JULY 30 2025

GRID FOUNDATION MODELS FOR DISTRIBUTION SYSTEM STATE ESTIMATION

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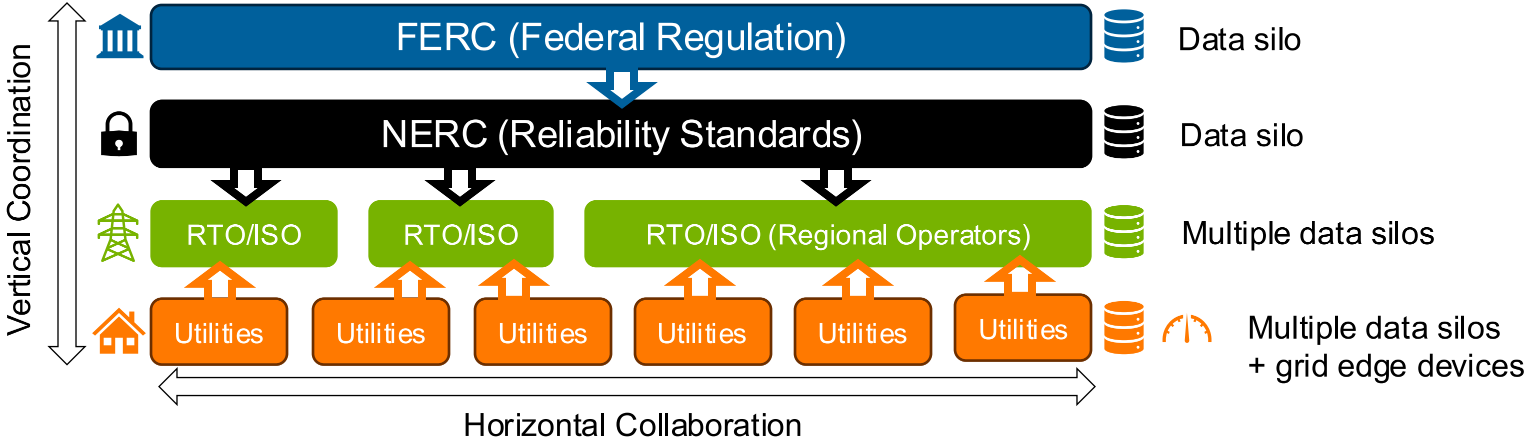
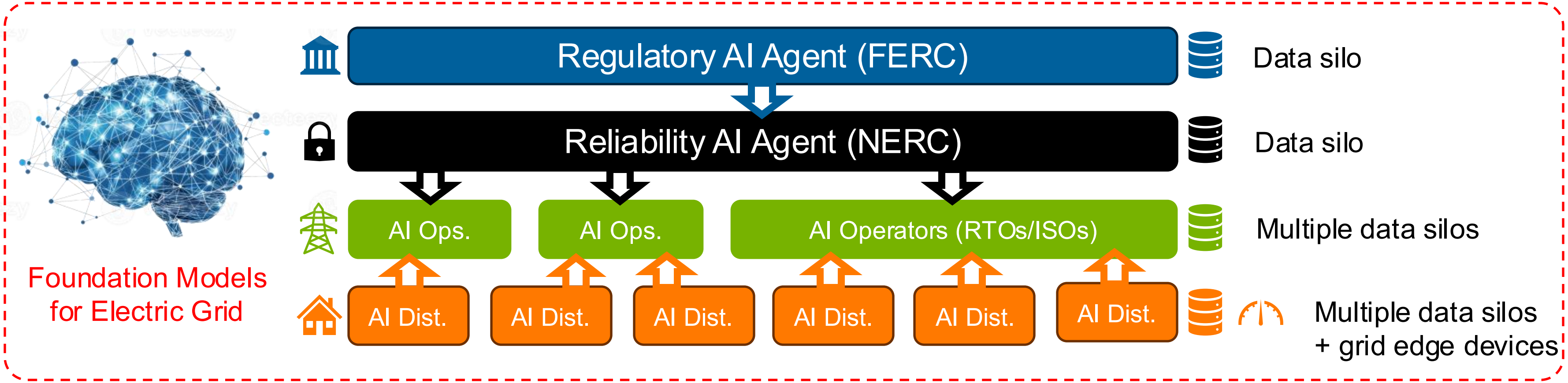
The Complex Landscape of the U.S. Electric Grid



- Multiple regulatory/operational layers with limited interoperability
- Each layer has different priorities, timelines, and data formats.
- Distributed data silos limit situational awareness and optimizing coordination.
- System-wide reliability depends on both vertical and horizon coordination.

GridFM: Coordinating AI Agents Across the Grid Hierarchy



- **GridFM** enables shared intelligence across layers while preserving autonomy.
- **AI agents** at each layer can fine-tune locally, while benefitting from global learning.
- Potential advantages:
  - Cross-layer situational awareness (e.g., transmission and distribution)
  - Faster and more informed response to dynamic events
  - Generalizable models for planning, operations, and emergency response.

MULTI-TASK TRAINING IN GRIDFM

Task	Full name	Task Description	AC or DC	1 or 3-phase	Learning task
DSSE	Distribution System State Estimation	Estimates current system status (voltages, power flows) using limited sensor data	AC	3	Infilling or Forecasting
ACOPF	Alternating Current Optimal Power Flow	Finds the most efficient way to operate the system while meeting demand	AC	1 or 3	Learning to optimize
SCUC	Security-Constrained Unit Commitment	Decides which power plants to turn on for the next day	DC	1	Learning to optimize
RA	Reliability Assessment	Determine if the system can handle contingency without causing power outages	DC	1	Learning to optimize

RELATIONSHIP BETWEEN THREE TASKS

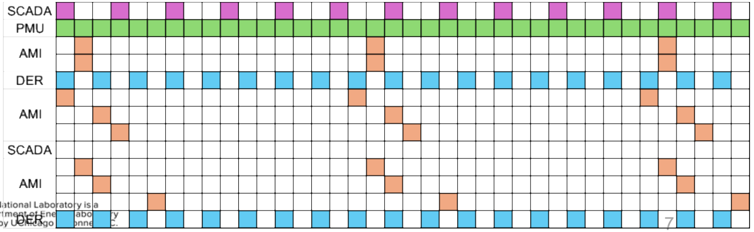
Decision-making Task	Real-time schedule adjustment	Short-term system operation schedule	Long-term system expansion planning
Time scale	**Minutes**	**Days**	**Years**
Model	ACOPF	SCUC	RA
Information Transfer	Robust unit commitment	Reliable system configuration	
Technical Challenge	**Non-convex optimization**	**Mixed-integer optimization**	**Repeated optimization**

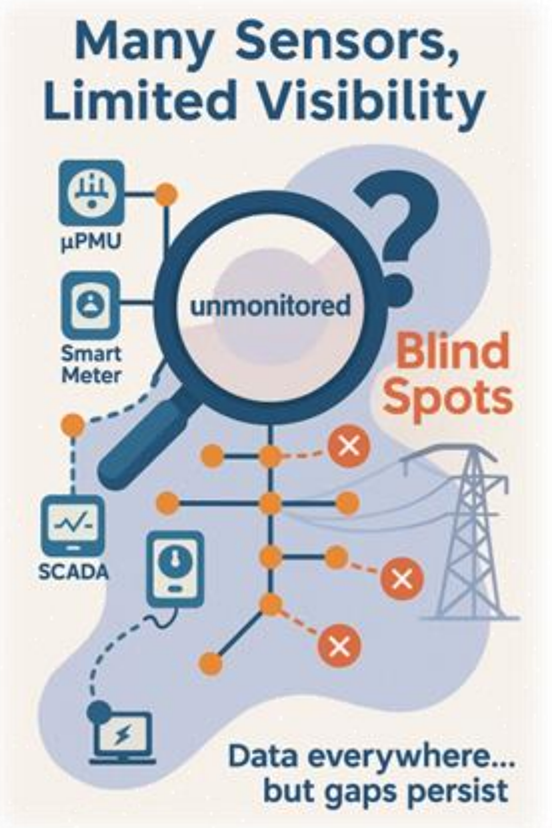
ACOPF: Alternating Current Optimal Power Flow	3-phase AC system	1 snapshot
SCUC: Security-Constrained Unit Commitment	1-phase DC system	24 continuous hours
RA: Reliability Assessment	1-phase DC system	100,000 * 24 hours

MONITORING OPPORTUNITY AND CHALLENGES

More Sensors ≠ More Visibility

Pain Point	Why it matters
Clock Mismatch	µPMU(30-120sps), SCADA(2-4s), AMI(15min), DER inverter (1s)
Data Silos & Access	OT, IT and DER portals use different protocols. Integration requires bespoke gateways
Sparse Coverage	<10% nodes carry sensors Pseudo-measurements inflate estimation error
Latency & Cyber Risk	Communication infrastructure adds delay NERC CIP, privacy rules and potential spoofing throttle real-time streams.





DATA LANDSCAPE

Diverse Measurements, Resolutions, Latencies, and Clocks

Sensor Class	Spatial Granularity	Temporal Rate	Latency	Clock-Sync
AMI smart-meter	Every customer meter	1–60 min (15 min typ.)	1 h – 1 day	✗
SCADA RTU	Substation, feeder, breaker	2–4 s	2–4 s	✗
µPMU	Critical node (very sparse)	30-120 sps (<16 ms)	< 50 ms	✓
DER inverter	Each PV / BESS unit	1 s	5–10 s	✗ (NTP)
Line sensor	Selected spans	128 samples / cycle	< 1 s	✓ (GPS)
Weather node	Service-area clusters	1 min	< 5 s	✗
BESS monitor	Per battery rack	1 s	< 1 s	✗ (NTP)

DATA GENERATION

AMI-Driven Synthetic Power-Flow Engine

Why Synthetic Data?

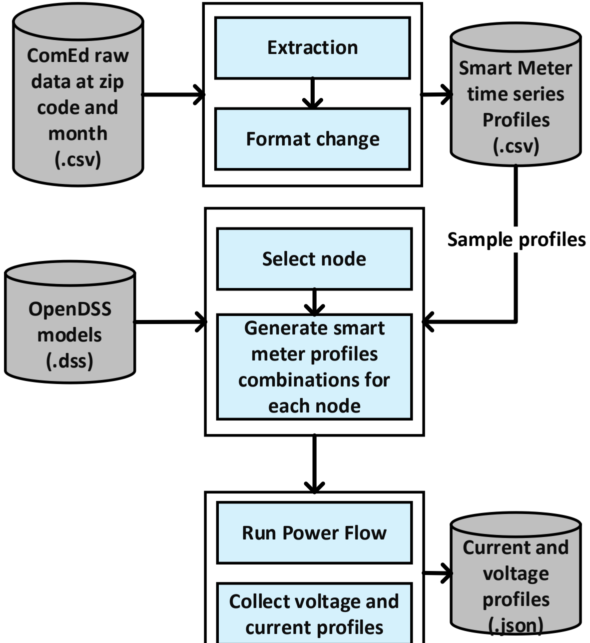
- ≥ 1 million multichannel samples required for training
- Utility sensors can't supply that volume from single feeder

Data Pipeline

1. Map real AMI data → synthetic feeder nodes
2. Up-sample node-level load profiles for every 1s tick
3. Run OpenDSS at each tick → complete power flow data
4. Export time-aligned data sets (μPMU + AMI, SCADA, DERs)

Key Benefits

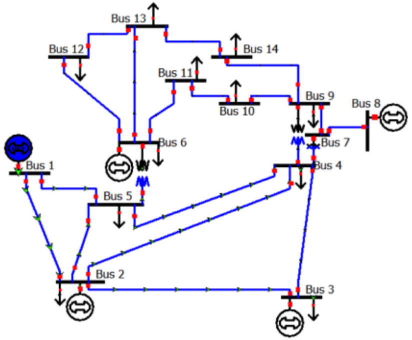
- Field-anchored realism without disclosing customer data
- Unlimited scenario generation: DER mixes, faults, topology flips
- Time-stamped labels for physics-aware model training



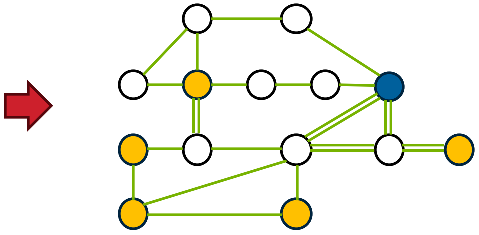
Synthetic Data Generation Pipeline

Heterogenous graph representation

- **Heterogeneous** graph
  - **Node**: bus, generator, storage, etc.
  - **Edge**: line, transformer, etc.
  - **Graph**: optimal solution, config, etc.
- Feature space:
  - Static graph
  - Static graph with temporal signal
  - Dynamic graph with temporal signal



Power Grid Data

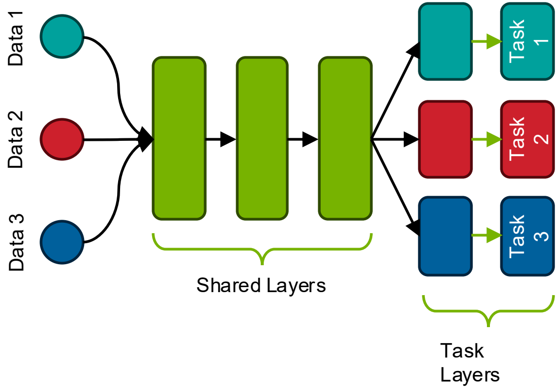


Static/Temporal
Hetero Graph Data
$\mathcal{N}_1(\mathcal{B},\mathcal{E}),\cdots\mathcal{N}_n(\mathcal{B},\mathcal{E})$

Key Challenge - feature **dimensions** will vary based on tasks

MUTLI-TASK LEARNING WITH GRAPHS

- **Hard** parameter sharing:
  - A significant portion of the model's architecture (e.g., encoder) is shared among all tasks.
  - Each task then has its own smaller, task-specific output layer.
  - The shared layers learn a general representation of the input data, while the task-specific layers fine-tune this representation for the nuances of each task.



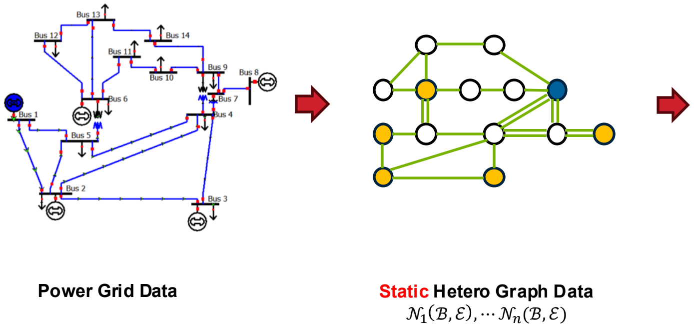
$$\ell_{\text{total}} = \sum_{t \in \mathcal{T}} w_t \ell_t$$

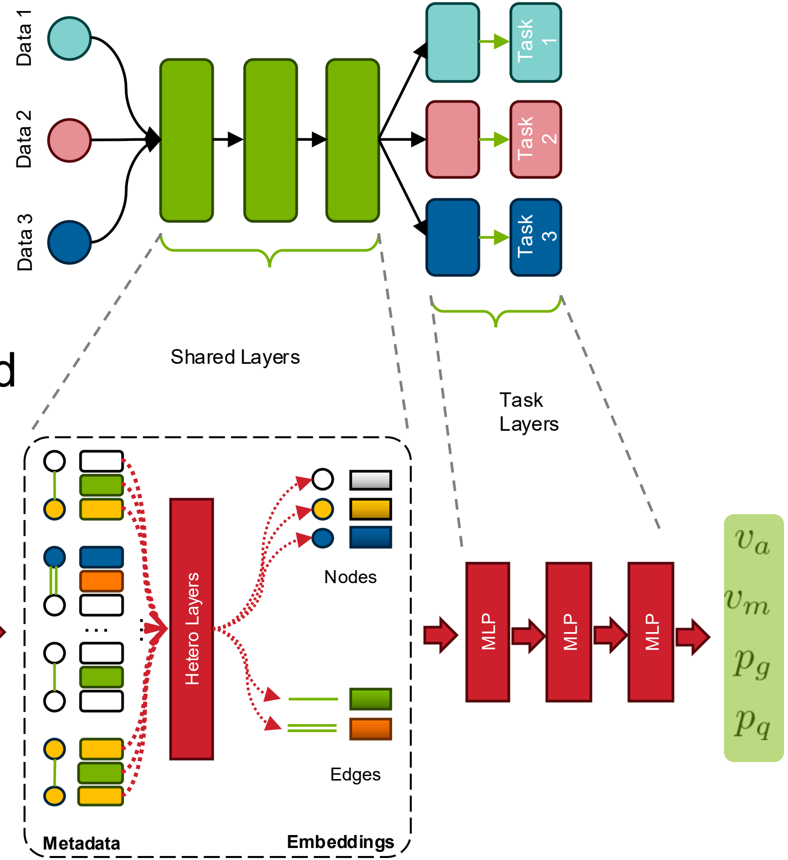
TASK LAYERS

- ACOPF:
  - Regression task with MLP layers and Physics-loss

ML loss Physics loss

$$\ell_{\mathrm{ACOPF}} = \ell_{\mathrm{MSE}}(y, y') + \ell_{\mathrm{PI}}(y')$$





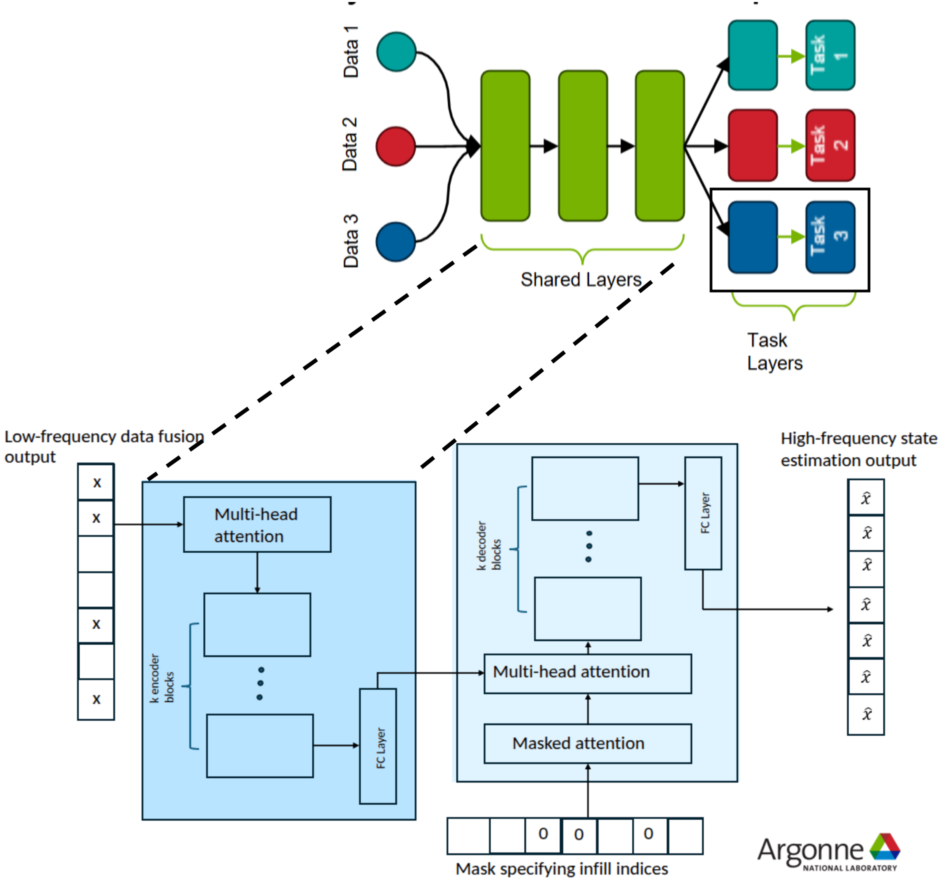
Not all hidden embeddings are used for task-specific layers

DISTRIBUTION SYSTEM STATE ESTIMATION

Converts heterogeneous sensor feeds into a unified, physics-consistent state vector.

Why a Graph-Transformer NN?

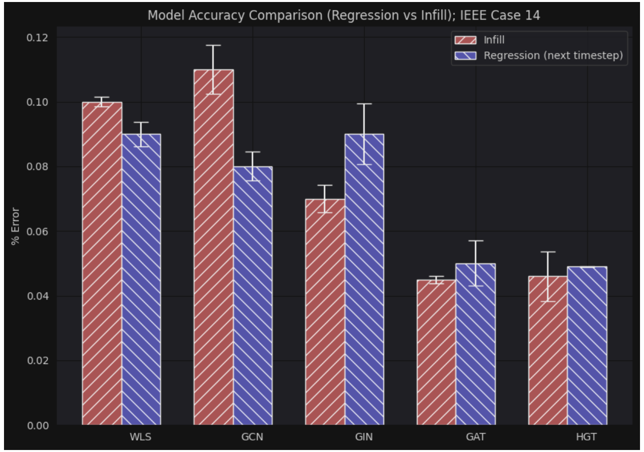
- **Graph representation** embeds feeder topology – nodes embed local measurements & connectivity.
- **Multi-head attention** captures long-range electrical interactions missed by standard GNN message-passing.
- **Masked attention** seamlessly up-samples low-frequency data (AMI) to high-frequency estimation (μPMU).
- **Physics-aware loss** penalizes infeasible power-flow states, ensuring physically valid estimates.
- Shared encoder layers across infill and forecasting task variants;



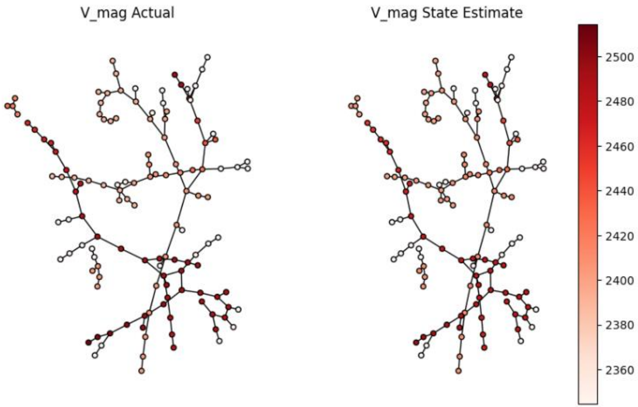
PRELIMINARY RESULTS

Preliminary Results:

- Demonstrate promising initial performance on IEEE 13-bus and 123-bus test feeders.
- Transformer-based models (e.g., GIN, GAT) outperform baseline GCN models.
- Cross-task training on infilling and forecasting task variations with hard sharing of encoder layer parameters shows potential for integration into general GridFM context.



Comparison of reconstruction error across range of WLS and GNN methods [1-4]. Transformer models show most promising results (GAT, HGT) show significantly lower error.



Voltage magnitude heatmaps using our best-performing Graph Transformer. Consistent over-estimation of time-varying fluctuations by naïve methods shows opportunity.

[1] **GCN: Graph Conv Net.** Kipf, Thomas N., and Max Welling. "Semi-supervised classification with graph convolutional networks." *arXiv preprint arXiv:1609.02907* (2016).

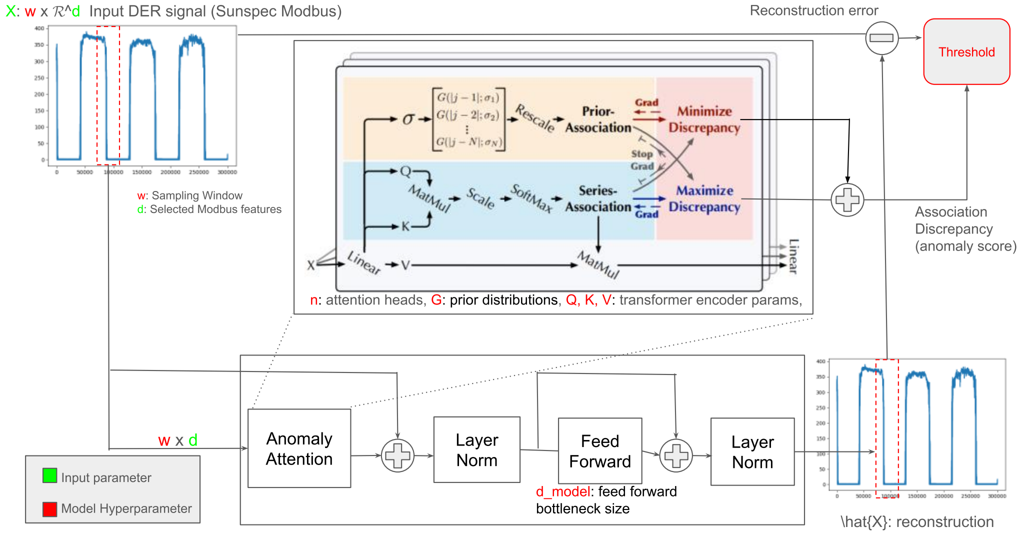
[2] **GAT: Graph Attention Transformer.** Veličković, Petar, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. "Graph attention networks." *arXiv :1710.10903* (2017).

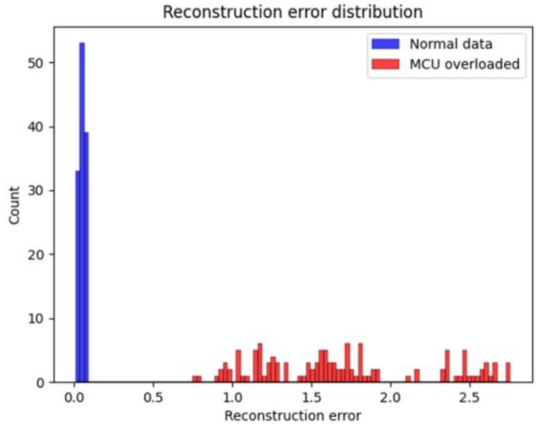
[3] **GIN: Graph Isomorphism Network.** Xu, Keyulu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. "How powerful are graph neural networks?." *arXiv preprint arXiv:1810.00826* (2018).

[4] **HGT: Heterogeneous Graph Transformer.** Hu, Ziniu, et al. "Heterogeneous graph transformer." *Proceedings of the web conference 2020*. 2020.

STATE ESTIMATION EXTENSION: ANOMALY DETECTION

- Latent grid state estimate from shared encoder layers can be diffed across time steps;
- State vector variation across time steps exceeding threshold -> potential anomaly;
- Tested on solar inverters, AMI, and solar home data streamed from at 1s to 15 minutes time resolutions;
- Nominal vs Abnormal data clearly linearly separable in shared encoder latent space;
- Next steps: Incorporate into cross-task training on other GridFM tasks.

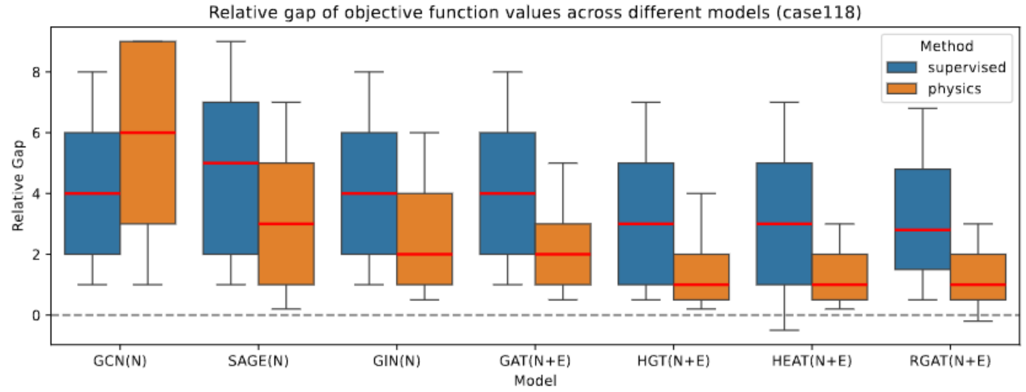


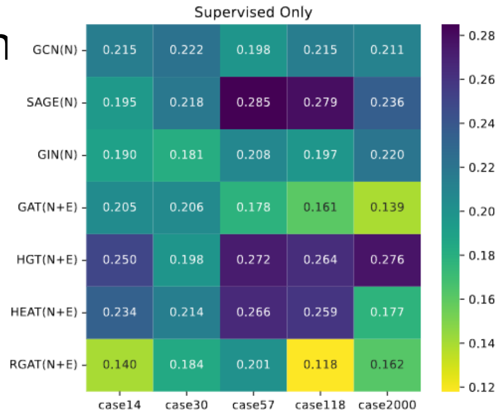


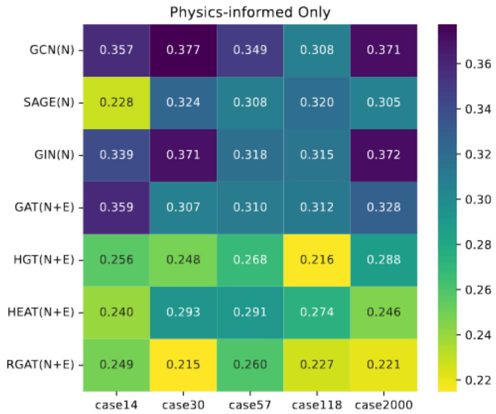
PRELIMINARY RESULTS: OPTIMAL POWER FLOW

- Edge features are important to incorporate in training, especially for physics-informed learning.
- Transformer- and graph-attention mechanisms outperform.
- Generalization performance to unseen network systems (train on multiple networks, prediction with the remaining one)

Our current single-task model has about **1.6B** parameters on **1.5TB** ACOPF data





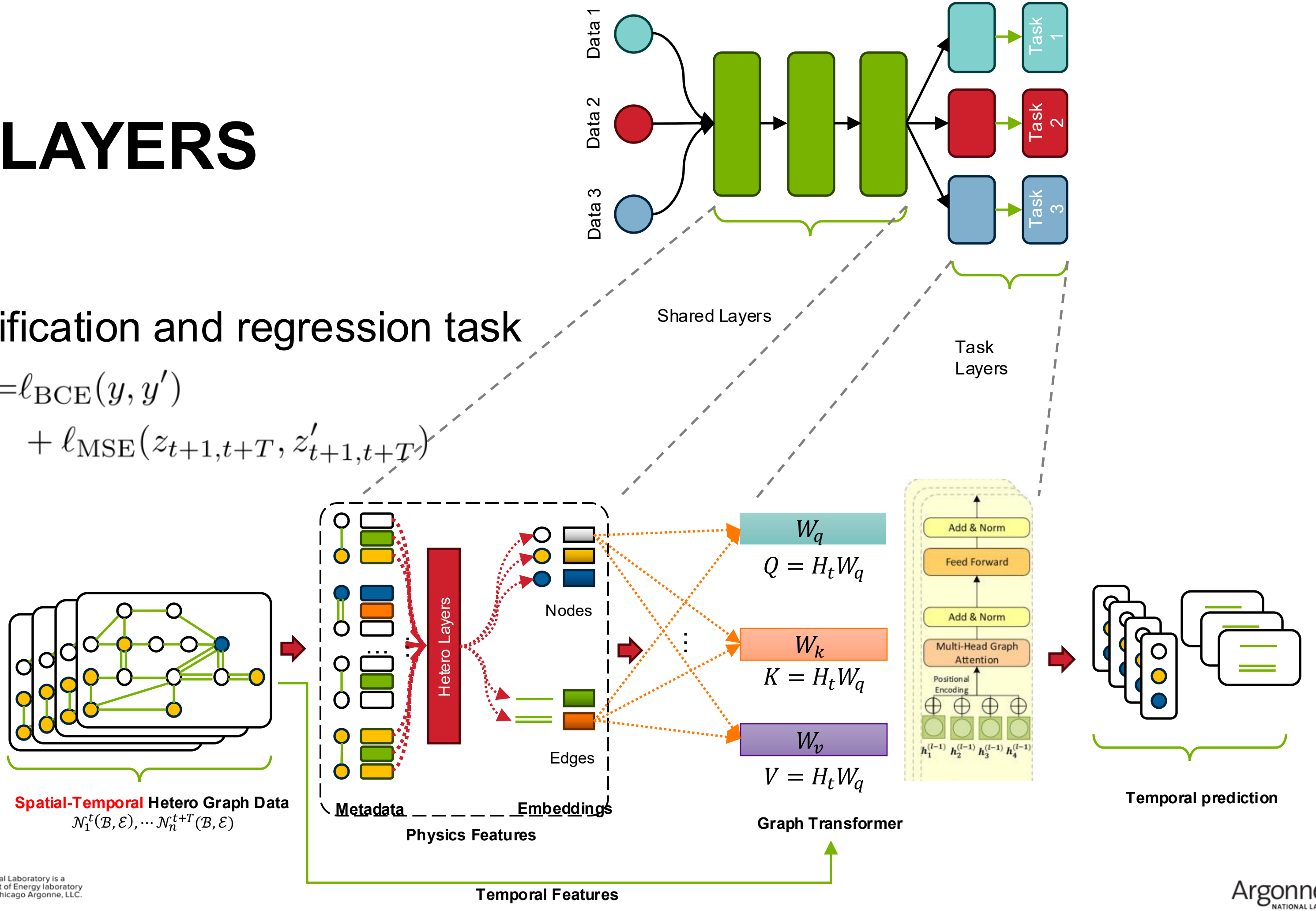


> 1000x faster inference compared with optimization on grid with 2000 nodes

TASK LAYERS

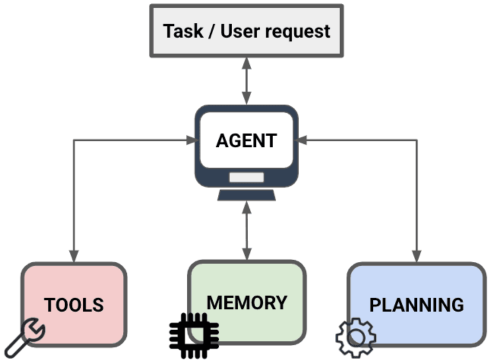
- SCUC:
  - Classification and regression task

$$\ell_{\text{SCUC}} = \ell_{\text{BCE}}(y, y') + \ell_{\text{MSE}}(z_{t+1,t+T}, z'_{t+1,t+T})$$



GRIDMIND – AI AGENTS

- Provide ACOPF AI Agent show case
- Integrate **human-in-the-loop** functionalities to ensure optimal performance and reliability
- **Function calls** to existing tools
- Intuitive **chat interface** and seamless tool calling capabilities
- Inquiry status, modify the system, ask question




```
Welcome

GridMind: ACOPF AI Agent Showcase

An intelligent agent for solving AC Optimal Power Flow problems.

Available Commands:
• Solve IEEE test cases: "Solve IEEE 118 case"
• Modify loads: "Increase bus 10 load to 150 MW"
• Get status: "What's the current network status?"
• Ask questions: "What are the voltage violations?"

Example IEEE Cases: 14, 30, 57, 118, 300 bus systems

Type 'quit' or 'exit' to end the session.
```

ACOPF AGENT

Chat interface

```
You: Solve IEEE 118 case
2025-07-28 18:04:26,183 | INFO | agent.acopf_agent:process_reques
t:254 - Processing request: Solve IEEE 118 case...
2025-07-28 18:04:26,186 | INFO | agent.acopf_agent:solve_acopf_ca
se:95 - Solving ACOPF for case: ieee 118
⠹ Agent is thinking...2025-07-28 18:04:26,615 | INFO | pandapower
.convert_format:correct_dtypes:124 - These dtypes could not be co
rrected: {'trafo': ['tap_neutral', 'tap_min', 'tap_max', 'tap_pos
']}
2025-07-28 18:04:26,617 | INFO | tools.pandapower_solver:load_sta
ndard_case:35 - Loaded IEEE 118-bus case
.: Agent is thinking...2025-07-28 18:04:29,182 | INFO | tools.pand
apower_solver:solve_acopf:104 - OPF attempt 1 with settings: {'al
gorithm': 'nr', 'init': 'pf'}
⠋ Agent is thinking...2025-07-28 18:04:29,565 | INFO | tools.pand
apower_solver:solve_acopf:108 - OPF converged on attempt 1
2025-07-28 18:04:29,566 | INFO | tools.pandapower_solver:solve_ac
opf:157 - PandaPower OPF solved successfully in 2.948s
2025-07-28 18:04:29,567 | INFO | tools.pandapower_solver:solve_ac
opf:158 - Objective value: 129704.74
2025-07-28 18:04:29,567 | INFO | validators.solution_validator:va
lidate_solution:59 - Solution quality assessment: Overall=7.2/10
2025-07-28 18:04:29,567 | INFO | api.argo_client:chat_completion:
46 - Sending request to Argo API: https://apps-dev.inside.anl.gov
/argoapi/api/v1/resource/chat/
⠋ Agent is thinking...2025-07-28 18:04:31,958 | INFO | httpx:_sen
d_single_request:1740 - HTTP Request: POST https://apps-dev.insid
e.anl.gov/argoapi/api/v1/resource/chat/ "HTTP/1.1 200 OK"
2025-07-28 18:04:31,958 | INFO | api.argo_client:chat_completion:
60 - Successfully received response from Argo API
Agent: I've successfully solved the ieee 118 case. Here are the r
esults:
```

Pandapower solver

Agent thinking and tool calling

Natural language responses

```
Agent: I've successfully solved the ieee 118 case. Here are the results:

**Network Summary:**
- Buses: 118
- Generators: 53
- Lines: 173
- Total Load: 4242.0 MW

**Solution Results:**
- Converged: Yes
- Objective Value: 129704.74
- Solve Time: 2.948 seconds
- Voltage Violations: 0
- Line Violations: 0
- Power Balance Error: 373.6112 MW

**Quality Assessment:**
- Overall Score: 7.2/10 if quality else 'N/A'
- Convergence: 6.0/10 if quality else 'N/A'
- Constraint Satisfaction: 10.0/10 if quality else 'N/A'

I'll begin by solving the AC Optimal Power Flow (ACOPF) for the IEEE 118 bus s
ystem.
Please hold on while I run the computations.

 (Calling solve_acopf_case("118"))
```

ACOPF Solution Summary

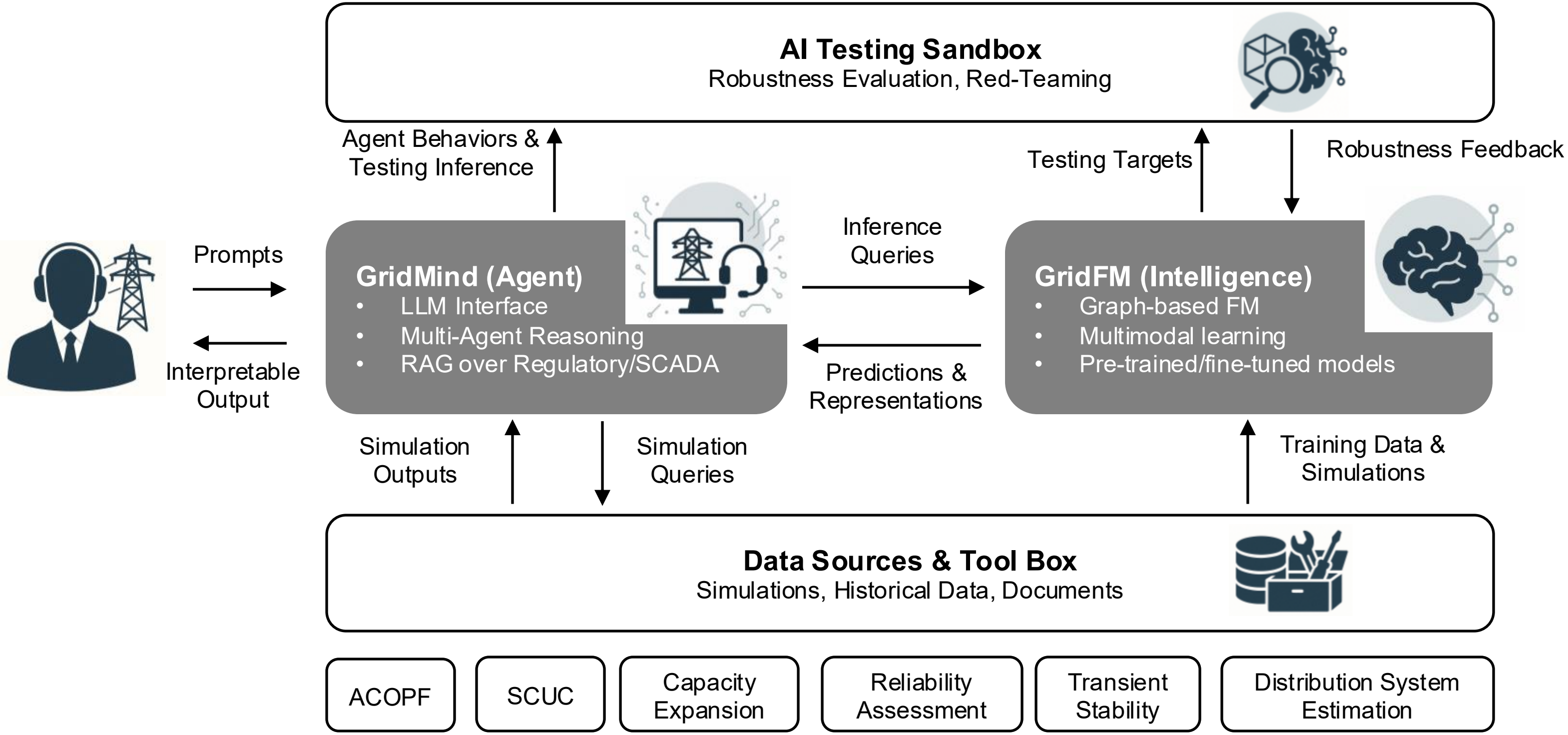
Metric	Value	Status
Convergence	Yes	✓
Objective Value	129704.74	✓
Solve Time	2.948s	✓
Voltage Violations	0	✓
Line Violations	0	✓
Power Balance Error	373.6112 MW	⚠

Solution Quality Assessment

Aspect	Score	Rating
Overall	7.2/10	Good
Convergence	6.0/10	Good
Constraints	10.0/10	Excellent
Economics	7.0/10	Good
Security	6.0/10	Good

Agent response

SUMMARY


AI Testing Sandbox
Robustness Evaluation, Red-Teaming
Agent Behaviors & Testing Inference
Testing Targets
Robustness Feedback
Prompts
Interpretable Output
GridMind (Agent)
• LLM Interface
• Multi-Agent Reasoning
• RAG over Regulatory/SCADA
Inference Queries
Predictions & Representations
GridFM (Intelligence)
• Graph-based FM
• Multimodal learning
• Pre-trained/fine-tuned models
Simulation Outputs
Simulation Queries
Training Data & Simulations
Data Sources & Tool Box
Simulations, Historical Data, Documents
ACOPF
SCUC
Capacity Expansion
Reliability Assessment
Transient Stability
Distribution System Estimation

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