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U.S. DEPARTMENT OF ENERGY

Hierarchical Machine Learning-based Optimal Parameterization Scheme for WECC Composite Load Model under All Disturbances

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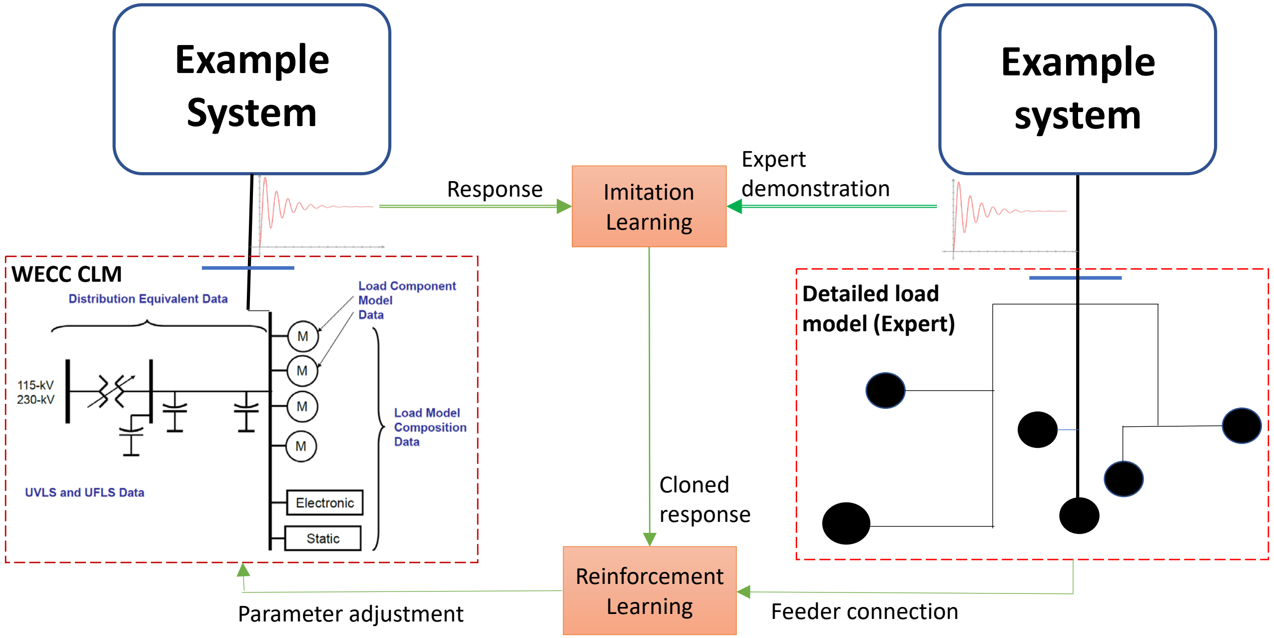
Background

- A large number of disparate load devices spread along with feeders of different structures
  - Voltage levels seen by individual loads during a fault event differ
  - Control and protection settings of individual dynamic loads can be different
- Current load modeling practices rely on field knowledge and experience based on only a limited number of disturbance and operating condition scenarios
  - Details of individual load devices at distribution levels are unavailable for modeling
  - Experience has shown that the CLM parameters carefully selected usually cannot achieve satisfactory performance in another fault

Proposed Solution

- An optimal parameterization scheme for the WECC CLM assisted by machine learning (ML) techniques including imitation learning (IL) and reinforcement learning (RL) based on
  - A simulation approach

  or
  - Unknown or very limited information about load devices in distribution feeders



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Technical Approach

- Verify and validate the performance of CLMs parameterized via an RL approach by
  - Building detailed load models in distribution feeders including protection, control, and fault ride-through functions
  - Generating training and validation datasets for transmission-originated disturbances
- Develop a practical solution to parameterizing CLMs based on real-world measurements only
- Develop alternative mathematical functions to CLM for modeling dynamic load

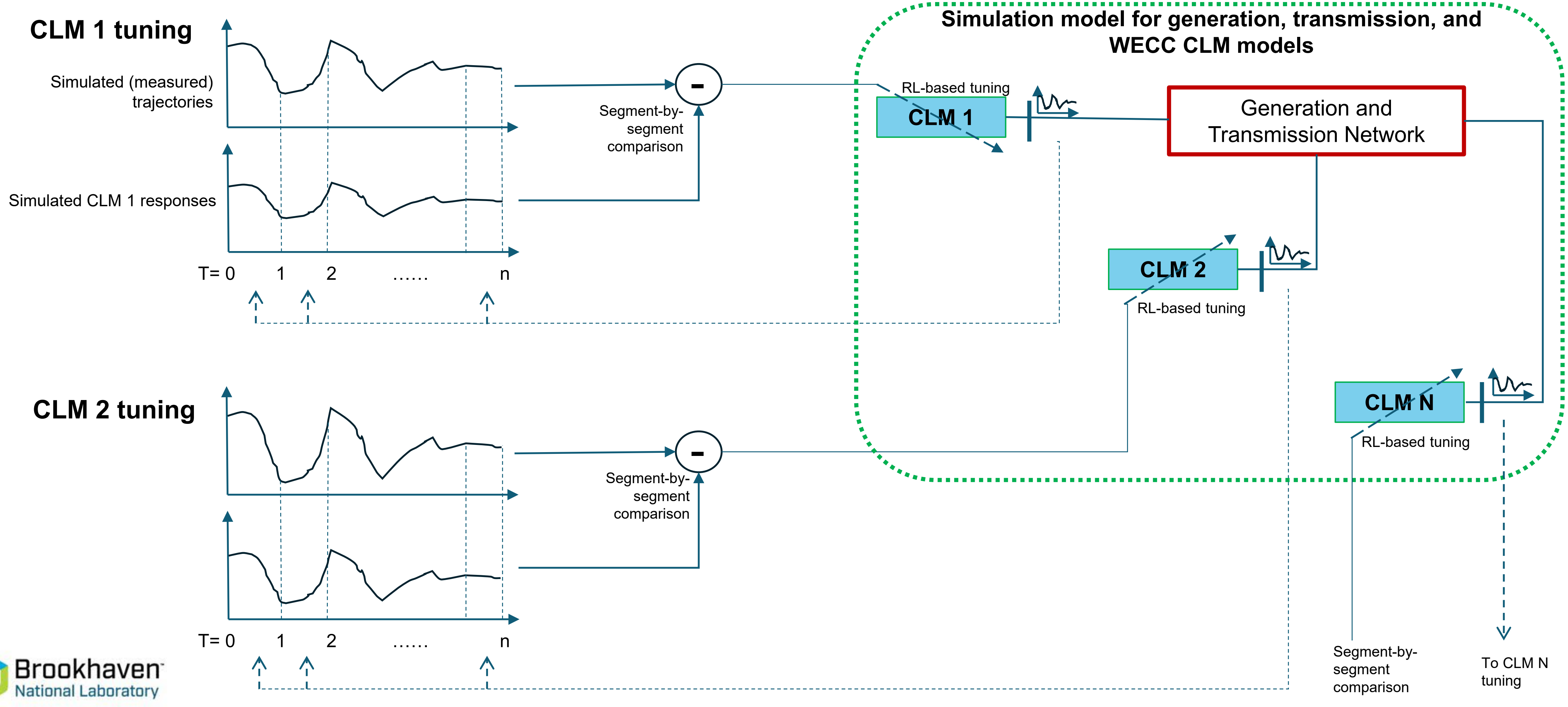
Problem Formulation and Assumptions

- Problem Statement:
  - Optimize CLM parameters for load devices in distribution feeders connected to a transmission substation (i.e., point of interconnection or POI) such that dynamic contingency analysis can be performed for the transmission network
- Assumptions:
  - Availability of details of individual load devices in distribution feeders for integrated T&D simulation

  or

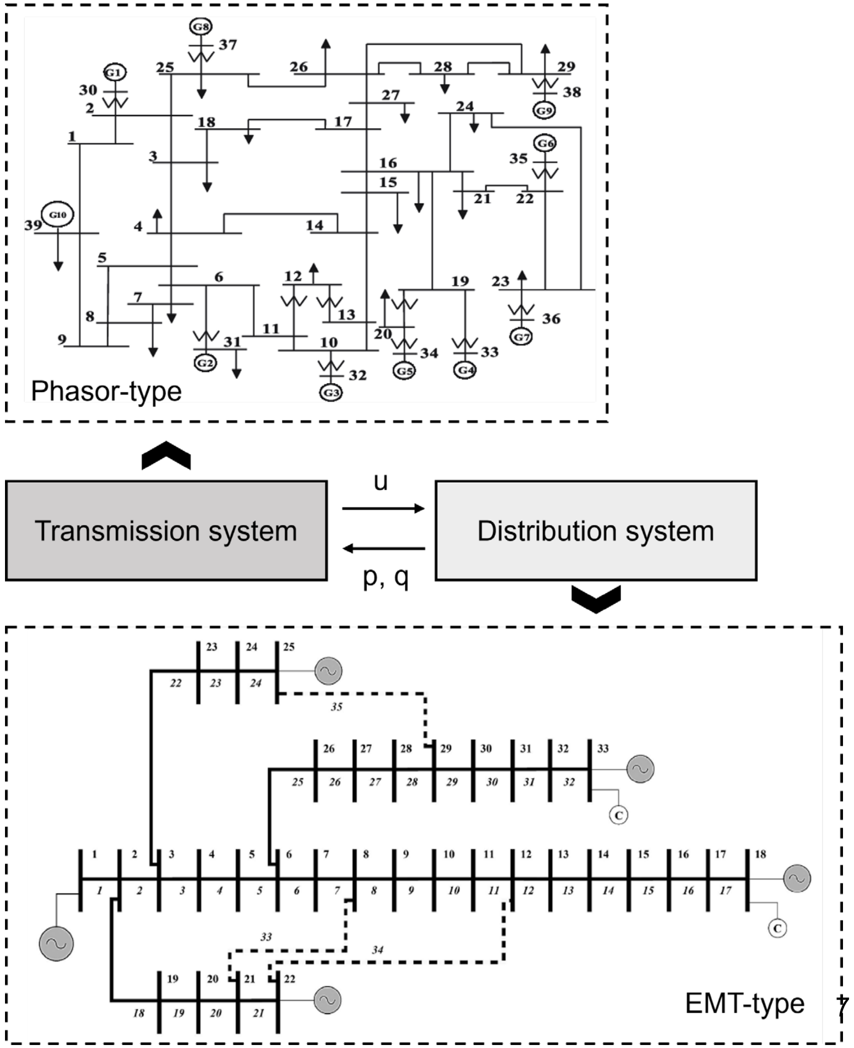
  - Availability of at least timestamped, post-disturbance dynamic responses at the POI of distribution feeders

CLM Parameterization Based on Simulated/ Measured Trajectories at POI



Technical Approach 1: RL-based CLM Parameterization based on Simulated Data

- Hybrid EMT-phasor type simulation platform of transmission and distribution system
  - Transmission system: IEEE 39-bus power system built by using ePHASORsim
  - Distribution system: modified IEEE 33-node test feeder of EMT-type
    - ➢ 10 constant impedance loads, 3 induction motor loads, 2 DERs, and 2 Variable Frequency Drives (VFDs)
    - ➢ Detailed modeling of protection and controls: fault ride-through, fault-induced delayed voltage recovery (FIDVR), etc.
  - Simulation condition: single-bus and two-bus faults, line outages
- RL-based CLM parameterization based on simulated data is ongoing



Technical Approach 2: CLM Parameterization Based on Measurements Only

- Motivation: Unknown details about the distribution load devices
- Challenges:
  - Challenge 1: Insufficient measurements under large disturbances
    - Solutions:
      - ✓ Measurement data under both large (e.g., faults) and small disturbances (e.g., load fluctuations)
      - ✓ Data augmentation via a generative model for rare events (large disturbances)
  - Challenge 2: Complexity of RL-based CLM parameter tuning
    - Solutions:
      - ✓ Load decomposition to categories of individual load models in CLM (i.e., Motor, Static, etc.
      - ✓ Tune parameters of individual models in CLM using the corresponding category data of load

Technical Approach 2: Time-series diffusion model: Diffwave

- Inspired by non-equilibrium thermodynamics, a diffusion model defines a Markov chain of diffusion steps
  - In forward process, Gaussian noise is gradually added
  - In reverse process: denoise the data to get real distribution
- The neural network (NN) takes a noised data sample as input and outputs the predicted noise.
  - Data collection: Multi-state trajectories under different faults
  - Training: Noised samples are used to train the NN by optimizing the variational bound on negative log-likelihood
    - A desired trajectory is also input to the conditioner to implement conditional generation
  - Sampling: Pure noise is sampled gradually and denoised with the trained NN to generate trajectories with the desired characteristics

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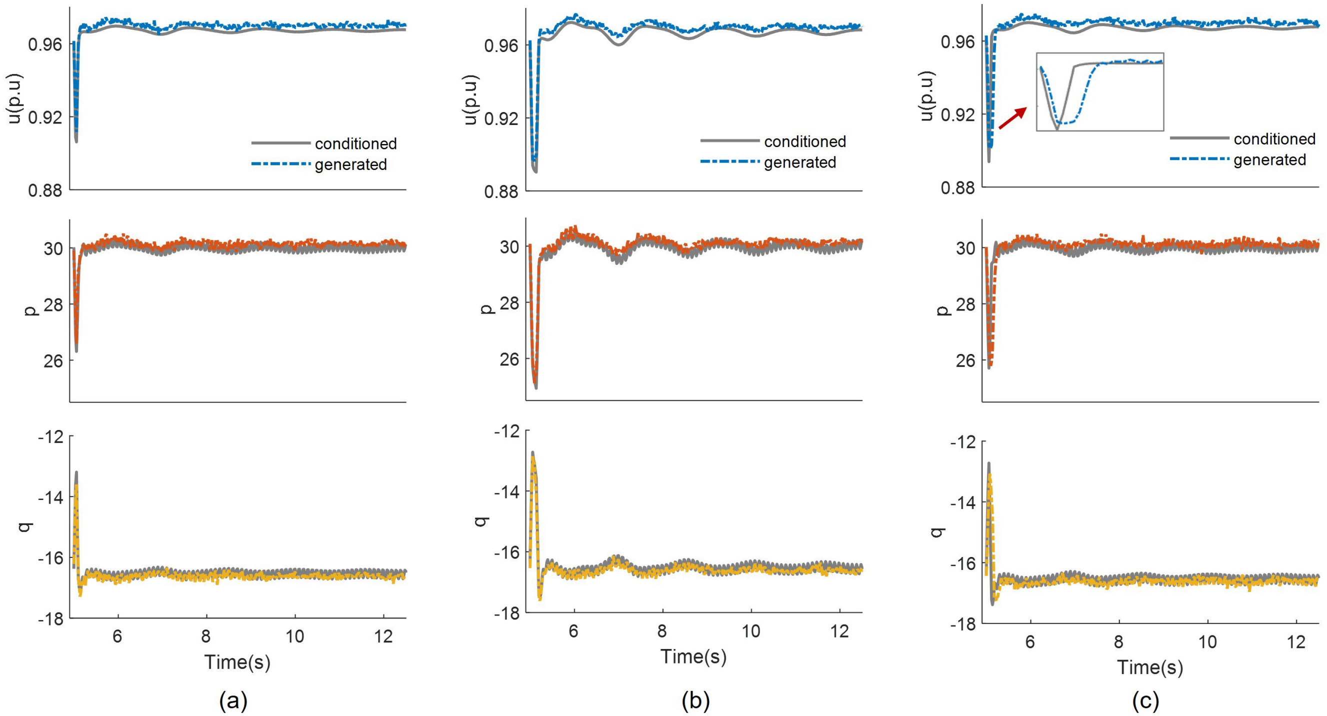
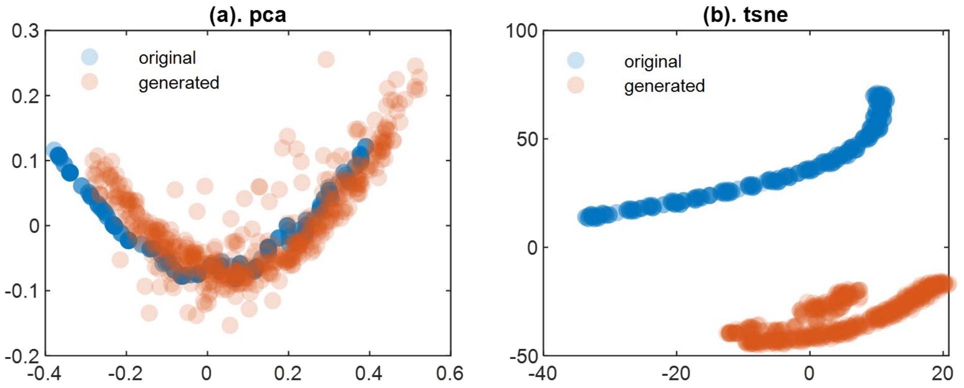
Technical Approach 2: Generative Model-based Dynamic Load Responses

- Additional trajectories were generated by imitating dynamic behaviors of the conditioning trajectories in terms of oscillation shape and frequency and recovery time
  - May present diversity in some characteristics such as postfault recovery time.



Performance Visualization

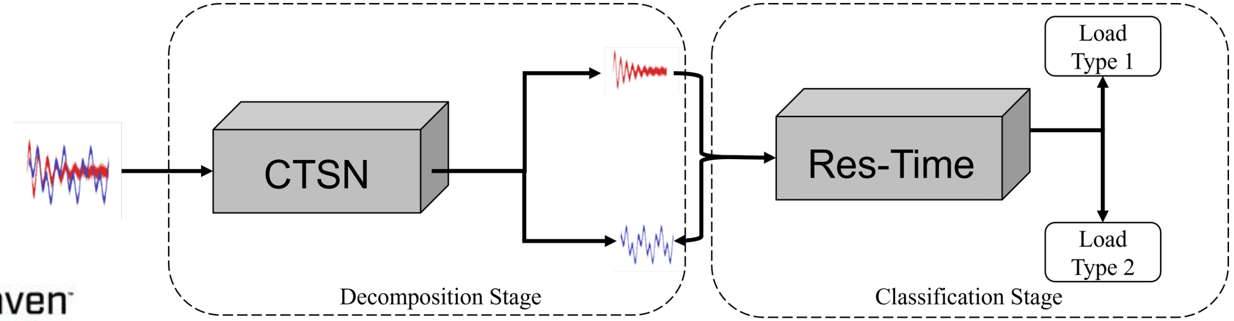


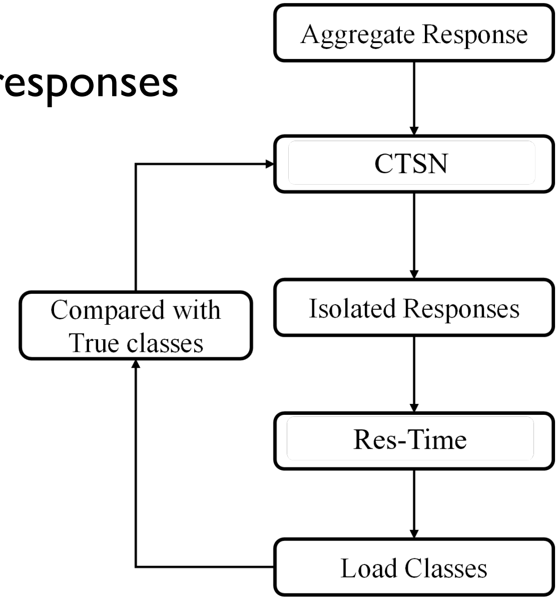
Technical Approach 2: Load Decomposition and Classification

- Tuning CLM model is complicated for a large number of parameters
- To reduce the parameter tuning complexity, we proposed to isolate the responses corresponding to types of load models, e.g., motor, electronic, static
  - Load models of different types in a CLM can be tuned separately
- Rather than unsupervised clustering, a pipeline for load decomposition and classification is needed that provides a more physically interpretable evaluation metric
  - A downstream model classifies responses separately according to load types.

Technical Approach 2: Dynamic Source Separation Network for Load Decomposition and Classification

- Dynamic Source Separation Network (DSSN): an innovative End-to-End framework for decomposition and classification
  a) CTSN: a fully Convolutional Time-domain Separation Network for decomposition
  b) Res-Time: A Residual model handles a long Time series for classification
- DSSN provides:
  - A more physically interpretable method beyond decomposition to supplement the commonly-implemented load decomposition
  - Taking an aggregate response as input, CTSN first decomposes it into isolated responses without labeling.
  - Res-Time is then used to predict the load type of the isolated responses.





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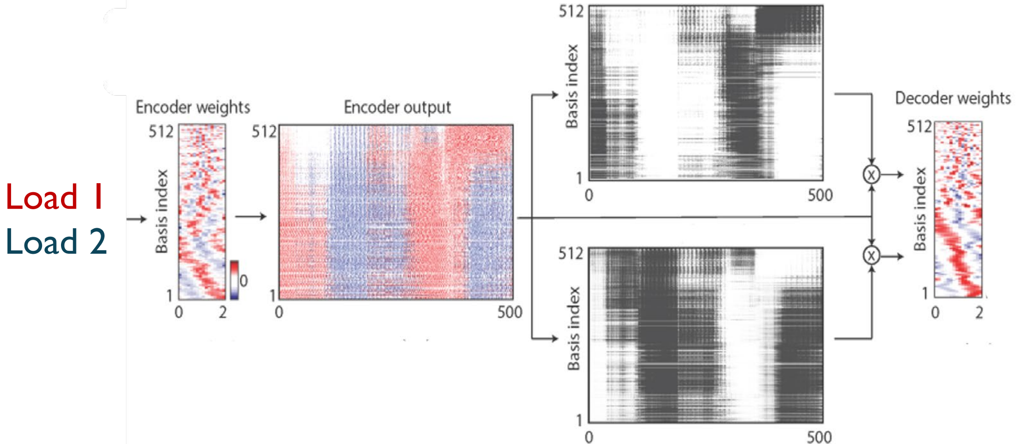
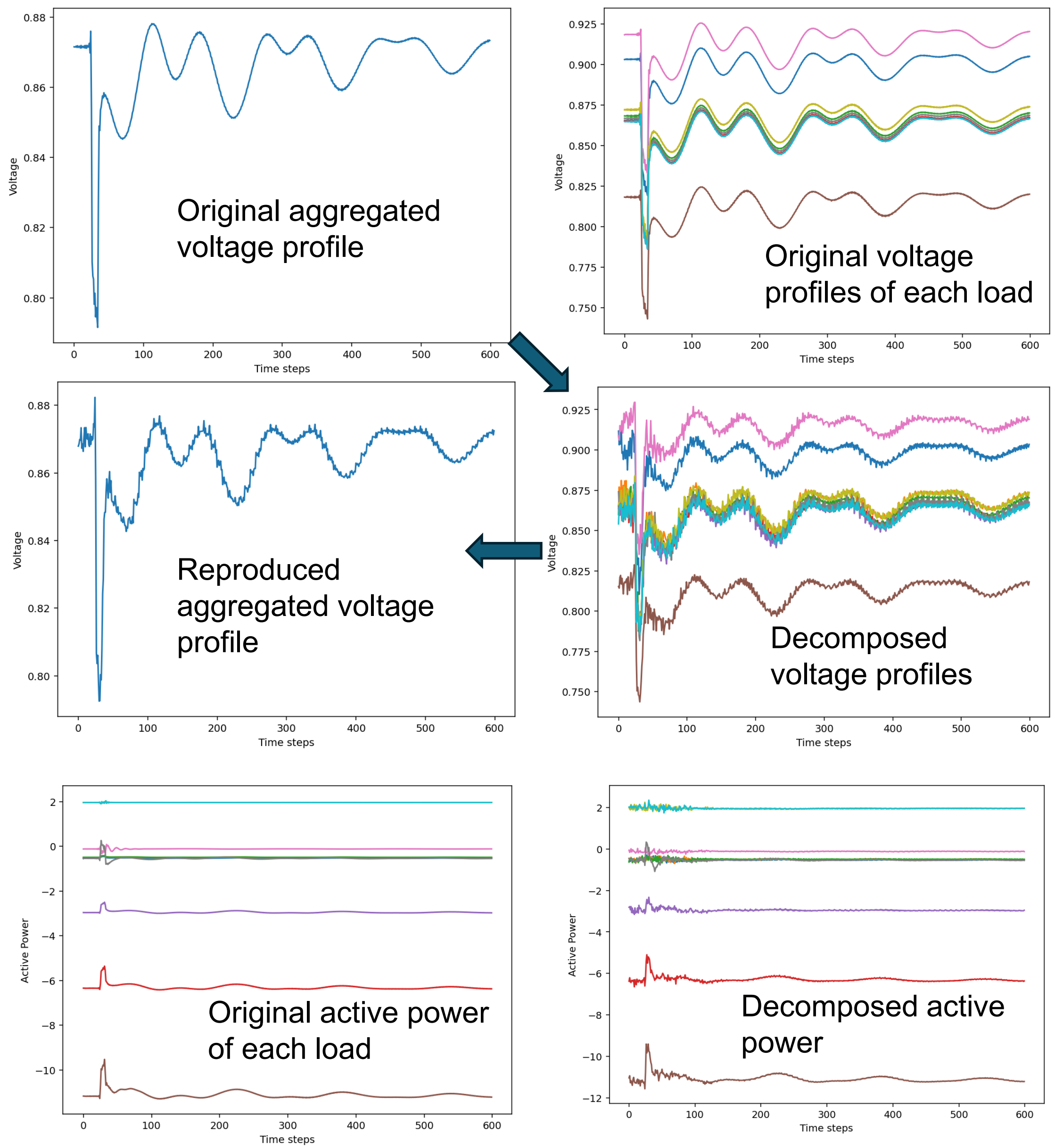
Technical Approach 2: Case Study - Load Decomposition and Classification

- Case 1: Reproducing aggregated response using the aggregated response of two different loads



- Case 2: Decomposition of aggregated response of ten different loads)
  - 4 Constant Impedance Loads
  - 3 Induction Motors
  - 2 PV DERs
  - 1 Variable Frequency Drive



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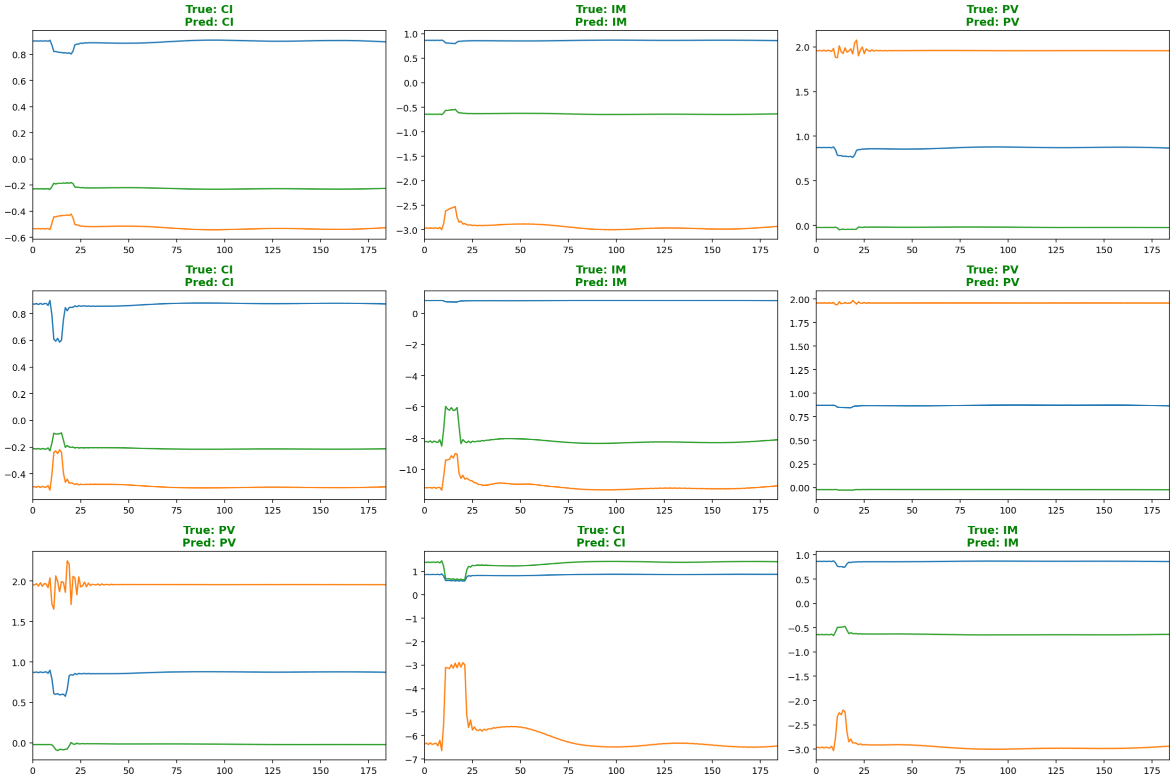
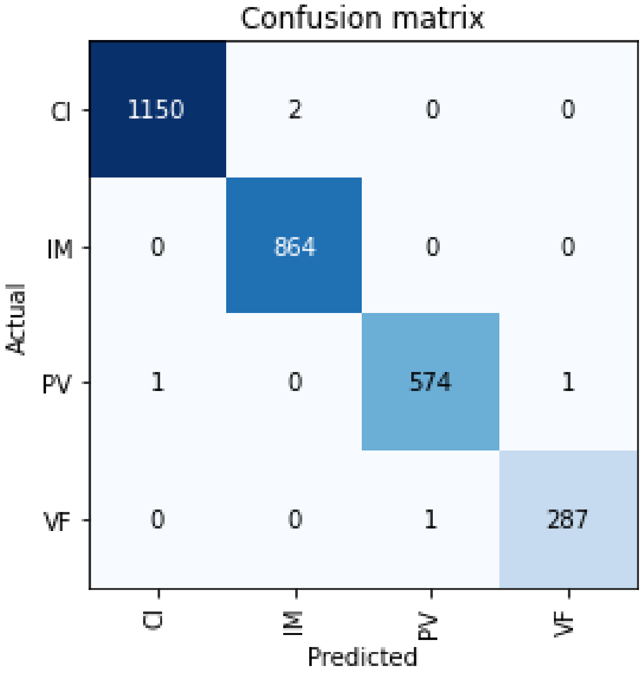
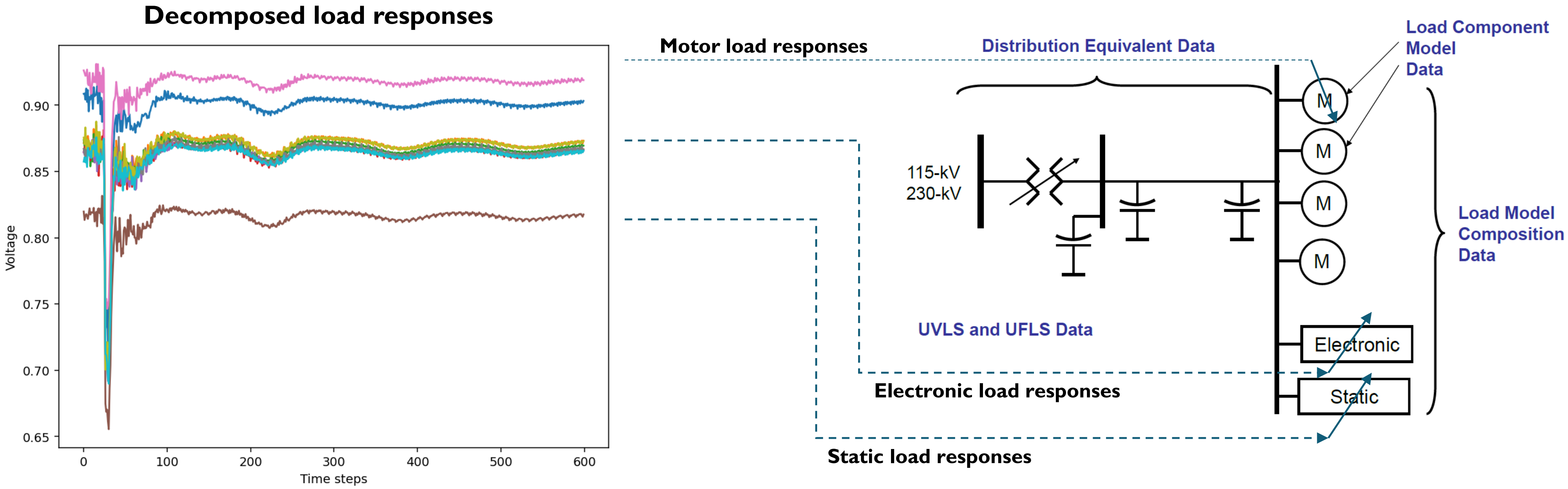
Technical Approach 2: Case Study - Load Decomposition and Classification (cont'd)

- Case 3: Aggregate response with Ten mixtures (Classification of decomposed signals)





Technical Approach 2: CLM Parameterization Based on Load Decomposition and Classification (Ongoing)



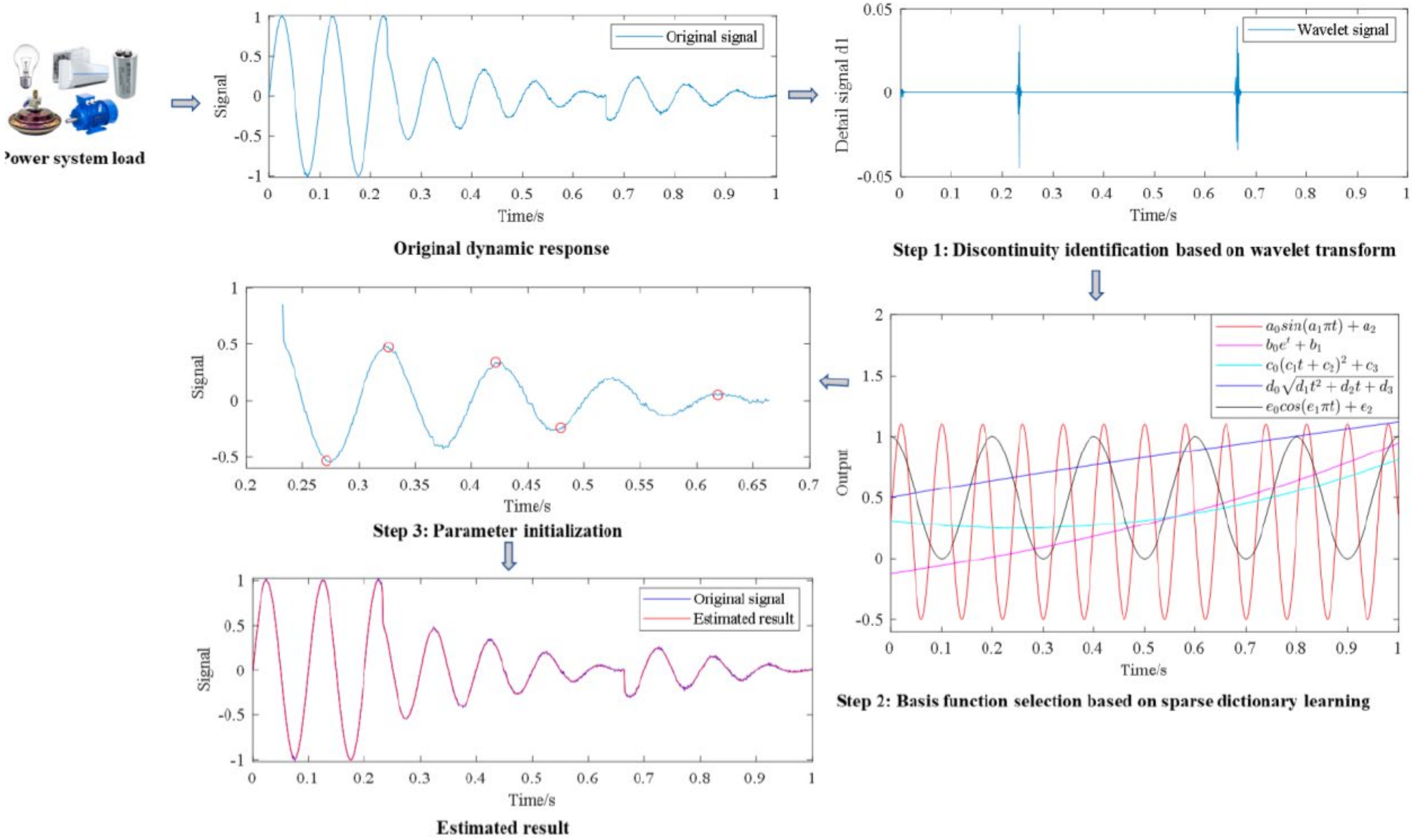
Technical Approach 3: Challenges of Conventional Load Models*

- **Inflexibility**: Traditional load models may not adapt well to rapidly changing conditions, especially with the integration of renewable energy sources.
- **Inaccuracy**: These models might not accurately represent the actual load profile due to fixed parameters, possibly leading to inaccurate simulations and forecasts.
- **High Complexity**: Some conventional load models involve complex structures and algorithms, making them computationally intensive and challenging to manage and analyze.
- **Solution:** Basic physical principles of the dynamic process are reflected in the mathematical functions
- **Approach:** The dynamic power response of the load is directly approximated as the superposition of various mathematical functions that produce a dynamic response.

$$
\begin{cases}
\text{Exponential function} : a_0 e^{a_1 x + a_2}; \\
\text{Trigonometric function} : b_0 \cos(b_1(x + b_2)); \\
\text{Polynomial function} : c_0 + c_1 x + c_2 x^2 + \cdots + c_n x^n; \\
\text{Product of the above functions}; \\
\text{Other practical mathematical functions.}
\end{cases}
$$

*: Being led by Prof. Jianhui Wang at Southern Methodist University.

Technical Approach 3: Proposed Framework*



A framework of the proposed free-form dynamic load model

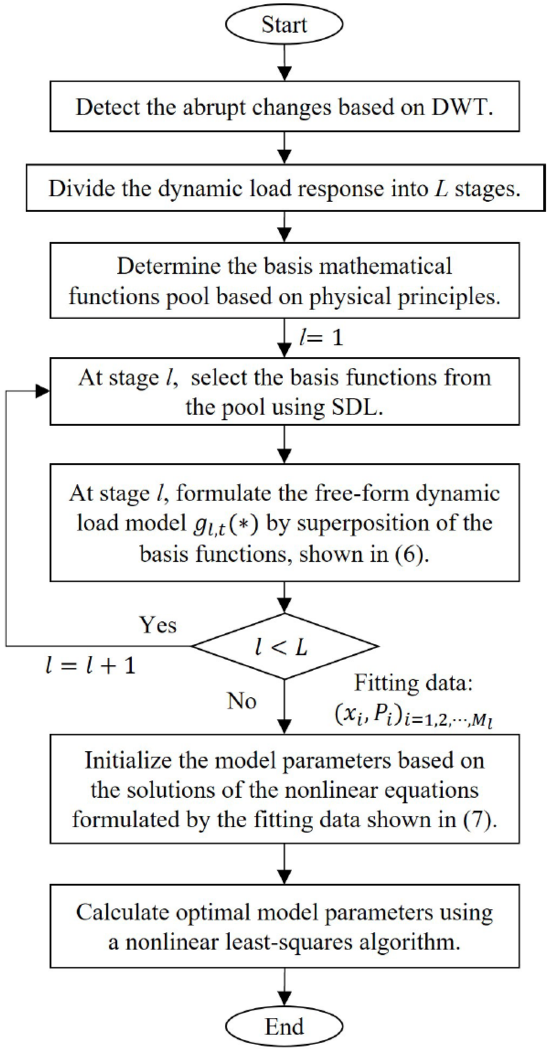
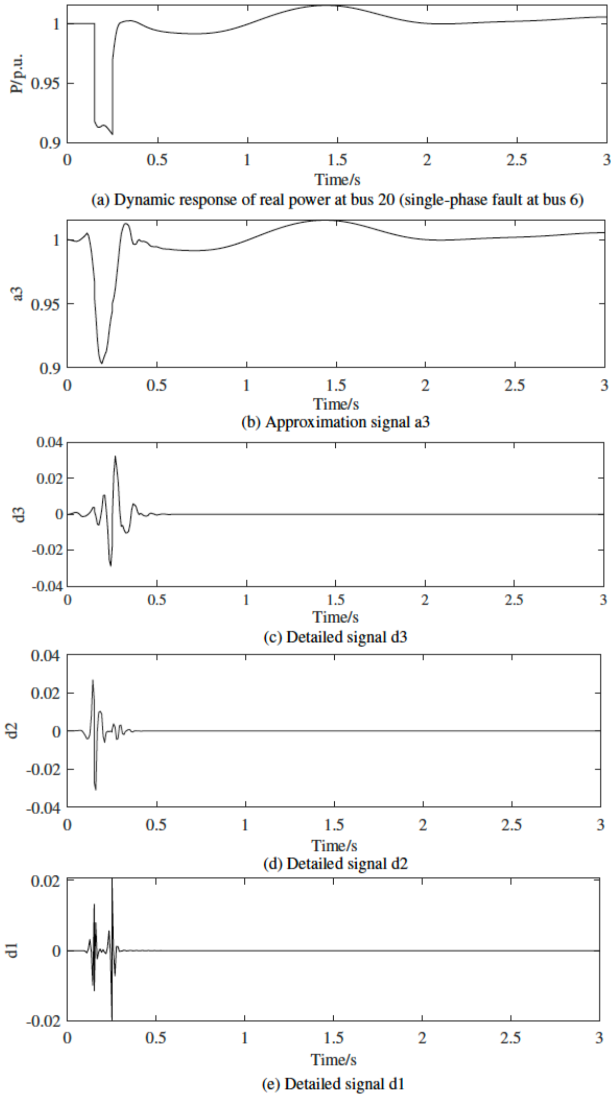


Diagram of the proposed free-form dynamic load model

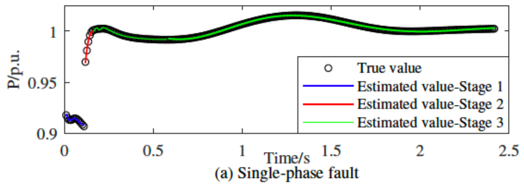
*: Y. Lin, J. Wang, and M. Yue, "Free-Form Dynamic Load Model Synthesis with Symbolic Regression Based on Sparse Dictionary Learning," accepted by IEEE Transactions on Power Systems, early access.

Technical Approach 3: Case Study

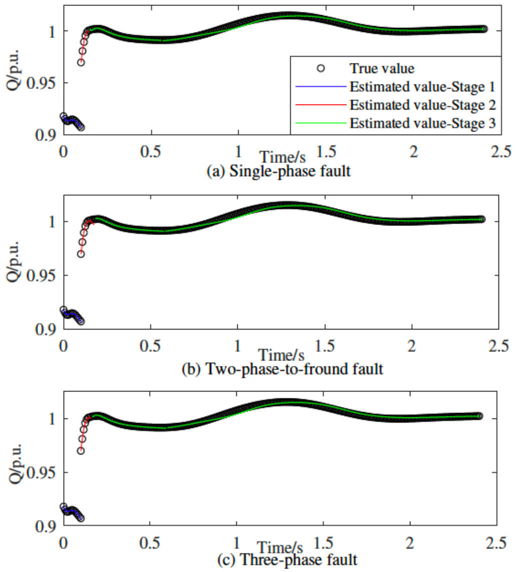
- IEEE 39 bus system with a WECC composite load model connected at Bus 20
- Single-phase ground fault, two-phase to ground fault, and three-phase fault performed separately in Buses 6, 14 and 21
  - Fault applied at 0.15 s and cleared at 0.25 s



Original dynamic response of real power P and its corresponding wavelet decomposition signals



Estimated real power at bus 20 under different fault scenarios at bus 6.



Estimated reactive power at bus 20 under different fault scenarios at bus 6.

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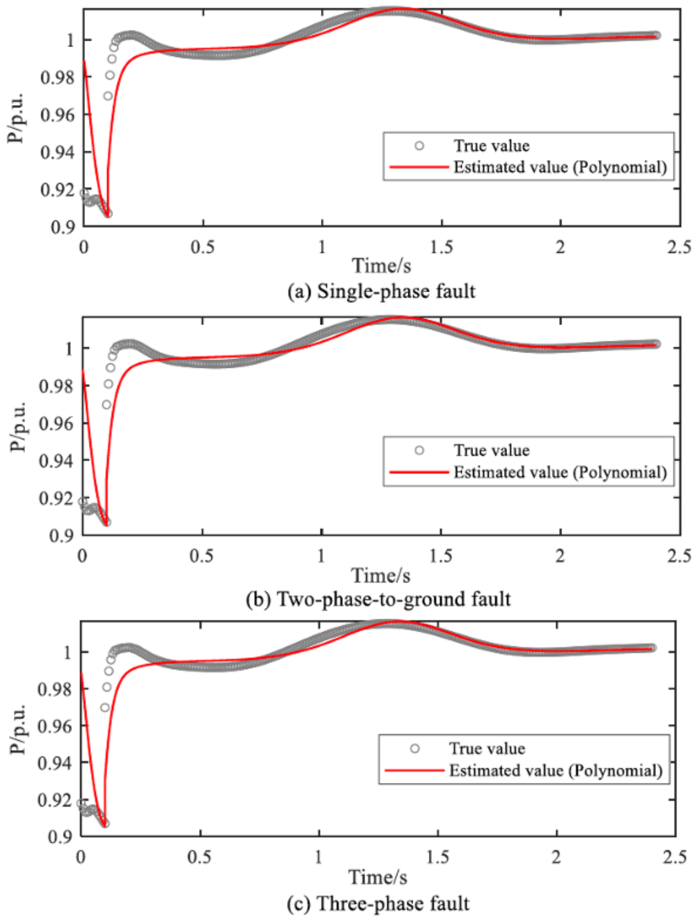
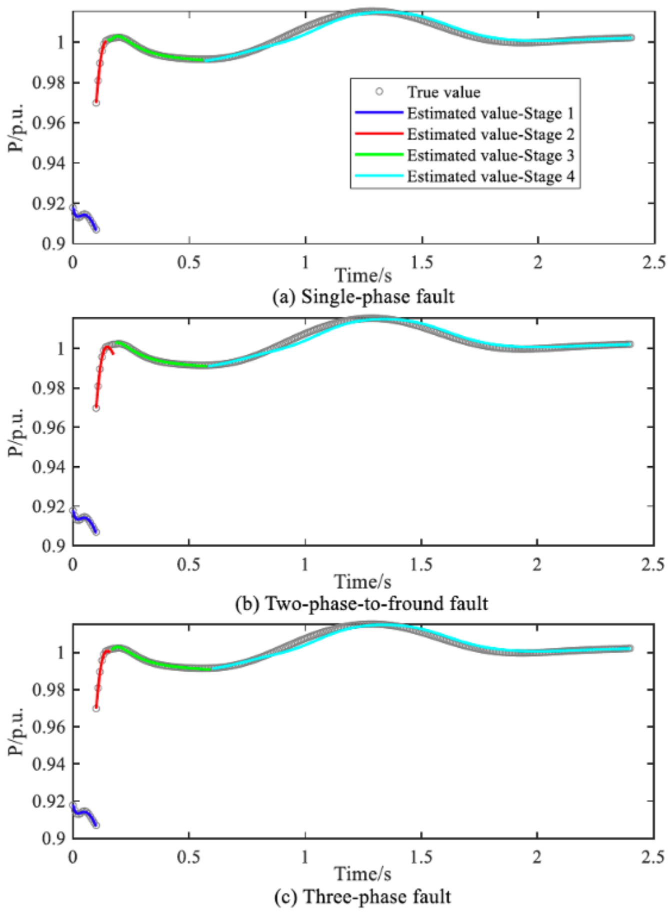
Technical Approach 3: Case Study (cont'd)



Estimated real power in different fault scenarios with fault at bus 6 (Polynomial model without stage detection)



Estimated real power in different fault scenarios with fault at bus 6 (Polynomial model with stage detection)

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Technical Approach 3: Case Study (cont'd)

- Basis Function Selected by sparse dictionary learning

$$\hat{P}_t \text{ or } \hat{Q}_t = \begin{cases} w_{1,1}(a_0 + a_1 x) + w_{1,2}(b_0 \cos(b_1(x + b_2))) & \text{stage 1} \\ w_{2,1}(a_0 + a_1 x) + w_{2,2}(b_0 \cos(b_1(x + b_2))) & \text{stage 2} \\ w_{3,1}(a_0 + a_1 x) + w_{3,2}(j_0(j_1 x + j_2)^{2/3}) & \\ +w_{3,3}(\sqrt{o_0^2 + (o_1 x + o_2)^2}) & \text{stage 3} \end{cases}$$

- Parameterization
  - The equations can be further simplified as below.
  - The total number of model parameters at stages 1, 2, and 3 are 5, 5, and 9, respectively.
  - Optimal parameters are further solved using a nonlinear least-squares algorithm.

$$\hat{P}_t \text{ or } \hat{Q}_t = \begin{cases} \xi_{1,1} + \xi_{1,2} x_1 + \xi_{1,3} \cos(\xi_{1,4} x_1 + \xi_{1,5}) & \text{stage 1} \\ \xi_{2,1} + \xi_{2,2} x_1 + \xi_{2,3} \cos(\xi_{2,4} x_1 + \xi_{2,5}) & \text{stage 2} \\ \xi_{3,1} + \xi_{3,2} x_2 + \xi_{3,3}(\xi_{3,4} x_2 + \xi_{3,5})^{2/3} & \\ +\xi_{3,6}\sqrt{\xi_{3,7}^2 + (\xi_{3,8} x_2 + \xi_{3,9})^2} & \text{stage 3} \end{cases}$$

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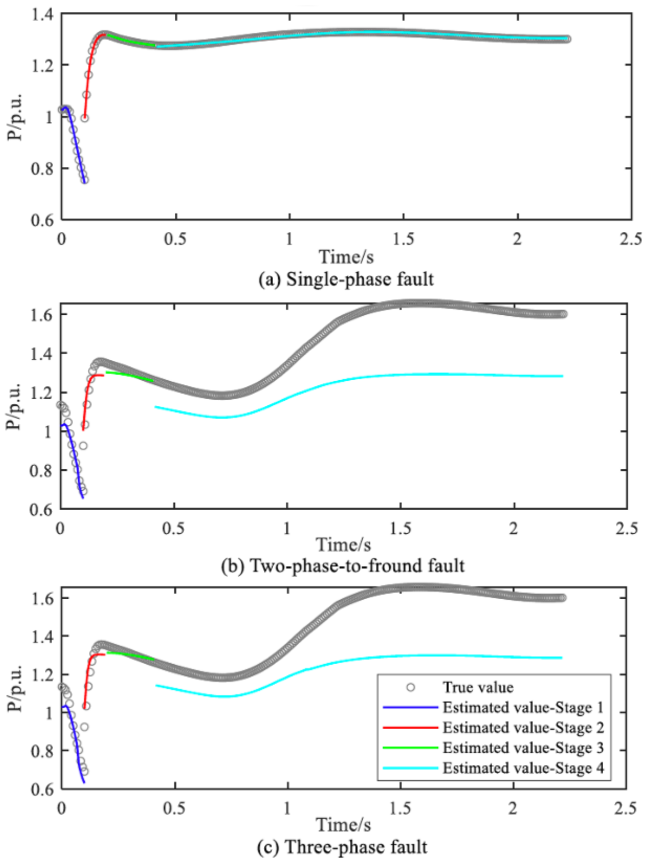
Technical Approach 3: Case Study (cont'd)

- Polynomial model does not work well when the dynamic responses in different fault scenarios are quite different.
- Basis Function selected by sparse dictionary learning brings flexibility.
- Comparison with ZIP and artificial neural network (ANN)
  - ZIP model has much higher NRMSEs than the proposed model in all scenarios.
  - The ANN-based model is more accurate than the proposed method in the scenario used to train the model but not robust in the other scenarios

Normalized Root Mean Square Errors (NRMSEs) for Real Power P at Bus 20 Estimated by Different Load Models (%)

Fault Scenario		Proposed Model	ZIP	ANN
Bus 6	Single-phase	0.045	0.19	0.032
	Two-phase-to-ground	0.1	0.27	0.051
	Three-phase	0.079	0.26	0.055
Bus 14	Single-phase	0.082	0.25	0.21
	Two-phase-to-ground	0.13	0.26	0.18
	Three-phase	0.11	0.23	0.22
Bus 21	Single-phase	0.073	0.24	0.19
	Two-phase-to-ground	0.11	0.27	0.24
	Three-phase	0.092	0.26	0.25



Estimated real power in different fault scenarios with fault at bus 21 (Polynomial model with stage detection)

Next Steps

- Online/offline RL-based parameterization of CLM to minimize the deviation of CLM responses from the simulated or measured trajectories based on
  - simulated trajectory data or
  - real-world trajectory measurements that are augmented by generative models and assisted by measurements under small disturbances (or normal operation)
- Combination and parameterization of mathematical functions for load modeling

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