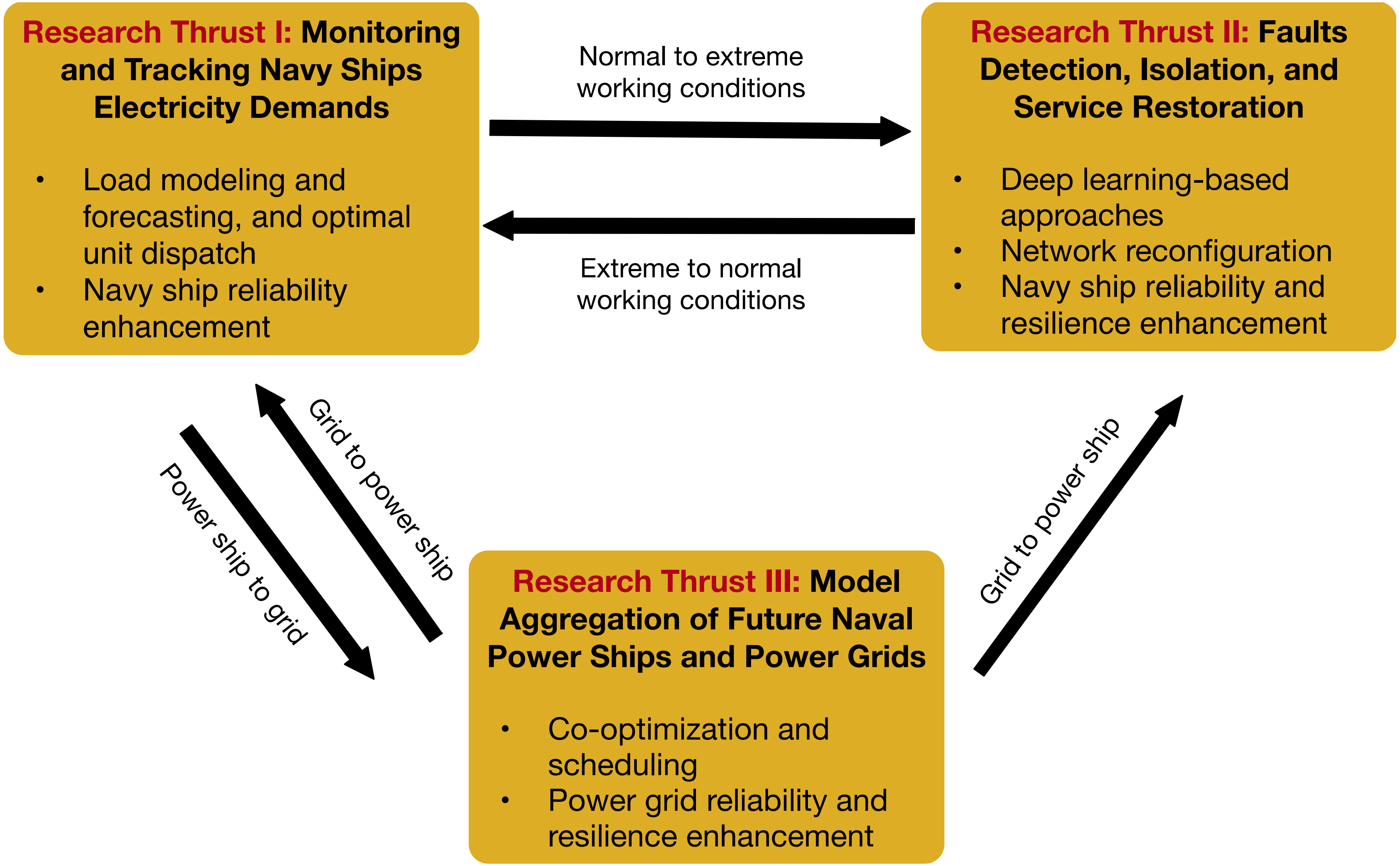
**Soroush Senemmar**
Advisor: Dr. Jie Zhang

Department of Electrical Engineering
The University of Texas at Dallas
Feb. 2024

# 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.

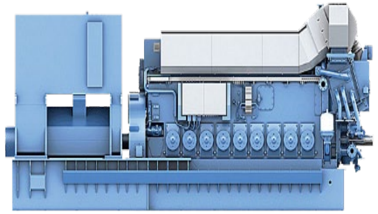
# Research thrusts



# Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

## Generation

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

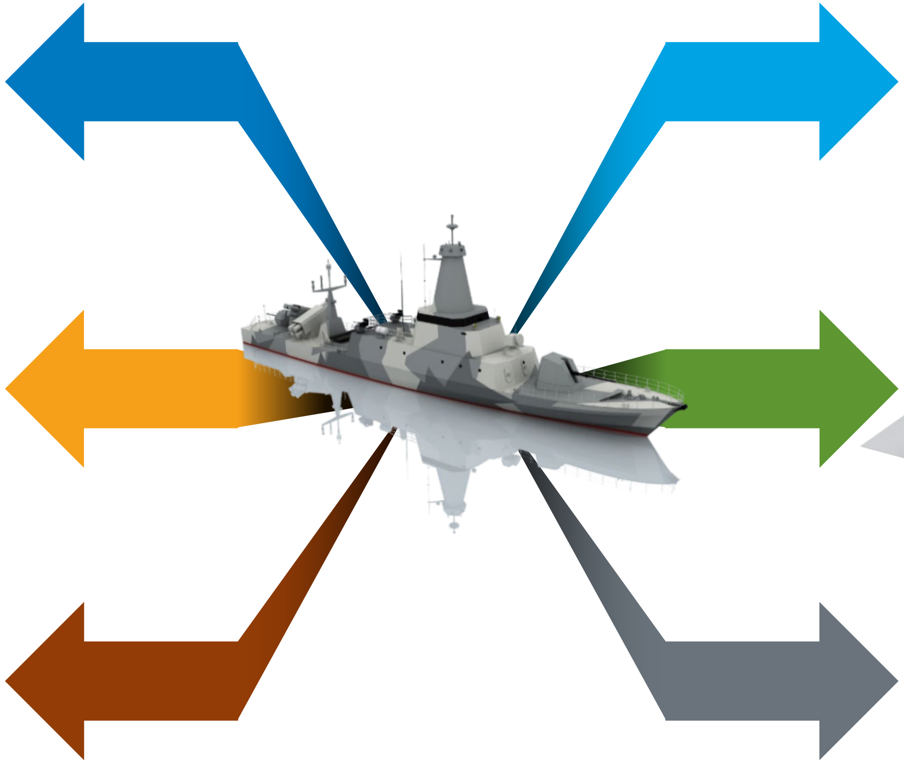


## Energy Storage System

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

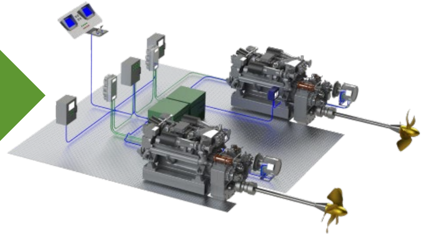
## Power Conversions

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



## Pulsed Loads

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



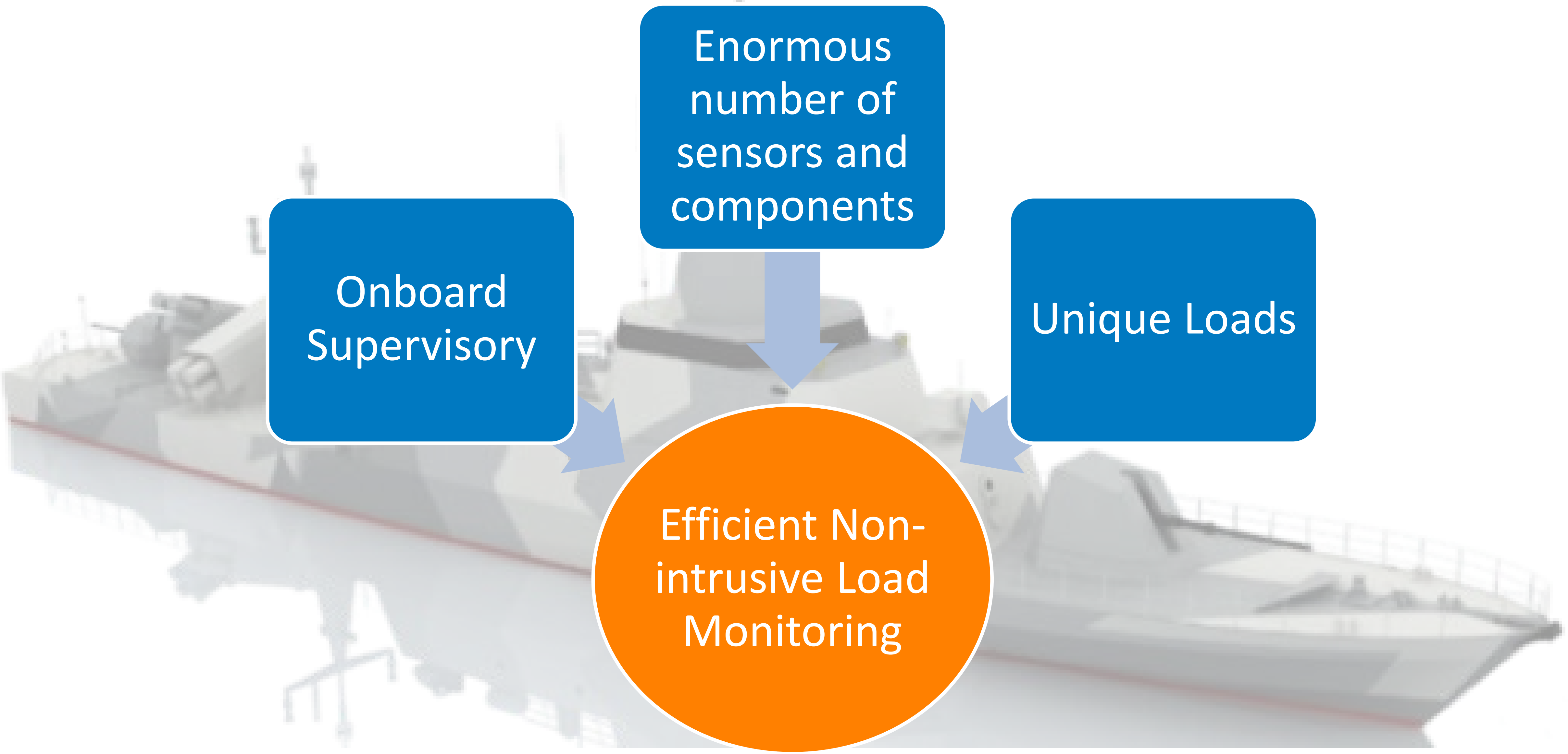
## Integrated Power and Energy System

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

## 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

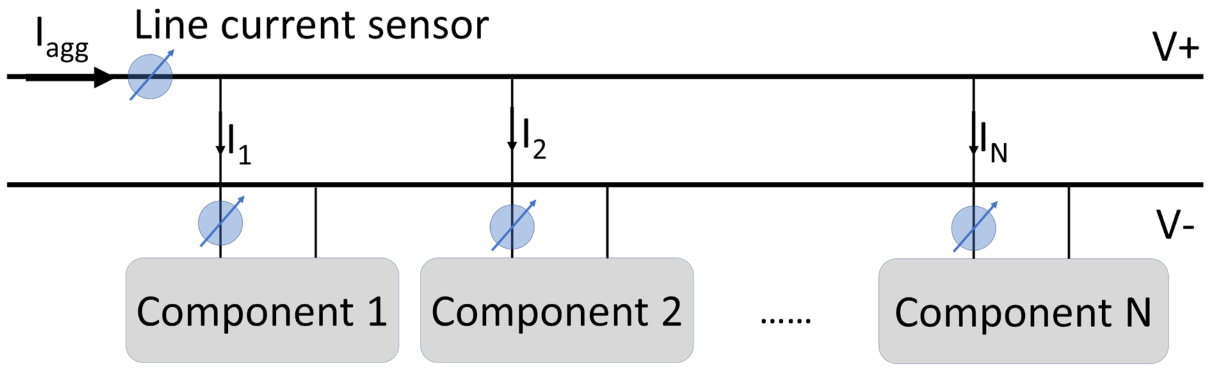


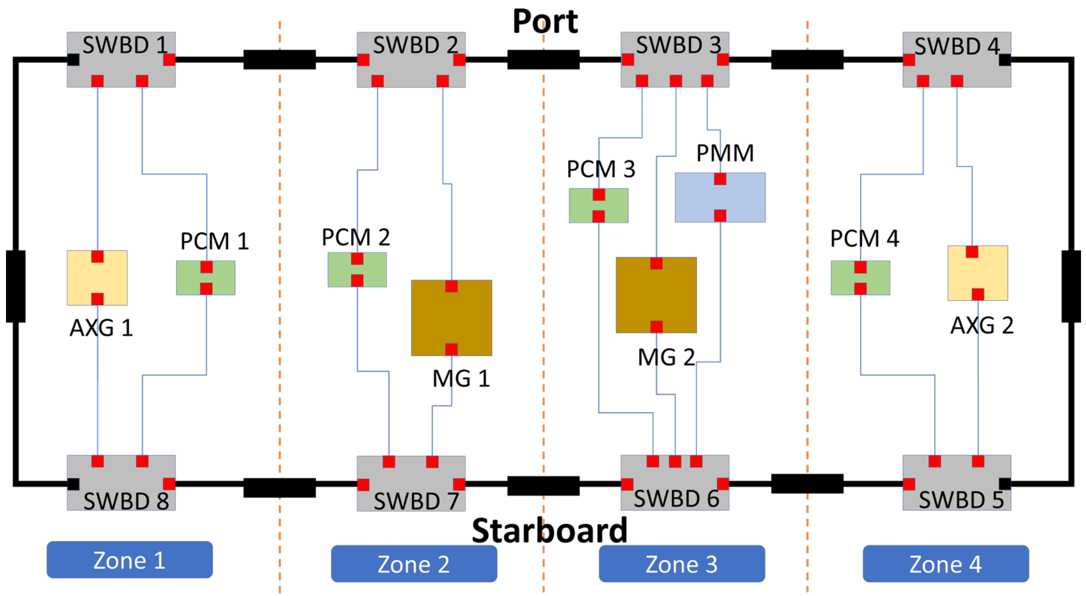
# Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

- **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.

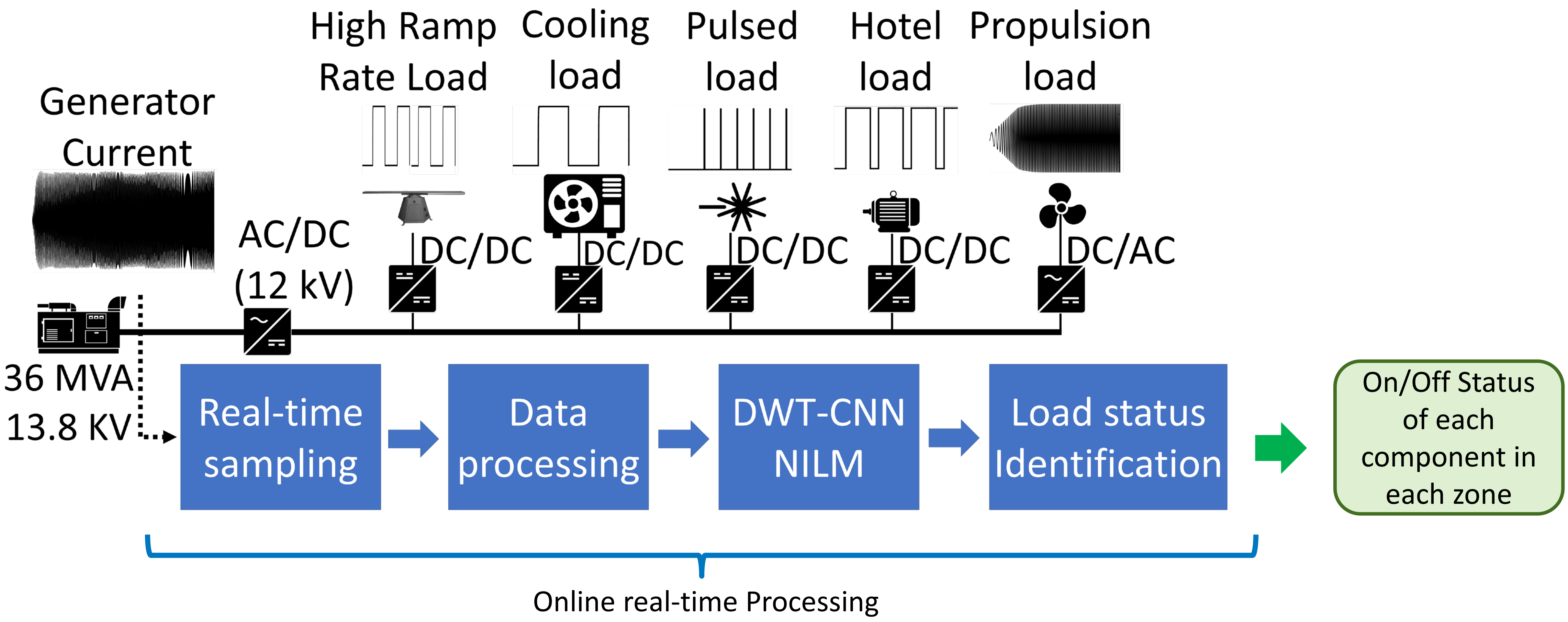
# Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

- 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.

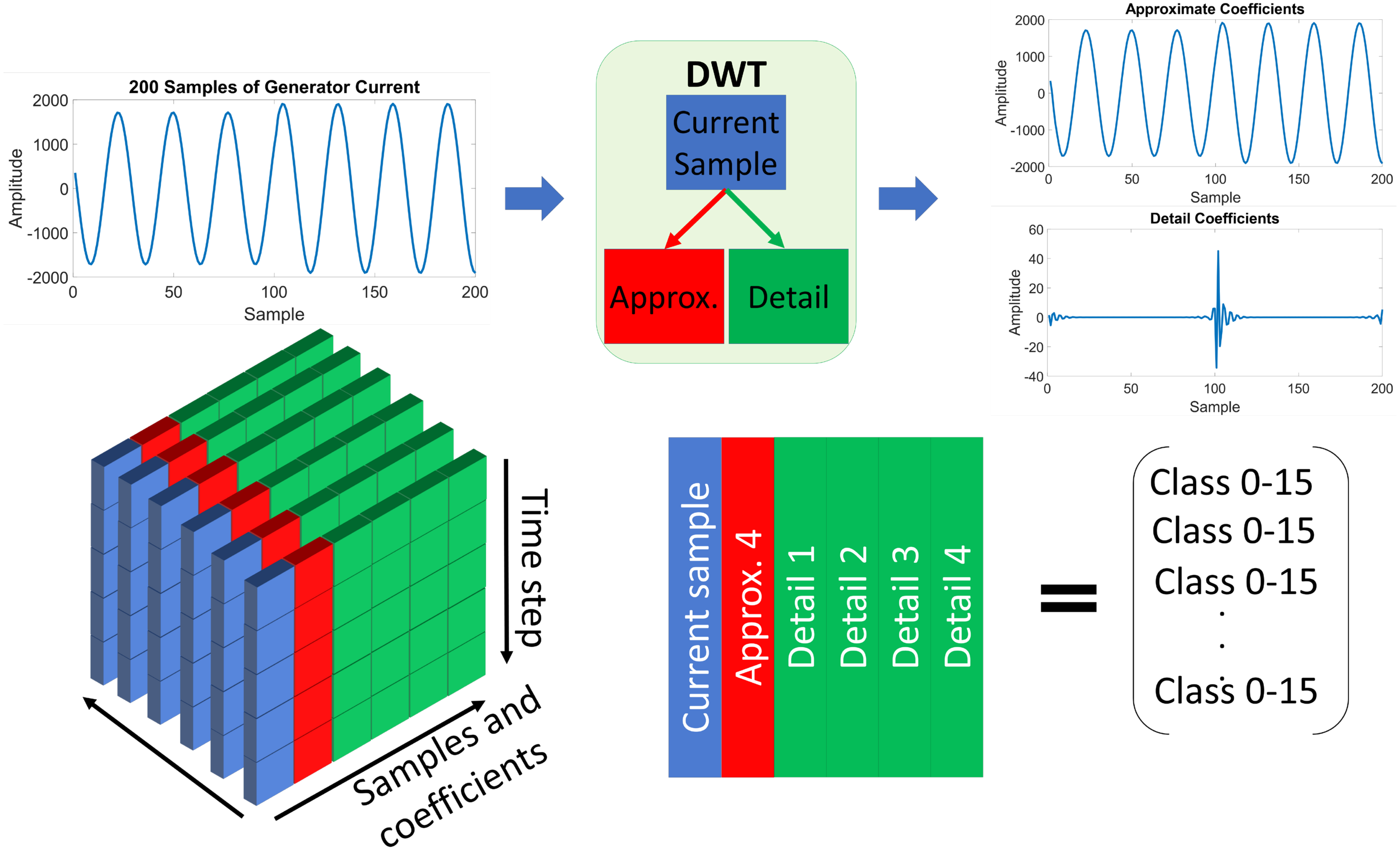


# Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands



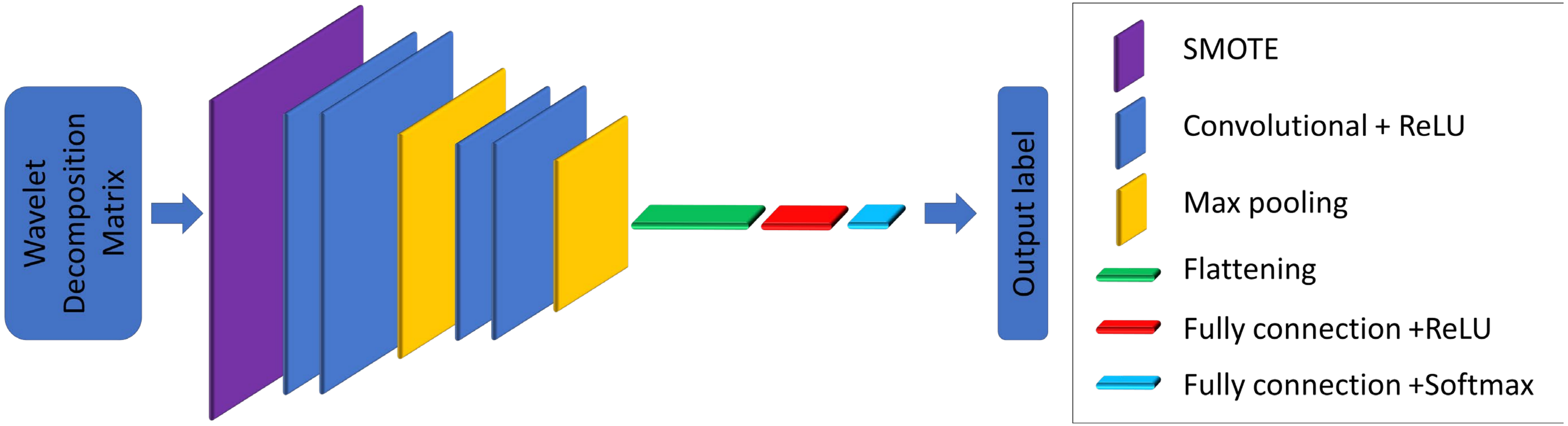
# Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands



# 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.

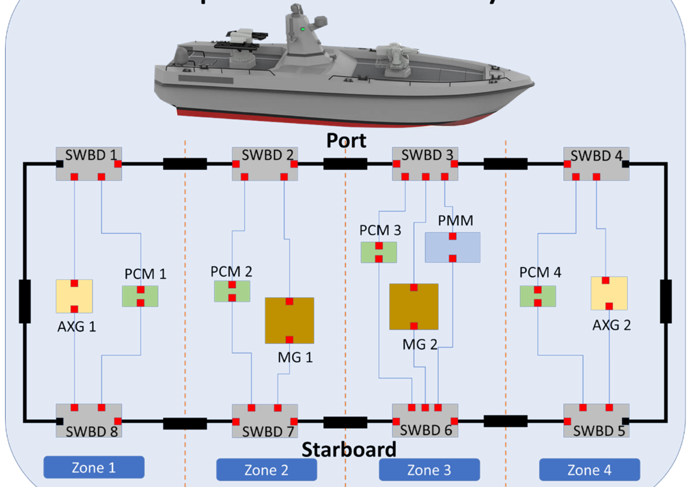
$$Y_j^l = f\left(\sum_{s\in M_{j(l-1)}} \sum_{(u,v)\in K^{(l)}} W_{js(u,v)}^{s}\, x_s^{(l-1)}(c+u, r+u) + b_j^{(l)}\right), \quad Y_j^l = down\left(Y_j^{(l-1)}\right), \quad o_j^l = f\left(\sum_{i=1}^{n} x_i^{(l-1)} w_j i^{(l)} + b_j^{(l)}\right)$$



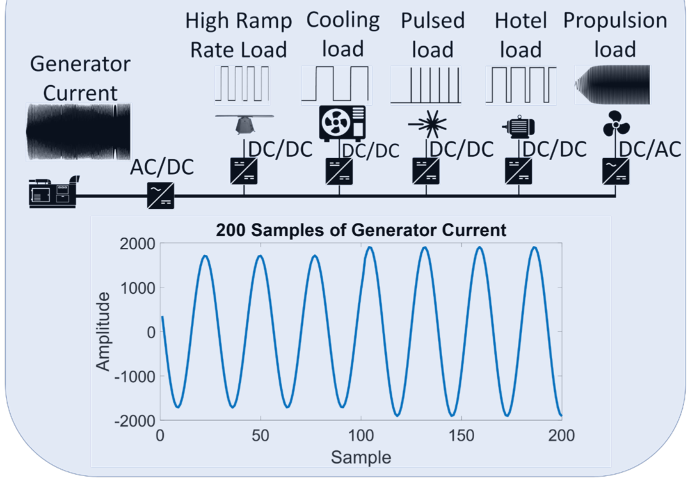

SPS MVDC model → Load Variation scenarios are simulated → Wavelet transform for feature extraction → Deep learning models to classify the current signal → Different load disaggregation

# Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

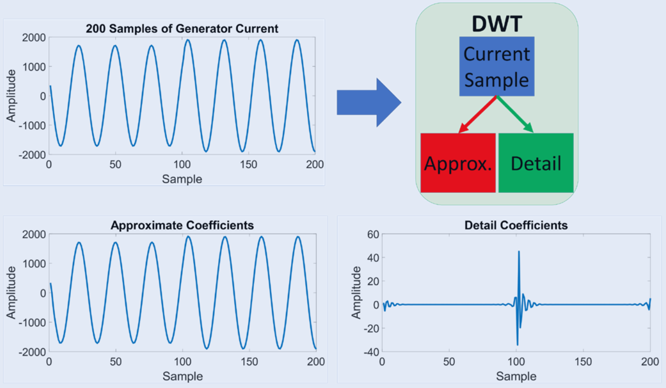
## 1- Shipboard Power System



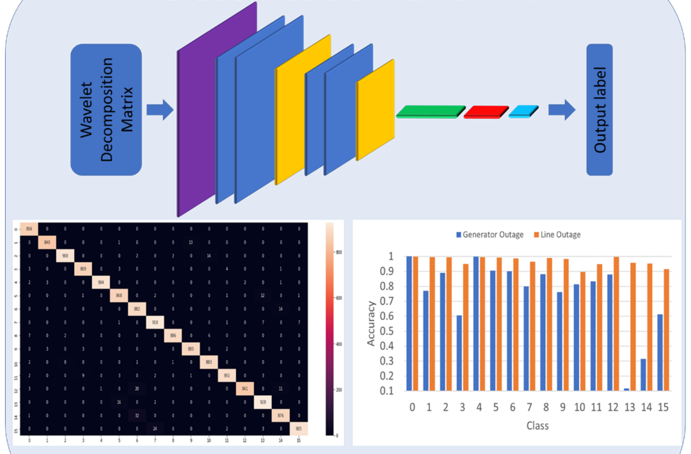

## 2- Sampling and Measurement




## 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)**

| Model | Training Accuracy | Testing Accuracy | Loss |
|---|---|---|---|
| Wavelet-DNN | 52.42 | 51.96 | 1.199 |
| Wavelet-LSTM | 82.3 | 78.96 | 0.455 |
| Wavelet-CNN | 90.08 | 89.23 | 0.241 |

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

| Model | Training Accuracy | Testing Accuracy | Loss |
|---|---|---|---|
| Wavelet-DNN | 54.38 | 54.19 | 1.66 |
| Wavelet-LSTM | 84.24 | 82.19 | 0.452 |
| Wavelet-CNN | 98.62 | 98.14 | 0.0437 |

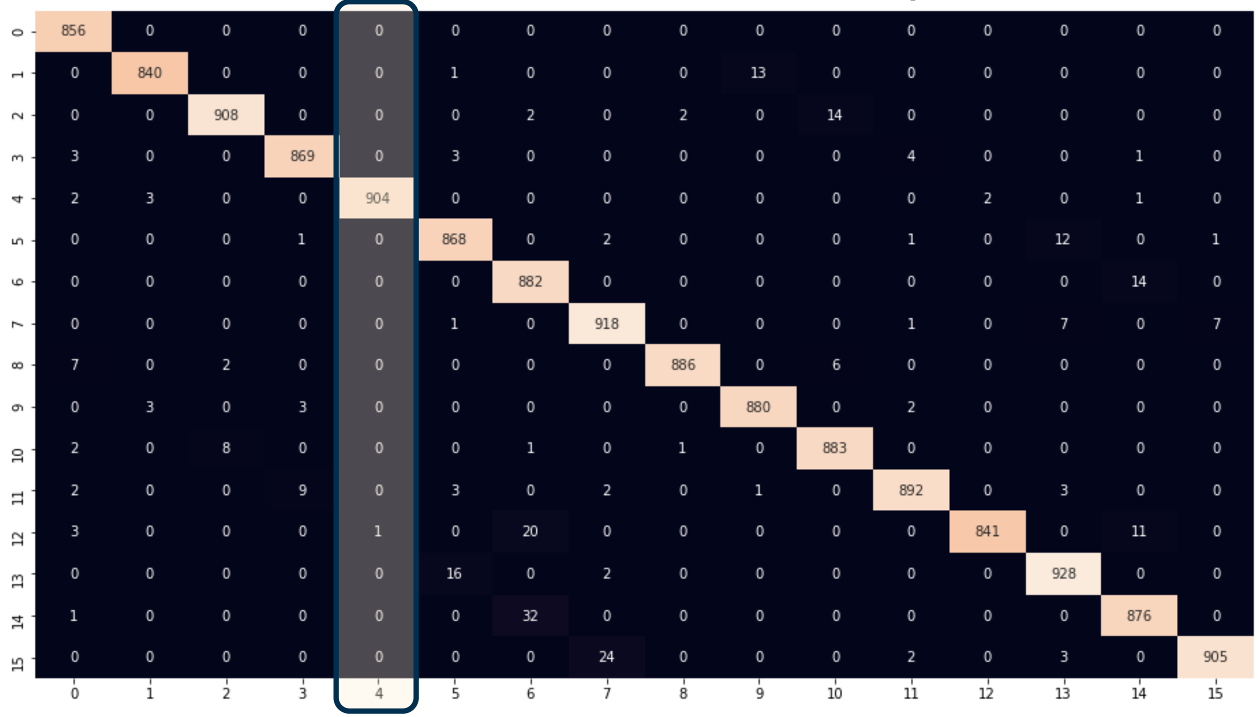
$$F1 = 2 \times \frac{precision \times recall}{precision + recall}$$

$$precision = \frac{TP}{TP + FP} \quad , recall = \frac{TP}{TP + FN}$$

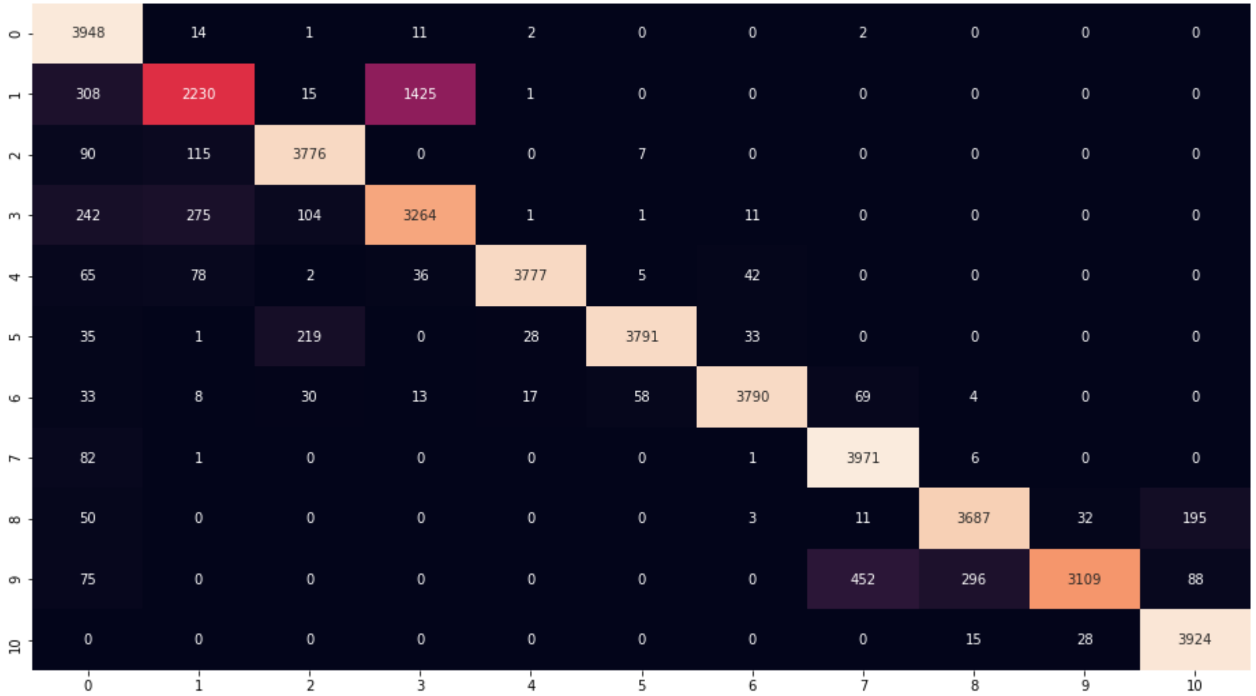
| Metric | Accuracy |
|---|---|
| F1-score | 99 |
| Precision | 98.5 |
| Recall | 99.6 |

# Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

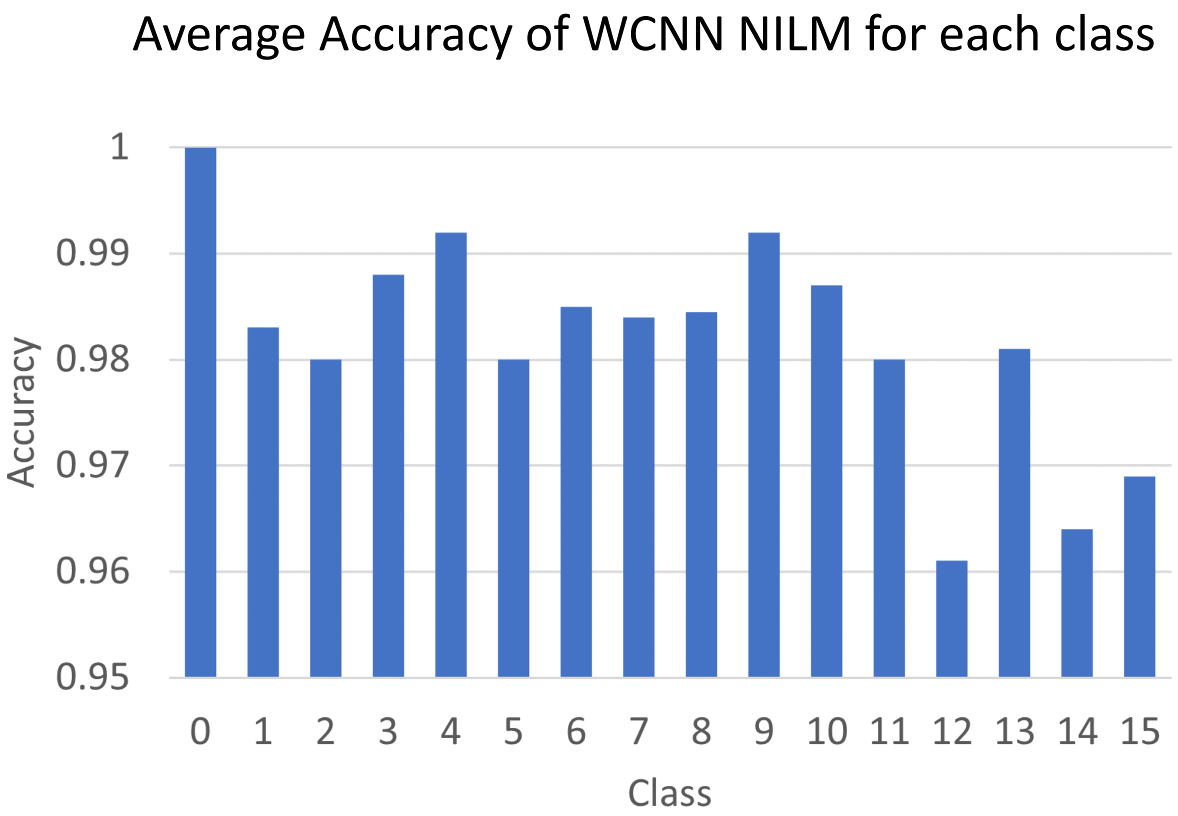
Confusion matrix for zonal components

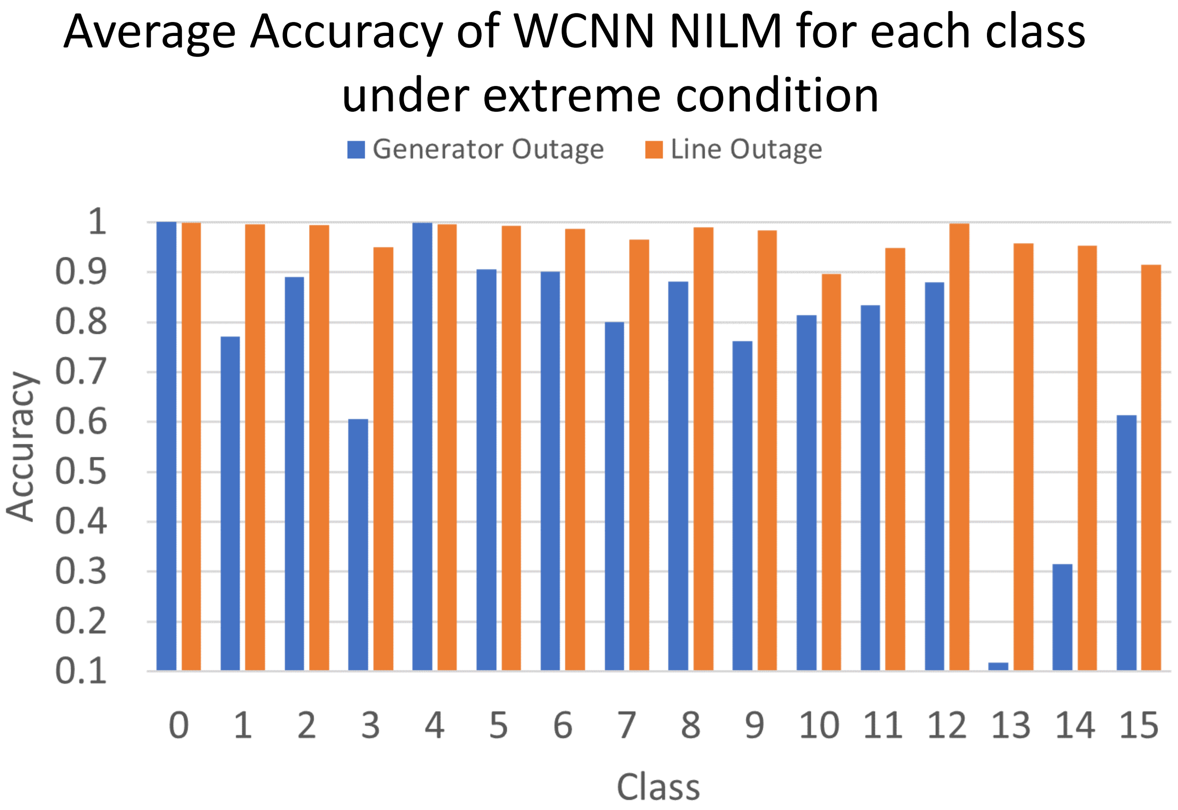



Confusion matrix for propulsion system



# Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands



# Research Thrust I: Monitoring and Tracking Navy Ship Electricity Demands

## Conclusion

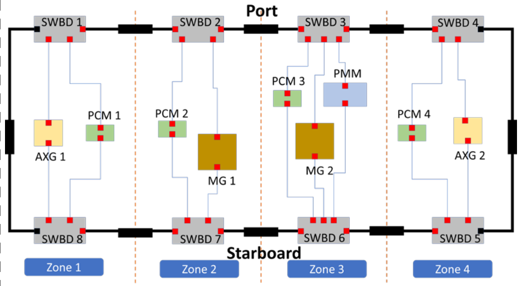
- Three deep learning-based models, including **Wavelet-DNN, Wavelet-LSTM, and Wavelet-CNN**, were developed for **non-intrusive load monitoring** in MVDC shipboard power systems.
- **Discrete wavelet transform** has a great capability to detect pulsed loads in aggregated current signals.
- The wavelet-CNN 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.

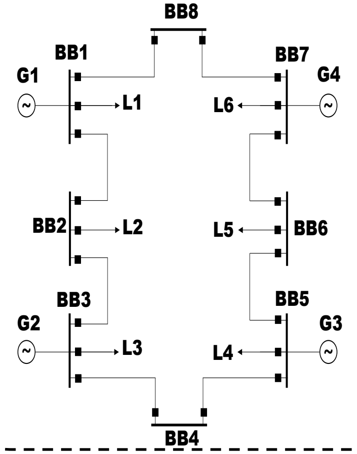
## Outcomes

- S. Senemmar and J. Zhang, "Non-intrusive Load Monitoring in MVDC Shipboard Power Systems using Wavelet-Convolutional Neural Networks," 2022 IEEE Texas Power and Energy Conference (TPEC), College Station, TX, USA, 2022, pp. 1-6, doi: 10.1109/TPEC54980.2022.9750745.
- S. Senemmar and J. Zhang, "Convolutional Wavelet Neural Network Based Non-Intrusive Load Monitoring for Next Generation Shipboard Power Systems," Engineering Applications of Artificial Intelligence Journal(Under Review).

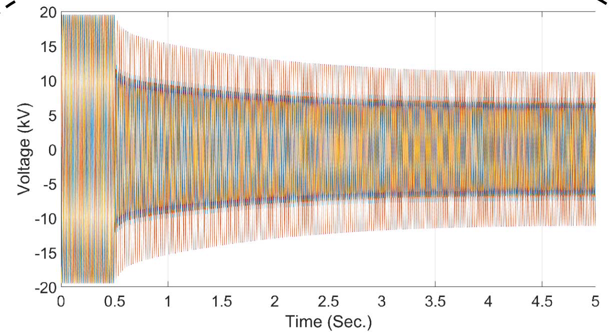
# Research Thrust II: Faults Detection, Isolation and Service Restoration

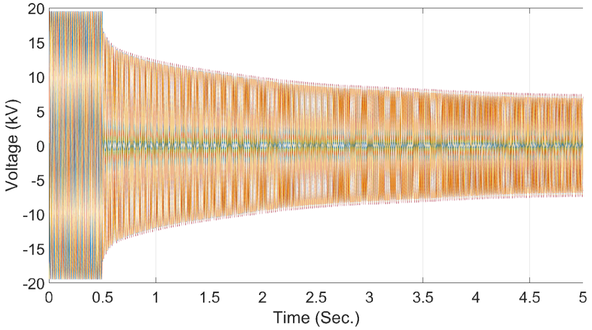
## SPS Model

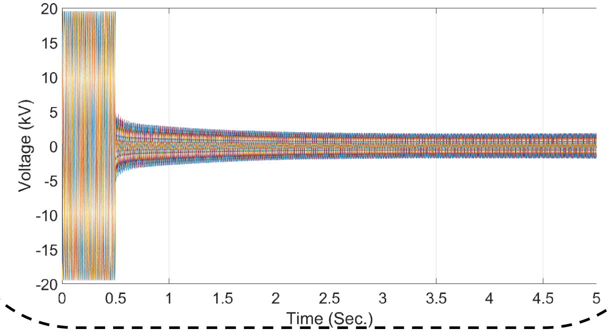


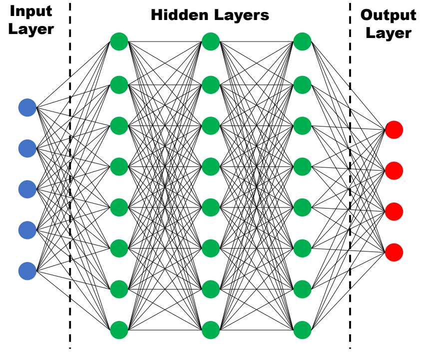

## Fault scenarios and simulations

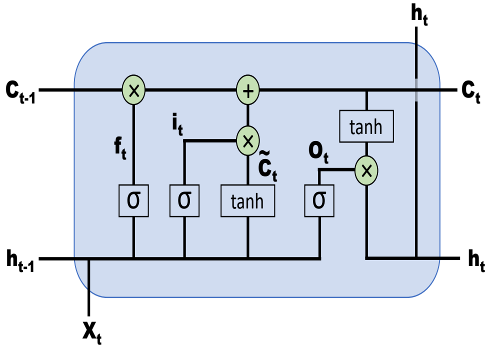


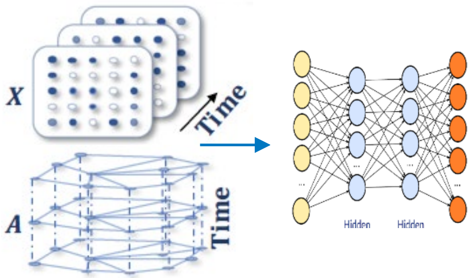




## Deep learning models



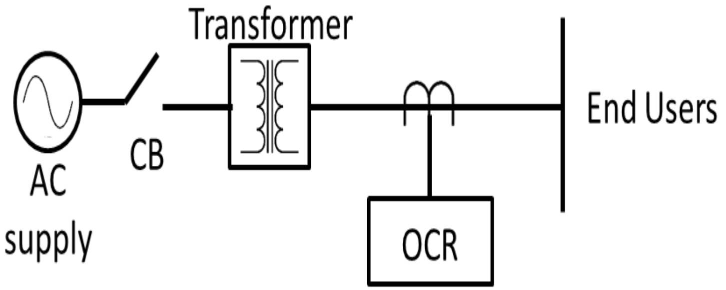




## Output

- No fault
- Fault
  - Type (SLG, LLG, 3LG)
  - Location (Busbar number)

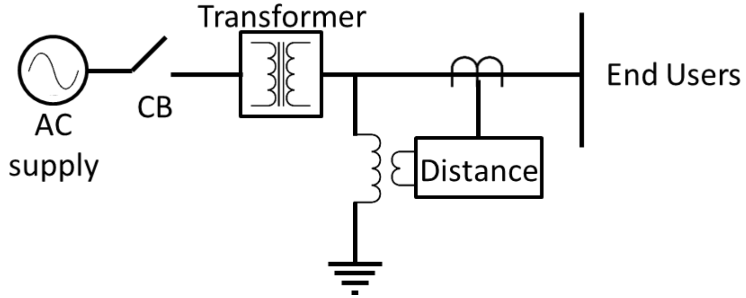
# Research Thrust II: Faults Detection, Isolation and Service Restoration

## Overcurrent protection



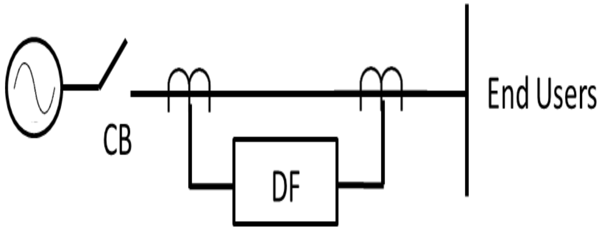

Accuracy≅85%, Fault Detection ✓
Classification and Location ✗

## Distance protection



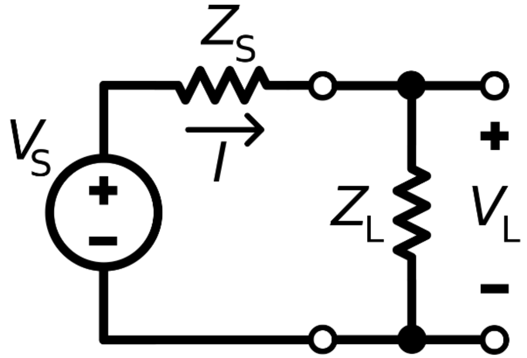

Accuracy ≅ 90%, Fault Detection and Location ✓, Classification ✗

## Current differential



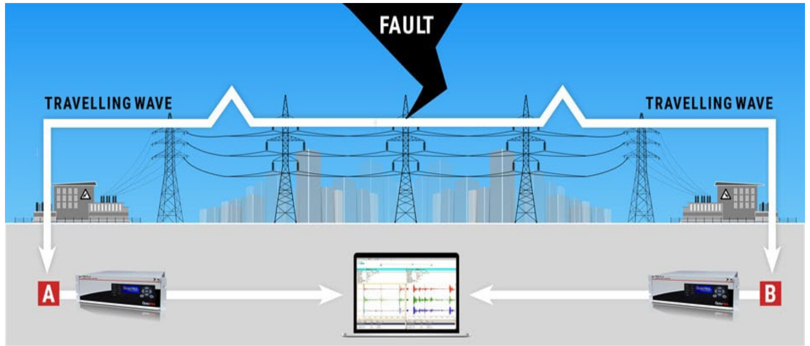

Accuracy ≅ 96%, Fault Detection ✓
Classification and Location ✗

## Active impedance estimation



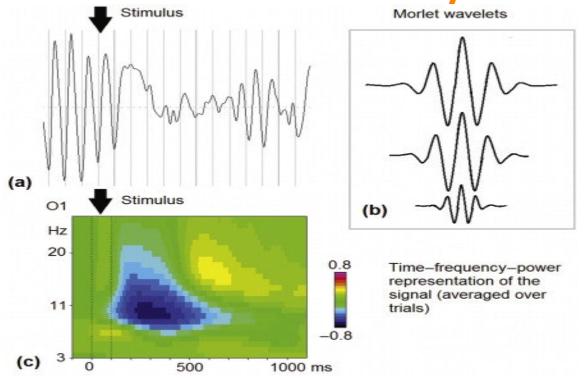

Accuracy ≅ 97%, Fault Detection and Location ✓, Classification ✗

## Traveling wave fault location[1]




Accuracy ≅ 97%, Fault Detection and Location ✓, Classification ✗

## Wavelet analysis

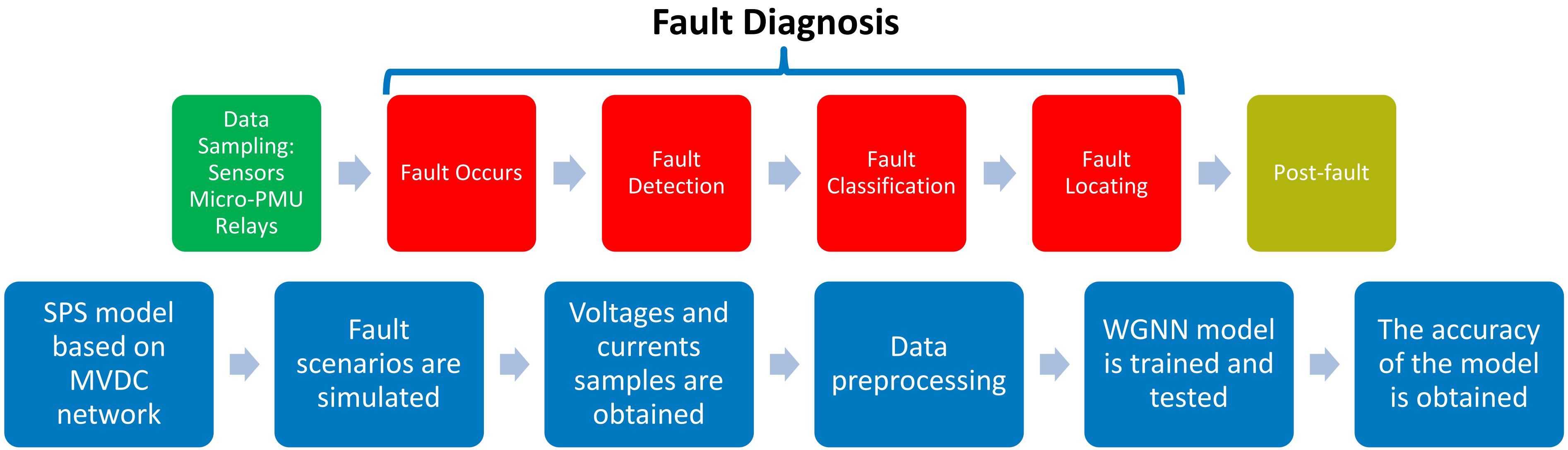



Accuracy ≅ 98%, Fault Detection, Classification and Location ✓

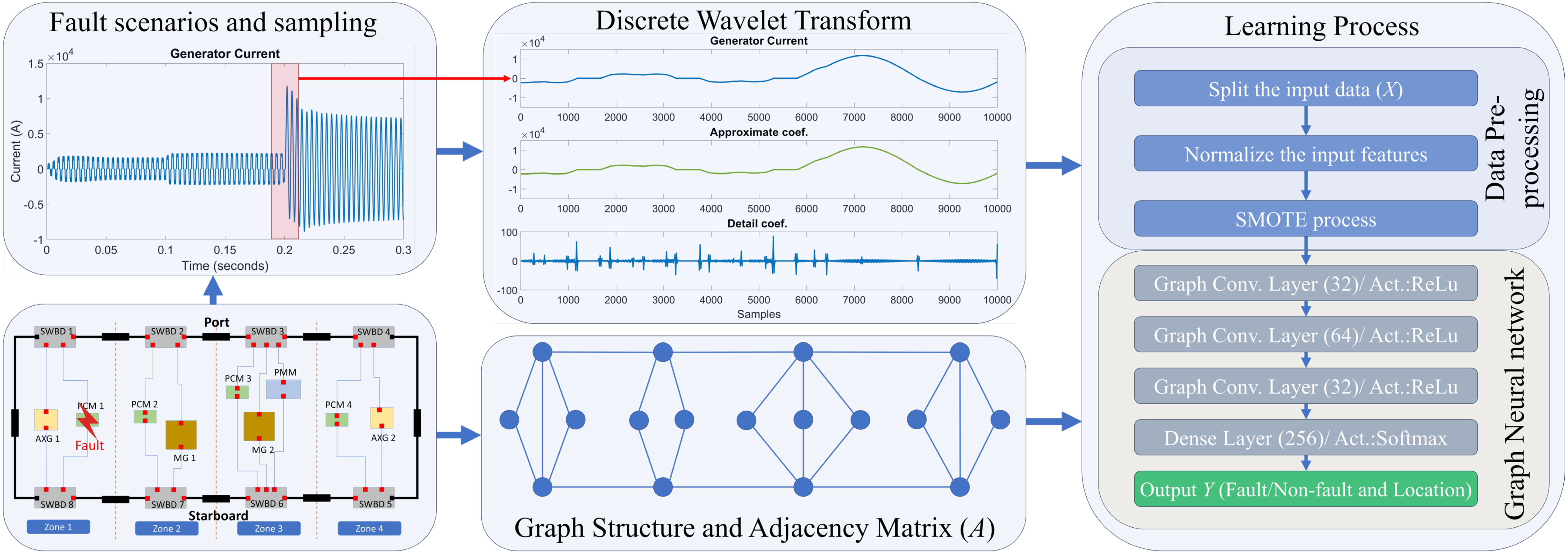
1 "What is Traveling Wave Fault Location? | Qualitrol Corp." 30 June 2021, www.qualitrolcorp.com/resource-library/blog/what-is-traveling-wave-fault-location.

# 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

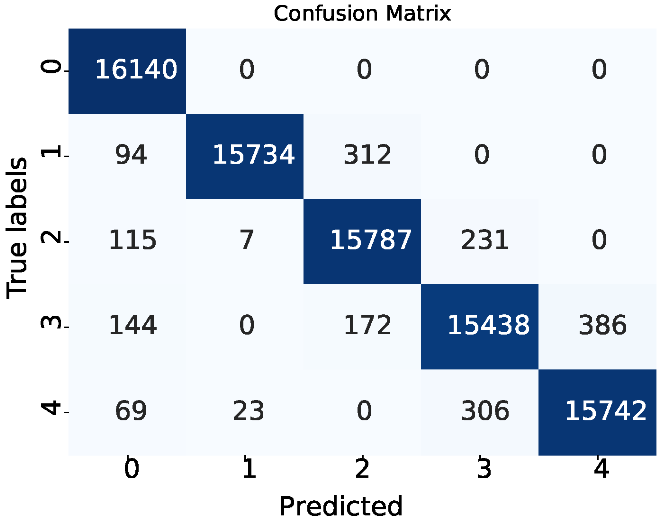


# Research Thrust II: Faults Detection, Isolation and Service Restoration

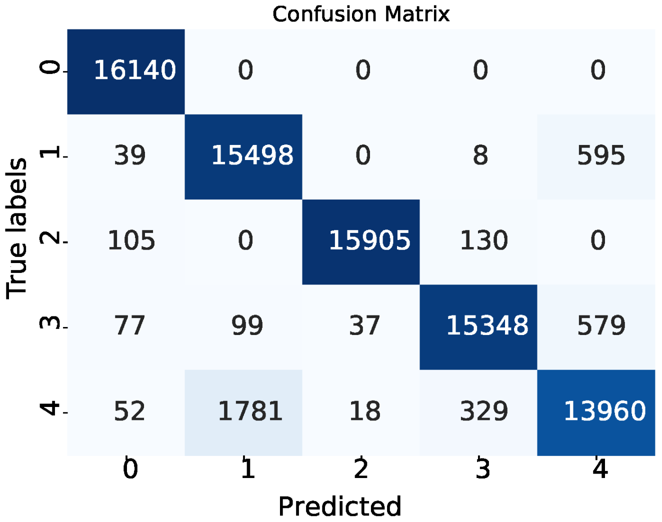
- **Case I:** Intrusive fault detection
- **Case II:** Non-intrusive fault detection
- **Case III:** Non-intrusive fault detection with pulsation load

| Case | Training Accuracy | Training Loss | Testing Accuracy | Testing Loss |
|---|---|---|---|---|
| **Case I** | 99.99% | 0.225e-4 | 99.99% | 7.01e-4 |
| **Case II** | 97.26% | 0.0851 | 97.70% | 0.0392 |
| **Case III** | 94.44% | 0.1392 | 95.23% | 0.1180 |

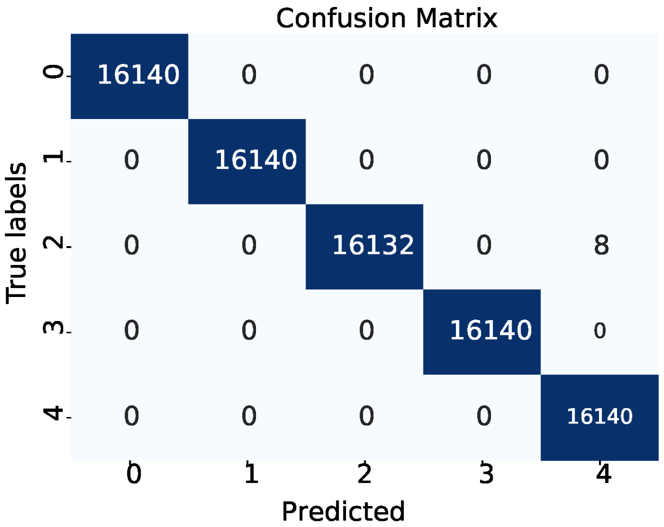
## Case I



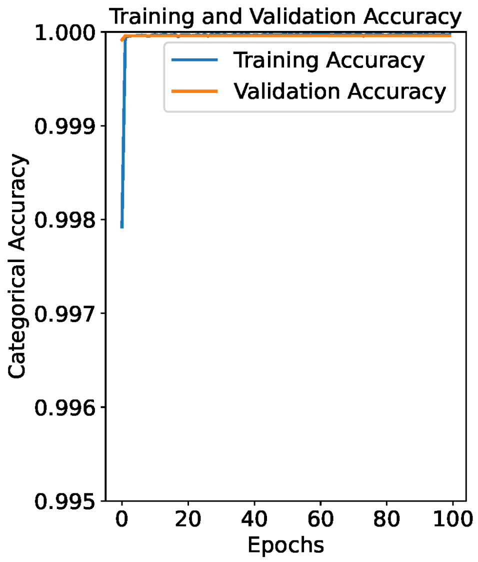

## Case II



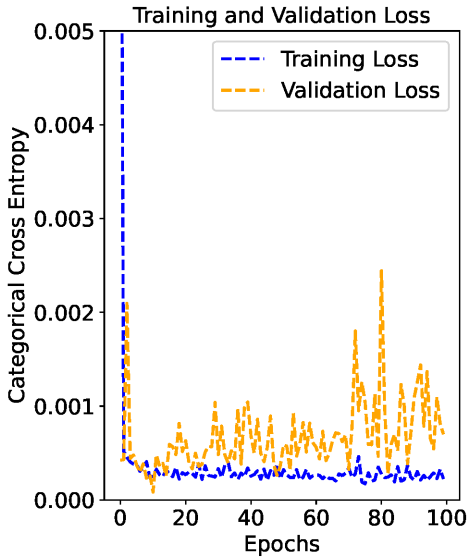

## Case III

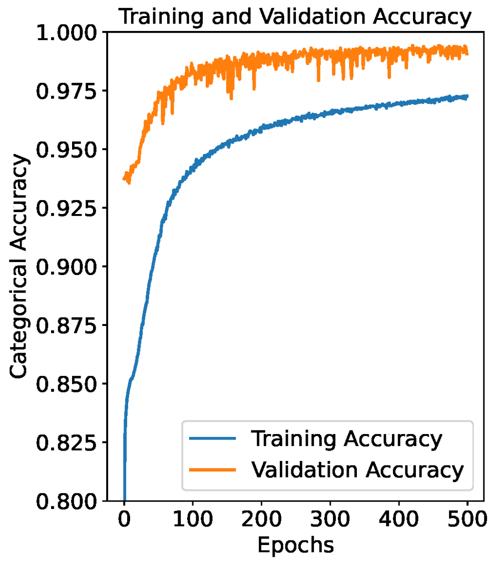


# Research Thrust II: Faults Detection, Isolation and Service Restoration

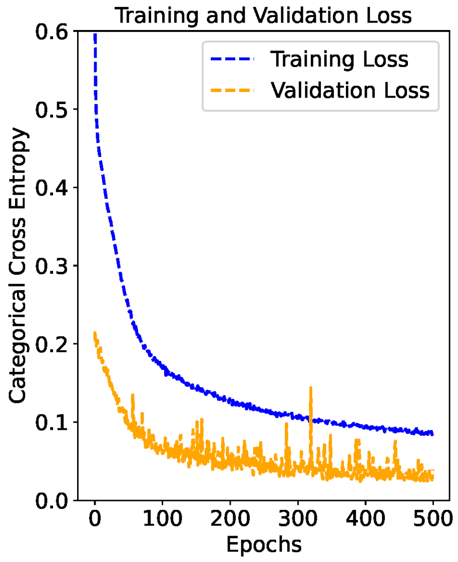


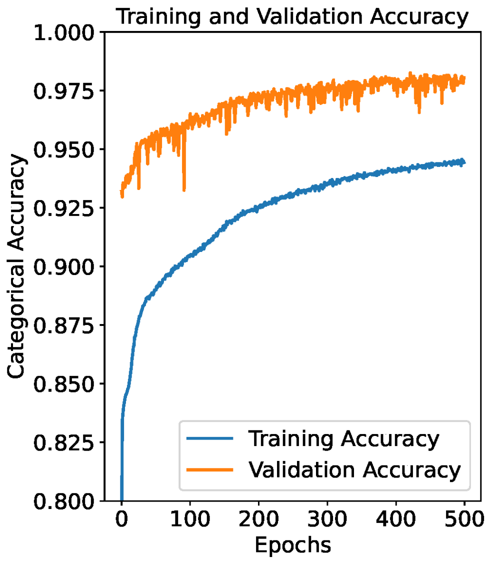

## Case I



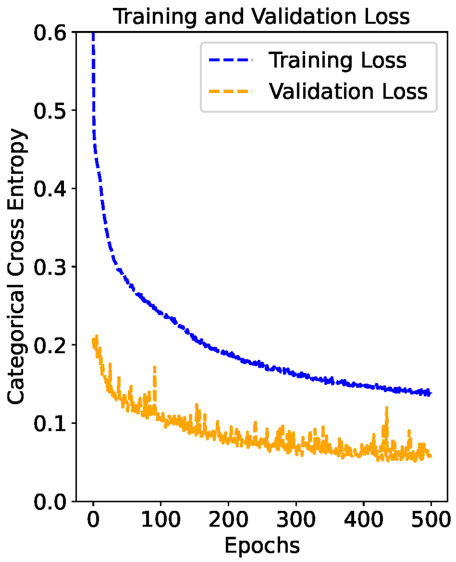



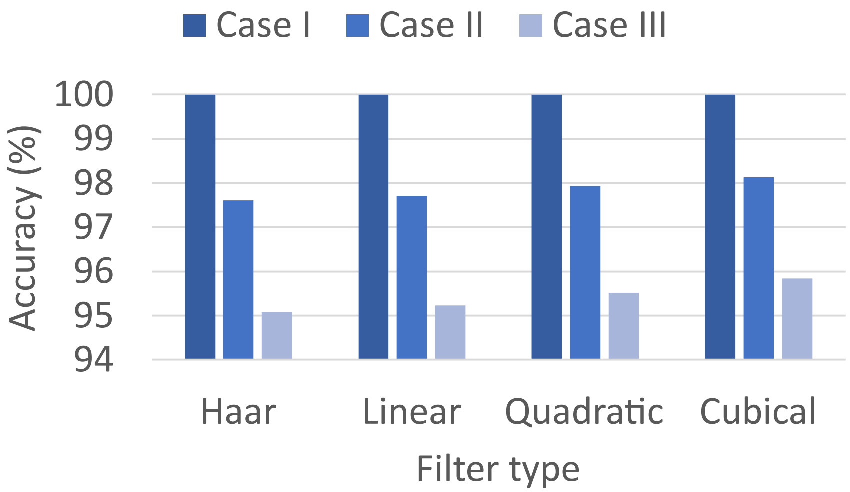

## Case II




## Case III




| Filter bank in WGNN | SNR (dB) | | | | |
|---|---|---|---|---|---|
| | -5 | -2 | 0 | 2 | 5 |
| Harr | 82.1% | 89.5% | 95.1% | 94.2% | 92.1% |
| Linear | 84.5% | 90.2% | 95.2% | 94.9% | 92.8% |
| Quad. | 85.1% | 89.8% | 95.5% | 95.2% | 92.5% |
| Cub. | 85.2% | 91.4% | 95.6% | 95.1% | 93.2% |

# Research Thrust II: Faults Detection, Isolation and Service Restoration

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

$$L_G = I - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \qquad (1)$$

$$L_G = \Theta \Lambda \Theta^T$$

**Normalized Laplacian and its eigen decomposition**

$$\mathbf{x} *_g \mathbf{U} = \mathcal{F}^{-1}(\mathcal{F}(\mathbf{x}) \circ \mathcal{F}(\mathbf{U})) \qquad (2)$$

$$= \Theta(\Theta^T \mathbf{x} \circ \Theta^T \mathbf{U})$$

**Graph convolution of the graph signal x with a filter U**

$$\mathbf{x} *_g \mathbf{U} = \Theta \mathbf{U} \Theta^T \mathbf{x} \qquad (3)$$

$$\mathbf{x} *_g \mathbf{U} = \sum_{k=0}^{K} \alpha_k H_k(\tilde{\lambda}) \mathbf{x} \qquad (4)$$

$$\Lambda = diag(e_0, e_1, e_2, .., e_{n-1}),$$

$$\tilde{\lambda} = 2\lambda / max(e_0, e_1, .., e_{n-1}) - I$$

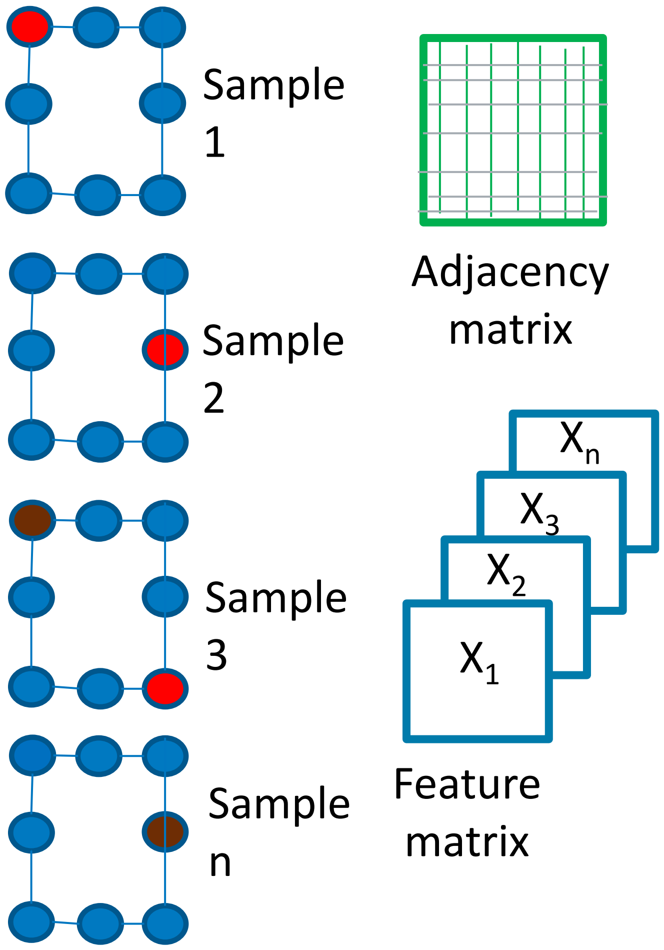
**First order approximated Chebyshev filter**

$$\boxed{\mathbf{x} *_g \mathbf{U} = \alpha(I + D^{-\frac{1}{2}} A D^{-\frac{1}{2}})\mathbf{x} \qquad (5)}$$

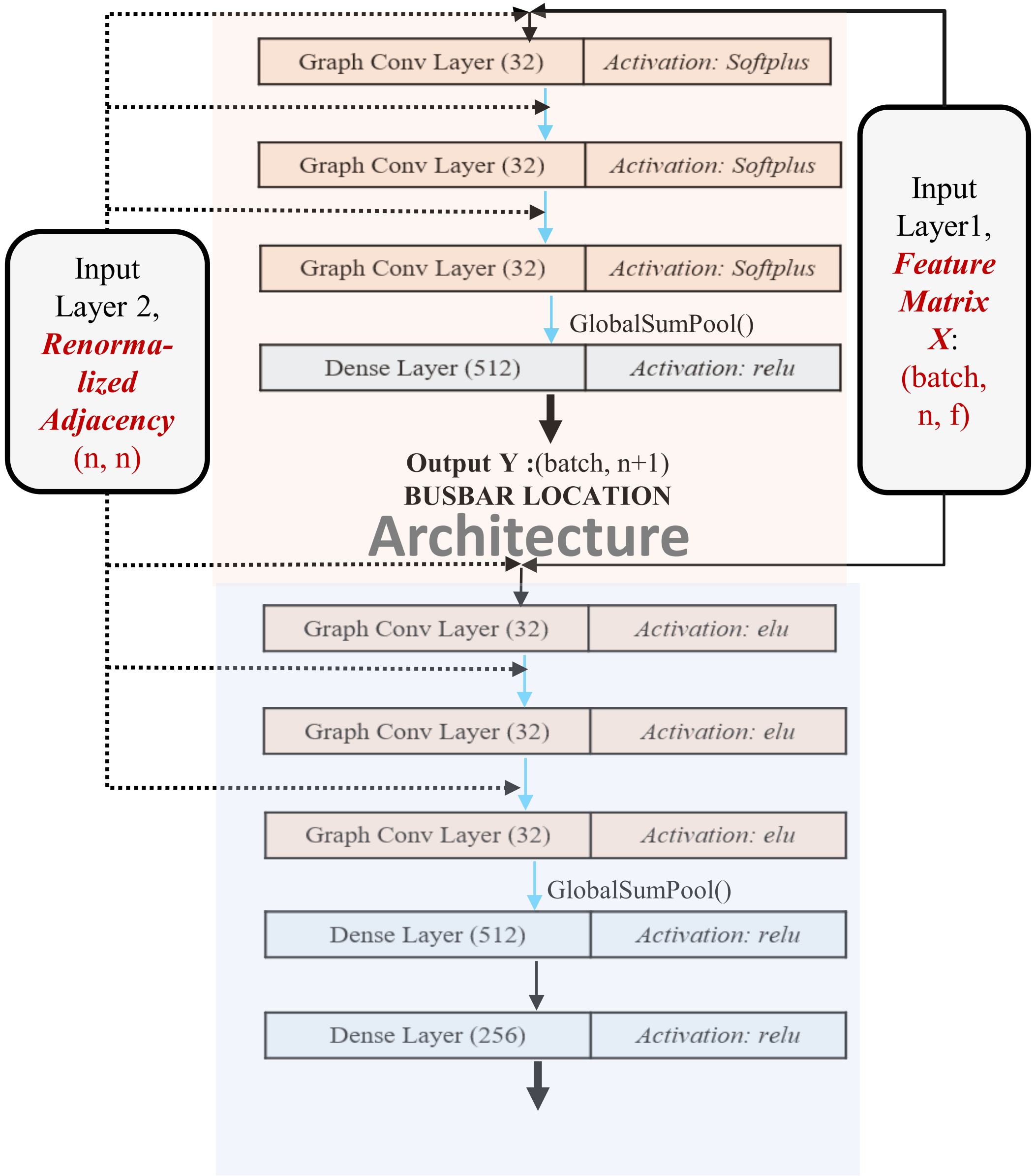
**Convolution of the graph signal in terms of A and x**

$$K = 1, \ \alpha_0 = -\alpha_1 = \alpha, \ max(e_0, e_1, .., e_{n-1}) = 2$$

- Graph: $\boldsymbol{G} = (\boldsymbol{N}, \boldsymbol{E})$
  - Adjacency matrix: $A \epsilon \mathbb{R}^{NXN}$
  - Feature matrix: $X \epsilon \mathbb{R}^{NXF}$



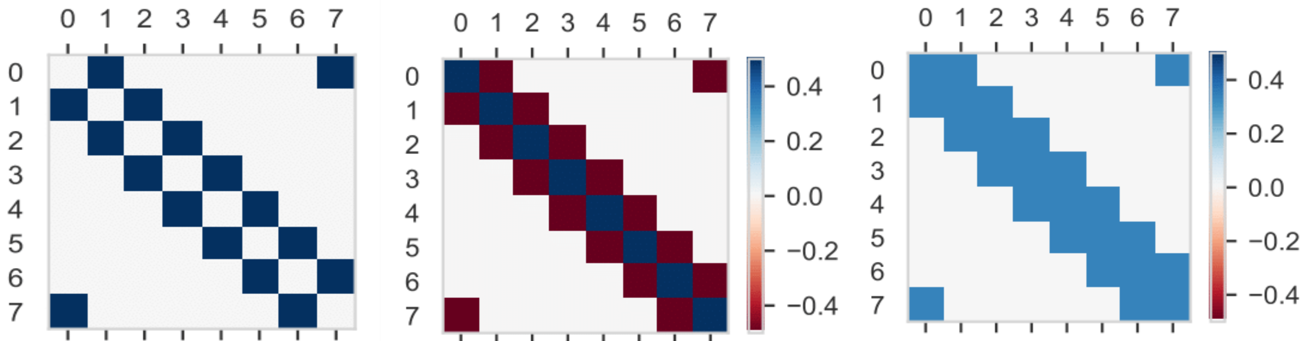
# Research Thrust II: Faults Detection, Isolation and Service Restoration




Architecture

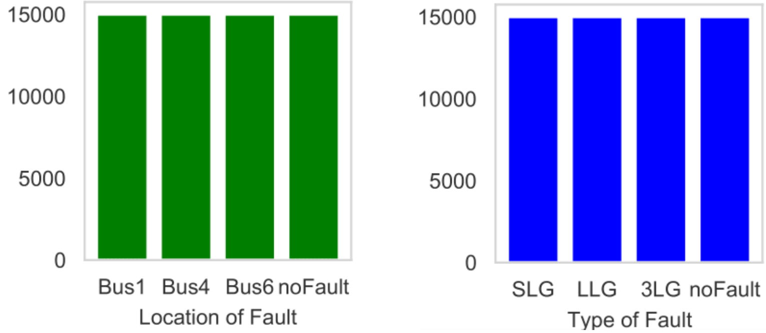
- The node attributes of the graph and the adjacency matrix are normalized.

$$\tilde{X}_k = \frac{X_k - \hat{X}}{max(X)} \quad (8)$$




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

Data Distribution



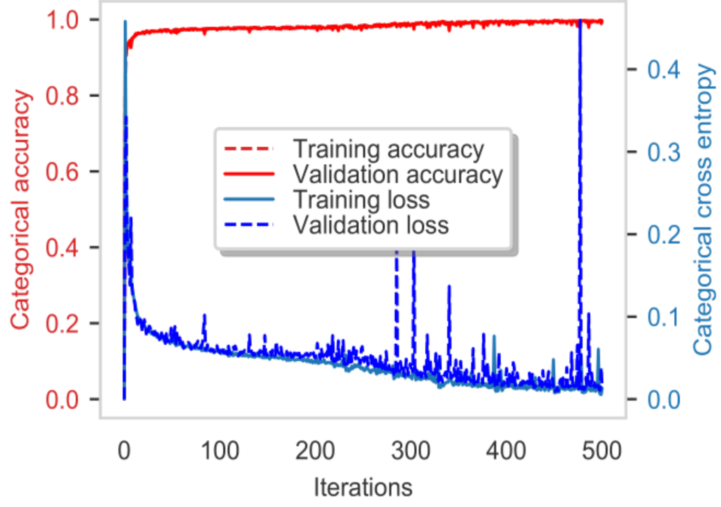
# Research Thrust II: Faults Detection, Isolation and Service Restoration

## Performance of the learning networks during Test phase

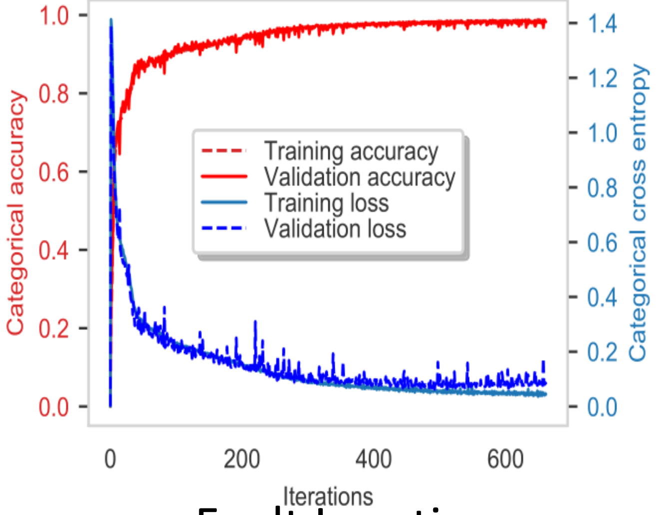
| Network | Categorical Accuracy | Categorical Loss |
|---|---|---|
| Fault Location | 99.38% | 0.027 |
| Fault Type and Detection | 99.75% | 0.015 |

| Model | Accuracy | | |
|---|---|---|---|
| | Fault Detection | Fault Classification | Fault Location |
| Proposed GCN model | 99.75% | 99.75% | 99.38% |
| Decision Tree | 97% | 85% | - |
| K-nearest neighbors | 90.4% | 90.4% | - |
| Fully-connected DNN | - | 99.58% | - |
| Differential Relay | 96% | - | - |

## Performance during Training



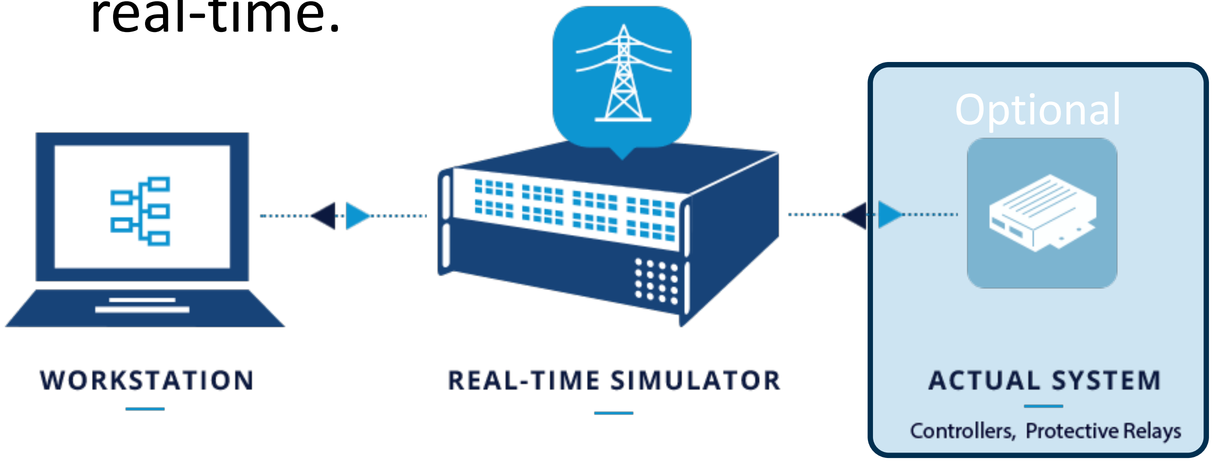

Fault Type




Fault Location

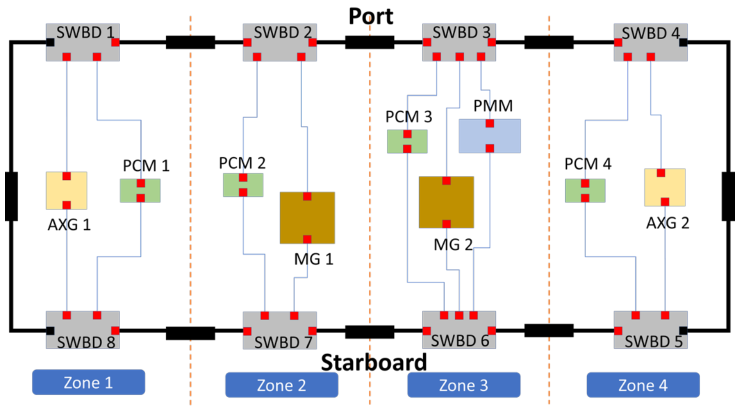
# Research Thrust II: Faults Detection, Isolation and Service Restoration

- 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.

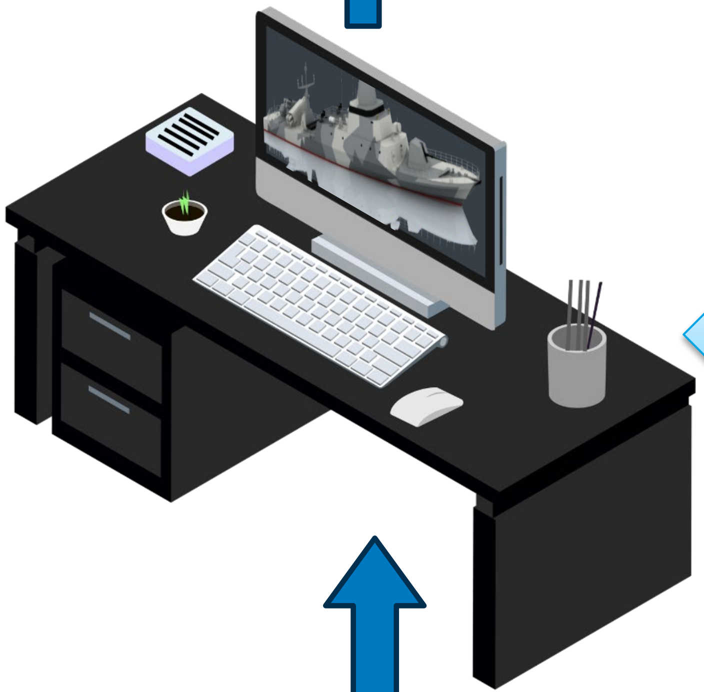



# Research Thrust II: Faults Detection, Isolation and Service Restoration

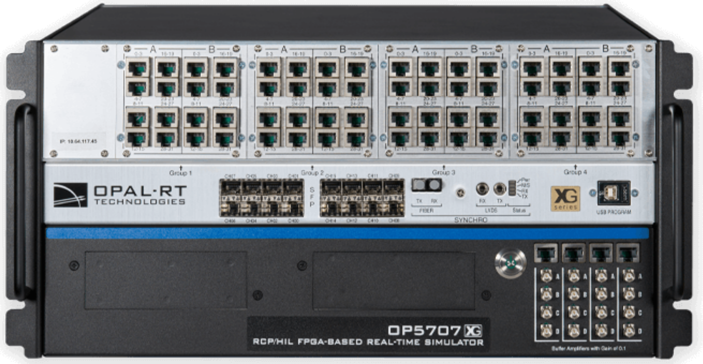
System modeling using Simulink MATLAB

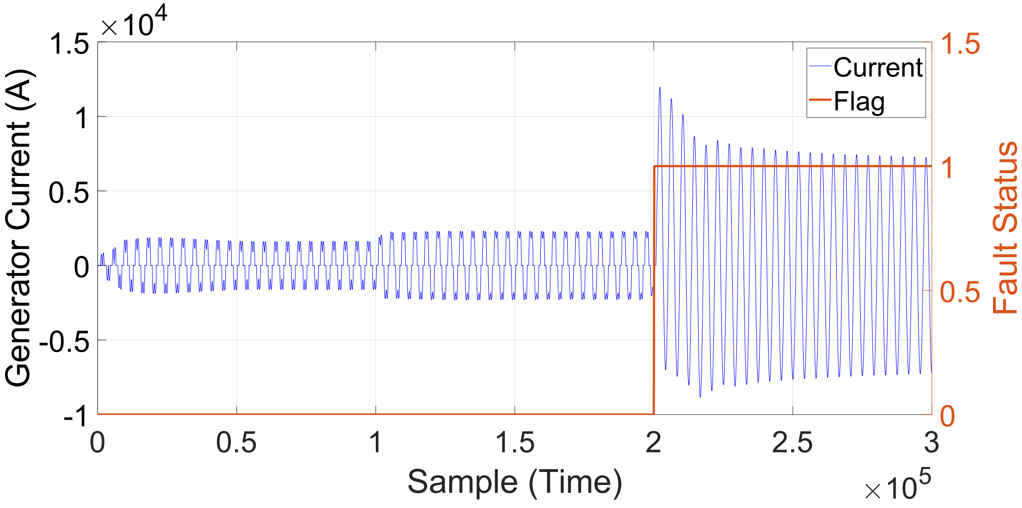



Converting simulation to C language and implement on the HIL



TCP/IP Communication

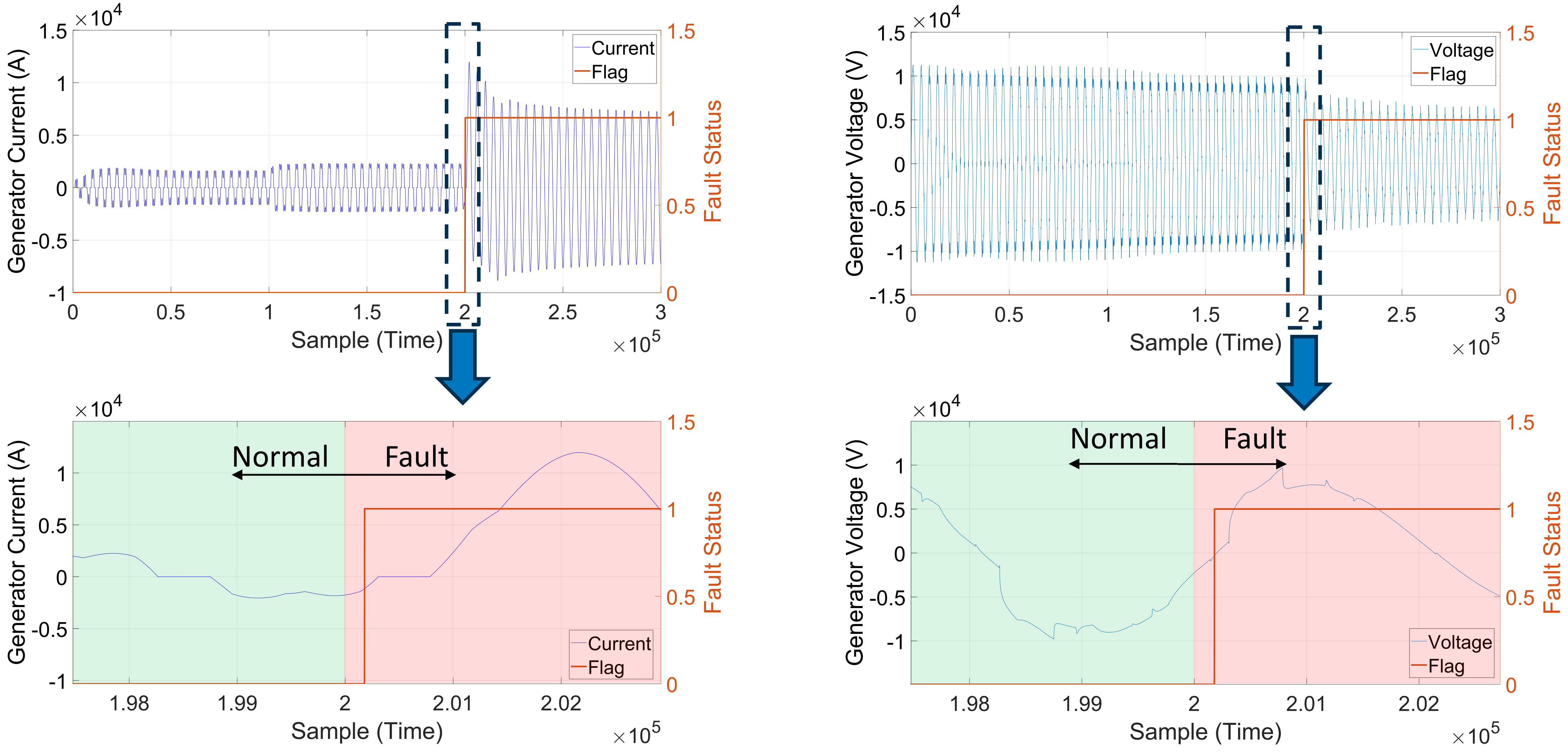



Sending the results to the monitoring console

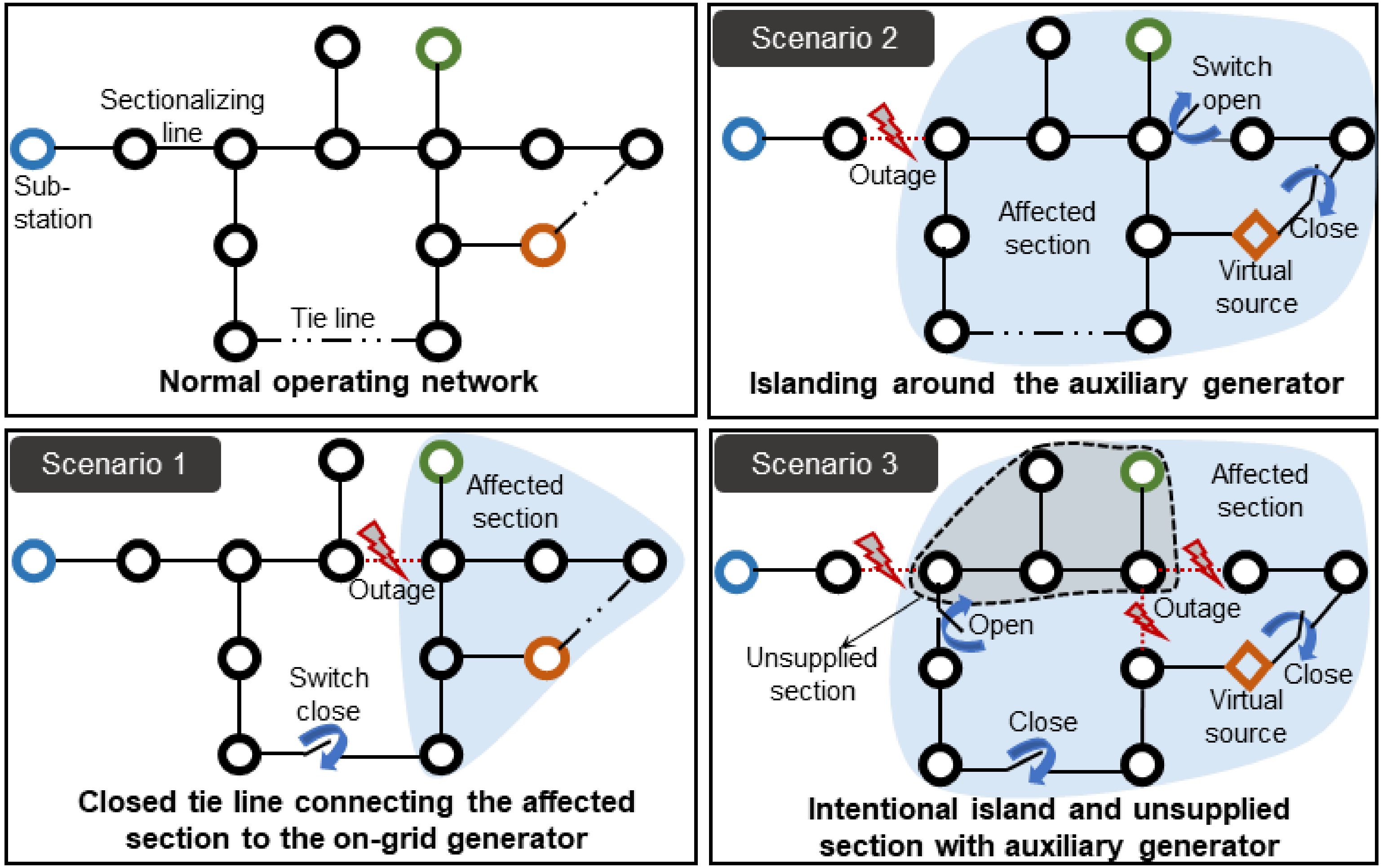
Simulating the real time response of physical system

# Research Thrust II: Faults Detection, Isolation and Service Restoration

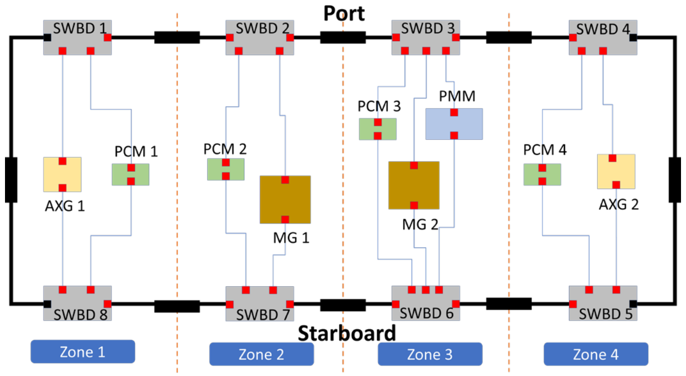


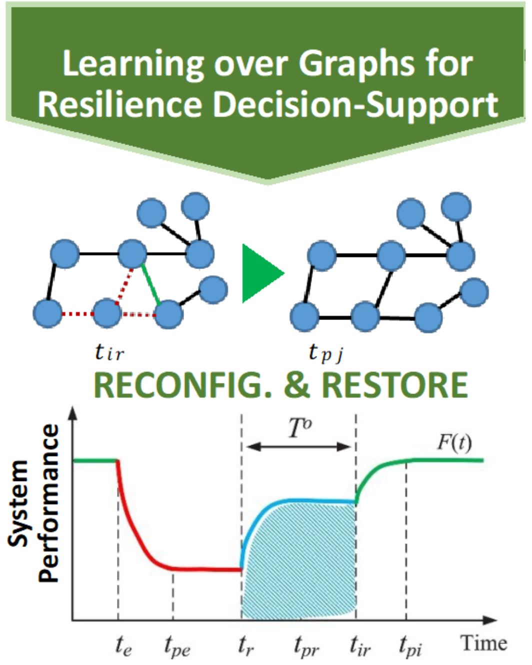
# Research Thrust II: Faults Detection, Isolation and Service Restoration

**Schematic of outage management in an example SPS network with main and auxiliary generators, and sectionalizing/tie switches.**




*The concept of learning over graphs*



# Research Thrust II: Faults Detection, Isolation and Service Restoration

## Learning Framework

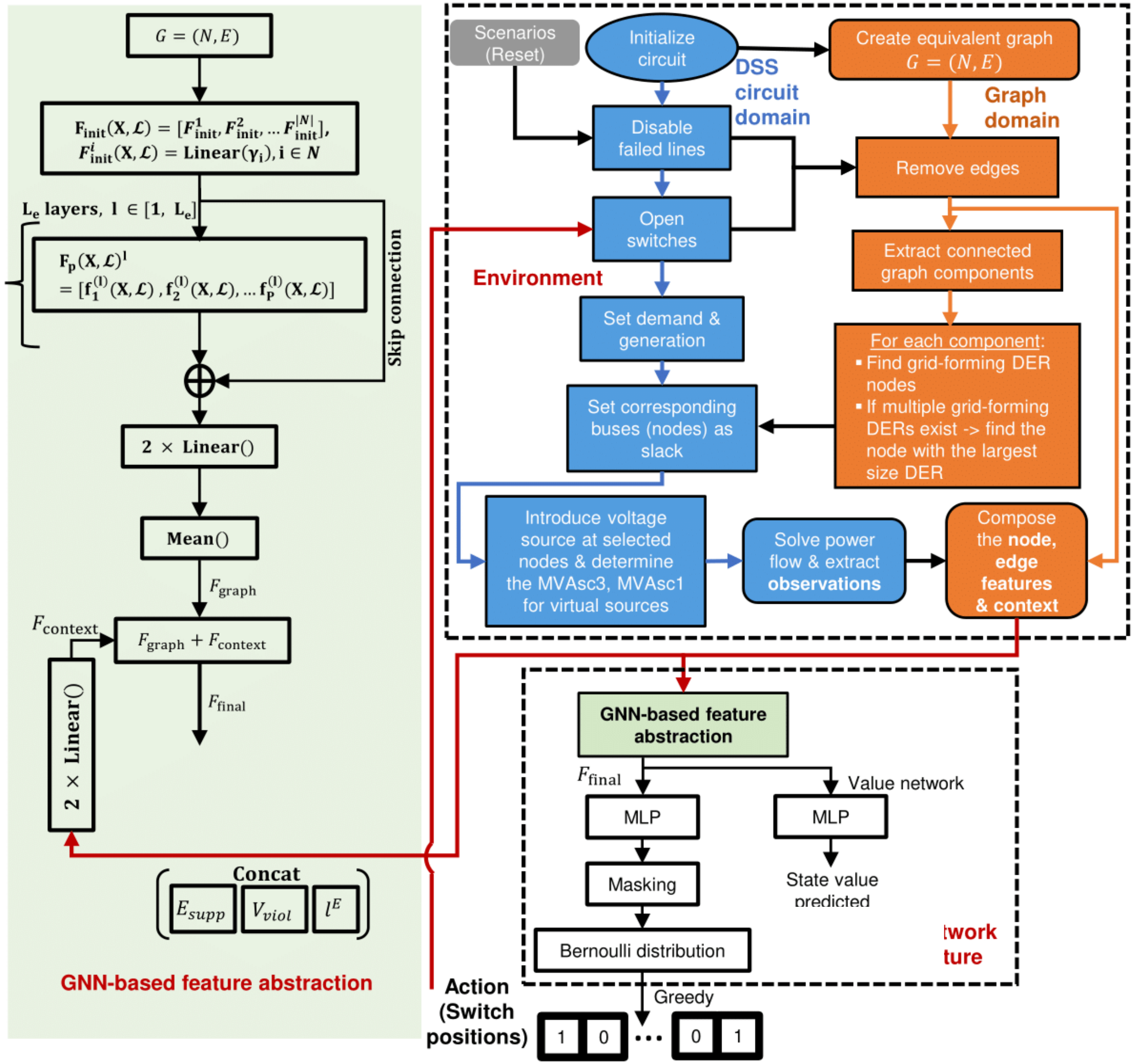
The shipboard power system is simulated using Simulink Matlab.

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 $\gamma_i = [P_d^i, Q_d^i, P_g^i, Q_g^i, V^i]$

Context $[E_{supp}, V_{\text{viol}}, l^E]$



# Research Thrust II: Faults Detection, Isolation and Service Restoration

## 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

- S. Senemmar and J. Zhang, "Deep Learning-based Fault Detection, Classification, and Locating in Shipboard Power Systems," 2021 IEEE Electric Ship Technologies Symposium (ESTS), Arlington, VA, USA,
- 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,
- S. Senemmar, R. A. Jacob and J. Zhang, " Non-Intrusive Fault Detection in Shipboard Power Systems using Wavelet Graph Neural Networks," Measurement Energy (to be submitted).

# Questions


multidisciplinary
design
optimization
linear system failure solar data cost engineering deformation statistical battery fidelity energy experiments optimum surrogate
learning evaluation reliability decomposition methodology
renewable mathematical stochastic algorithm
bounds illustration exploration minimization approximation displacement objective
complex equivalence uncertainty computing probabilistic criteria
metamodeling wind inequality nonlinear integer mining
bayesian gradient heuristic storage discrete machine power recursive structural loads value