PHYSICS-CONSTRAINED NEURAL NETWORKS FOR ELECTRO-THERMAL BATTERY MODELING AND EMULATION

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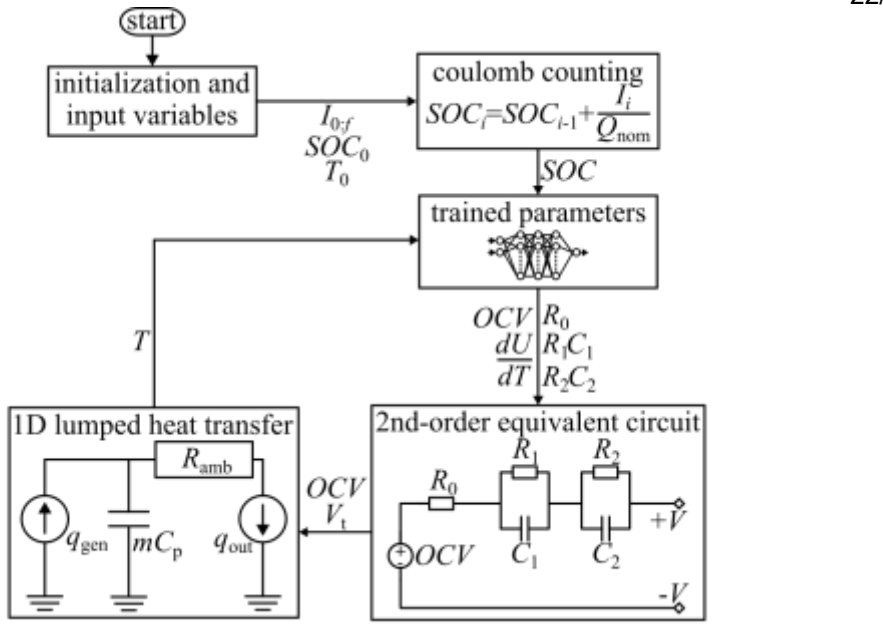
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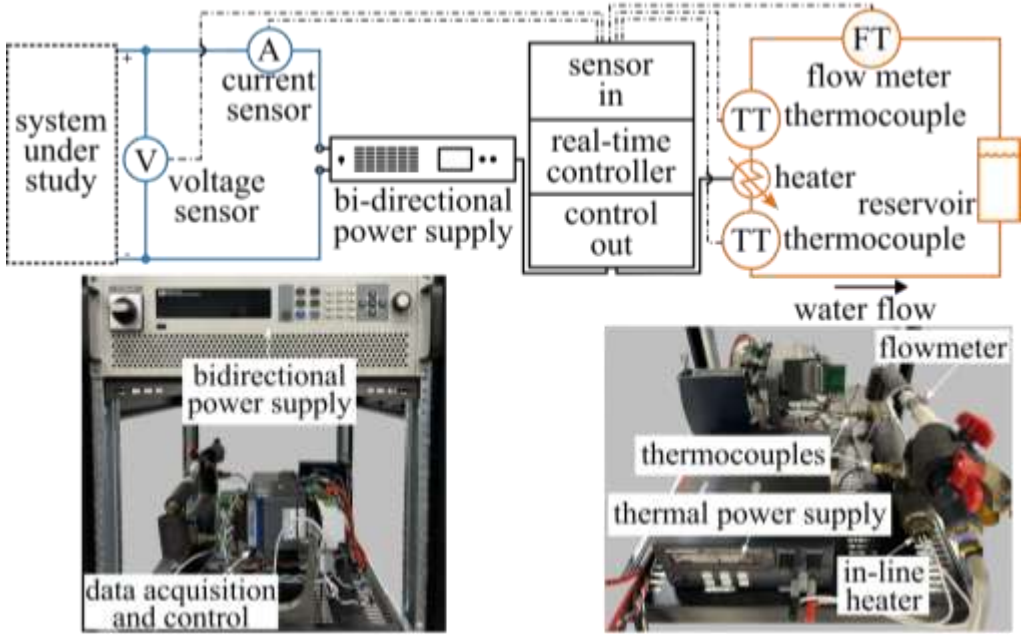


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OUTLINE

- Motivations
- Emulator Hardware Development
- Dataset Creation
- Physics Constrained ML
- Results
- Conclusions
- Future Directions

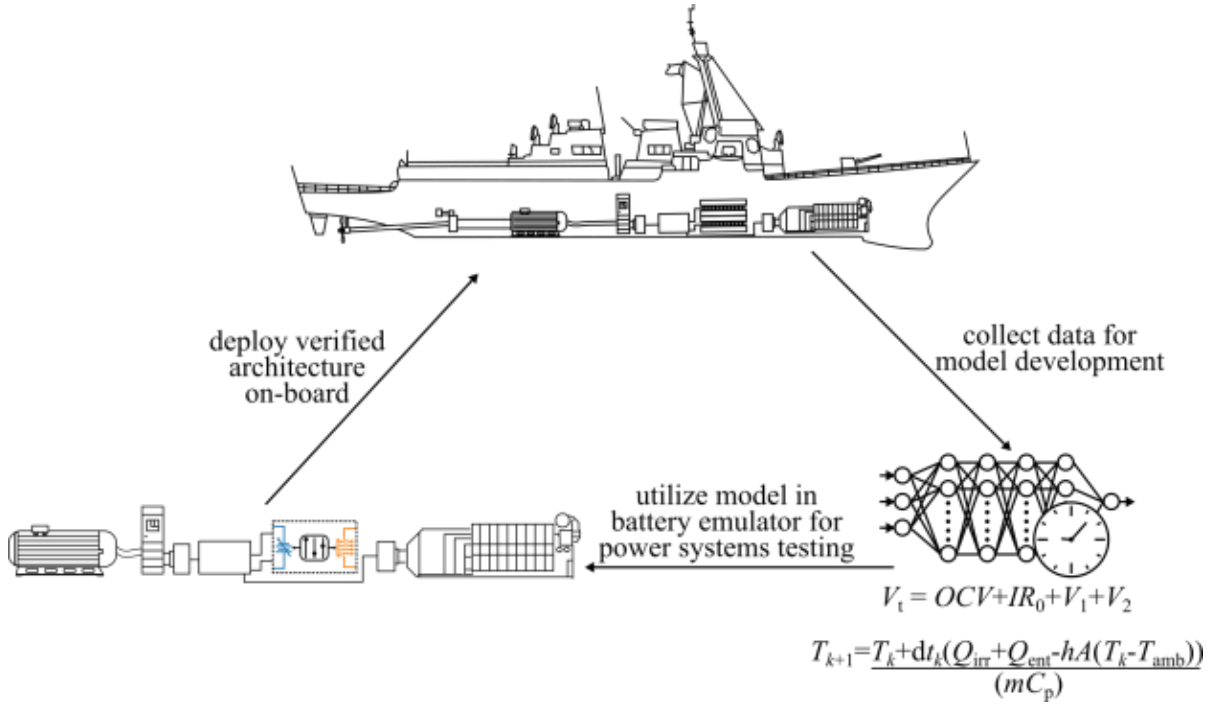




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MOTIVATIONS

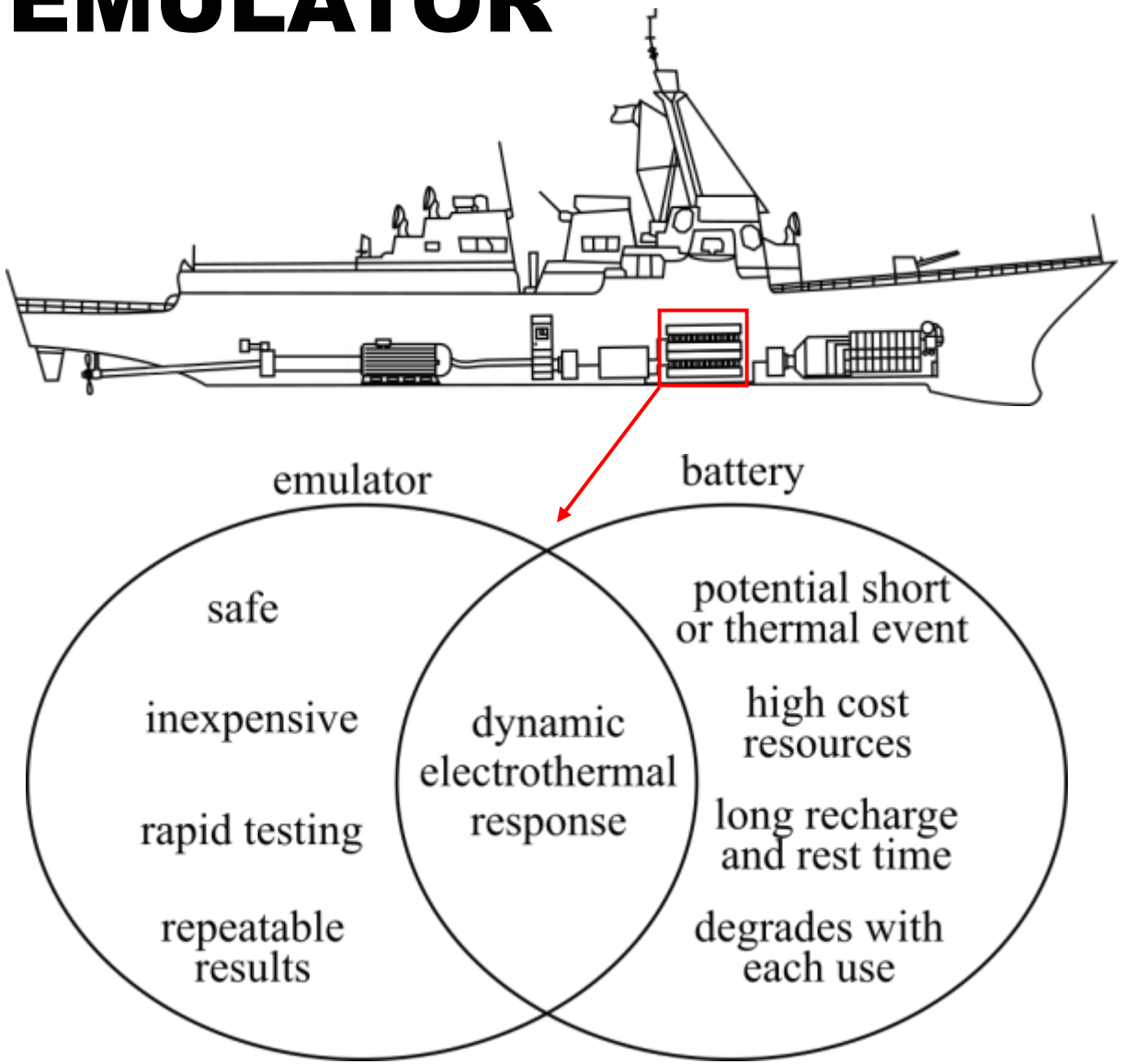
- For maritime applications, robust mobile ESS are necessary for smooth shipboard power
- Frequent battery testing during system design and development is inefficient
- Traditional battery modeling requires extensive computation and knowledge of electrochemical parameters



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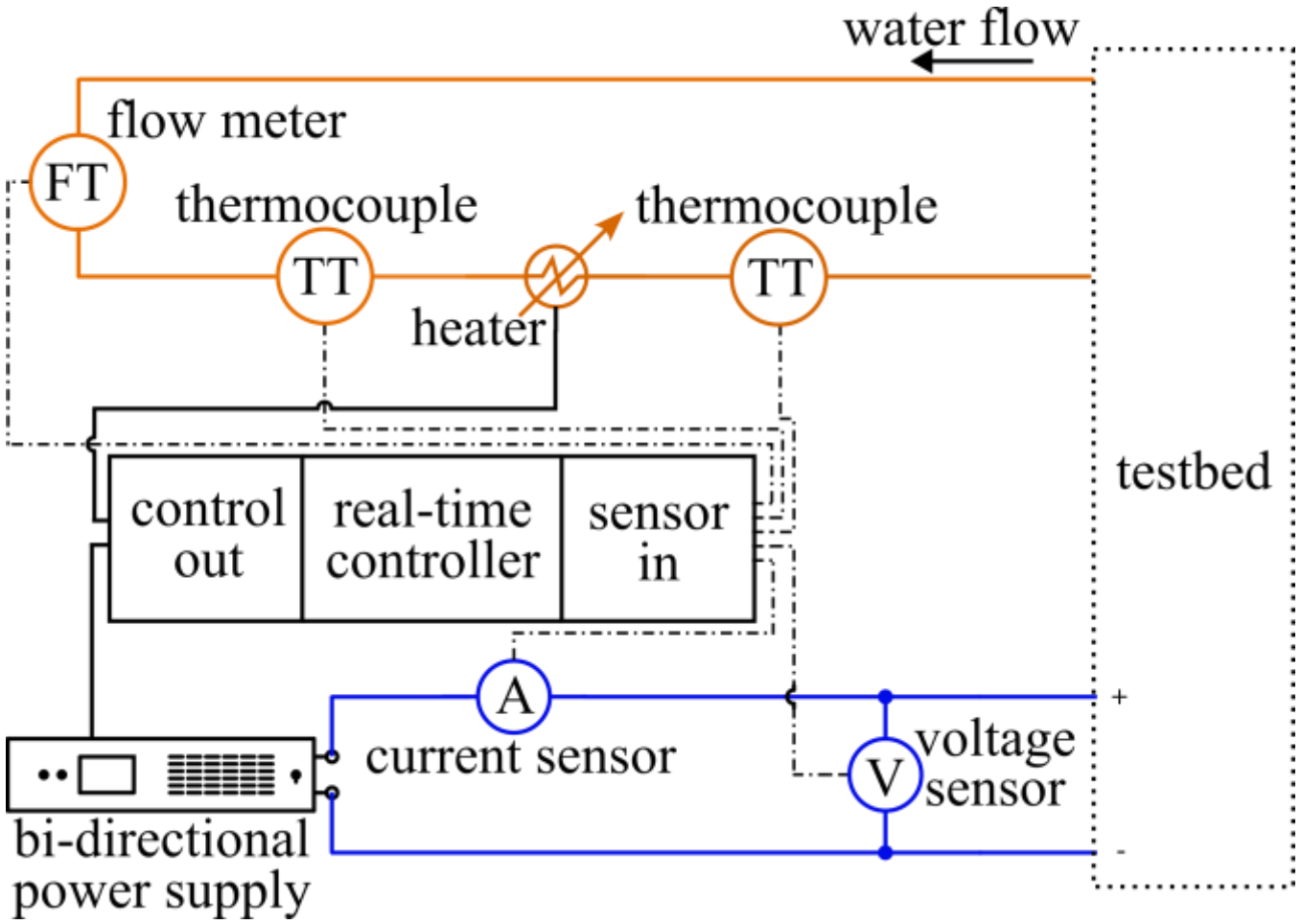
ELECTRO-THERMAL EMULATOR

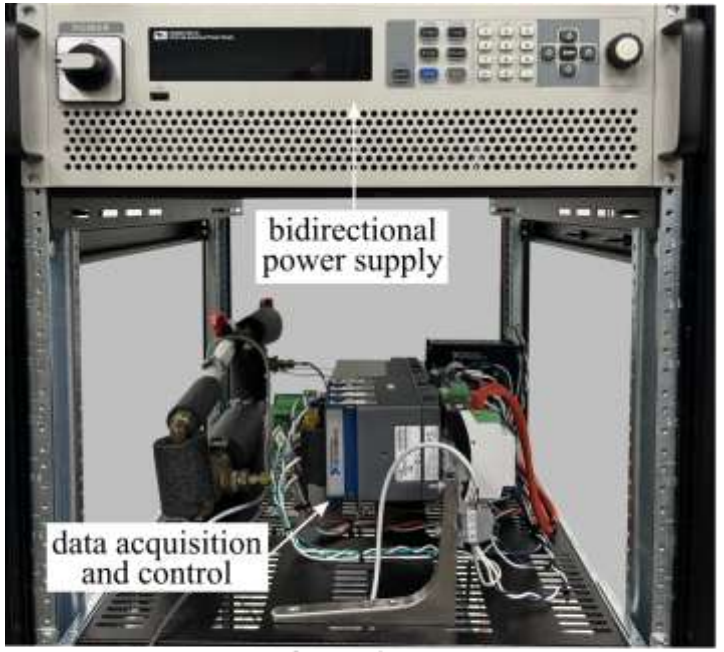
- Lithium-ion batteries are
  - dense and efficient energy storage
  - impractical for frequent testing
- Emulation provides:
  - Repeatable conditions
  - Reduced resource cost
  - Shortened testing downtime
  - Greater electrical and thermal safety



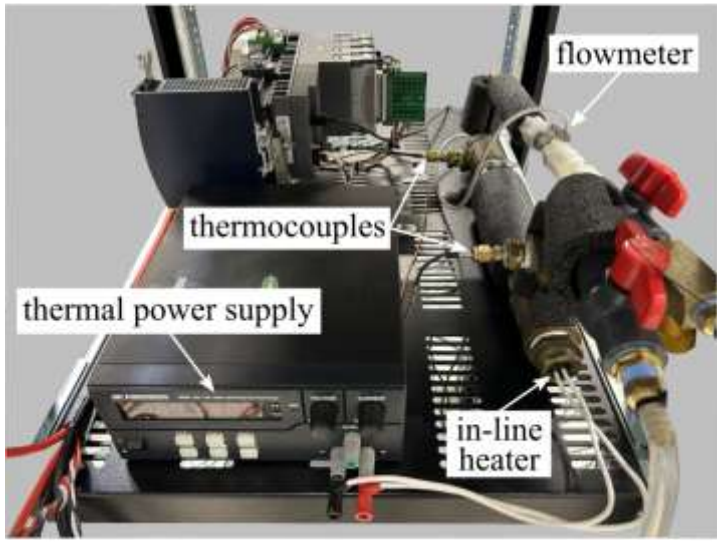
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HARDWARE





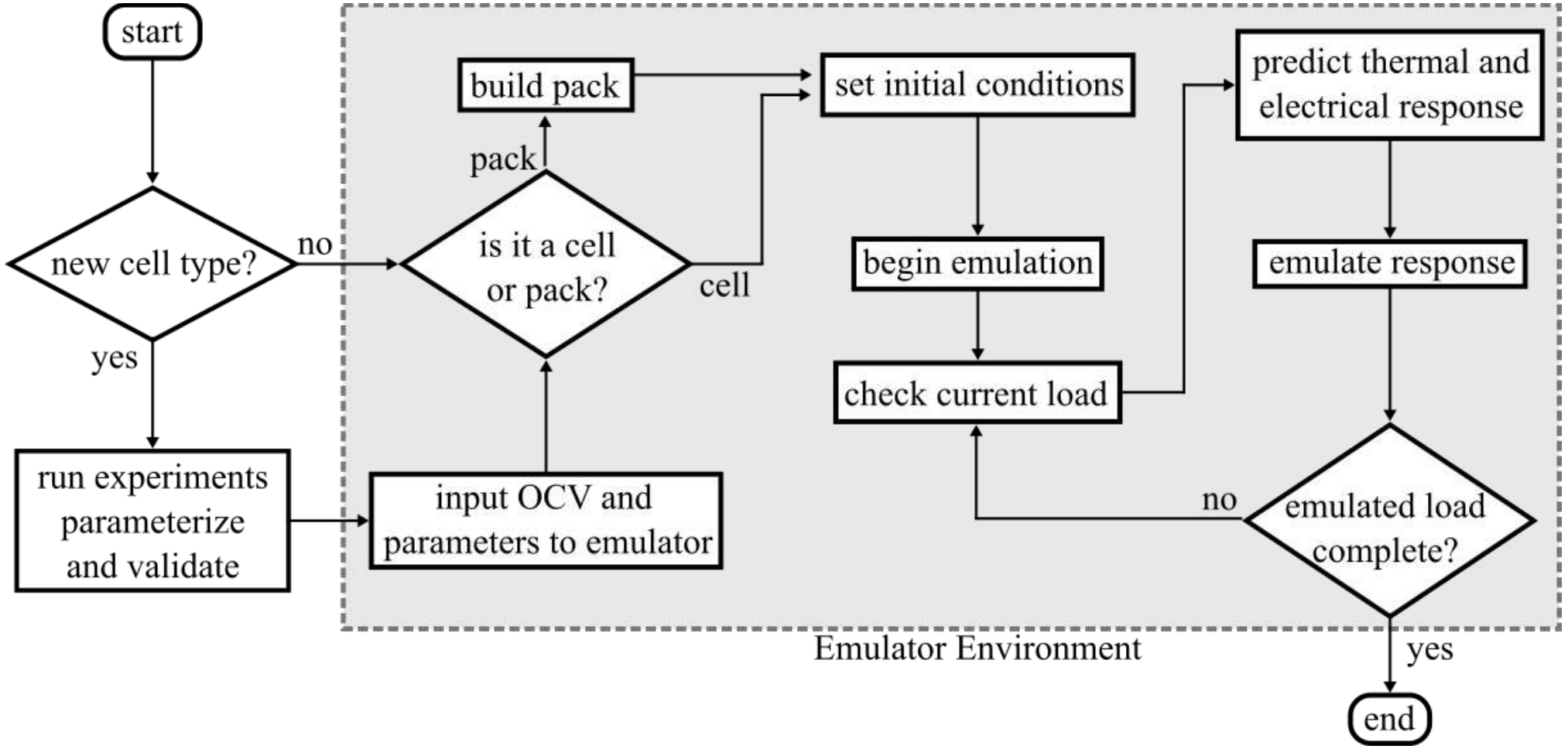
front view



rear view

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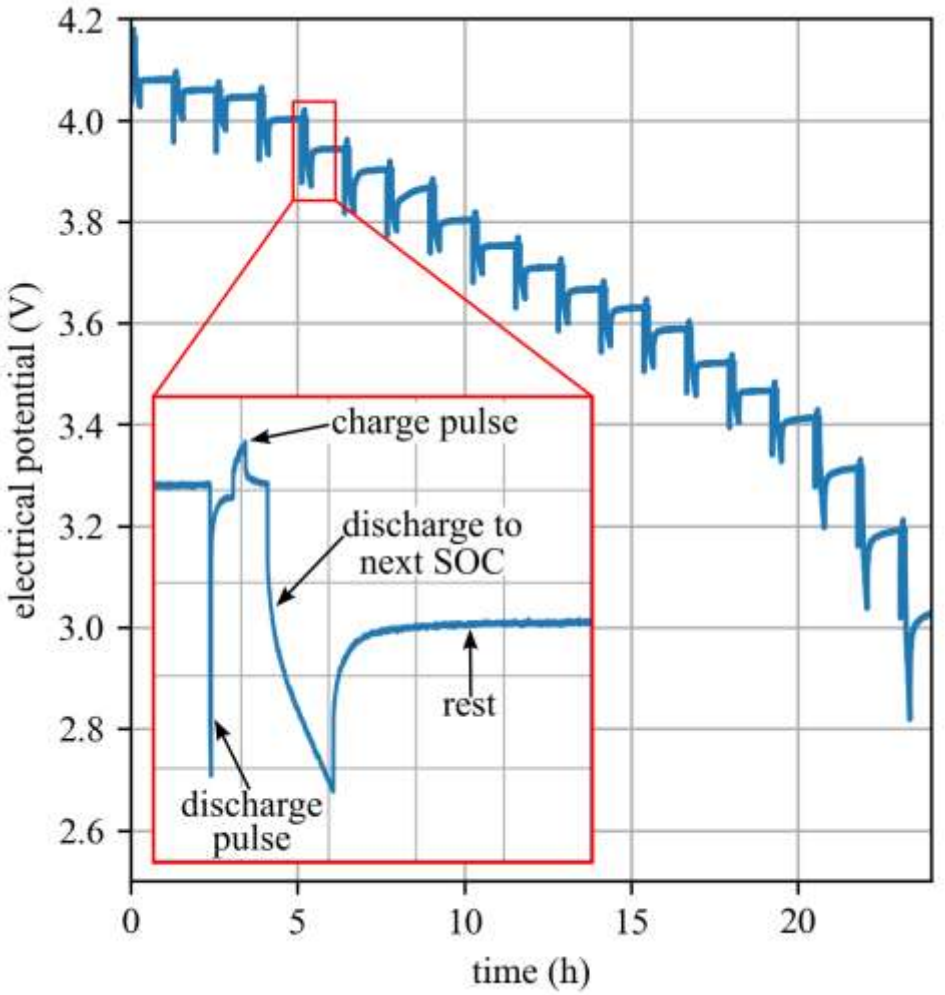
EMULATOR OPERATION



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DATA COLLECTION

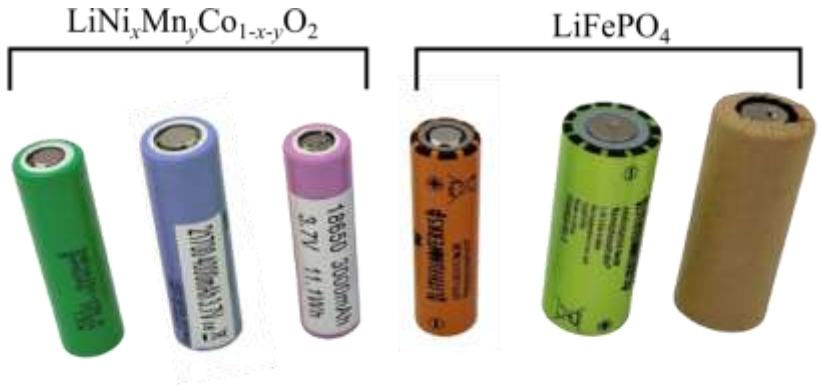
- Training data from Samsung 30Q 18650 3000mAh NMC batteries
- Hybrid Pulsed Power Characterization run on 3 cells each run at:
  - Discharge pulses at every 5% SOC
  - pulse rates 0.5C, 1C, and 2C
  - ambient temperatures of 20°C, 30°C, and 40°C
- Captures dynamic battery behavior under transient load
- Enables learning of nonlinear electrical and thermal behavior

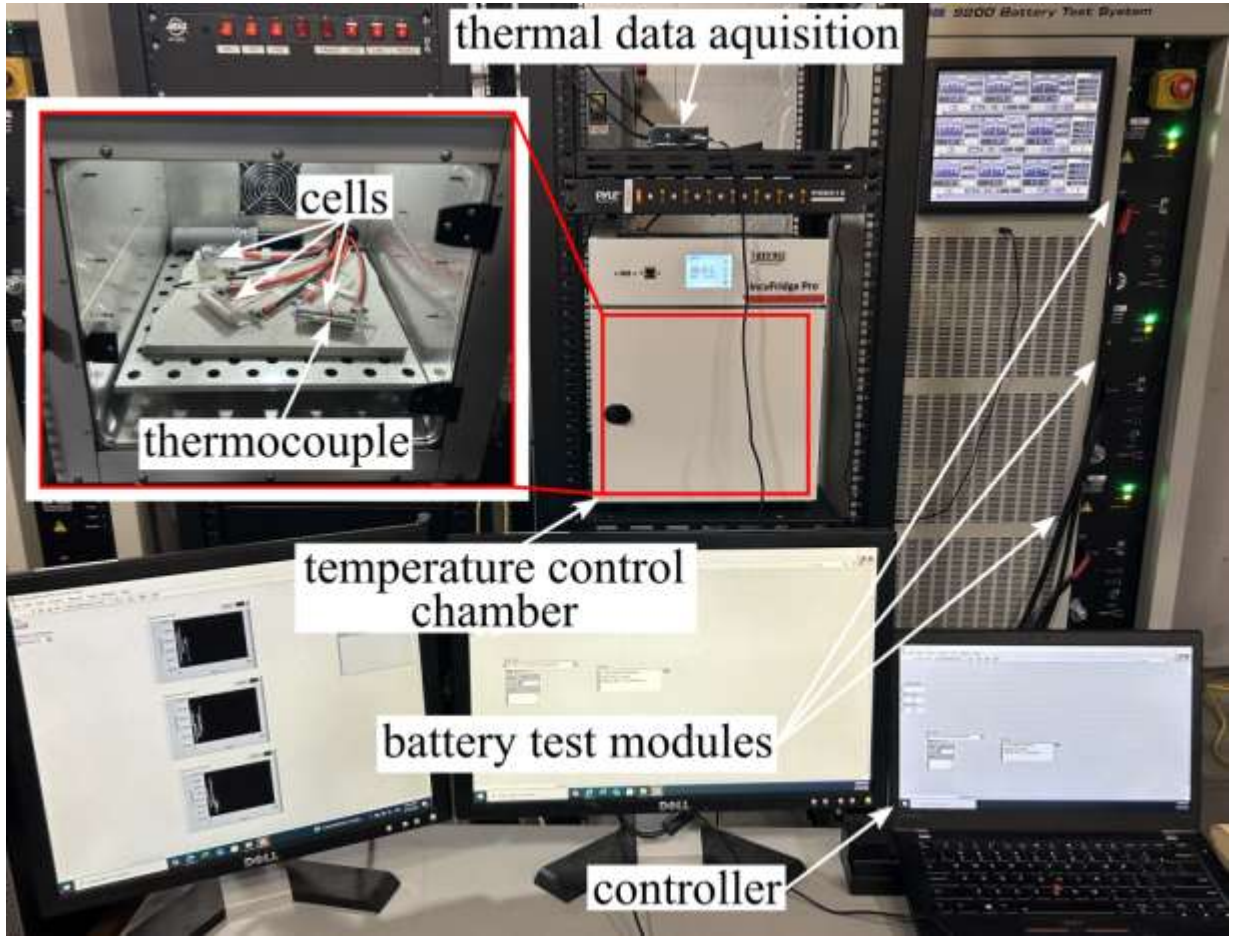


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BATTERY TESTING

- NHR 9200 Battery Tester
  - Machine is controlled using LabVIEW on a laptop
- Incufridge
  - Regulates the temperature of the battery
  - Temperature is tracked by two thermocouples

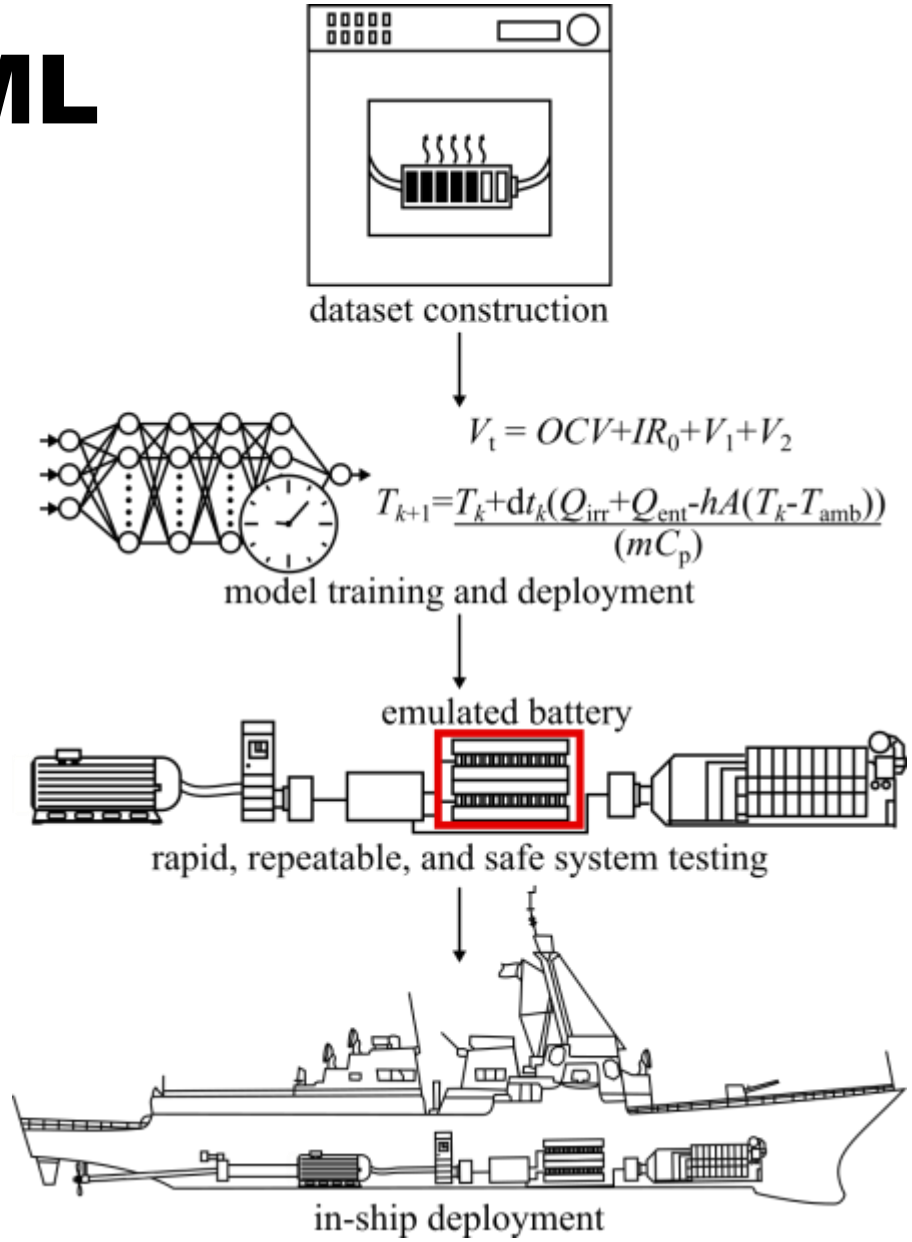




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PHYSICS-CONSTRAINED ML

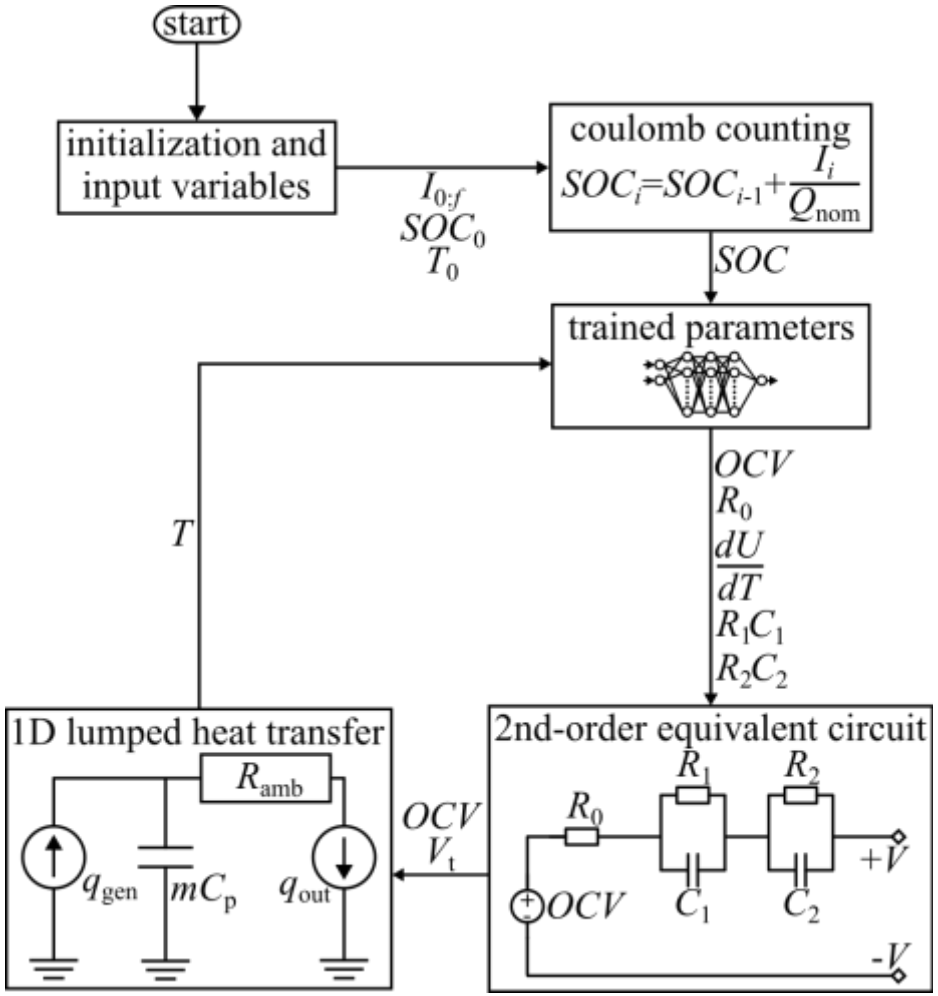
- Physical bounds and regularization are incorporated to enforce realistic behavior
- The framework emphasizes:
  - Interpretability
  - generalizability
  - deployment-oriented performance
    - computationally efficient, and suitable for recursive deployment
- Preserves the structure of an equivalent-circuit representation
- Learns non-linear state-dependent behavior directly from experimental data



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PROPOSED PCML STRUCTURE

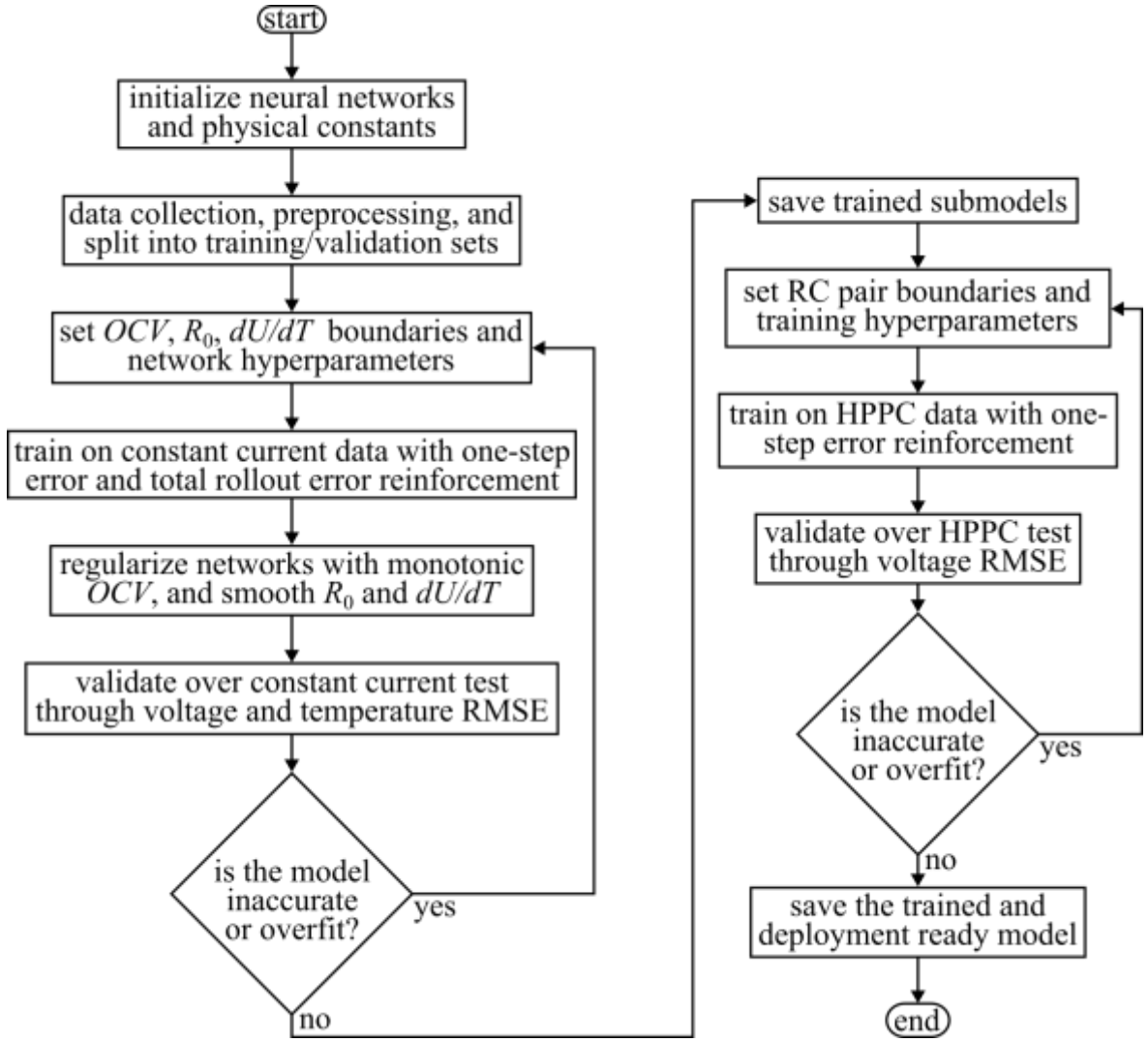
- Neural net works serve as bounded maps for parameters
  - expected to vary with state of charge and temperature
  - the governing electrical and thermal equations remain explicitly defined
- dynamic polarization parameters are not represented by networks
  - treated as static positive parameters identified from HPPC data



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PCML TRAINING METHODOLOGY

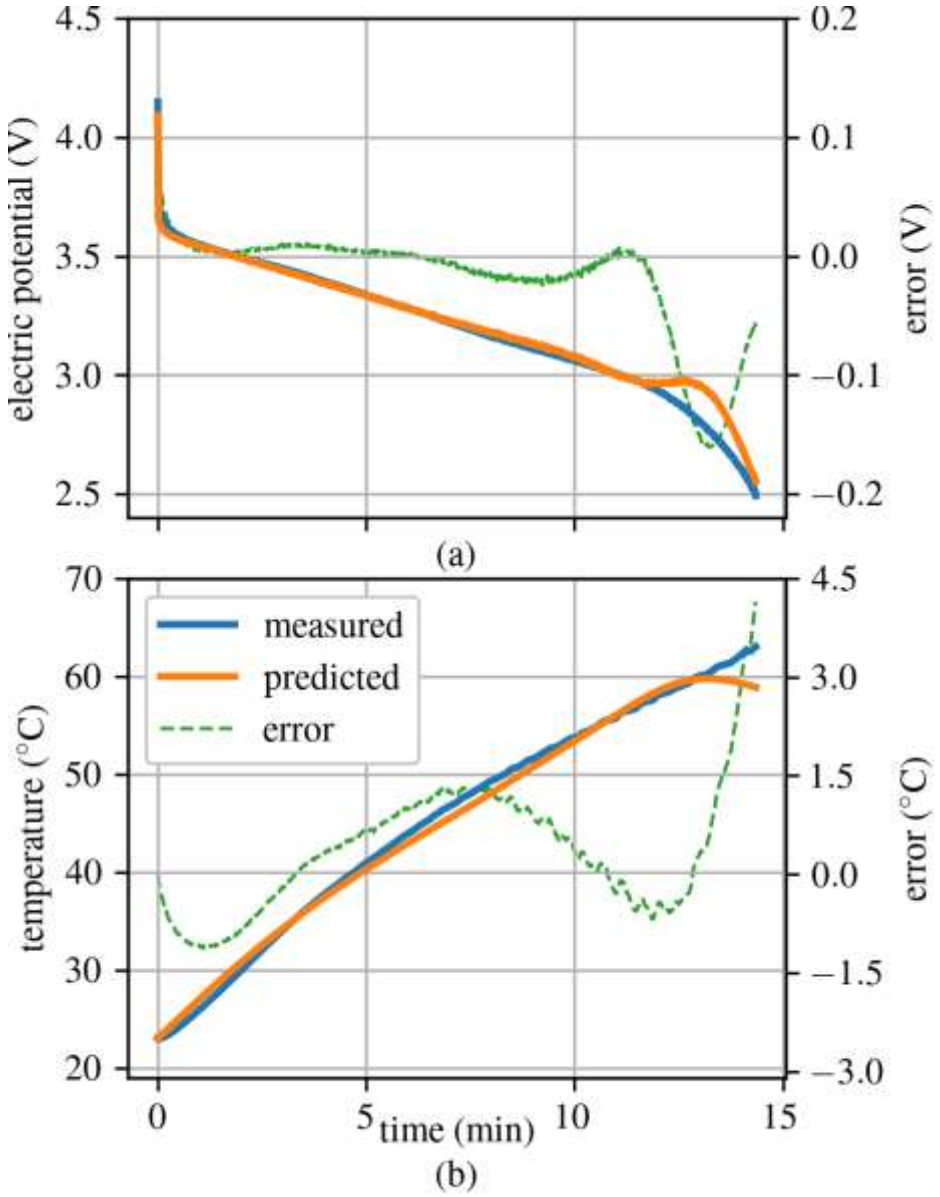
- training process is divided into two stages
  - constant-current experiments provide strong information for:
    - OCV behavior
    - ohmic response
    - Entropic heating
  - pulse-power experiments provide much stronger excitation of the dynamic RC states
    - prevents the networks from attributing pulse behavior to false OCV drops or ohmic spikes



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RESULTS

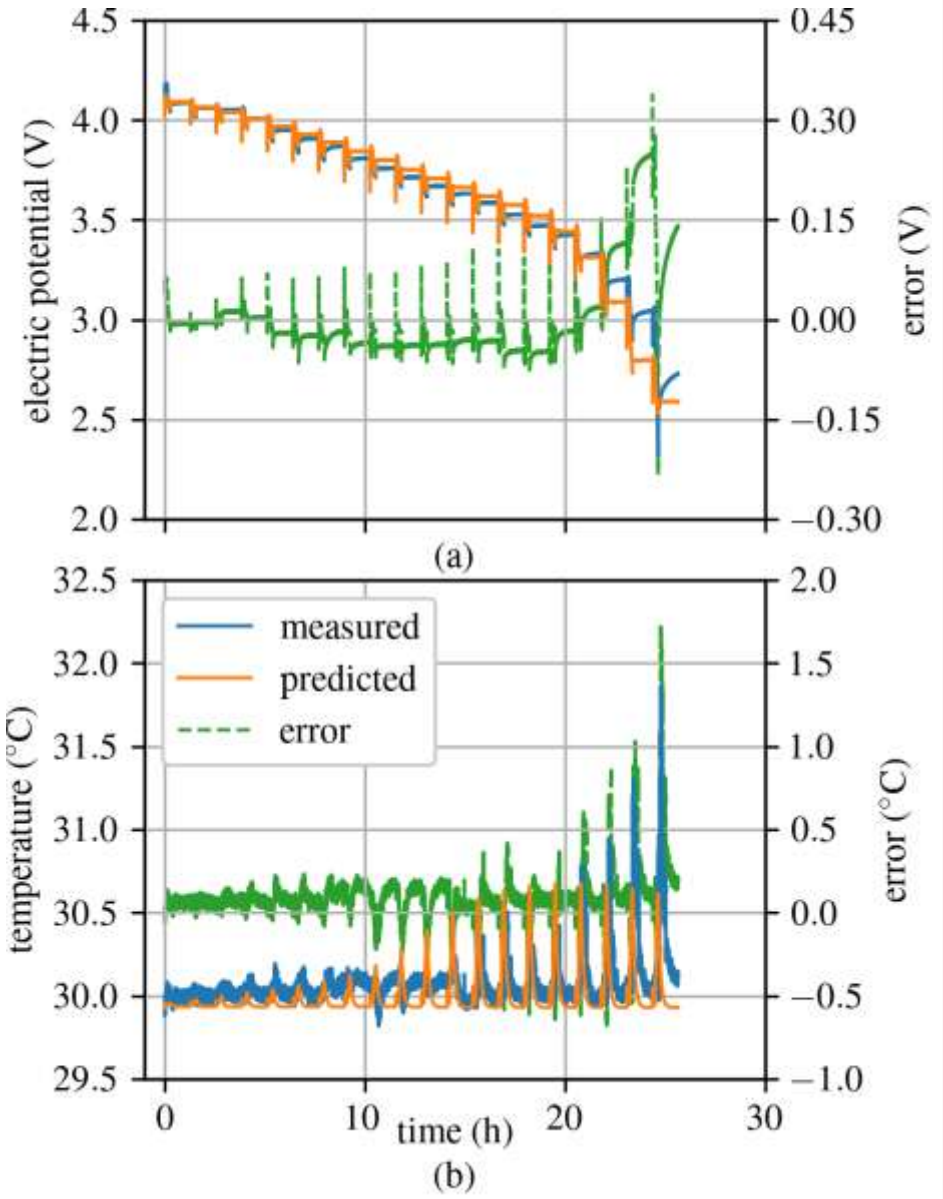
- model is evaluated on a 4C constant current test to observe generalizability
  - only rates below 3C were used in training
- good agreement above 20% SOC
  - The cell surpasses 55°C, the highest temperature trained on, at ~12 min
  - Aligns with 80% depth of discharge when the modeled voltage deviates from the experimental data
- Battery behavior becomes significantly more difficult to model at high C-rates
  - 49.0 mV voltage RMSE
  - 1.02°C temperature RMSE



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RESULTS

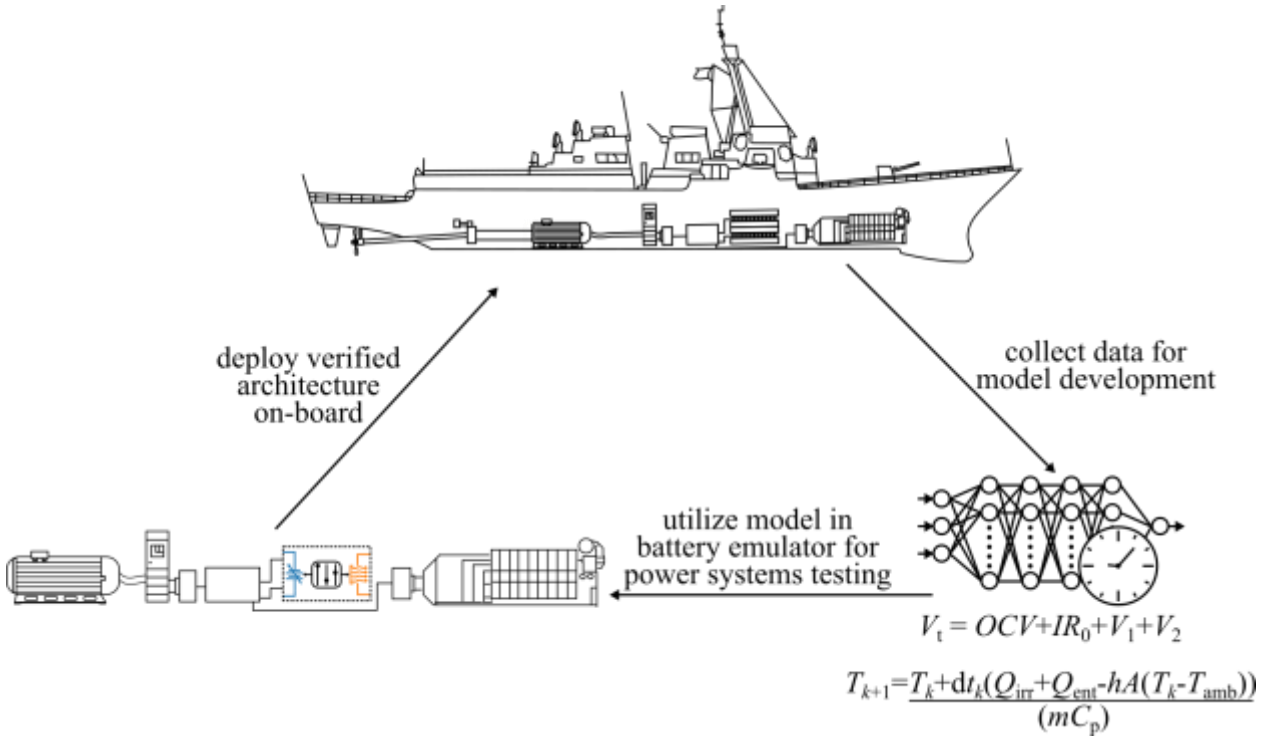
- 65.8 mV RMSE in electrical potential
- 0.205°C RMSE in temperature
- It was assumed that all experimental data remained within the SOC range [0, 1]
  - Could be a significant source of error
- Model saw limited exposure to HPPC data, only 3 profiles
  - due to long training times



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CONCLUSIONS

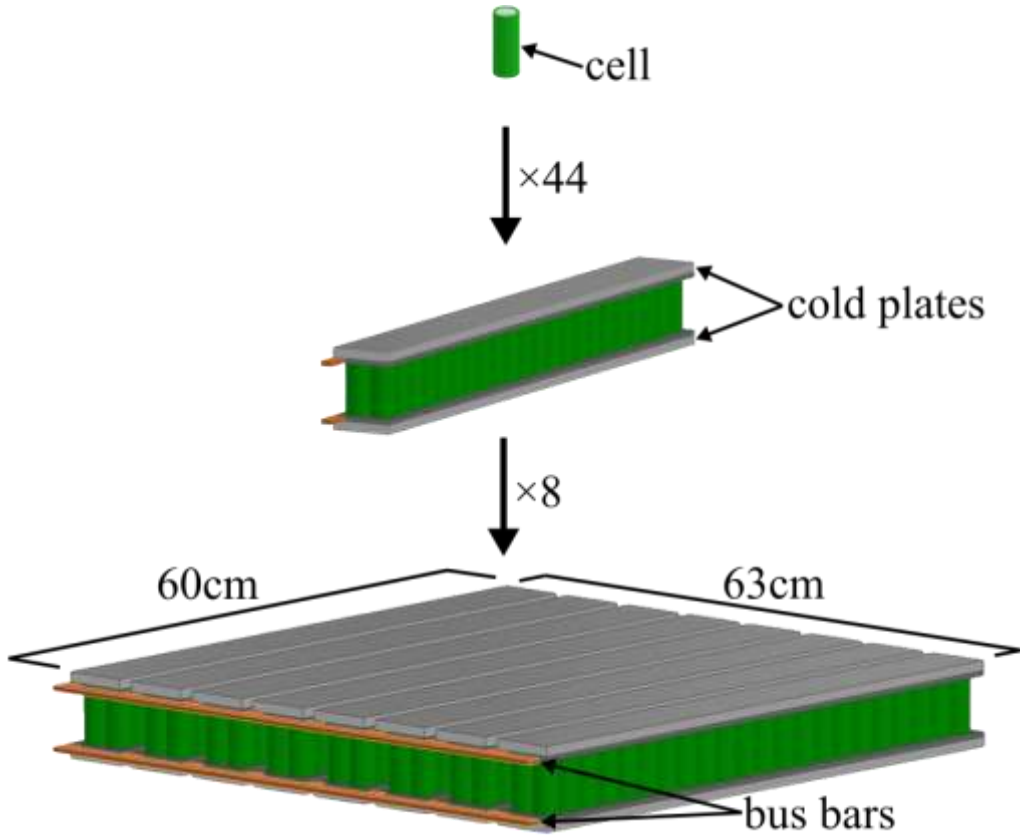
- The emulator is a hardware-in-the-loop platform to reproduce the electrical and thermal physical battery responses that:
  - Allows repeatable conditions
  - Reduces time between tests
  - Reduces cost of degredation
- Physics-constrained machine learning:
  - Preserves interpretability from physics-based equations
  - Allows computational efficiency from data-driven methods
  - Improves generalizability beyond the training domain



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FUTURE DIRECTIONS

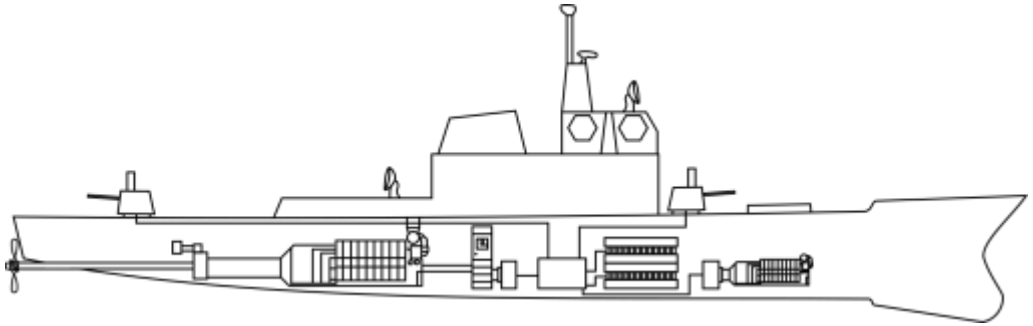
- Hardware should be expanded to emulate testbed scale ESS
- Modeling methods for cell to pack scaling should be incorporated
- Online learning for model adaptation as new data is collected
- Optimization for model training time and computation resources
- Higher fidelity battery models could improve explainability and model trust

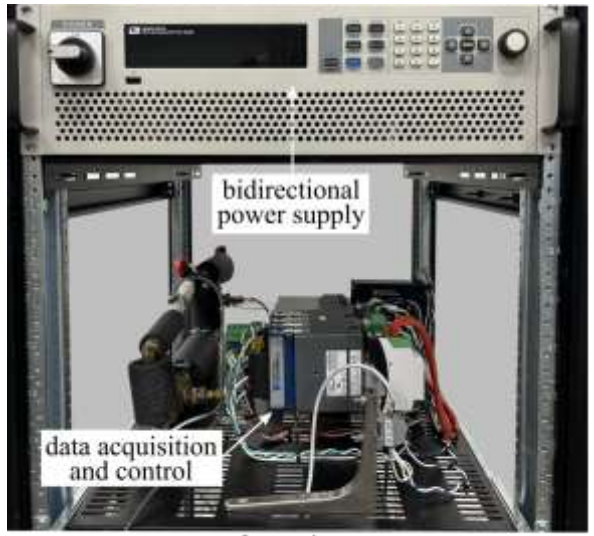


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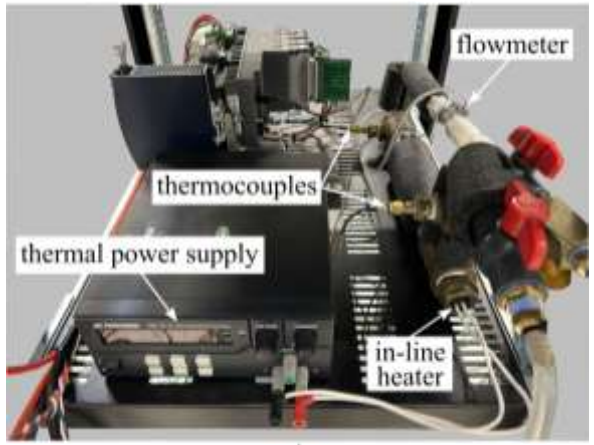
FULL SYSTEM INTEGRATION

- USC hoses the South Carolina Energy and Power Testbed for Engineering Research (SCEPTER) Lab.
- We plan to deploy the physics-informed data-driven models onto the electro-thermal battery emulator,





front view



rear view



ACKNOWLEDGMENT

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THANK YOU!

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