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AUTONOMOUS DIGITAL TWIN FRAMEWORK FOR REAL-TIME THERMAL MODEL UPDATING

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Molinaroli College of Engineering and Computing

CONTENTS

PUBLICATIONS IN THIS WORK

1. **Braden Priddy**, Richard Hainey, Tyler Deese, Austin R.J. Downey, Jamil Khan, and Herbert L. Ginn. Real-time thermal data assimilation for power electronics at the edge. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers, aug 2024

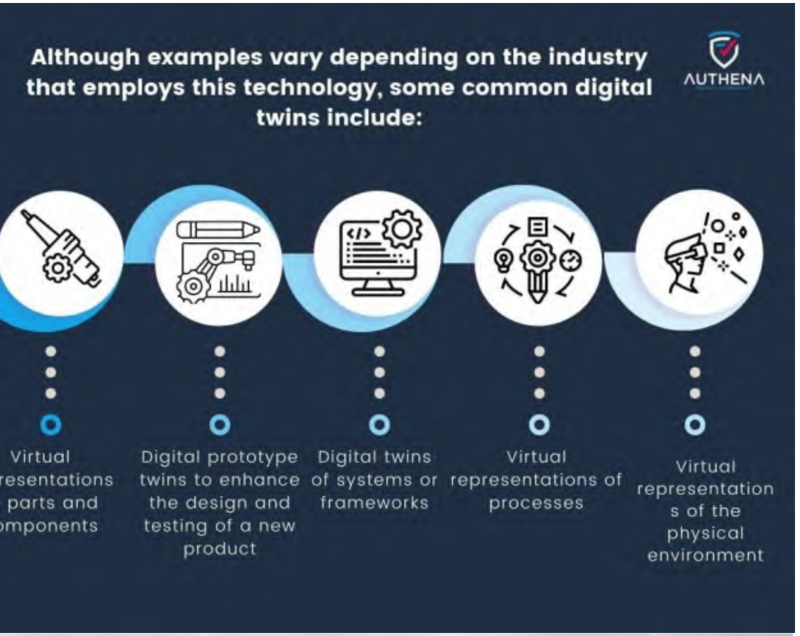
2. **Braden Priddy**, Kerry Sado, Richard Hainey, Austin R.J. Downey, Jamil Khan, Kristen Booth. Robust and autonomous framework for thermal model updating within digital twins. (Not yet submitted)

WHAT IS AND WHY USE A DIGITAL TWIN?

Relevance:

- Digital twins are becoming a more prevalent area of research.
- Can be leveraged to optimize real world systems, test new procedures, and conduct virtual tests without the need of the physical twin.
- As Naval systems become increasingly complex the need for data driven solutions will become essential in maintaining the overall health of a ship`s systems and subsystems.
- MATLAB Simscape model of a cooling loop was updated using particle swarm optimization (PSO) to minimize the error between experimental data and simulation data.

[1]



[2]

[1] Digital Twins are the foundation of future collaborations in an environment sometimes known as “The enterprise metaverse” - authena. (2022). https://authena.io/digital-twins-are-the-basis-for-future-collaboration-the-enterprise-metaverse/

[2] *DDG 51 Arleigh Burke class destroyer*. Military.com. (n.d.-b). https://www.military.com/equipment/ddg-51-arleigh-burke-class-destroyer

APPLICATION AREA EXAMPLE: RADAR ARRAY COOLING

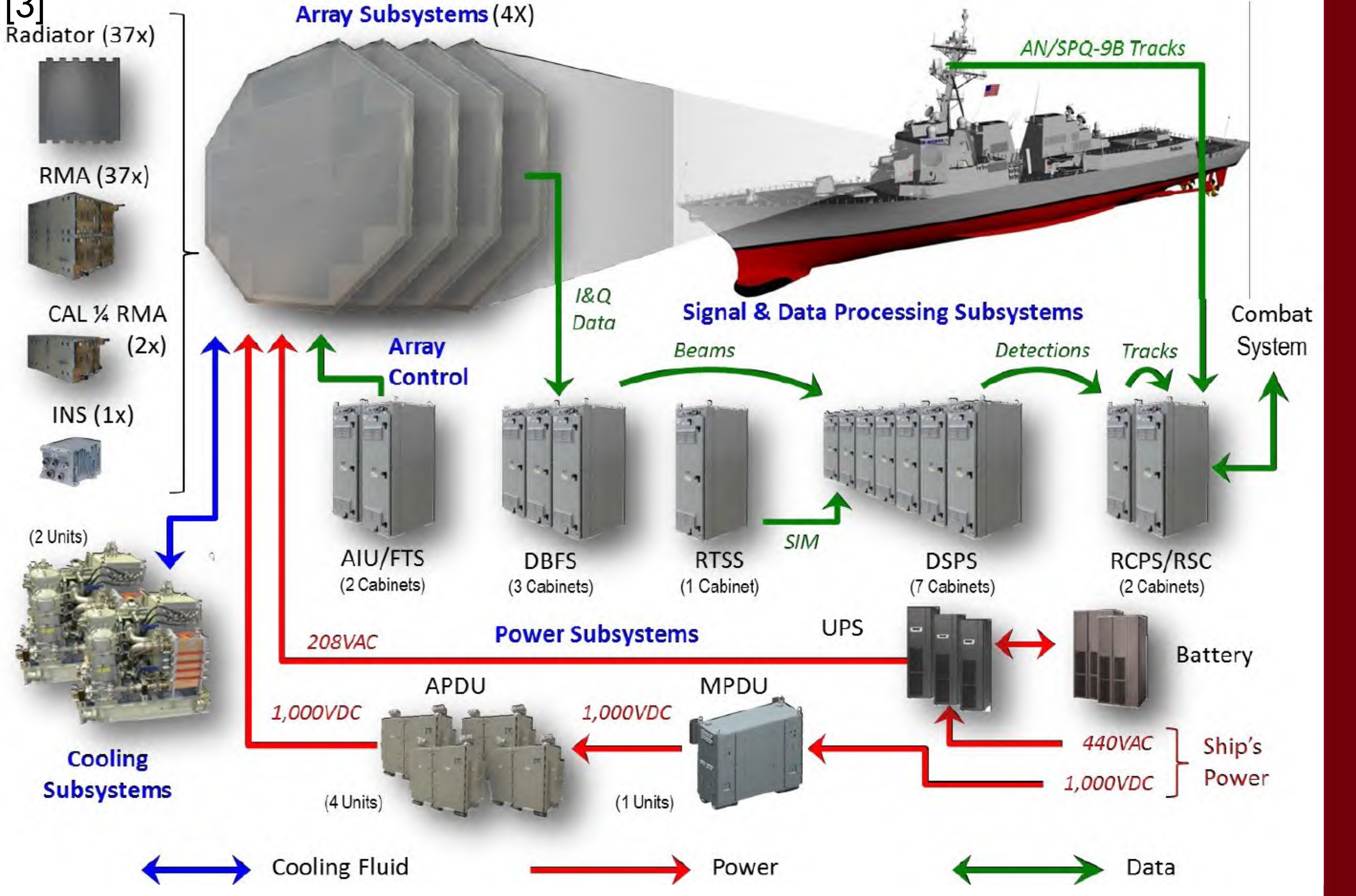
Heat management:

- The AN/SPY- 6(V)1 AMDR [*Air and Missile Defense Radar*] system on board the new flight III Arleigh Burke destroyers produce waste heat during operation.
- This heat is removed via a cooling subsystem equipped with liquid cooling.

Usefulness of PSO:

- A digital twin equipped with an PSO algorithm may monitor the condition of the coolant, e.g., blockage formations, coolant degradation.
- Digital experiments to test ship capabilities under varying test conditions may be performed. e.g., temperature rise within components under simulated power loads.
- Highly accurate simulations may be used to predict future conditions within the cooling subsystem, e.g., time to overtemperature.

[3]



[3] Ryan White, By, & White, R. (2021, February 25). *Report to U.S.Congress on U.S. Navy DDG-51 and DDG-1000 destroyers*. Naval Post- Naval News and Information. https://navalpost.com/report-to-congress-on-ddg-51-ddg1000-usnavy/

PHYSICAL TWIN – COMPONENTS AND LAYOUT

Pump:

- Centrifugal pump that circulates water through system. Flow monitored by flow rate sensor.

Manual Valve:

- Adjusts to simulate blockages through flow restriction.

Coolant Plate w/ Heating Pad:

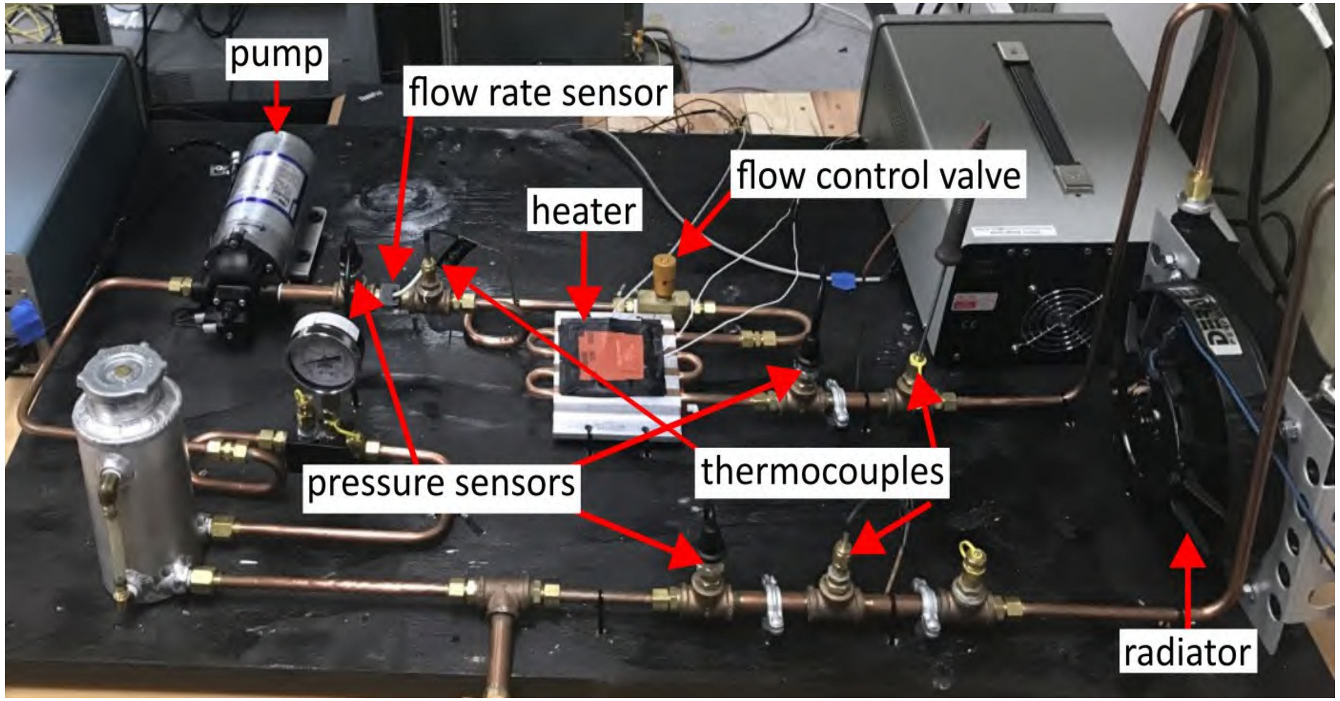
- Simulates waste heat injection, monitored by a thermocouple.
- Heat injection is constant [How much heat?]

Fan Radiator:

- Cools water, with temperature change monitored by thermocouples.

Expansion Tank:

- Regulates pressure and acts as reservoir.



PHYSICAL TWIN - DATA COLLECTION AND POWER CONTROL

Data acquisition:

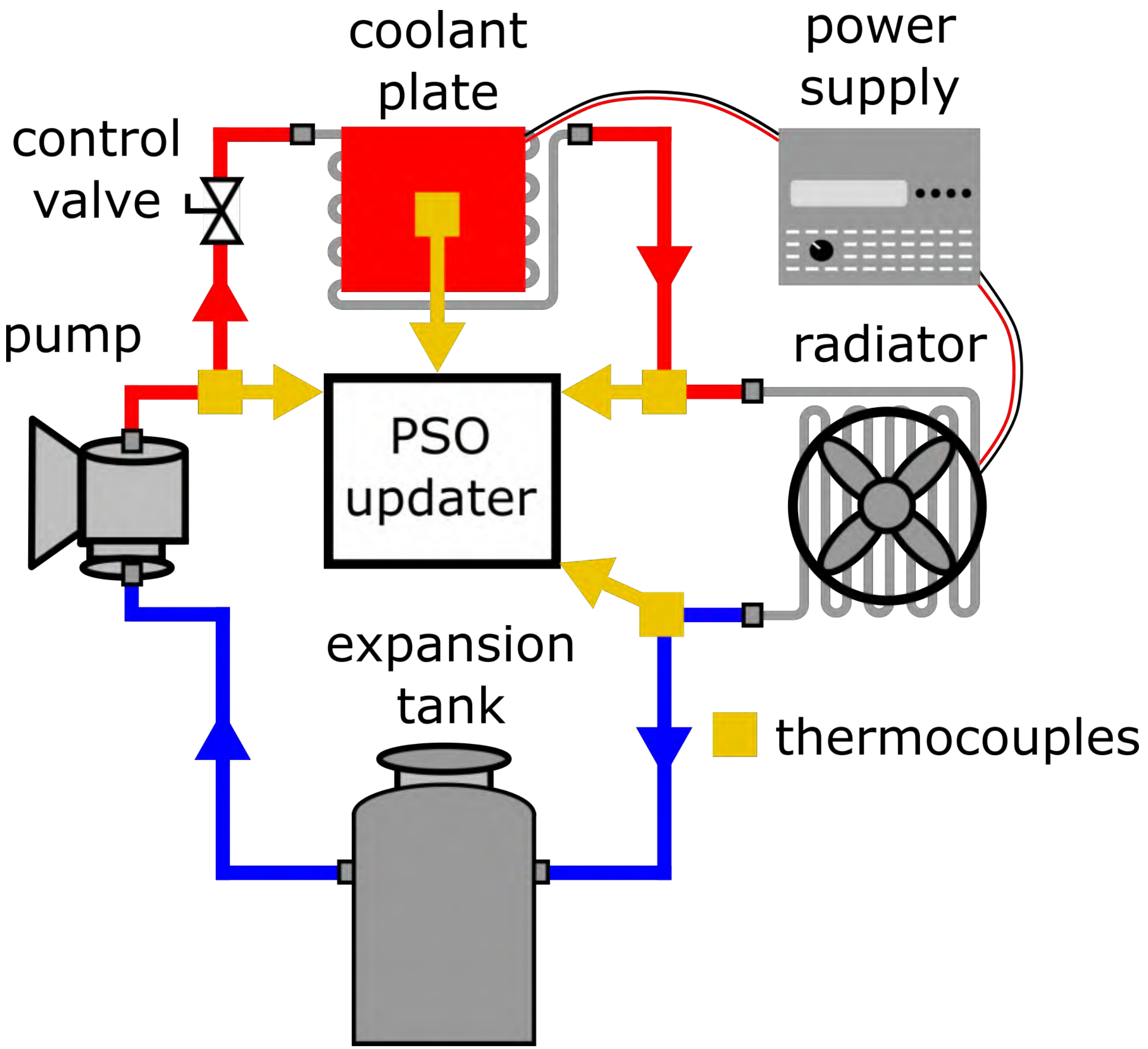
- "PSO updater" is an x64 Windows "edge" computer equipped with NI-DAQ with thermocouple data module.

Power supply:

- The power supply provides variable power to both the fan radiator and heating pad.
- Pump power is non-variable and supplied via wall outlet.

Heating element:

- Consists of a simple wire resistor heating element.
- Heating pad is an aluminum case with incased copper tubing to absorb waste heat.



DIGITAL TWIN - SIMSCAPE SIMULATION MODEL

Red:

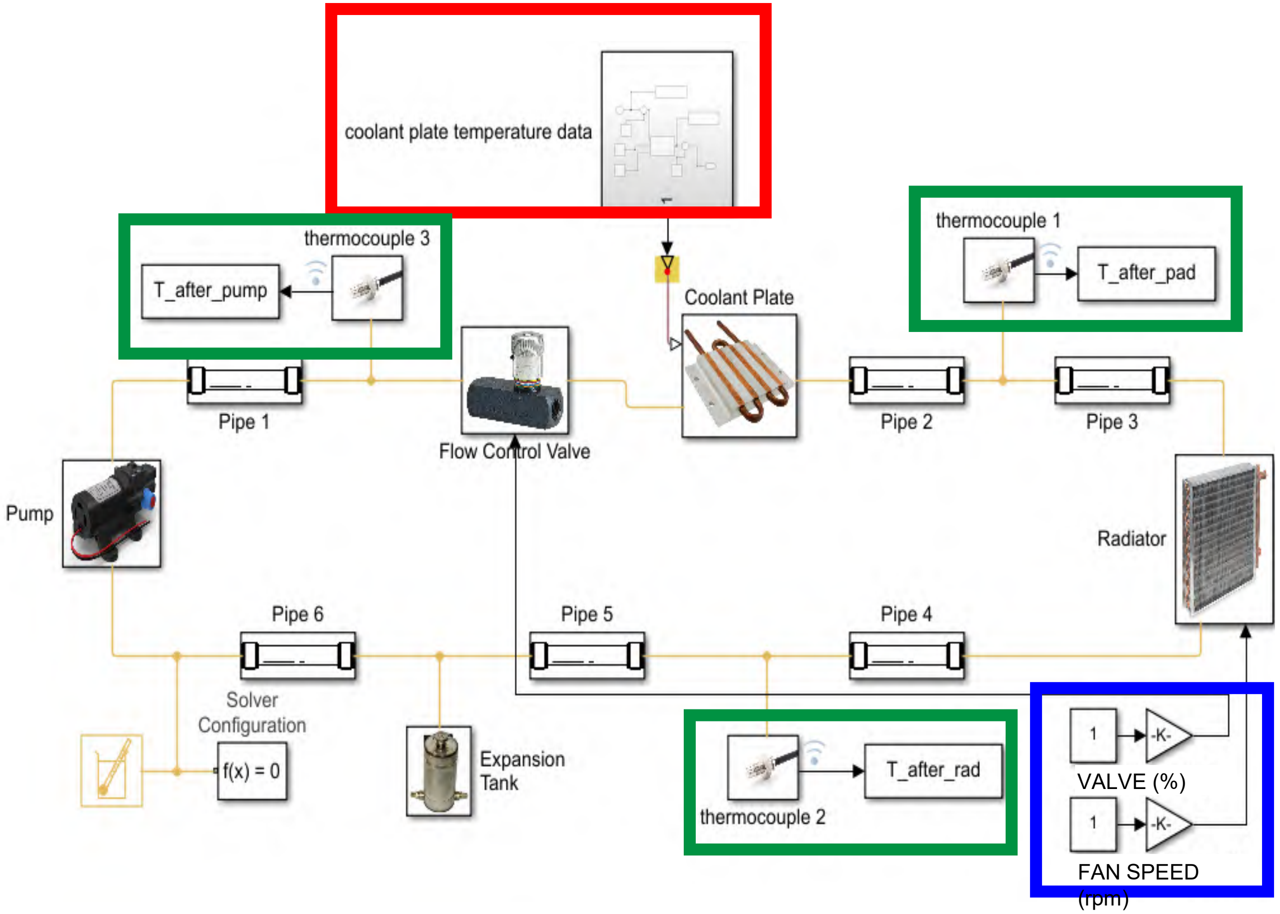
- Temperature data from physical twin is collected at five-minute intervals to calibrate heat load in simulation testbed.

Green:

- Thermocouples collect data after simulation is complete to be compared to the real data to determine RMSE [error].

Blue:

- Valve position and fan speed is set for each simulation, based on each PSO particle`s position in the RMSE plane. Calibration of the digital twin occurs via this means.



DIGITAL TWIN - SIMULATION METRICS

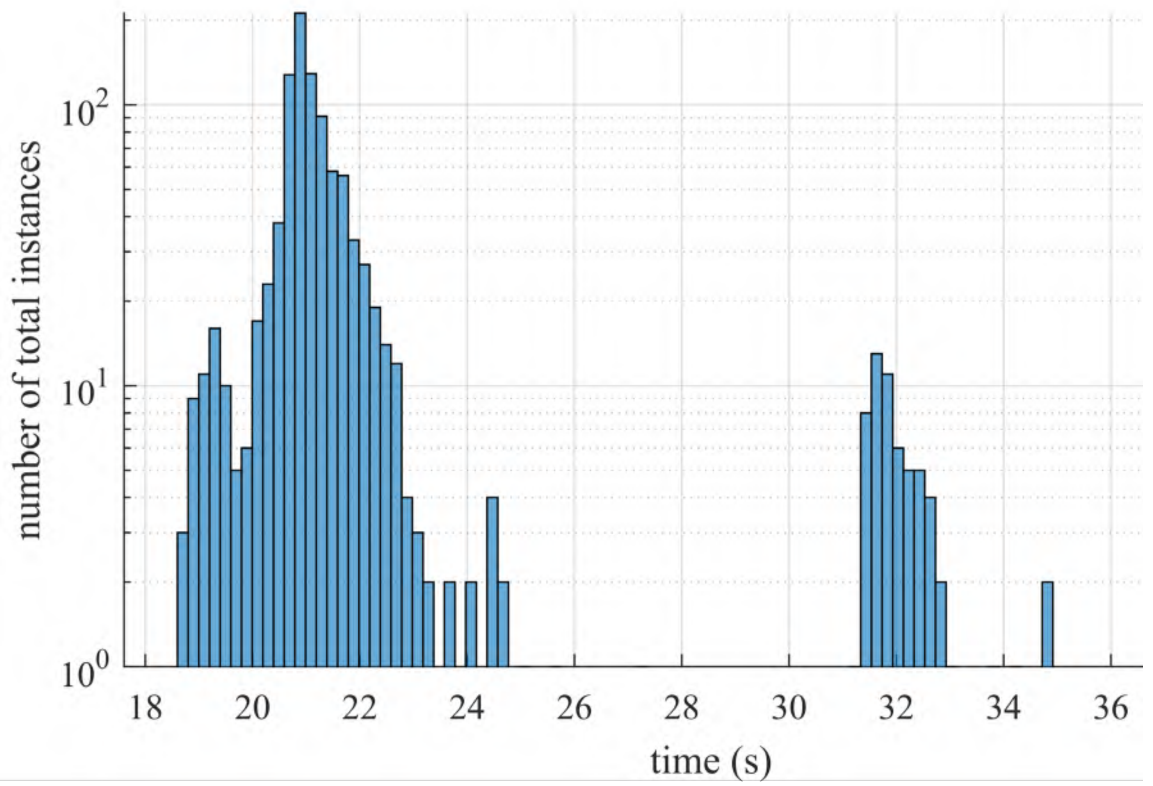
Procedure:

- 1000 simulations were conducted to determine the mean, standard deviation, and maximum time to finish the simulation.
- Length of the update window dependents on how fast the simulation can run.
- If the window is too small there will not be enough time for the particles to find the global minimum.

Results:

- Mean time: 21.76 seconds.
- Standard deviation: 2.8 seconds.
- Maximum time: 38.4 seconds.
- The max time limiting factor for how many particles can be used, while ensuring each particles' parameters converge.

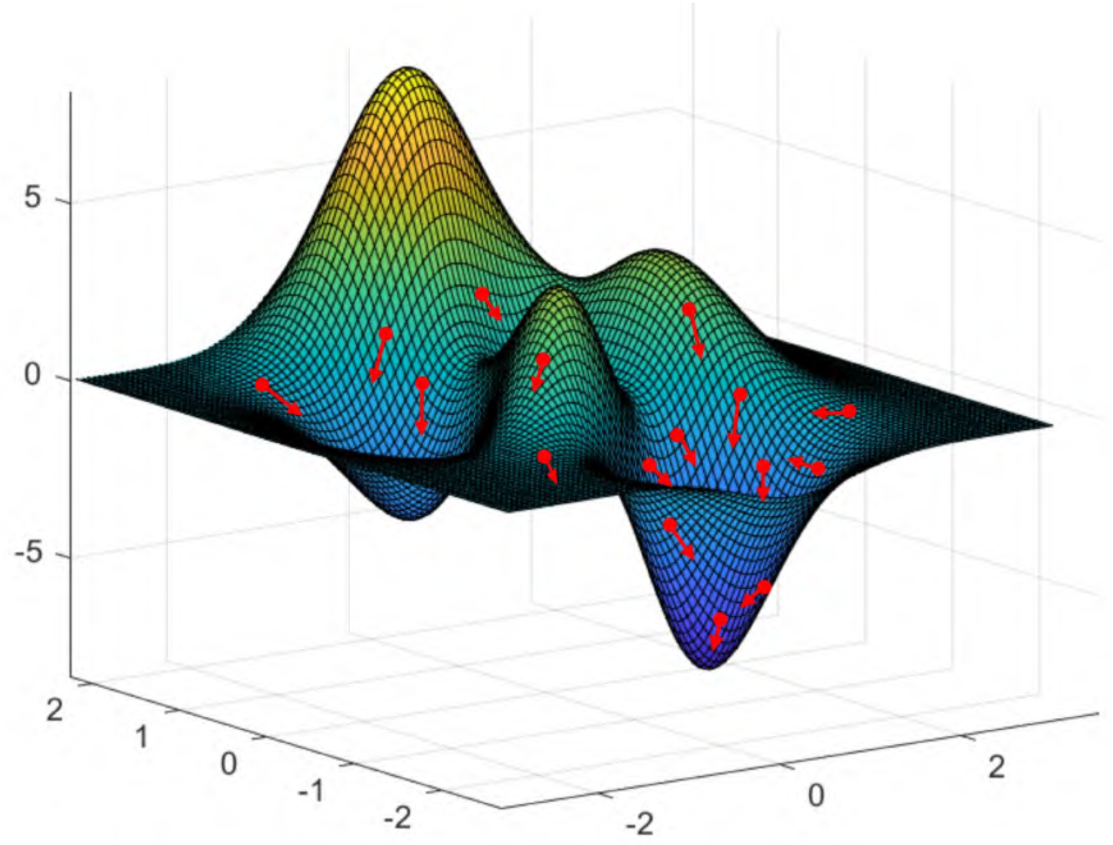
Mean: 21.76 (s) Std: 2.8 (s) Max time: 38.4(s)



PSO - PARTICLE SWARM OPTIMIZATION

Concept:

- PSO is a meta-heuristic, nature-inspired optimization technique based on bird foraging behavior. It uses a swarm of particles, each representing potential solutions, navigating a search space to find the global minimum or maximum of a target cost function.



Advantages:

- **Efficient**: High computational speed, making it suitable for real-time applications.
- **Versatile**: Adaptable to various problems with a definable cost function making it highly

PSO - EQUATION AND FUNCTION

The parameter W is the inertia weight and it is a positive constant, This parameter is important for balancing the global search, also known as **exploration** (when higher values are set), and local search, known as **exploitation** (when lower values are set).

Diversification: searches new solutions, finds the regions with potentially the best solutions.

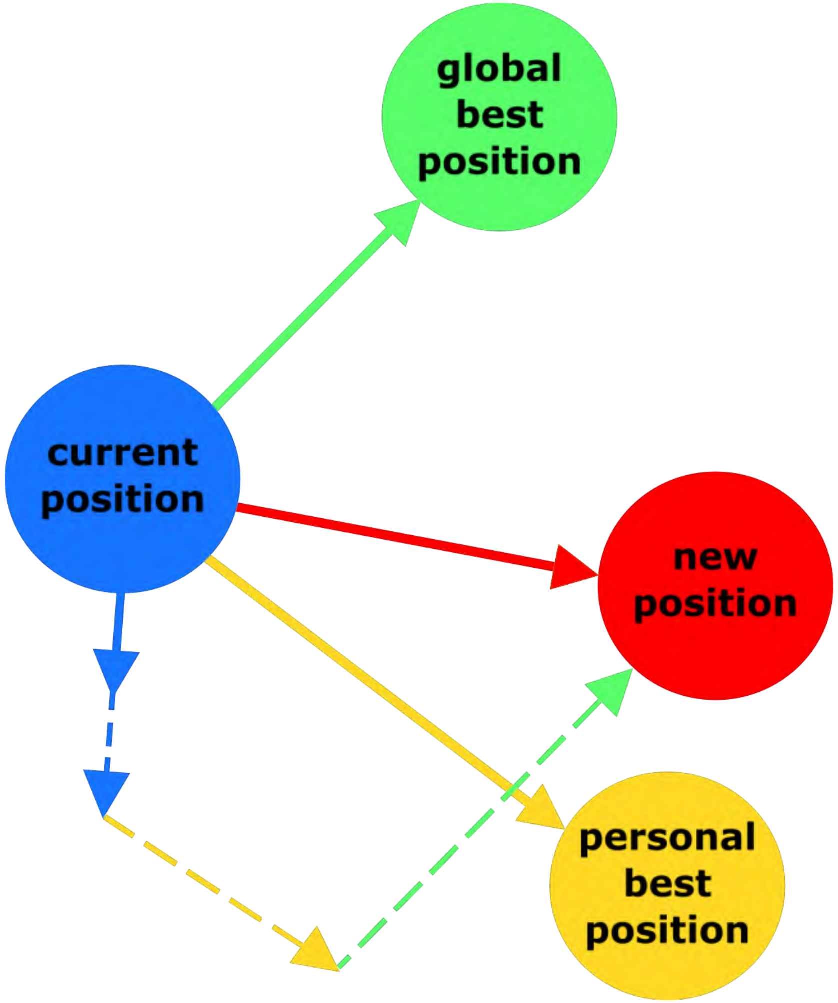
Intensification: explores the previous solutions, finds the best solution of a given region.

$$V_i^{t+1} = W.V_i^t + c_1U_1^t\left(P_{b_1}^t - P_i^t\right) + c_2U_2^t\left(g_b^t - P_i^t\right)$$

Inertia : Makes the particle move in the same direction and with the same velocity.

Personal Influence : Improves the individual. Makes the particle return to a previous position, better than the current.

Social Influence : Makes the particle follow the best neighbors direction.

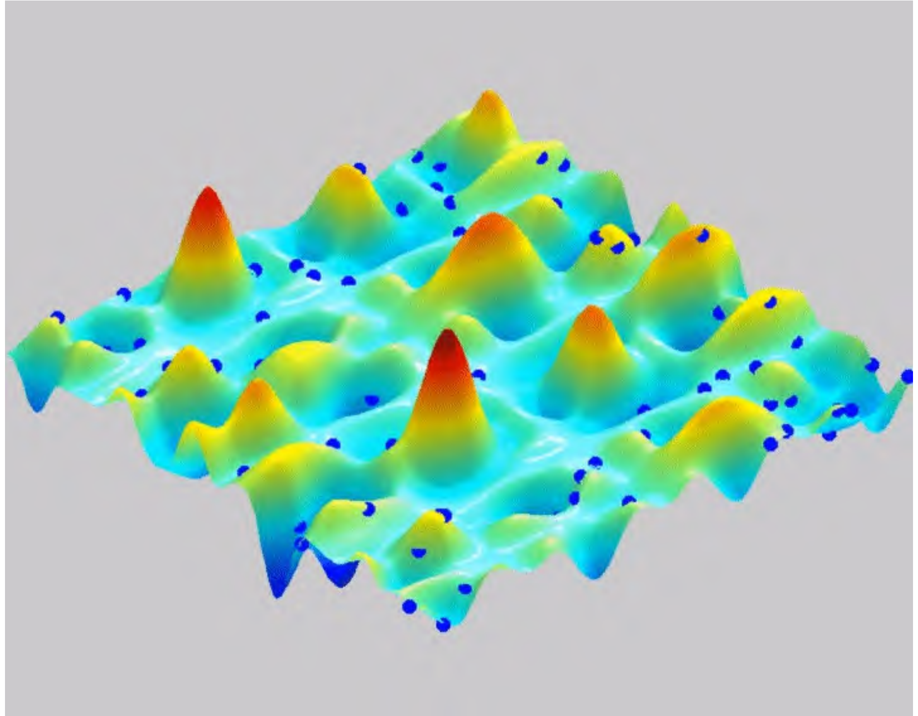


PSO - HOW A PSO ALGORITHM FINDS THE "OPTIMAL" VALUES FOR LOWEST RMSE

Process:

1. Program initializes
2. Particles are randomly distributed across the RMSE vector field.
3. X-axis is fan speed, y-axis is valve position, z-axis is RMSE.
4. Particles calculate their individual RMSE values based on fan power and valve position.
5. Particles locate their local best RMSE valves.
6. Particles communicate with each other to determine the "team best" RMSE.
7. Particles congregate toward the particle with the least RMSE value.
8. Steps 4-7 continue for the duration of the update window, i.e., five minutes.
9. All particles eventually congregate near a single "global best position". The x and y values here result in the lowest RMSE value. Simulation is now calibrated to the physical twin.

Demonstrative example:



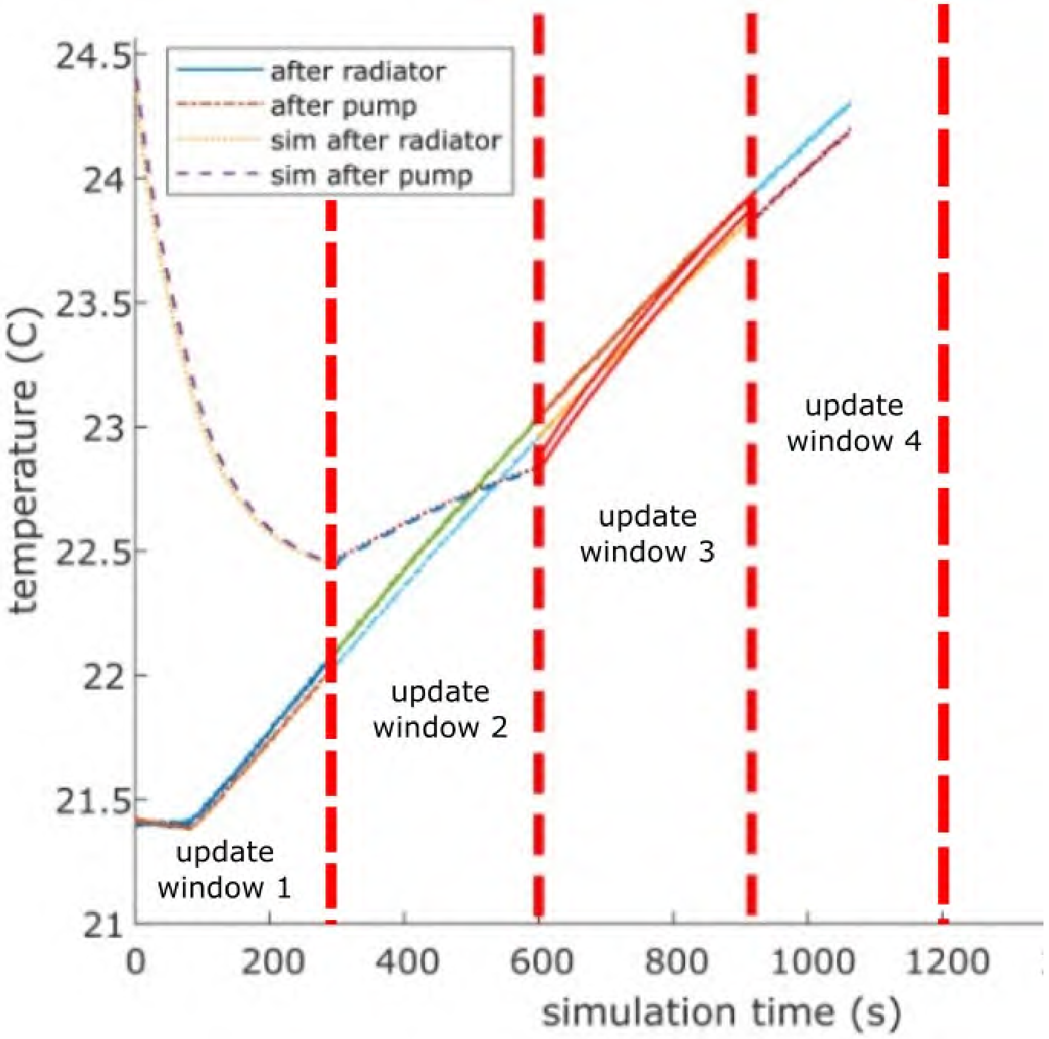
Credit: https://www.youtube.com/@Hennegrolsch

PSO - DATA COLLECTION AND CALIBRATION

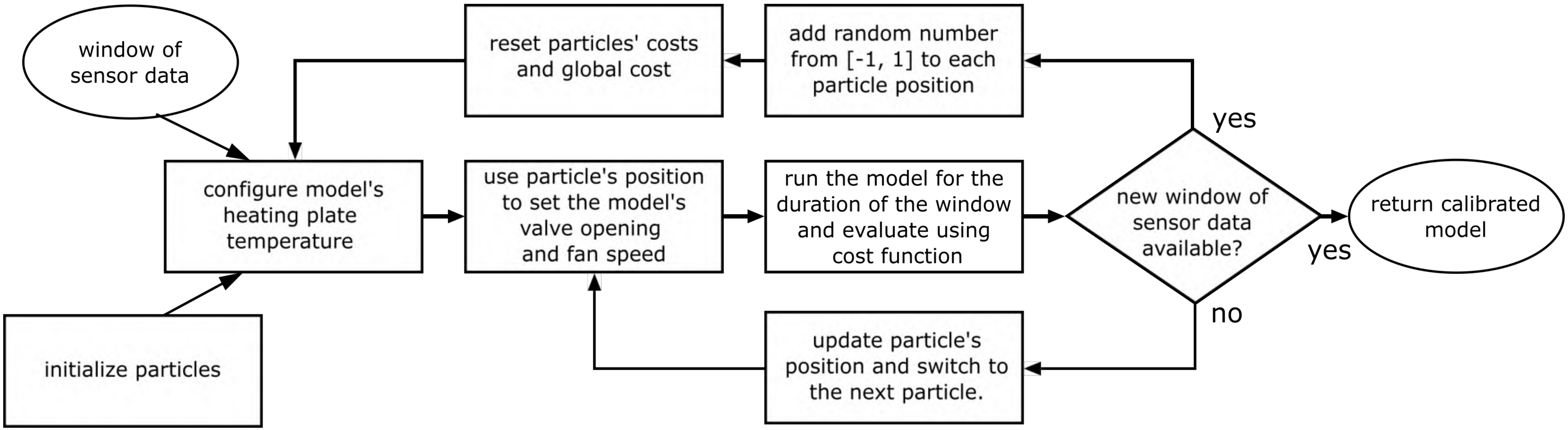
- The PSO seeks to minimize the difference between the simulated data and the real data using a cost function.

$$Error = \sqrt{\frac{\sum_{i=1}^{N} (x_{sim} - x_{real})^2}{N}}$$

- The PSO updates on a five-minute window until a new window of data becomes available.
- Once the model is sufficiently calibrated, it may be used for look ahead simulations for specific scenarios.



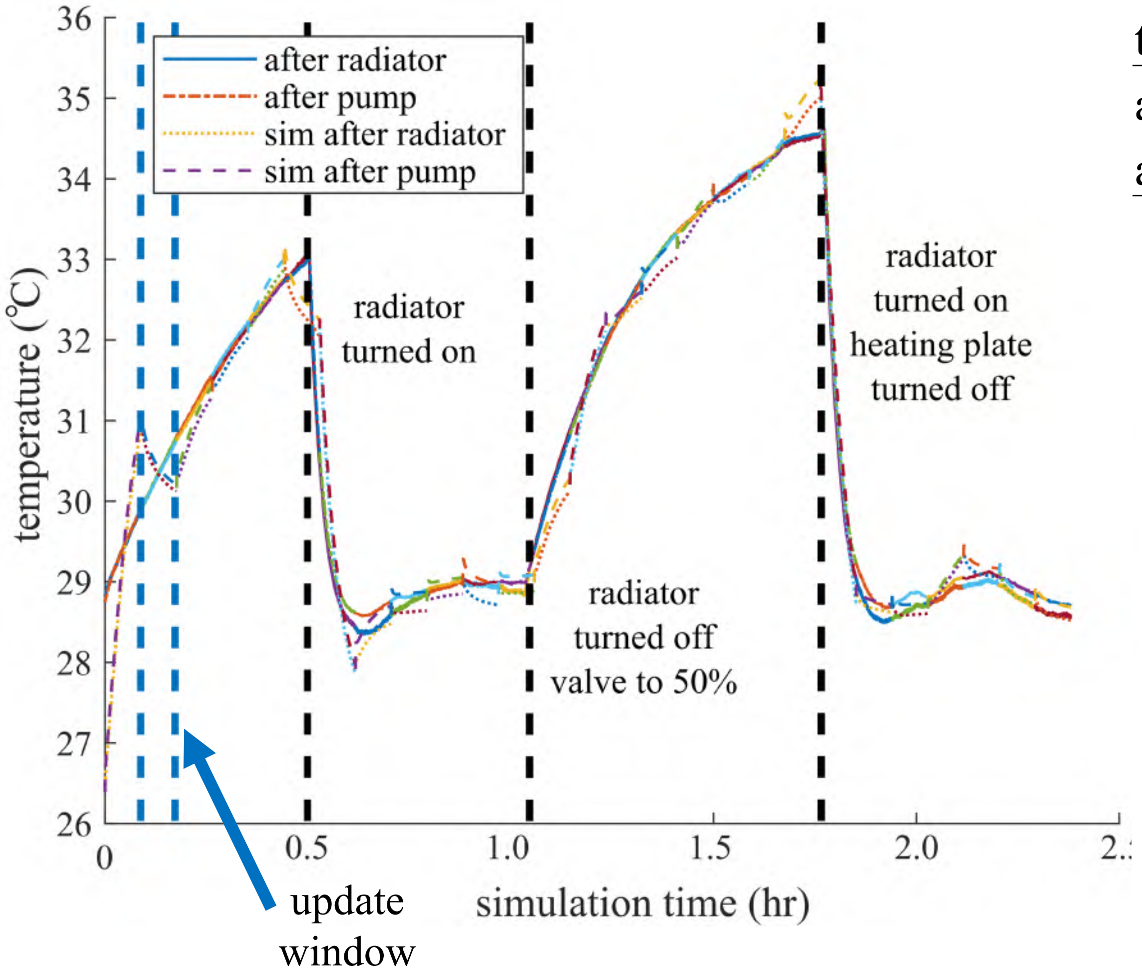
PSO - ALGORITHM FLOW CHART

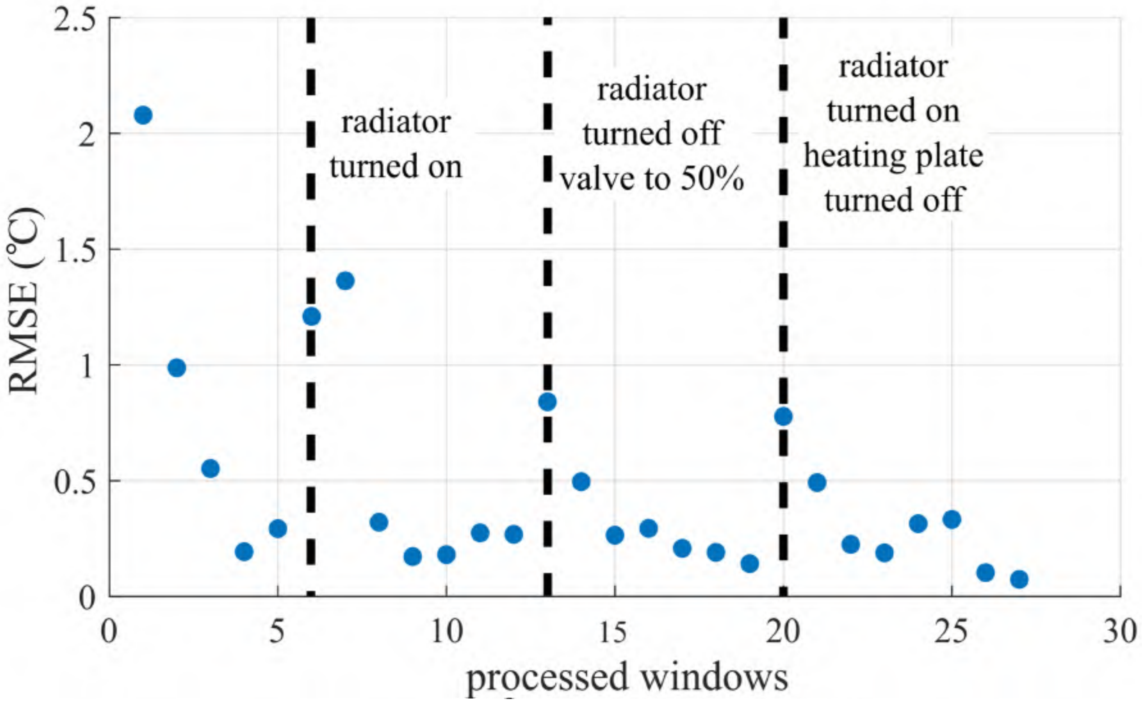


PSO - UPDATING AND CALIBRATION RESULTS

- 5 particles updated an average of 5 times per window.

thermocouple location	SNR (dB)	RMSE (°C)	MAE (°C)
after pump	39.60	0.323	-0.031
after radiator	39.07	0.342	0.070





CONCLUSION

- A thermal loop simulation was created to act as a component of a digital twin.
- This model was updated periodically using sensor data collected from its real-life testbed counterpart.
- By doing so, this supplies information to a particle swarm algorithm.
- Five particles would find the optimal radiator fan speed and valve opening to fit the model to the five-minute window of temperature data.
- Results show the ability of the particle swarm to return an accurate representation of the physical thermal loop every five minutes.
- Provides a numerical approach for the updating and testing of thermal models for power electronics.
- Experimental validation is carried out demonstrating that the proposed method can update a digital twin within a reasonable time.

FUTURE RESEARCH

- Improve data processing ability of edge computer to increase complexity of PSO algorithm.
- Improve the cost function and hyper-parameters of particle swarm algorithm to increase accuracy of digital twin.
- Work on implementing the digital twin on more complex electro-thermal systems.
- Begin investigating the usefulness of the updated digital twin for use in "lookahead" predictions.

INTRODUCTION

Relevance

- As Naval systems become increasingly complex the need for data driven solutions will become essential in maintaining the overall health of a ship's systems and subsystems.
- When a physical system changes, either by degradation or operator actions, A model of that physical system will cease to be accurate.
- Digital twins are a solution to this problem. They can utilize sensor data to update a model parameters in real-time.

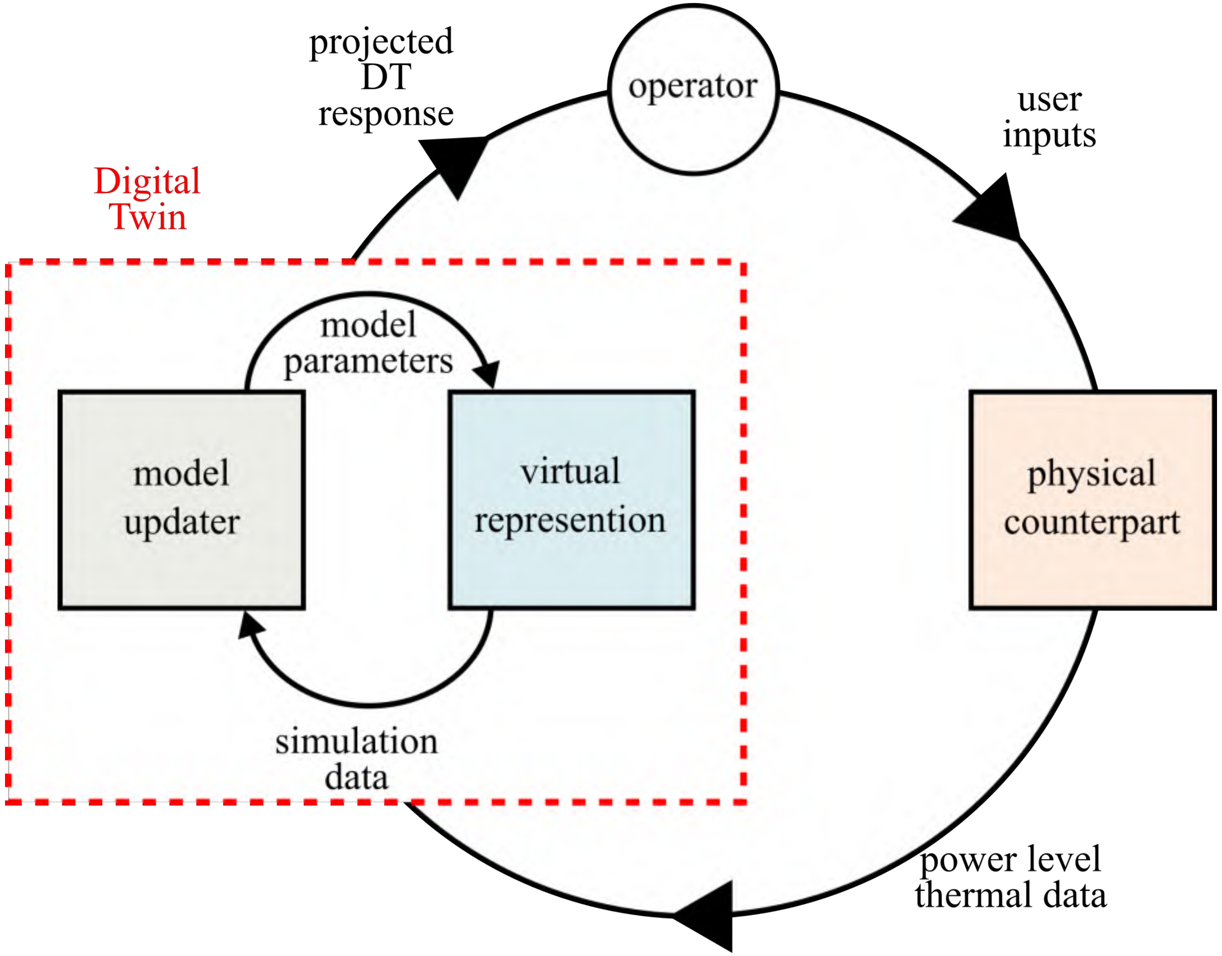
Objectives

- Provide a generic model updating scheme that can periodically update a Simulink model of a thermal system using real-time sensor data.
- Test the model updating scheme's robustness when handling physical changes to the system.

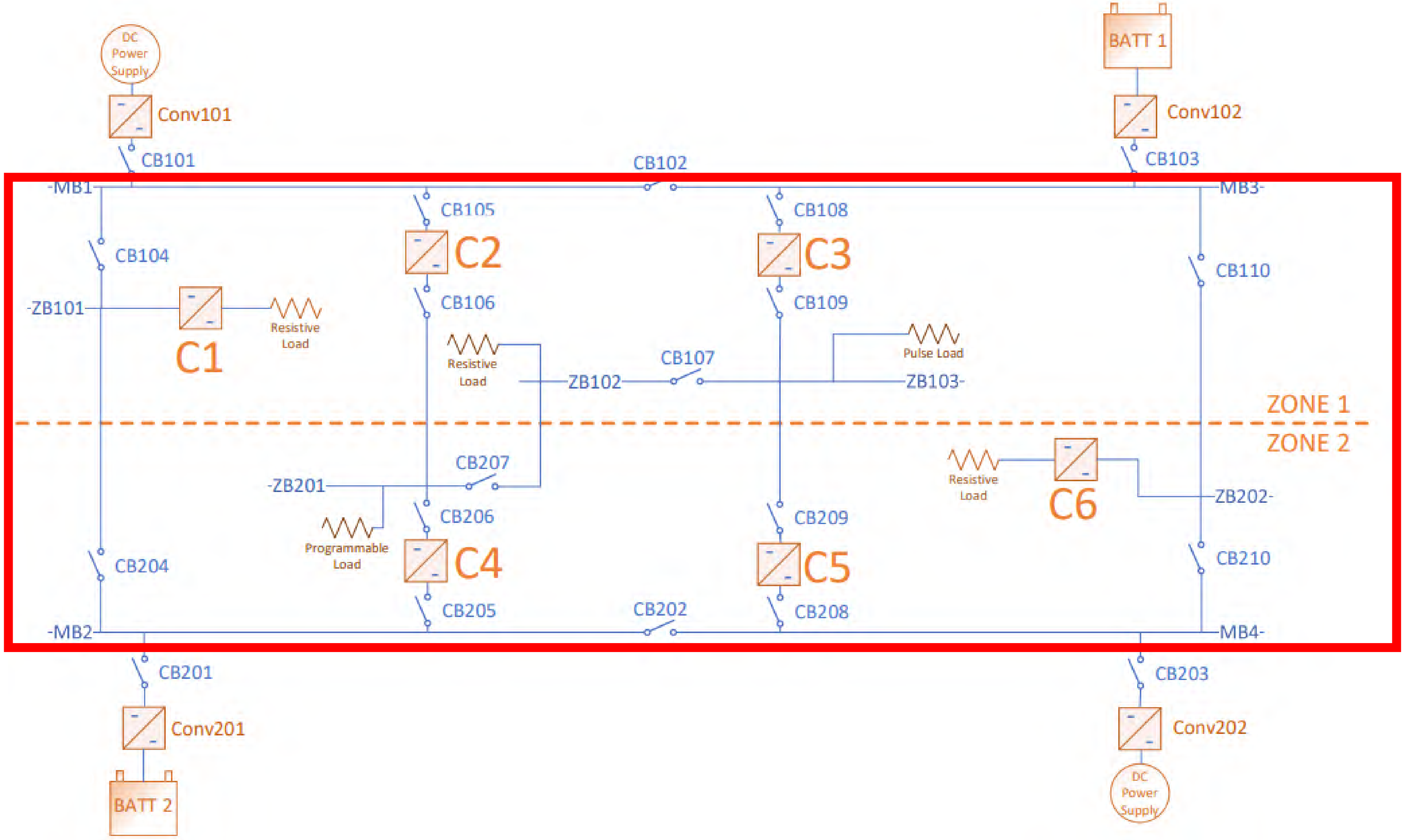
https://www.navy.mil/Resources/Photo-Gallery/

DIGITAL TWIN FRAMEWORK

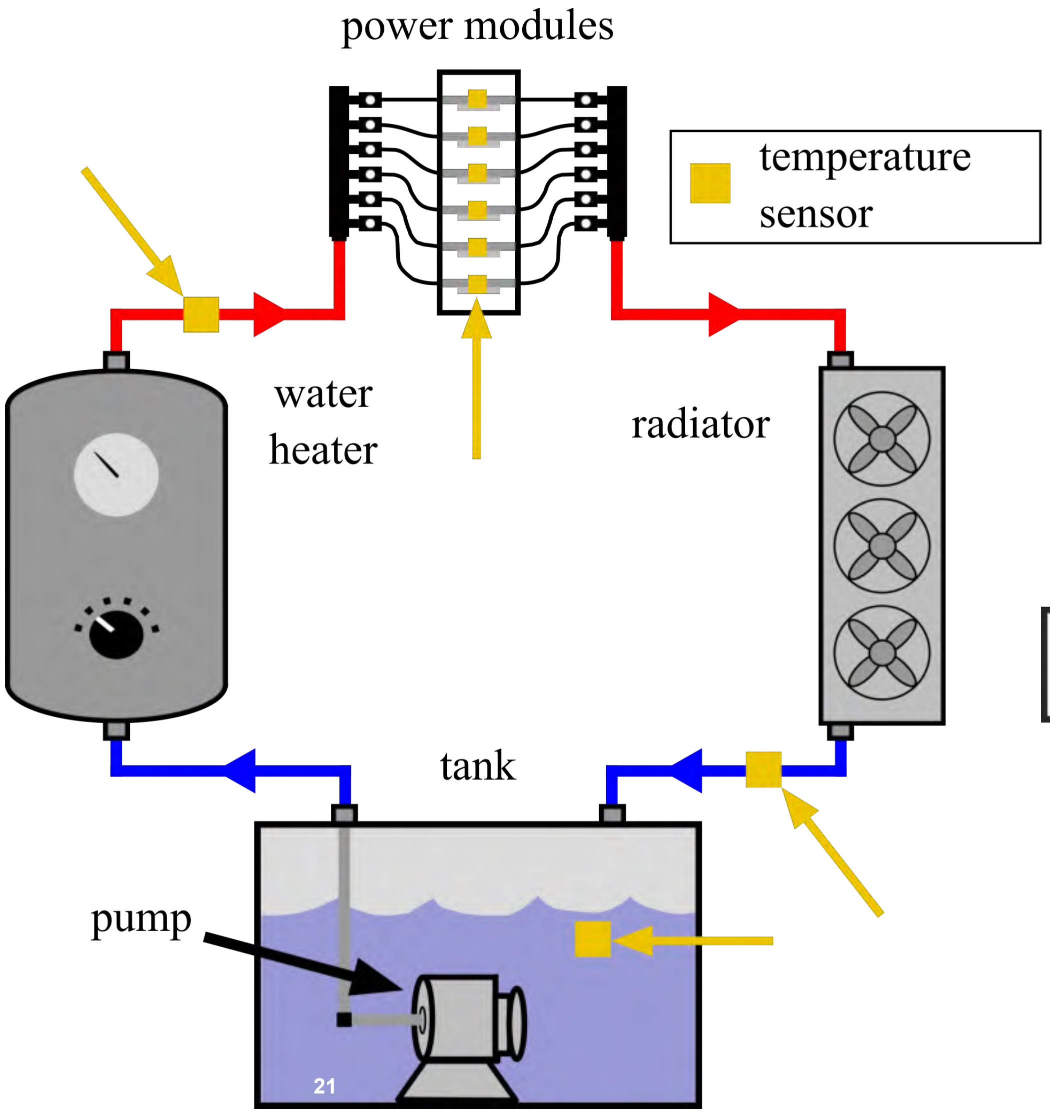
- Operator controls various ship systems.
- The physical counterpart: thermal system, handles the dissipated heat.
- The model updater utilizes real-time sensor data from the system to calibrate a virtual representation (thermal model)
- Projected Digital Twin (DT) response is returned to the user.

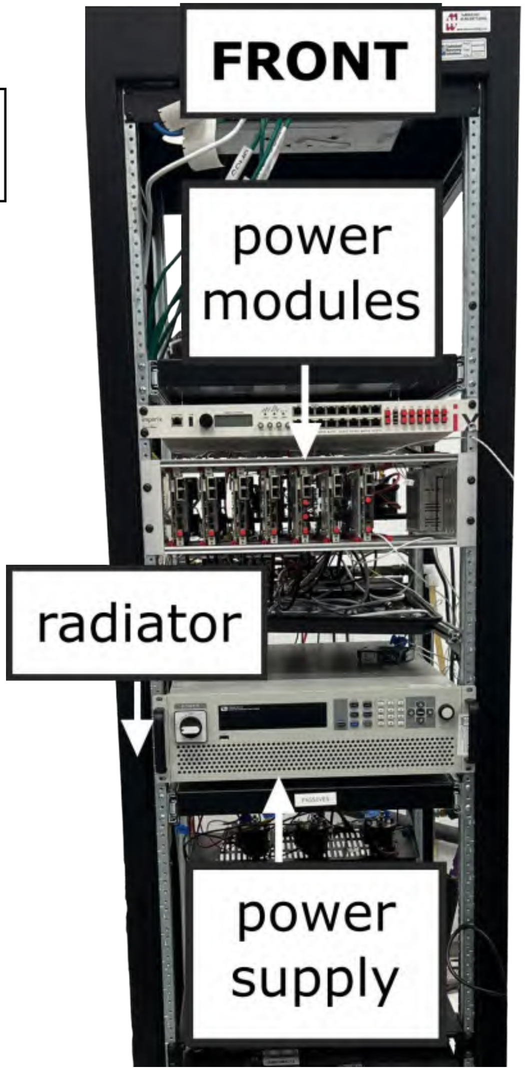


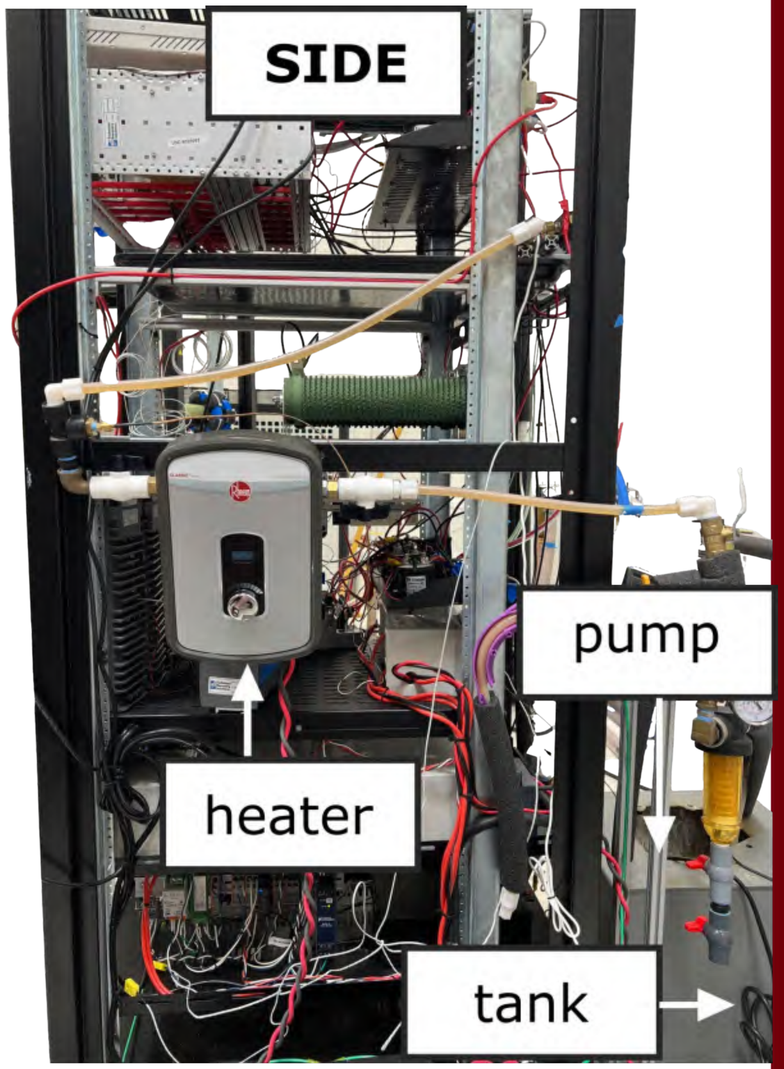
DERISKING STATION POWER MODULES



DERISKING STATION POWER MODULES

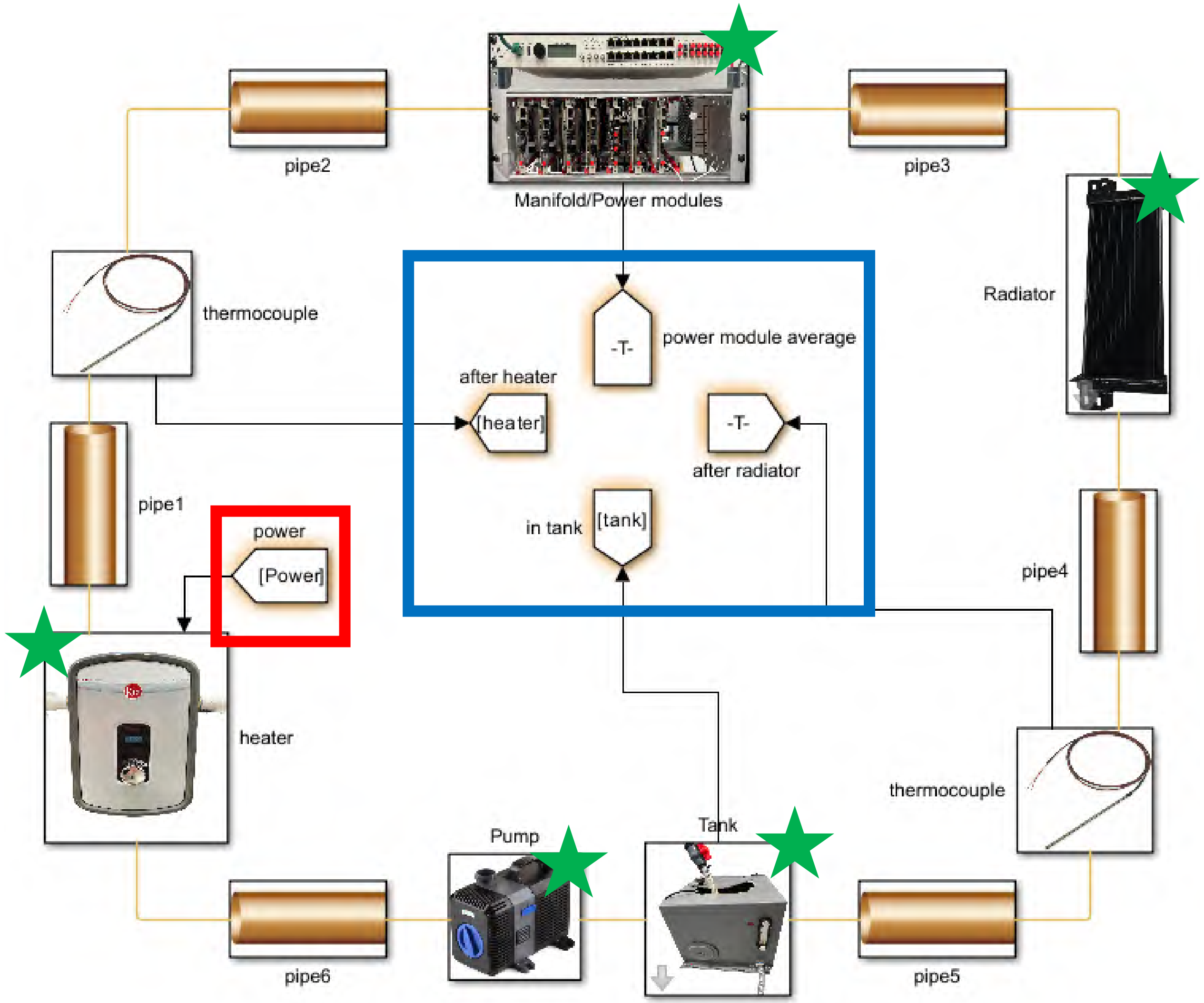






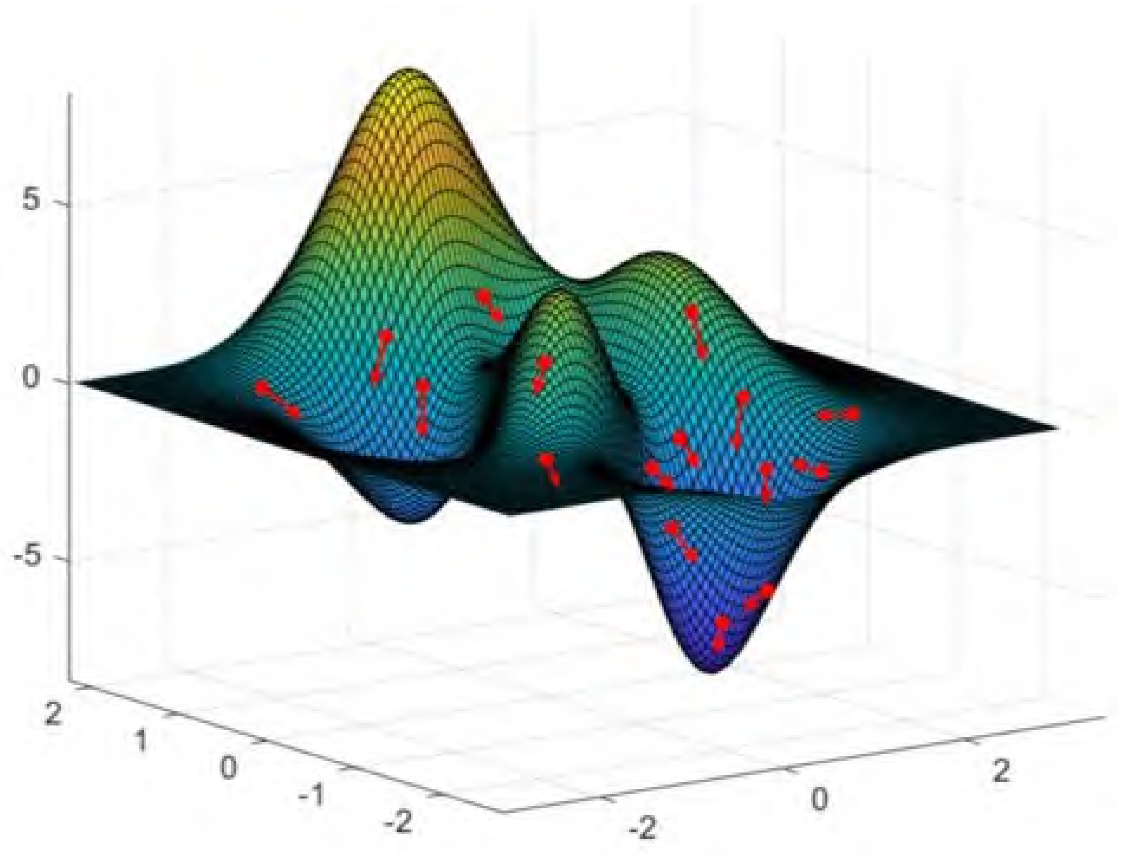
VIRTUAL REPRESENTATION (SIMSCAPE MODEL)

- Input: Simulated dissipated heat (W) is inputted into the model.
- Output: Simulated temperature data (°C) at four points to evaluate the model.
- Parameters: various model parameter that are updated.



PARTICLE SWARM OPTIMIZATION

- Particle Swarm Optimization (PSO) is a simple way to find the minimum in a search space.
- Particles work together to minimize the error between the acquired sensor data and simulation data.
- Particles' coordinates on the search space represent various model parameters.



HOW ARE THE MODEL PARAMETERS UPDATED?

1. Particles are initialized with random coordinates representing various model parameters (thermal masses, water/air flow rates, and heat transfer coefficients).
2. Models are run using the particle's coords/parameters and its performance is evaluated with a Cost Function. *Model must be run every time when evaluating a particle's position

$$Error = \sqrt{\frac{\left(T_{\exp\_heater} - T_{heater}\right)^2}{nSamples}} + \sqrt{\frac{\left(T_{\exp\_radiator} - T_{radiator}\right)^2}{nSamples}} + \sqrt{\frac{\left(T_{\exp\_module} - T_{module}\right)^2}{nSamples}} + \sqrt{\frac{\left(T_{\exp\_tank} - T_{tank}\right)^2}{nSamples}}$$

3. Error determines where the next particle position will be.

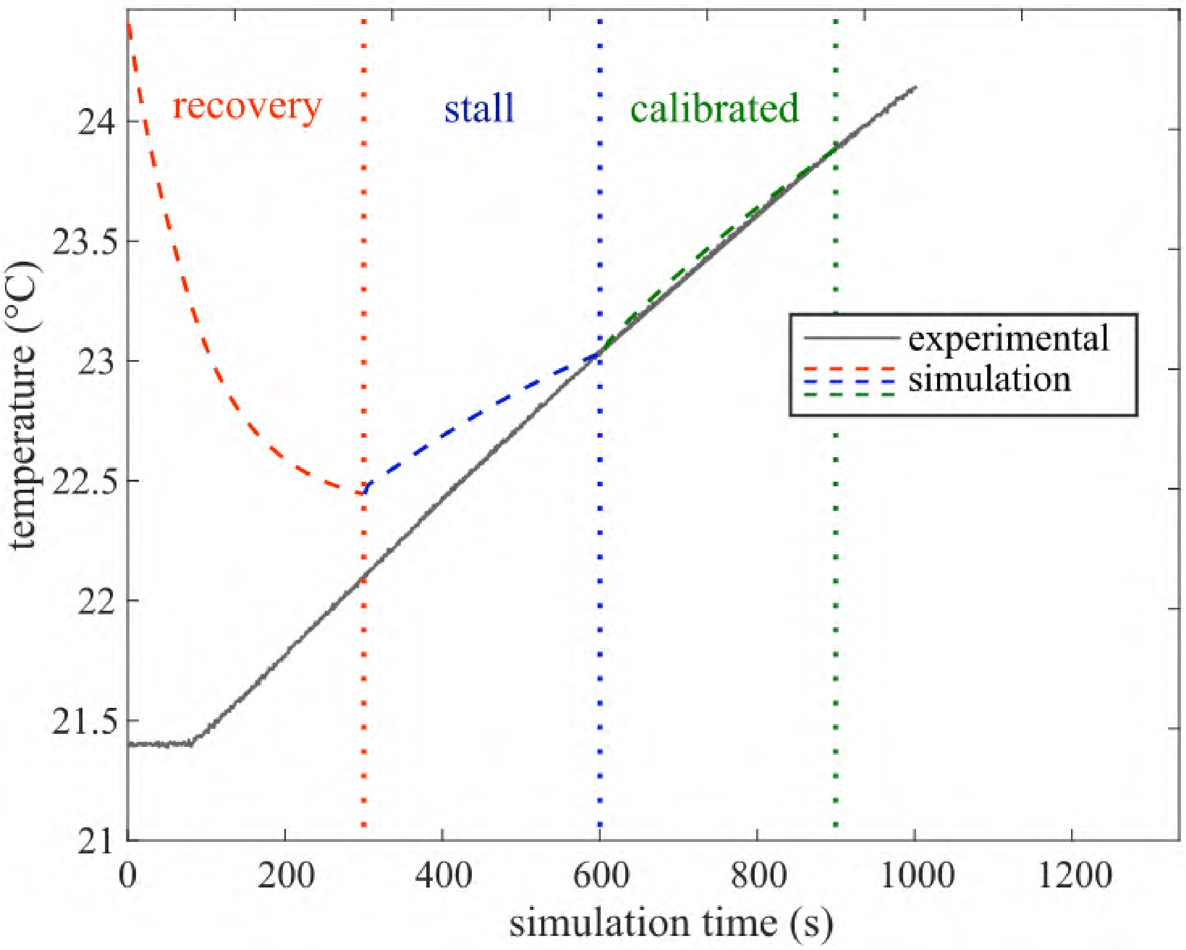
HOW THE ALGORITHM HANDLES REAL-TIME DATA?

- Model parameters are tuned on a window of temperature data.
- The model parameters will be tuned on the latest window until enough data for a new window is acquired.
- Depending on the error between initial temperatures, the algorithm will update its hyper parameters.

Recovery: increases particles acceleration

Calibrated: lower particles acceleration

Stall: mix between Recovery and Calibrated



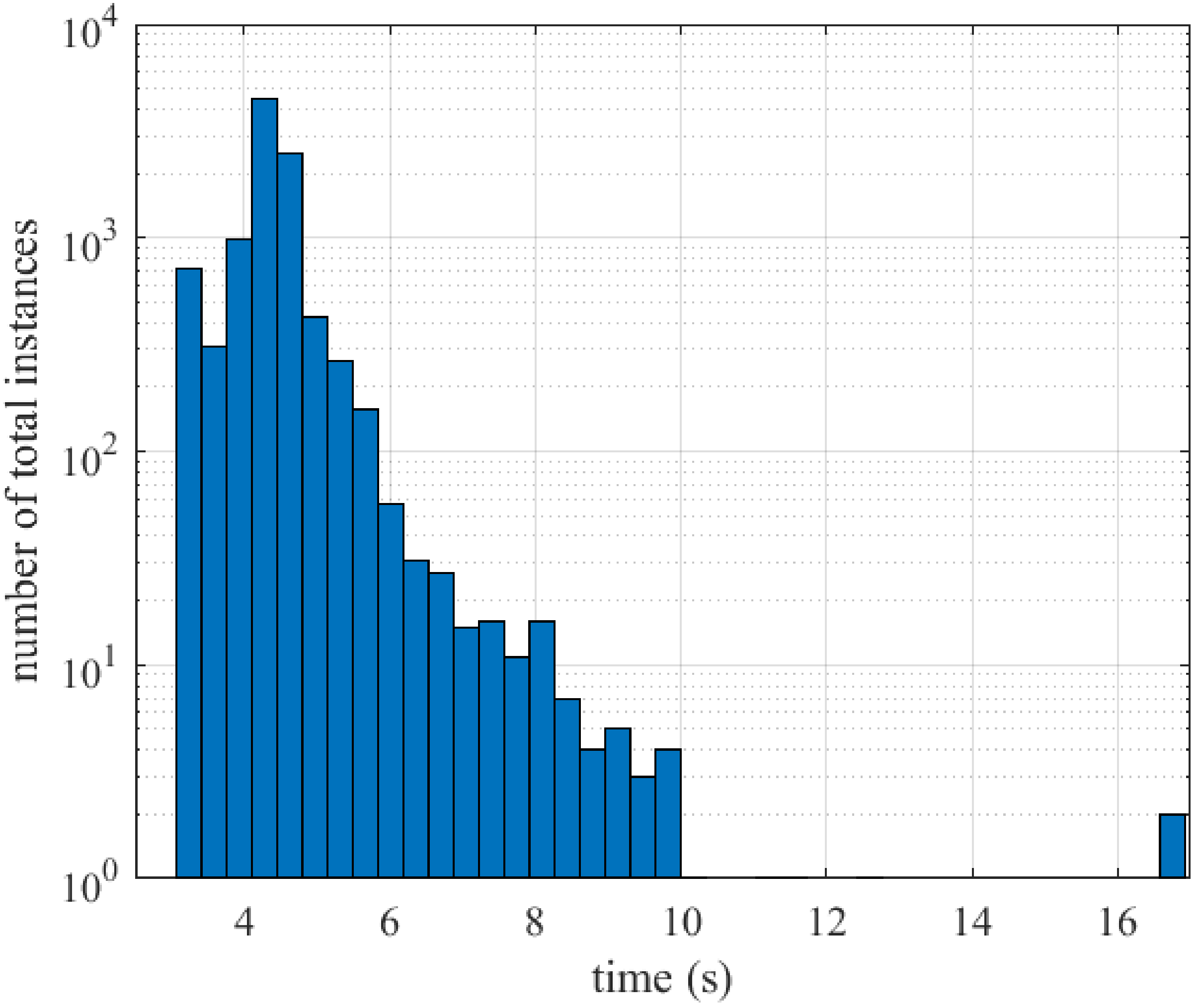
TIMING DISTRIBUTION

- Model was run 10,000 times to gather run time metrics.
- These metrics determine how large a window can be.
- 10-minute window was chosen

Results

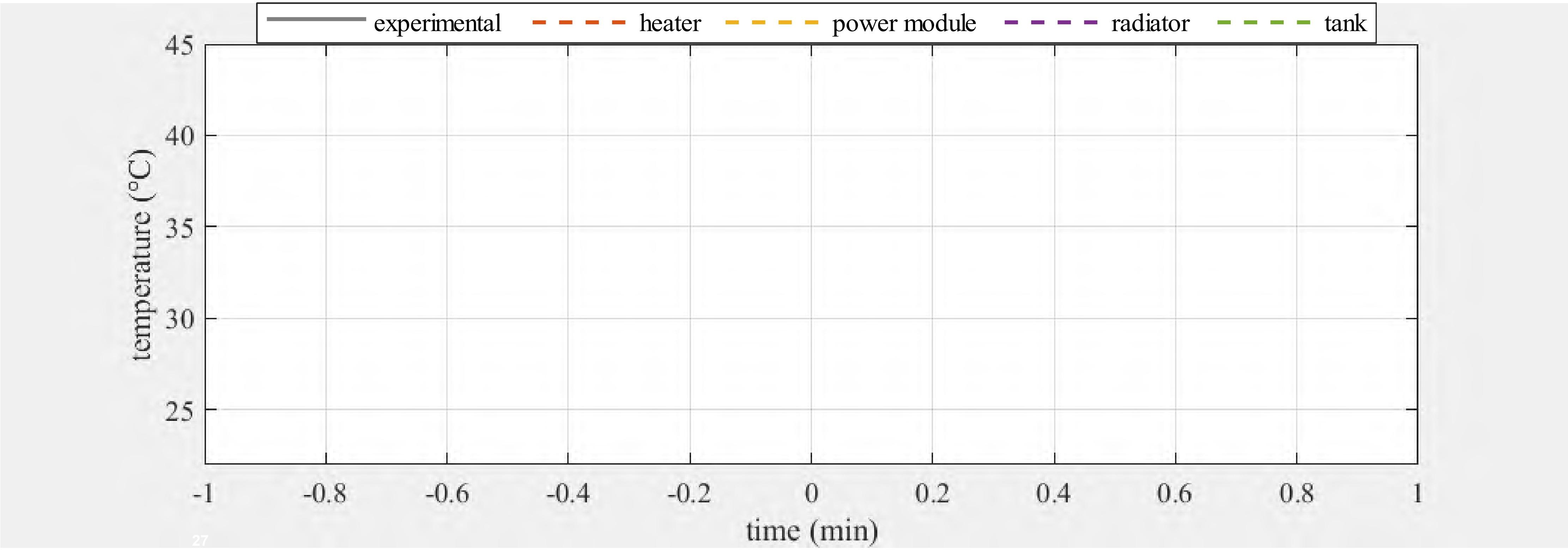
- Mean time: 4.636 seconds
- Standard deviation: 0.634 seconds
- Max time: 16.925 seconds

Mean: 4.636 (s) STD: 0.634 (s) Max: 16.925 (s)



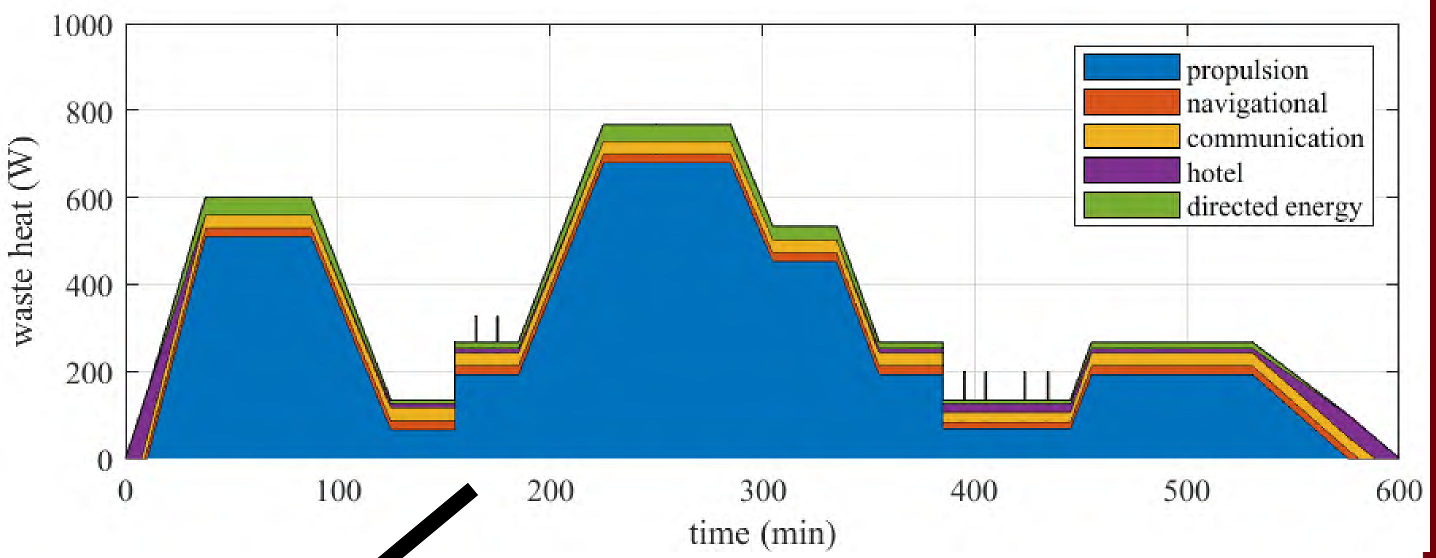
ALGORITHM DEMONSTRATION

- Algorithm waits until a ten-minute sensor window is available.
- Works on finding the ideal model parameters till a new window is available.



SIMULATED LOAD PROFILE

- Load profile of a simulated ship was constructed in MATLAB and deployed onto a power supply.
- Power supply and water heater replicate ship power electronics dissipated heat.
- The resultant temperature increase is recorded by thermocouples.

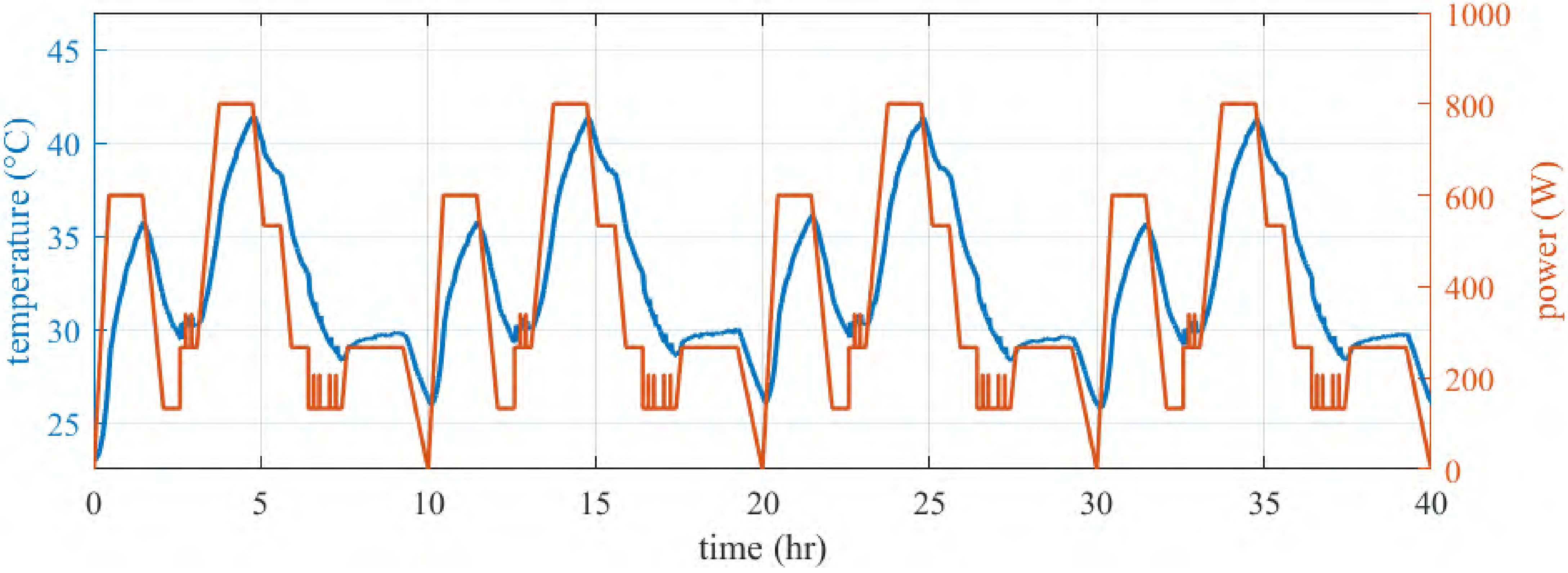


IT6000C Series Bi-Directional DC Power Supply

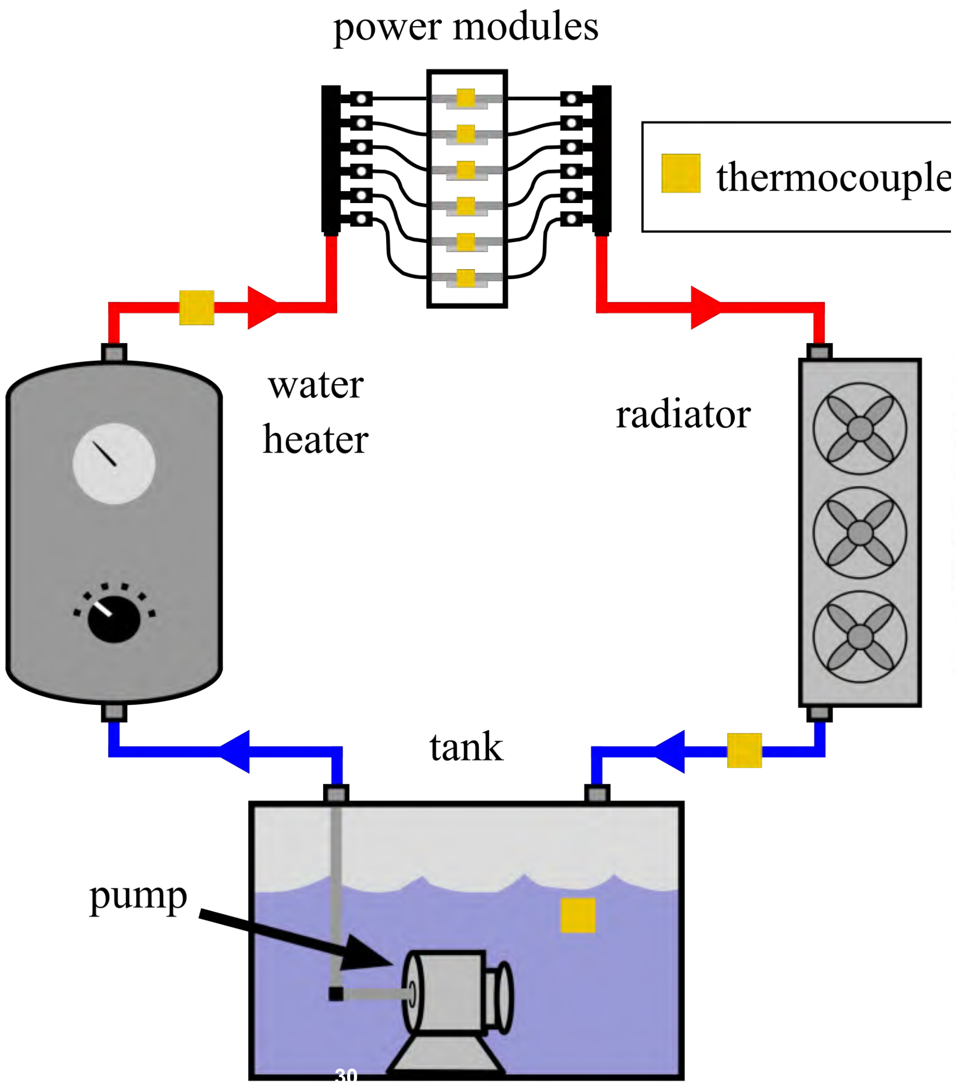
Rheem Water Heater

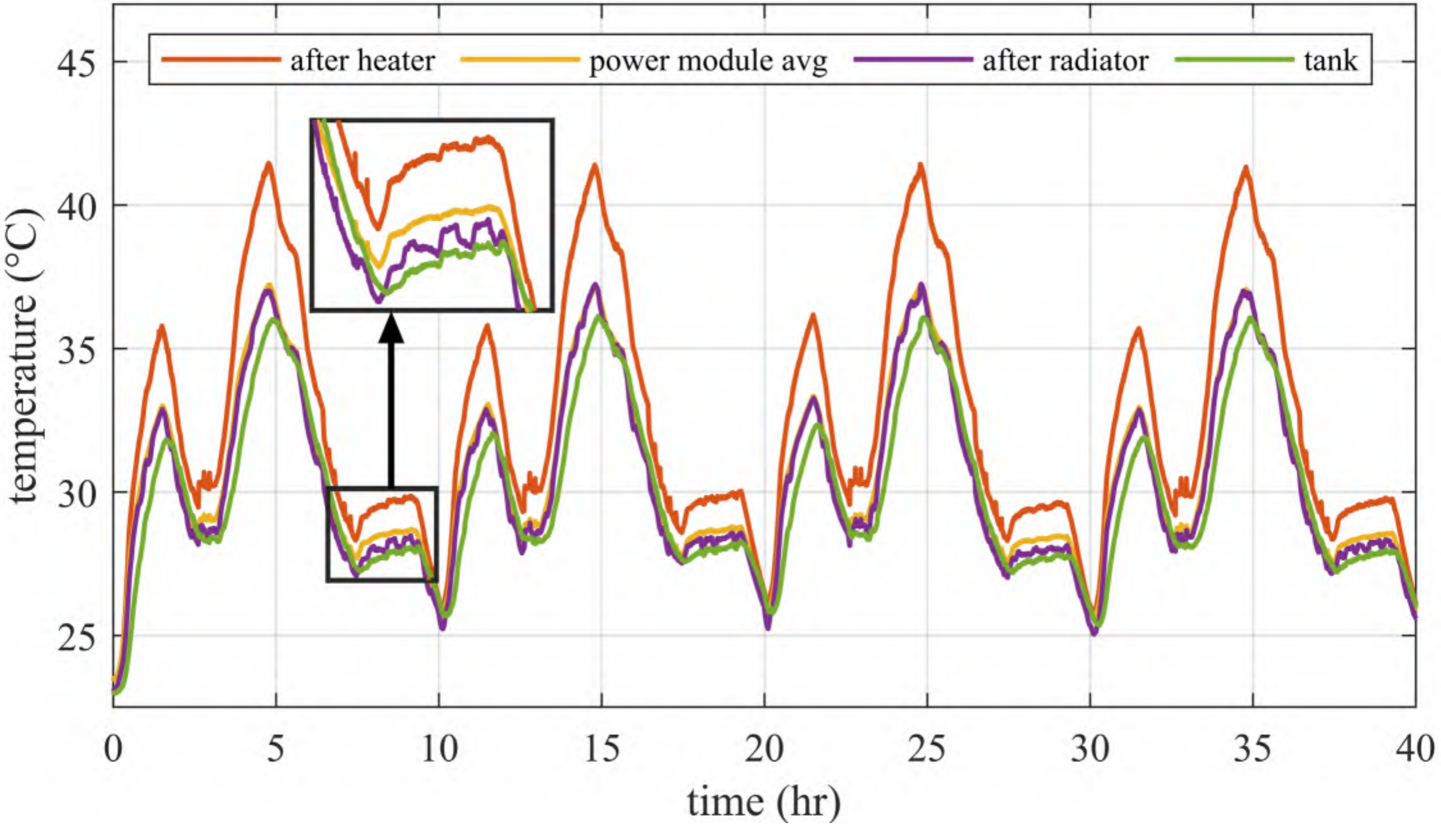
POWER PROFILE AND HEATER TEMPERATURE

- Ten-hour load profile of a simulated ship was repeated four times.



RAW TEST RESULTS

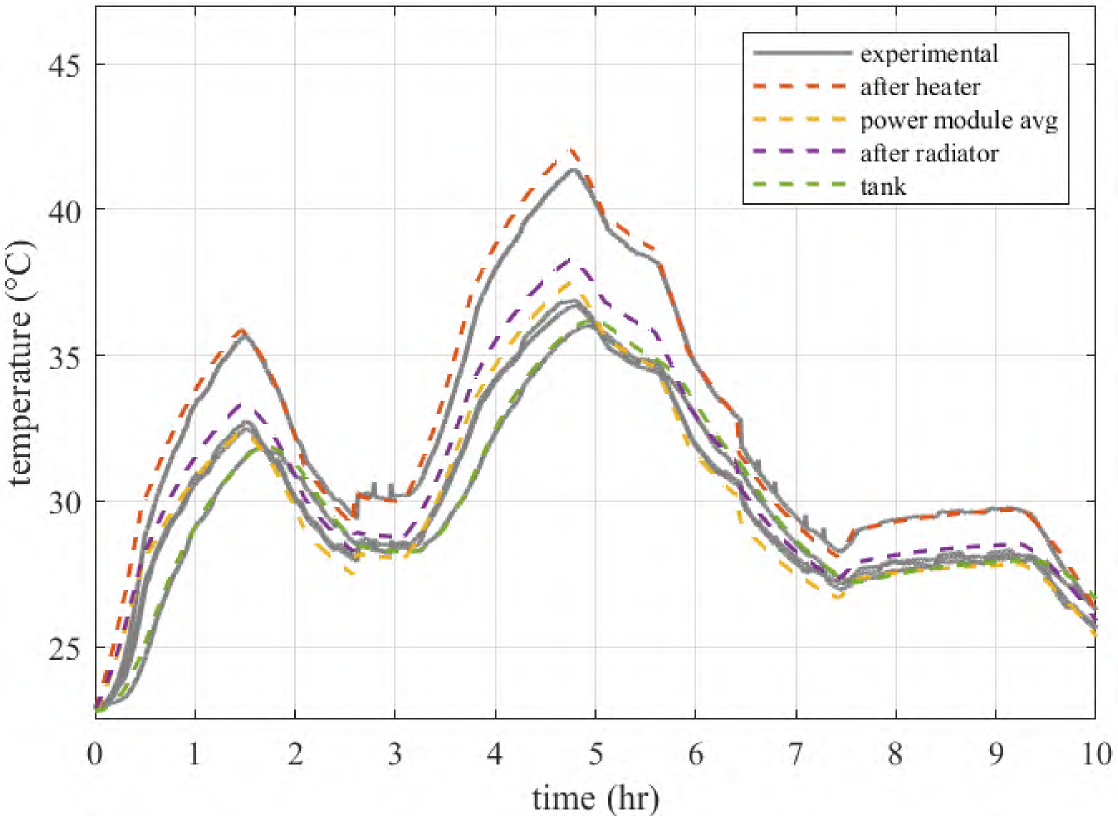




MANUALLY TUNED MODEL SIMULATION RESULTS

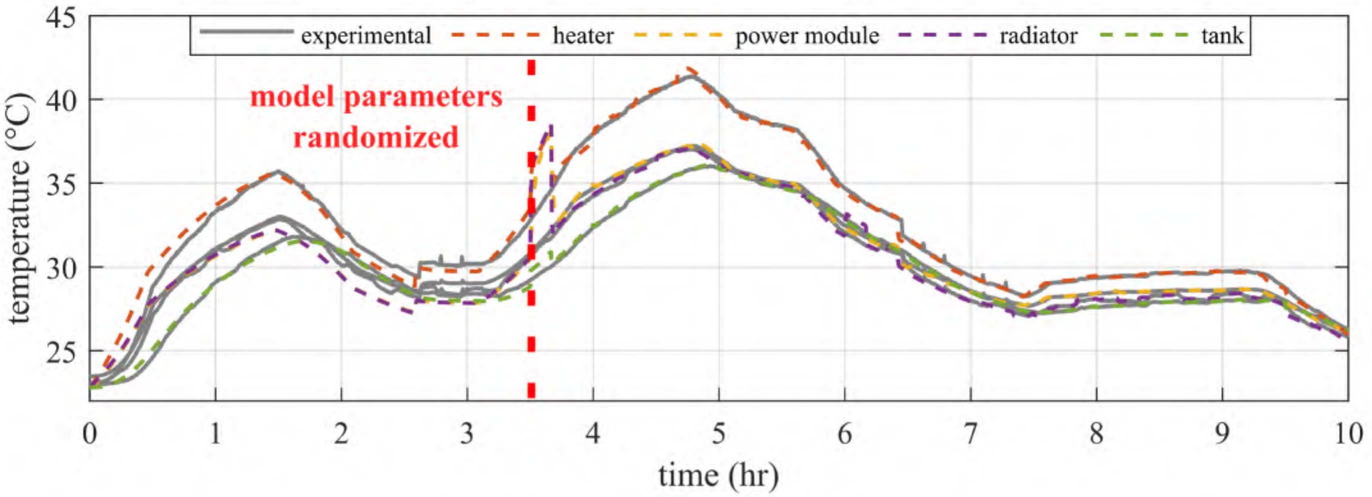
- Utilizing the temperature data gathered from the experiment the Simscape model was manually tuned.
- The tuned model is relatively accurate.
- Is used to test various scenarios by creating synthetic experimental data.

	heater	power modules	radiator	tank
MAE (°C)	0.500	0.420	0.447	0.249
MSE(°C)	0.501	0.260	0.315	0.101
RMSE(°C)	0.708	0.5102	0.562	0.318
NMSE	0.030	0.028	0.032	0.012



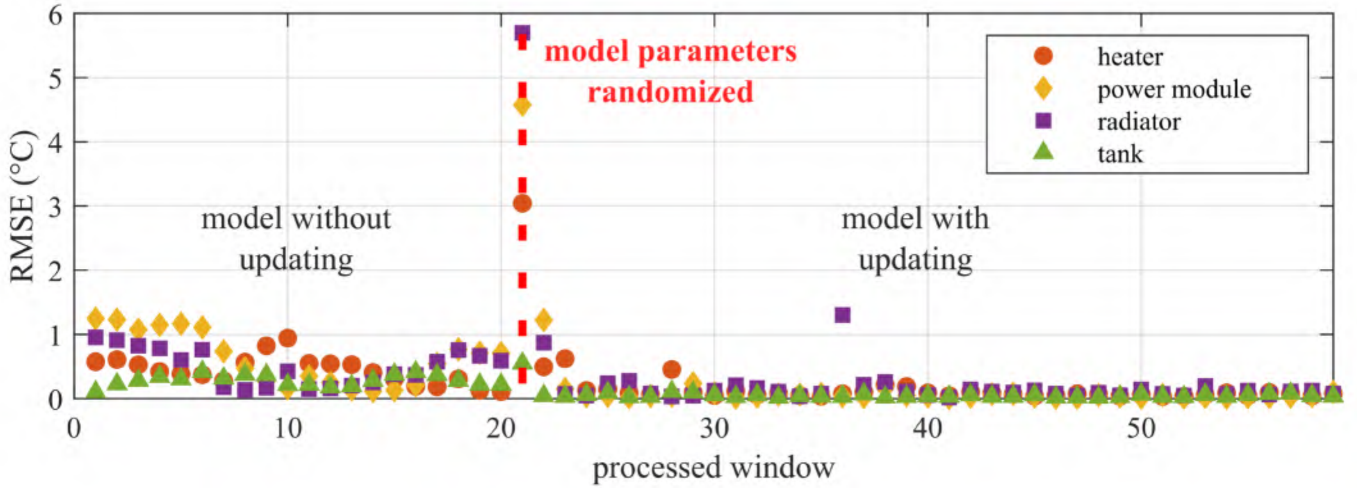
ROBUSTNESS OF THE MODEL UPDATING SCHEME

- To test the robustness of the model updating scheme. The manually tuned model was compared to one with updating scheme.
- Model parameters were randomized 3.5 hours into the simulation.



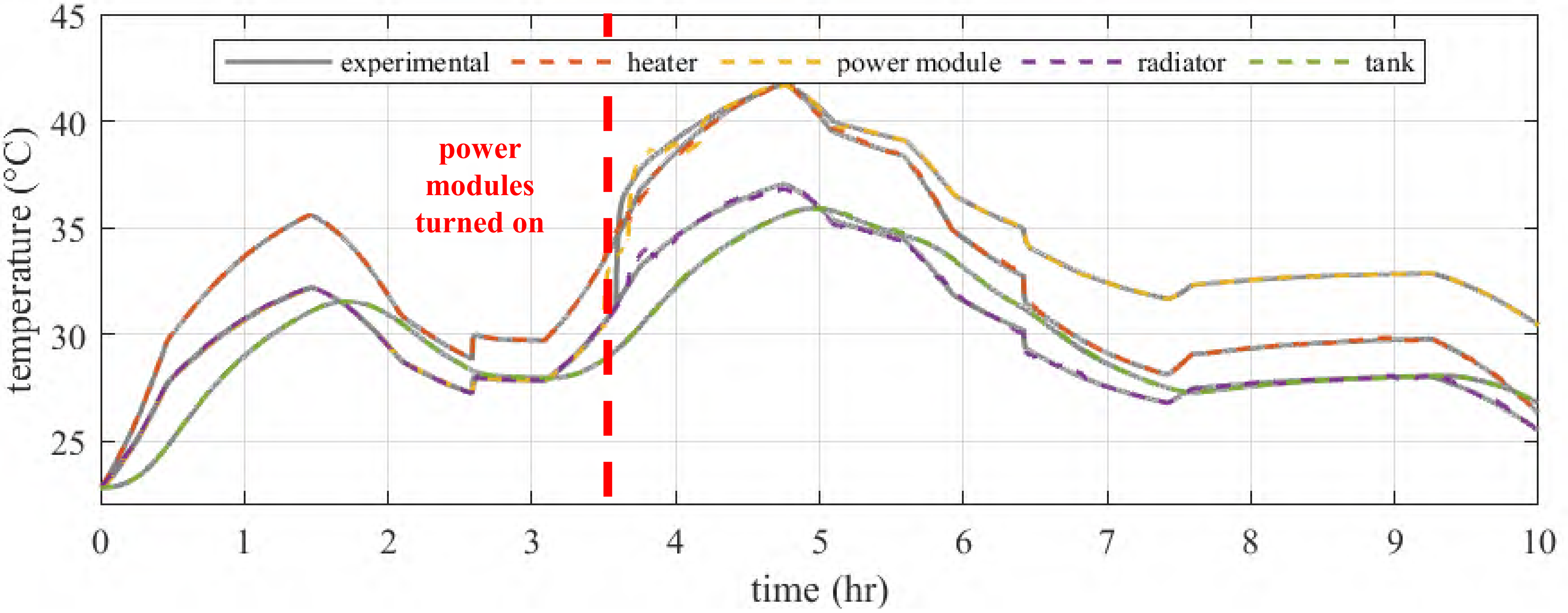
Metric results of model with PSO updating

	heater	power modules	radiator	tank
MAE (°C)	0.032	0.016	0.048	0.014
MSE(°C)	0.003	0.001	0.005	0.001
RMSE(°C)	0.051	0.024	0.024	0.021
NMSE	0.003	0.001	0.005	0.001
percent improvement RMSE	93%	95%	96%	93%



SCENARIO 1: POWER MODULES DISSIPATE HEAT

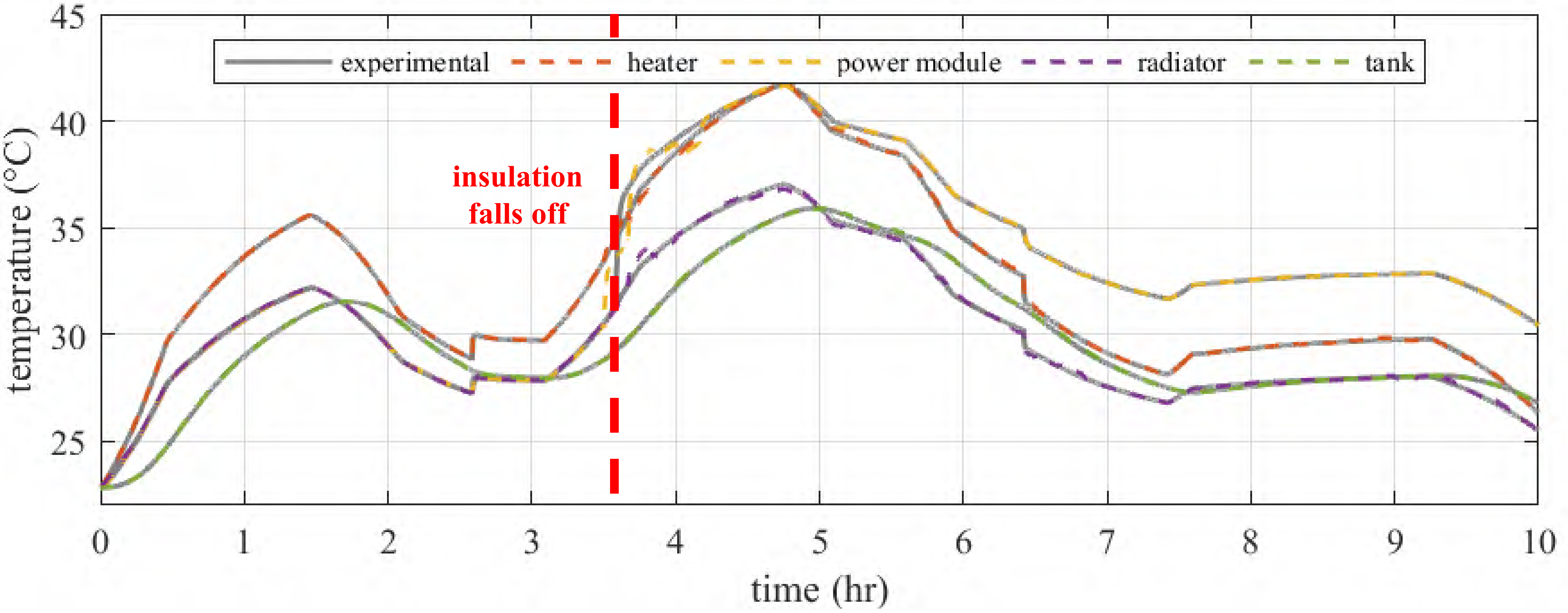
- Manually tuned model was used to create synthetic experimental data. To determine if the model updating scheme can handle changes in the physical system changes.
- At 3.5 hours power modules were turned on. Supplying 600W of dissipated heat to the system till the end of the test.



SCENARIO 2: INSULATION REMOVED FROM TANK

- At 3.5 hours insulation falls of the tank.

$$Error = \sqrt{\frac{\left(T_{\exp\_heater} - T_{heater}\right)^2}{nSamples}} + \sqrt{\frac{\left(T_{\exp\_radiator} - T_{radiator}\right)^2}{nSamples}} + \sqrt{\frac{\left(T_{\exp\_module} - T_{module}\right)^2}{nSamples}} + \sqrt{\frac{\left(T_{\exp\_tank} - T_{tank}\right)^2}{nSamples}}$$



CONCLUSION

- Numerical scheme for the updating of thermal models within digital twins.
- Carried out experimental validation demonstrating that the proposed method can update a digital twin within a reasonable time.
- Improved the performance of a static model by linking to its dynamic physical twin.

Future Work

- Work on implementing the digital twin on the larger NPES testbed thermal system.
- Begin investigating the usefulness of the updated digital twin for use in "lookahead" predictions.

THANKS!

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PUBLICATION CONTRIBUTIONS

1. **Braden Priddy**, Richard Hainey, Tyler Deese, Austin R.J. Downey, Jamil Khan, and Herbert L. Ginn. Real-time thermal data assimilation for power electronics at the edge. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers, aug 2024

2. **Braden Priddy**, Kerry Sado, Richard Hainey, Austin R.J. Downey, Jamil Khan, Kristen Booth. Robust and autonomous framework for thermal model updating within digital twins. (Not yet submitted)

3. Jarrett Peskar, **Braden Priddy**, Kerry Sado, Austin R.J. Downey, Kristen Booth, and Jamil Khan. Adaptive agent-based control for lithium-ion batteries in naval microgrids. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers, aug 2024

4. Yanzhou Fu, **Braden Priddy**, Austin Downey, and Lang Yuan. Real-time splatter tracking in laser powder bed fusion additive manufacturing. In Norbert G. Meyendorf, Ripi Singh, and Christopher Niezrecki, editors, NDE 4.0, Predictive Maintenance, Communication, and Energy Systems: The Digital Transformation of NDE. SPIE, apr 2023. doi:10.1117/12.2658544

5. Joud Satme, Daniel Coble, **Braden Priddy**, Austin R. J. Downey, Jason D. Bakos, and Gurcan Comert. Progress towards data-driven high-rate structural state estimation on edge computing devices. In Volume 10: 34th Conference on Mechanical Vibration and Sound (VIB). American Society of Mechanical Engineers, aug 2022. doi:10.1115/detc2022-90118

BACKUP

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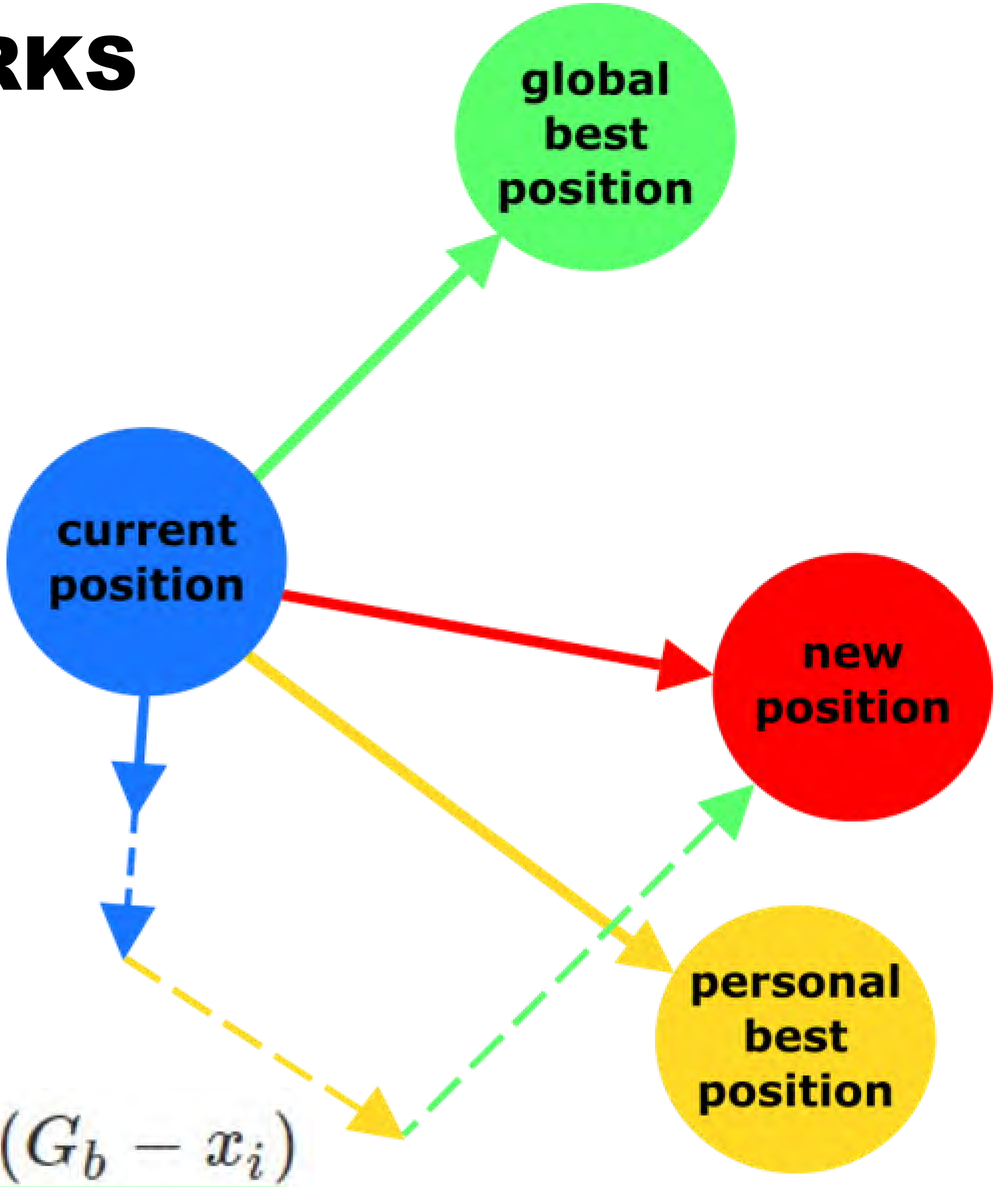
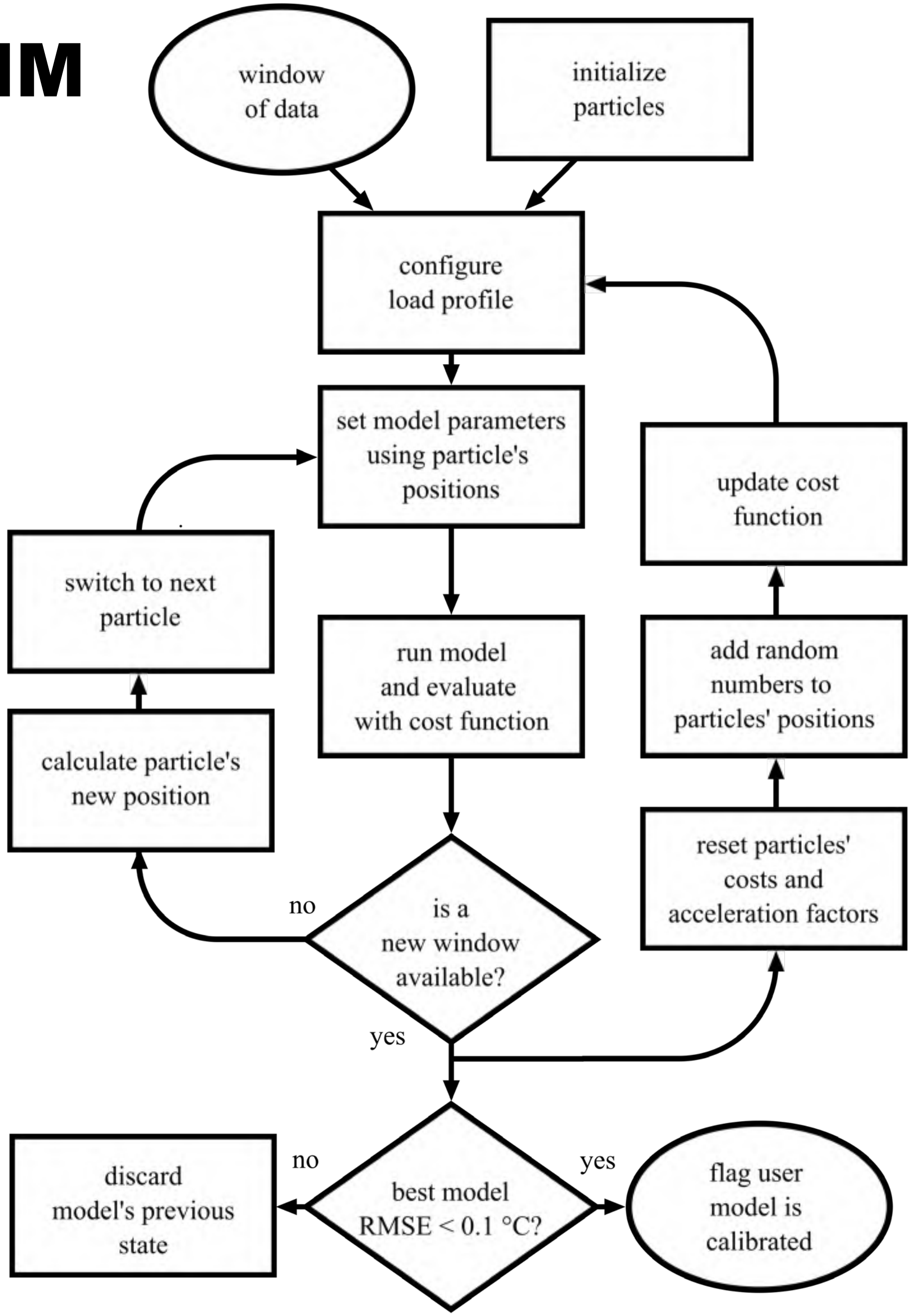
HOW THE PSO ALGORITHM WORKS

1. Particles are randomly initialized in the search space.
2. Particles' positions are evaluated by a cost function.
3. Global and personal best positions are updated.
4. New velocity component is calculated and added to the particle's new position.



$$\underline{x_{i+1}} = x_i + \underline{Wv_i} + \underline{c_1 r_1 (P_b - x_i)} + \underline{c_1 r_1 (G_b - x_i)}$$

UPDATED ALGORITHM



MOVING GLOBAL MINIMUM