Optimal Sensor Placement for State of Charge Estimation in Thermal Energy Storage Device

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Motivation

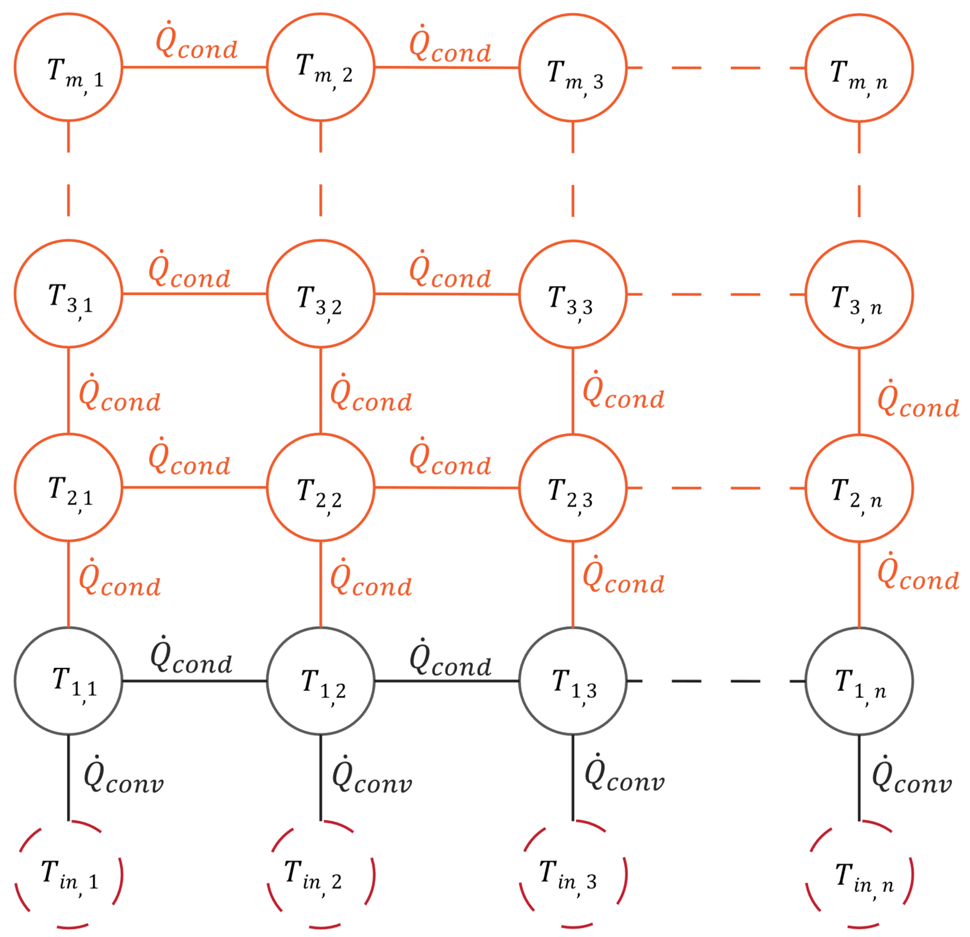
- **Thermal energy storage (TES)** can help manage misalignment between the supply and demand of power on the electrical grid through **load shifting** energy used to power HVAC systems
- To best utilize TES, an accurate estimate for the **state of charge (SOC)** is required. To achieve an improved estimate for SOC within a **composite phase-change material (CPCM)** based TES, dynamic modeling and **state estimation theory** can be applied
- For commercial viability of such a system, there is interested in **minimizing the number**, and **optimizing the location** of, thermocouples in the TES to maximize SOC estimation accuracy

Dynamic Modeling

- Dynamics of CPCM are **nonlinear and state dependent**, changing as the CPCM undergoes phase change
- A dynamic **graph-based model** [1] predicts the temperatures, x, of each CPCM control volume, and may be written as

$$C(x)\dot{x} = A(x)x + B(x)u$$

where $C(x)$ represents the **state dependent capacitance** of each vertex, $A(x)$ **represents thermal resistances** between vertices, and $B(x)$ accounts for thermal resistance between vertices and inputs, u, which are temperatures along refrigerant channel



Above: Dynamic graph-based model of TES heat exchanger, with **state-dependent dynamics**

Optimal Sensor Placement

- Objective is to place **sensors optimally** such that the error between estimated and true SOC is minimized
- This **non-linear mixed integer problem** is solved using a **genetic algorithm (GA)**
- Cost function J is defined as the weighted sum of S, mean squared error between the true ($s_k(x)$) and estimated ($\hat{s}_k(x)$) SOC over the duration of the simulation, and p, the number of sensors, with variable weighting coefficient α
- Constraints enforce integer decision variables, maximum number of allowable sensors, p_{max}, and maximum allowable error, e_{max}

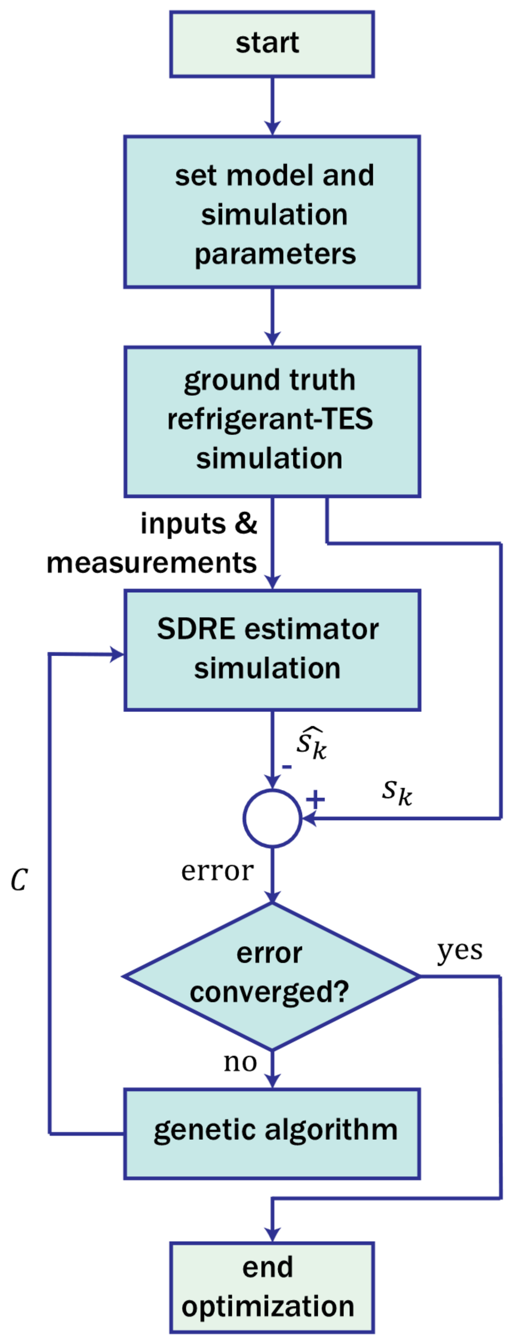
Minimize

$$J = \alpha S + (1-\alpha)p,$$

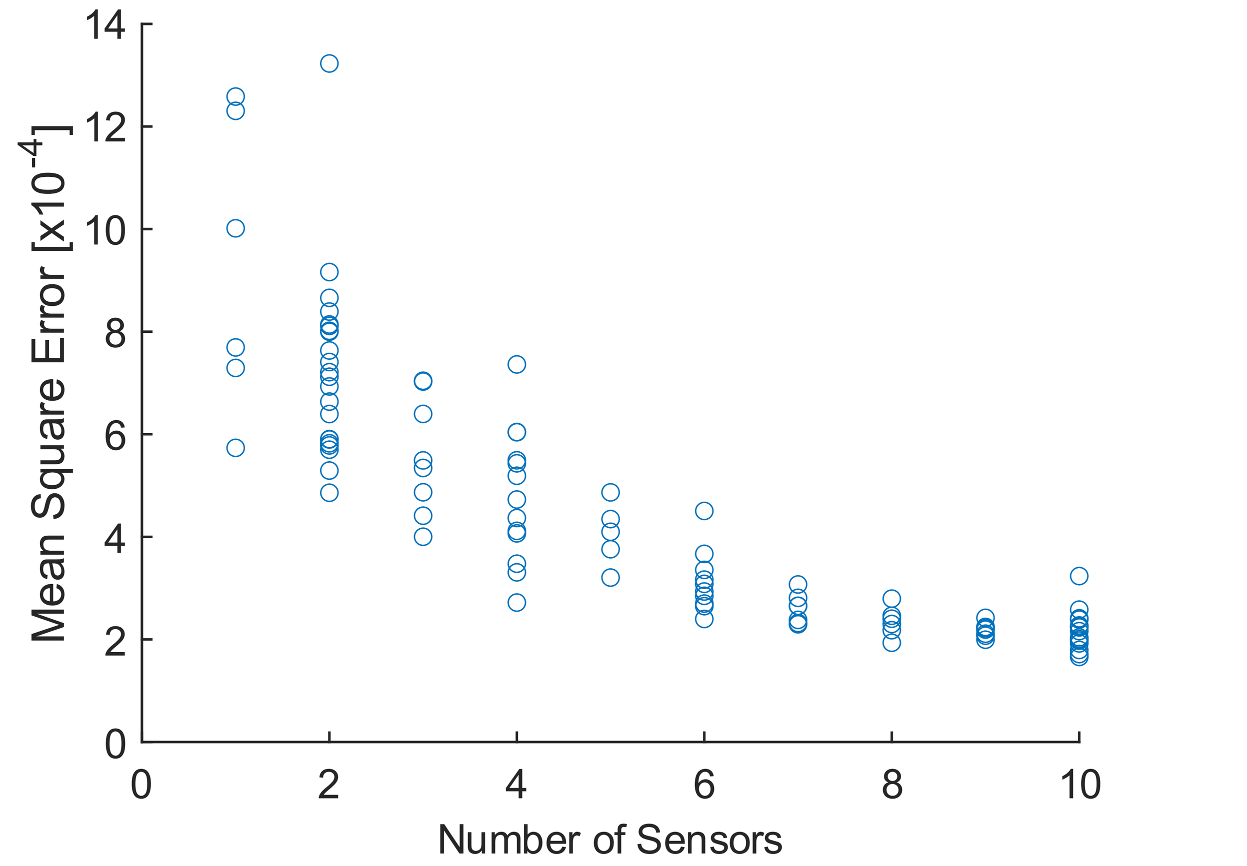
$$S = \frac{\sum_{k=1}^{N} ||s_k(x) - \hat{s}_k(\hat{x})||^2}{N},$$

subject to

$$\dot{x} = f(x,u)$$
$$\dot{\hat{x}} = g(\hat{x}, y, u)$$
$$C \in \mathbb{R}^{p \times n}$$
$$c_{i,j} = \begin{cases} 1 & \text{if } y_{k,i} = x_{k,j} \\ 0 & \text{otherwise} \end{cases}$$
$$\sum_{i=1}^{p} c_{i,j} \le 1, \forall j = 1,2,\dots n$$
$$p \le p_{max}$$
$$e_{max} \le 0.08$$

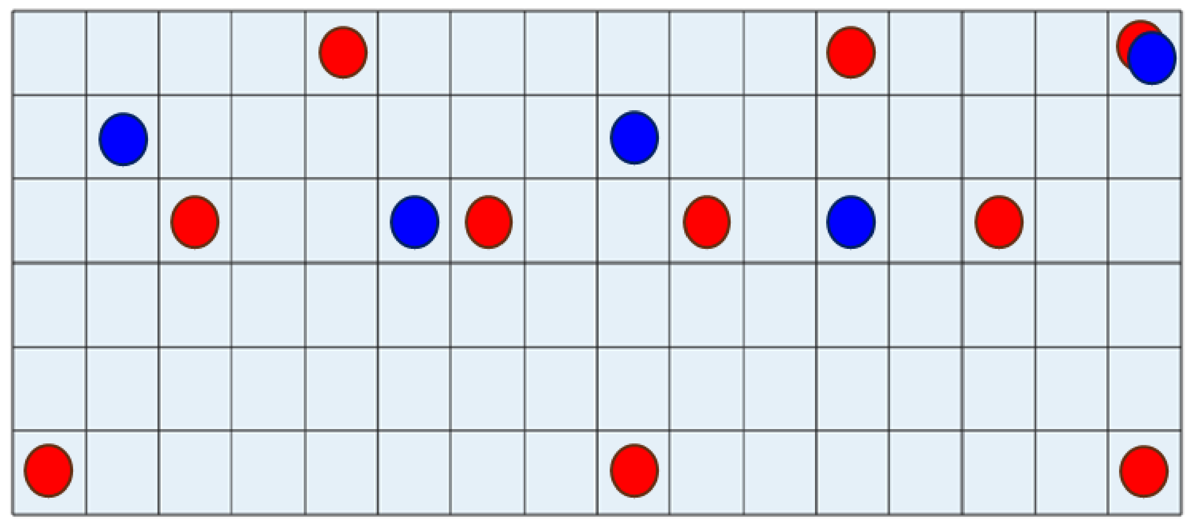


- Model with a fine discretization is parametrized and simulated; values from this simulation are used as "**ground truth**" values in the genetic algorithm
- Coarser discretization is used for solving the optimal sensor placement problem
- Model iterated upon using different sensor locations
- Optimization concludes once **error values converge** within specified tolerances



Above: Pareto front, generated by varying α, showing cost **tradeoff** between estimation error and number of sensors

Below: Discretized TES heat exchanger, showing location of **baseline sensor placement** and **optimal sensor placement** of 5 thermocouples



- From Pareto front, 5 sensors chosen as **ideal tradeoff** between minimizing error and minimizing number of sensors
- Using the GA, an optimal set of 5 sensors was generated and compared against a baseline set of 10 sensors

Conclusion

Key Contributions

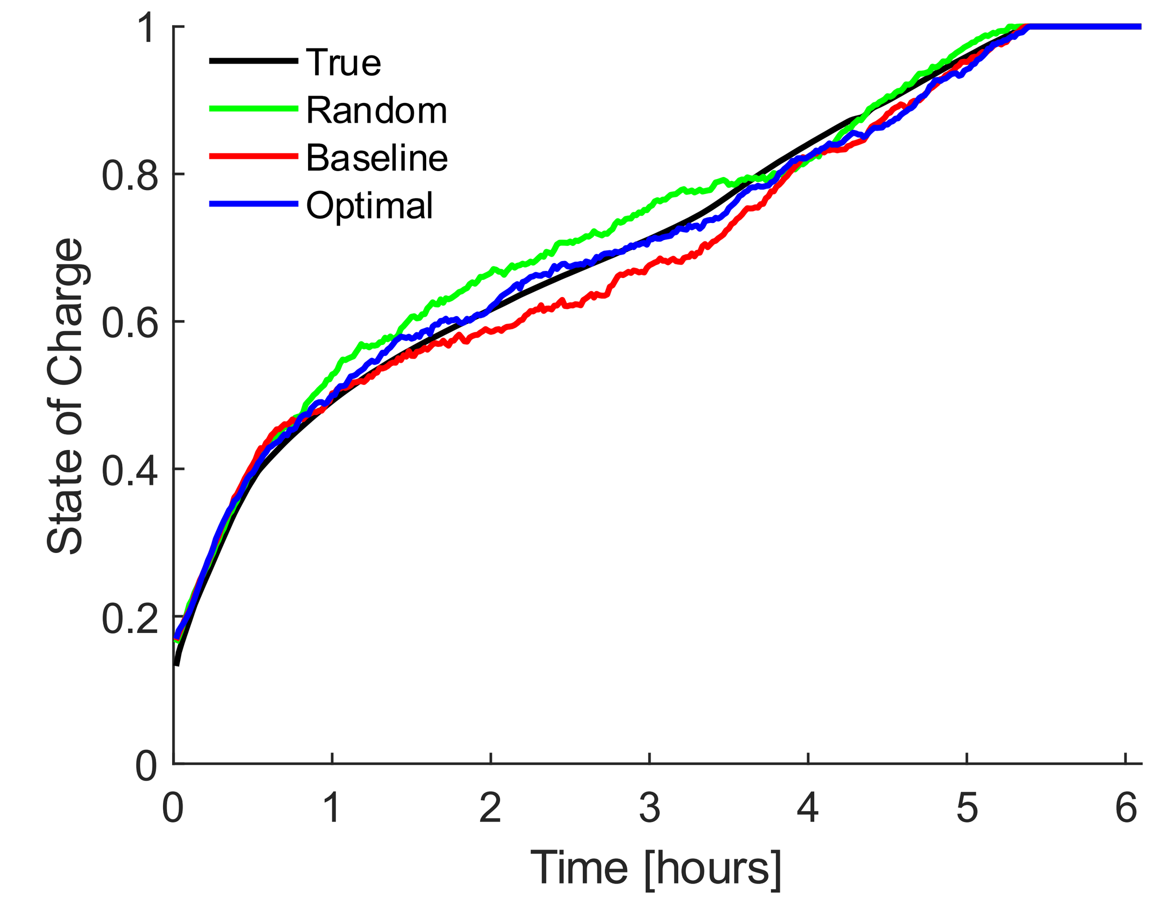
- Development of general approach to finding optimal placement of temperature sensors for SOC estimation with flexible cost function
- Demonstration of improved performance in simulation compared to baseline case, while using fewer sensors

Future Work

- Validate findings experimentally
- Explore different TES heat exchanger geometries

State Estimation

- Temperature **measurements are combined with predictions** from dynamic model to generate time-varying SOC estimate
- Estimation accomplished using state estimation theory, **state-dependent Riccati Equation** filter [2]



Above: Example of **SOC estimation** over duration of 6.5 hours of simulated time in condensing operation

Below: Example estimator performance in condensing mode - through choice of optimal sensor placements, **improved performance** achieved **with fewer sensors** than baseline case

Sensor Placement	Mean Square Error ($\times 10^{-4}$)
Randomly placed (10 sensors)	6.9
Baseline placement (10 sensors)	6.7
Optimal solution from GA (5 sensors)	2.1
Full measurements (ideal case)	1.8

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[1] M. Shanks, C. M. Shoalmire, M. Deckard, K. N. Gohil, H. Lewis, D. Lin, P. J. Shamberger, and N. Jain, "Design of spatial variability in thermal energy storage modules for enhanced power density," Applied Energy, vol. 314, p. 118966, May 2022.
[2] M. Shanks, U. Inyang-Udoh, and N. Jain, "Design and validation of a state-dependent riccati equation filter for state of charge estimation in a latent thermal storage device," vol. 145, no. 91002.