Role of AI in design and control of thermal energy storage (TES) systems: prediction and optimization

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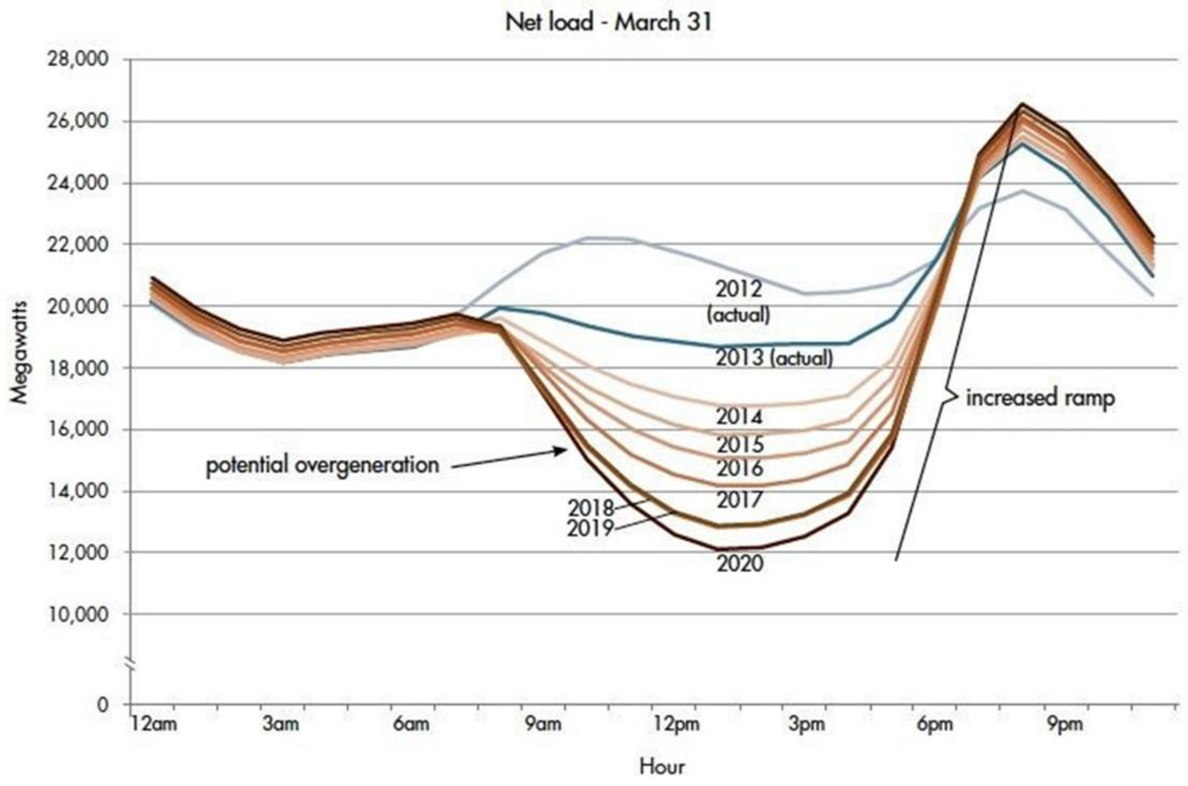
The importance of TES

Challenge of the fluctuating electricity demand (duck curve/camel curve)

- Midday dip: low demand with over-generated solar
- Evening spike: rapid increase of demand without solar



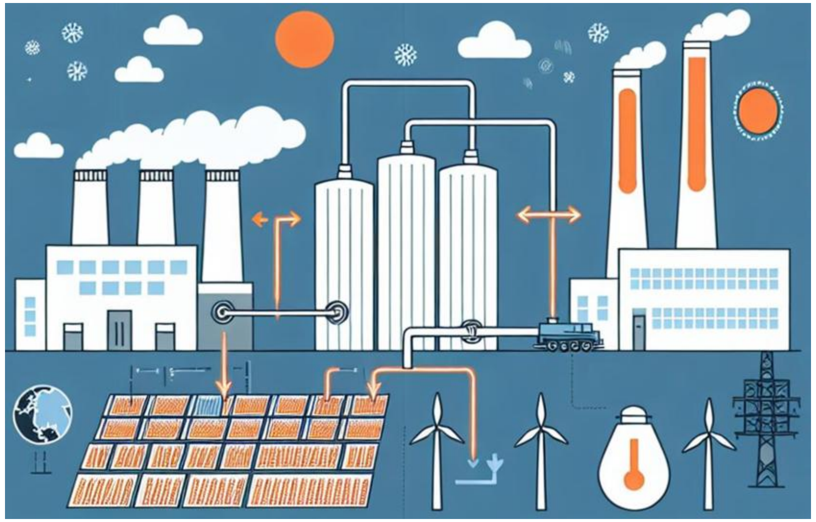
Solution:
Energy Storage can perform as a buffer for the mismatch of energy demand and supply

Thermal Energy Storage (TES)

- **High storage capacity (scalability)**
- **Long-term energy storage capability (days to months)**
- **Low fabrication and maintenance cost**
- **High energy efficiency for meeting thermal demands**

Application of TES

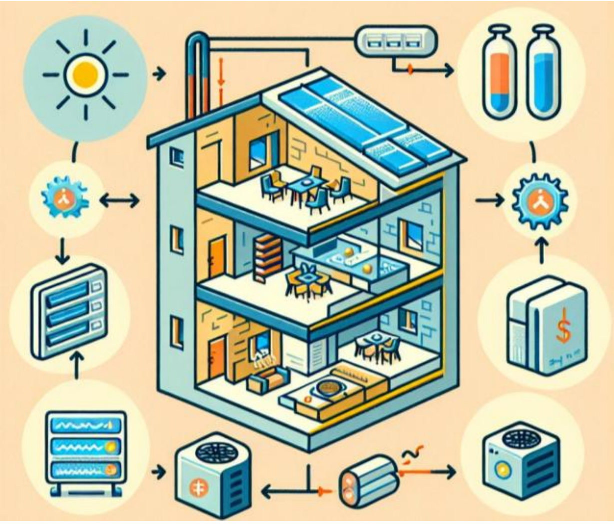
Industrial applications



- Larger-scale systems (MWh to GWh)
- High operational temperature range (100°C to 1000°C)
- Charging/discharging cycles ranging from hours to months

Requires customized design for each TES system based on different operational conditions and demand needs

Building sectors



- Small-scale systems (kWh to MWh)
- Low operational temperature range (below 100°C)
- Usually in daily charging/discharging cycles

Design and performance prediction of TES

Traditional approach

Design procedure:

Determine storage capacity (capacity, duration)

Choose type of storage system, material type of media and HTF

Design shape and dimensions of the system

Adjust design parameters

Performance prediction:

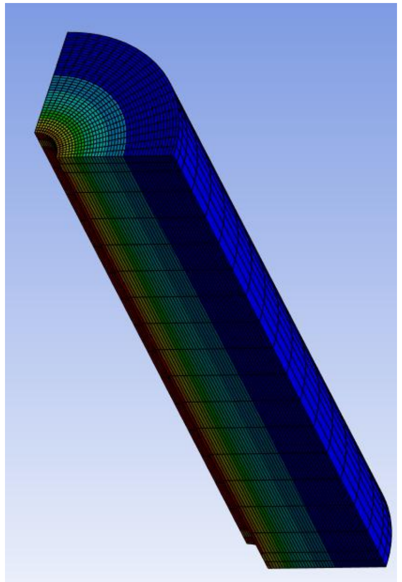
Compare system output with demand

Evaluate storage performance, charging/discharging efficiency

Apply operating conditions (energy input)

Achieved by finite element analysis (FEA)

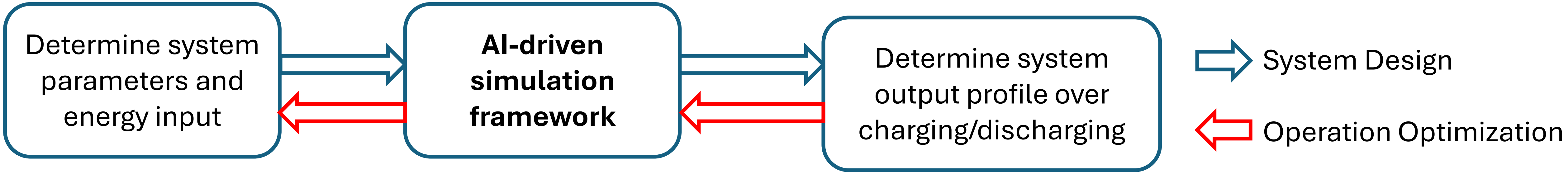
One simulation could take hours to days!



Is it possible to replace FEA with AI and machine learning, to avoid the time-consuming simulation of heat transfer and thermal dynamics?

Design and performance prediction of TES

Proposed new approach



Objective:

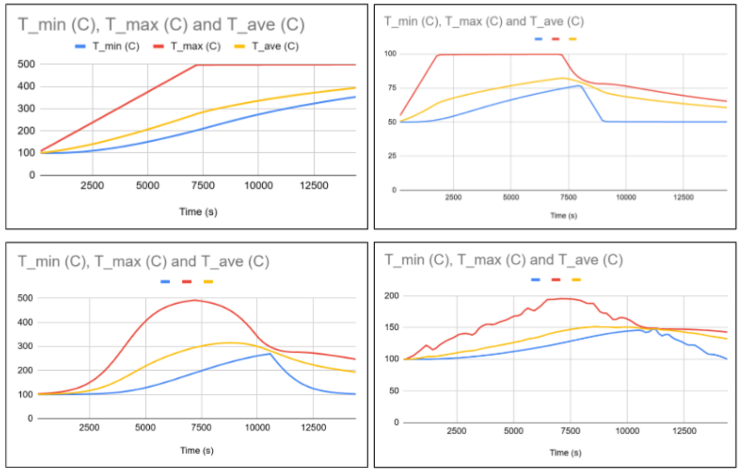
- Aim to achieve 1000-10000× acceleration in performance prediction compared to traditional FE simulations
- Facilitate innovative TES designs through parameter exploration, potentially identifying non-intuitive configurations
- Enable real-time control for TES systems integrated with various energy sources, enhancing grid stability and energy efficiency

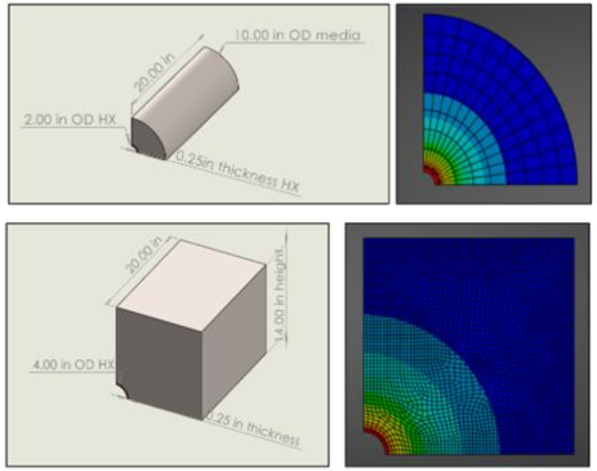
Model Development

1. High-Fidelity Training Data Generation

Training data of the AI model will be created through high-fidelity FE simulations, by capturing the complex physics of heat transfer and thermal dynamics of the TES system by systematically varying key parameters under four categories:

- **Operating Conditions**: Temperature ranges (25-600°C), heating/cooling rates (0.5-10°C/min), and operational cycles
- **Storage Media Properties**: Thermal conductivity, specific heat, density
- **Geometric Configurations**: Module dimensions, aspect ratios, and design of heat exchanger layouts
- **Heat Transfer Fluid (HTF) Parameters**: Fluid types, flow rates (0.1-10 kg/s), inlet temperatures, and pressure conditions





Thermal conductivity	Specific heat	Density
0.2 to 1 (every 0.1 W/m*K)	300 to 1000 (every 100 J/kg.K)	400 to 1000 (every 200 kg/m3)
1 to 2 (every 0.2 W/m*K)	1000 to 2000 (every 200 J/kg.K)	1000 to 4000 (every 500 kg/m3)
2 to 10 (every 1 W/m*K)		

Model Development

2. Machine Learning Model Development

Implement and compare multiple advanced ML architectures specifically designed for sequential data processing.

- **Hybrid RBF-RNN Models**: Combining Recurrent Neural Network layers for processing sequential data and Radial Basis Function Networks for learning complex nonlinear relationship within the time series data
- **Long Short-Term Memory (LSTM) Networks**: To capture long-term dependencies in thermal charging/discharging cycles
- **Gated Recurrent Units (GRUs)**: For efficient modeling of medium-term thermal dynamics with reduced computational complexity

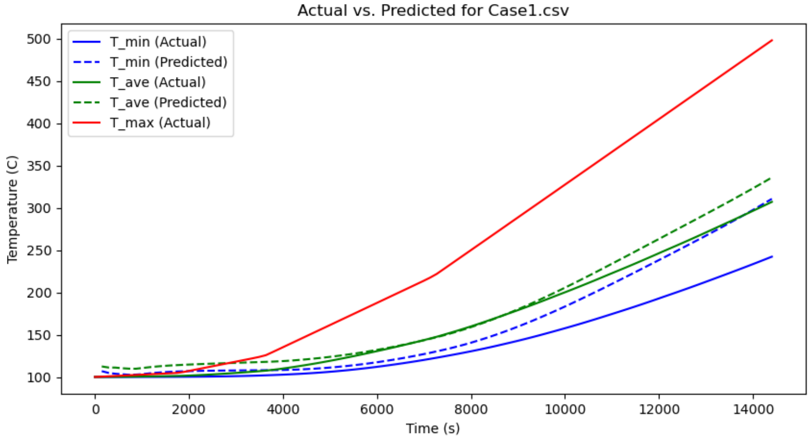
Model Development

3. Model Validation and Performance Evaluation

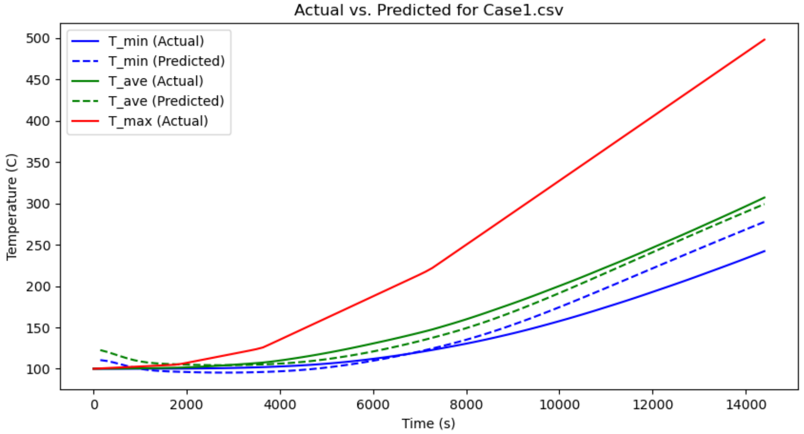
Compare ML-predicted thermal outputs with FE simulation results under identical input conditions to assess prediction accuracy

Case study example (training parameter: input temperature profile)

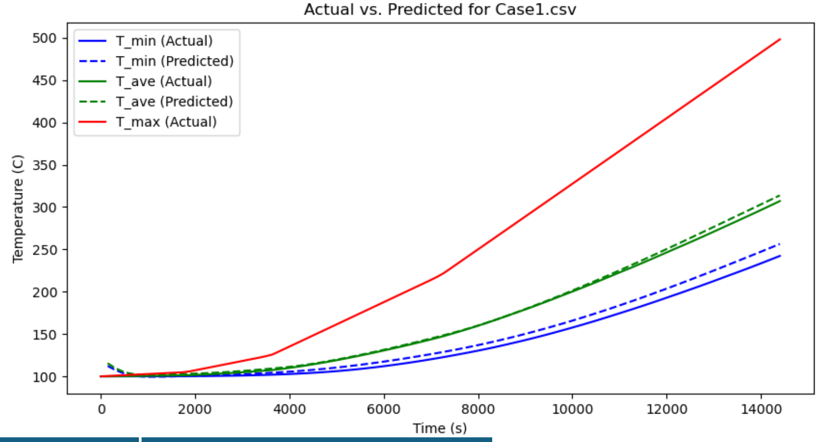
RBF-RNN model



LSTM model



GRU model



Computational cost:

CPU time	RBF-RNN	LSTM	GRU	FE models
Training	122 s	58 s	60 s	N/A
Testing	0.29 s	0.11 s	0.21 s	N/A
Total	122.29 s	58.11 s	60.21 s	20 min

Summary and Future plan

- In progress of establishing the complete dataset for ML training from high-fidelity FE simulations
- Expand the simulation from heat transfer to fluid dynamic to cover broader application scenarios
- Leverage the advantages of LSTM, GRU and hybrid RBF-RNN models for improved prediction performance
- Test the control capability (demand response) of the AL framework by inversely predicting required energy input under desired energy demand profile

Q&A?