FREEDM SYSTEMS CENTER

Building a Better Battery Model

Our webinar will begin in a few minutes.

Introduction

- Welcome
- FREEDM Overview
- Zoom Functionality

freedm.ncsu.edu

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Building a Better Battery Model

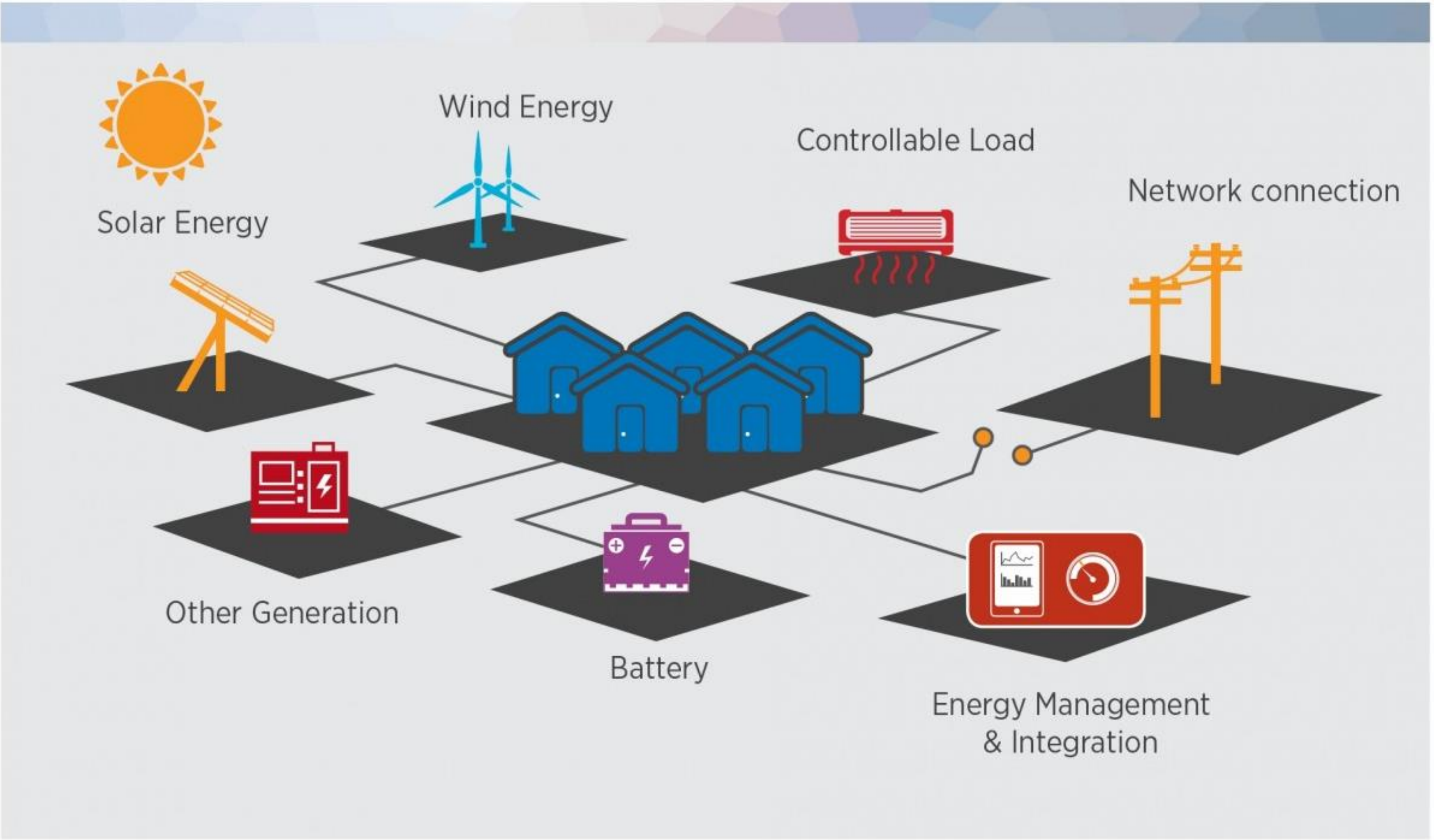
Fuhong Xie, Research Assistant

July 28, 2020

Xie, Fuhong, et al. "Battery Model Parameterization Using Manufacturer Datasheet and Field Measurement for Real-Time HIL Applications." *IEEE Transactions on Smart Grid* 11.3 (2019): 2396-2406.

Background

Microgrid modeling:

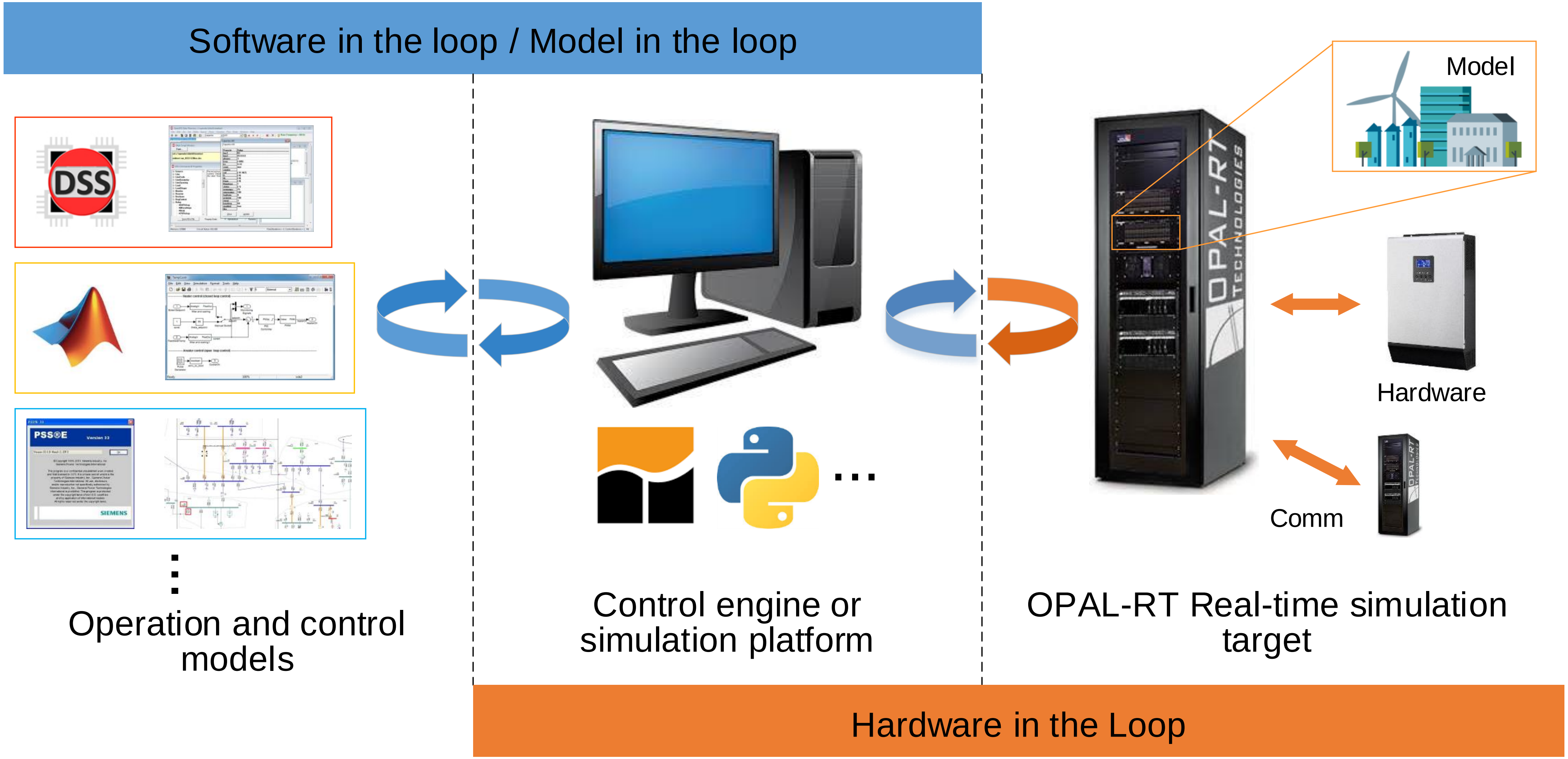


Overview

Outlines:

- Motivations and consideration
- Battery modeling
- Model parameterization
- Case studies
- Summary

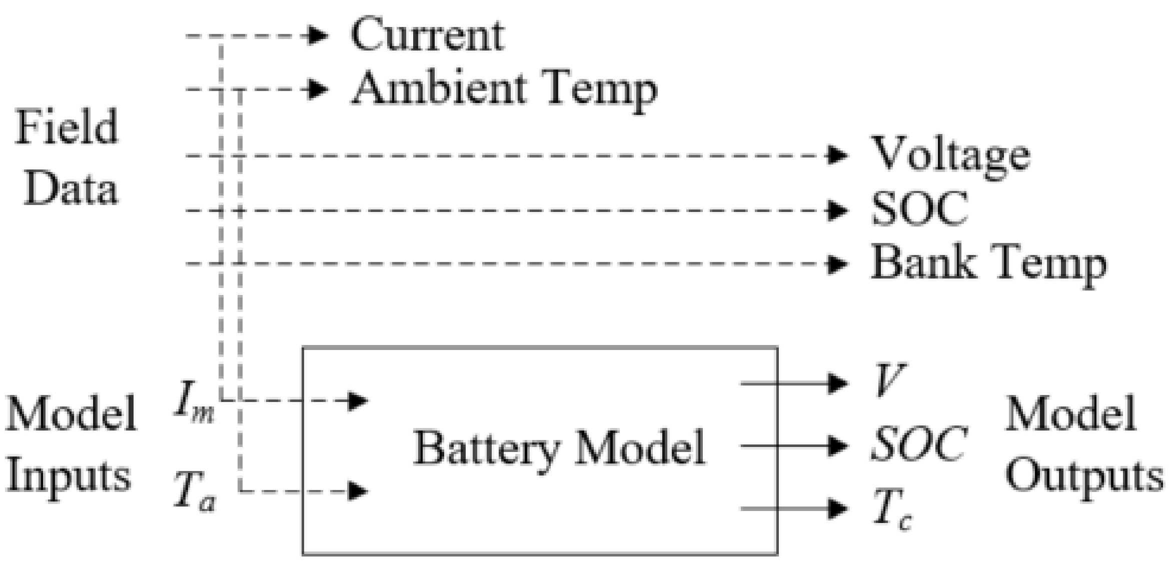
Motivations



J. Blanger, P. Venne, and J.-N. Paquin, "The what, where and why of real-time simulation," in IEEE PES General Meeting, Minneapolis, MN, USA, 25–29 July 2010.

Modeling Considerations

- Data availability
  - Manufacturer datasheet.
  - Field measurements of battery current, voltage, and state of charge (SOC), ambient and battery bank temperature.



Modeling Considerations

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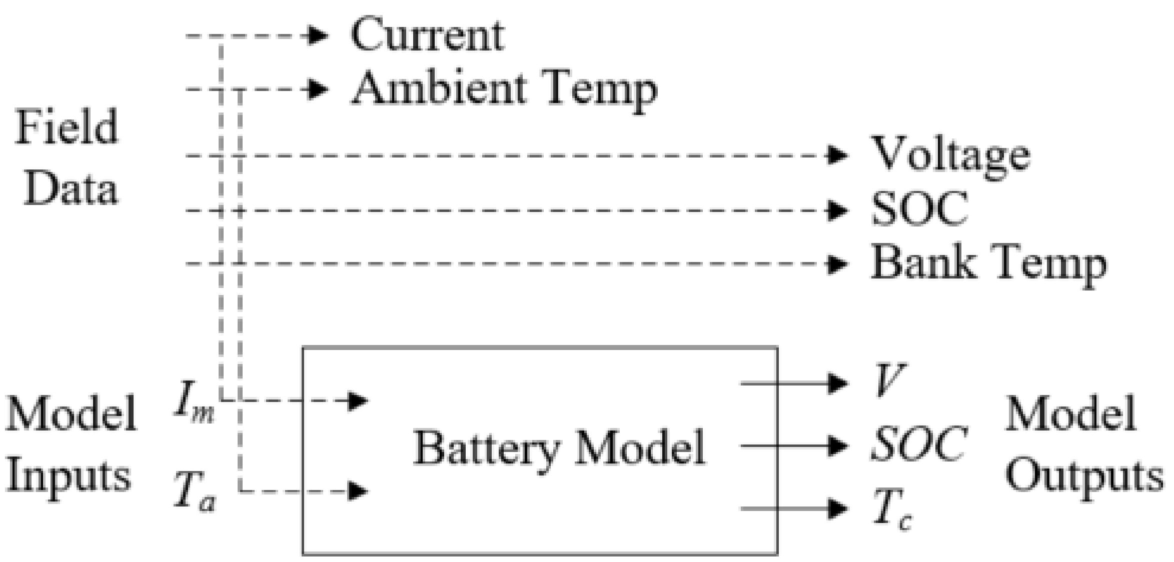
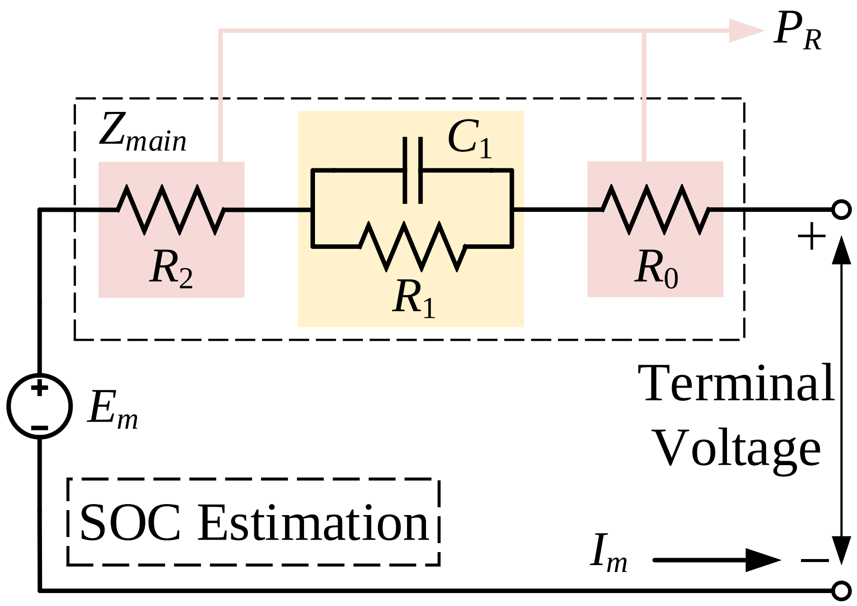


- Modeling objective
  - Simulated outputs should match the field data under different conditions.
  - Can capture dynamics caused by system status changes.

Battery Modeling

Equivalent circuit model

– Electrical main branch circuit.

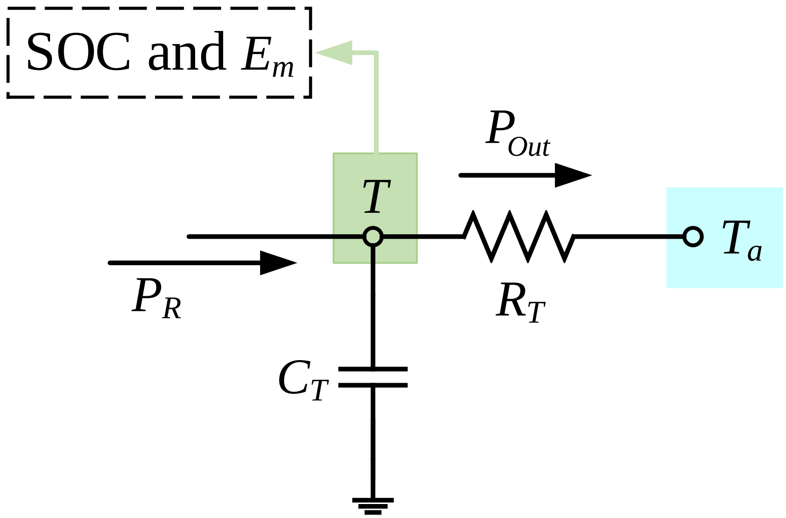


Variable	Unit	Description
E_m	V	Internal voltage source
R_0	Ω	Terminal resistance
R_1	Ω	Dynamics branch resistance
C_1	F	Dynamics branch capacitance
R_2	Ω	Thermodynamic resistance
Z_{main}	Ohm	Branch equivalent impedance
P_R	W	Internal heat loss from R_2 and R_0

Jackey, Robyn A. "A simple, effective lead-acid battery modeling process for electrical system component selection." *SAE Transactions* (2007): 219-227.

Equivalent circuit model

– Thermodynamic branch circuit.



Variable	Unit	Description
R_T	$W/(m^2 \cdot K)$	Thermal resistance
C_T	J/(°C·kg)	Battery thermal capacitance
P_R	W	Internal heat loss from R_2 and R_0
P_{Out}	W	Heat exchange
T	°C	Battery internal temperature
T_a	°C	Ambient temperature

Jackey, Robyn A. "A simple, effective lead-acid battery modeling process for electrical system component selection." *SAE Transactions* (2007): 219-227.

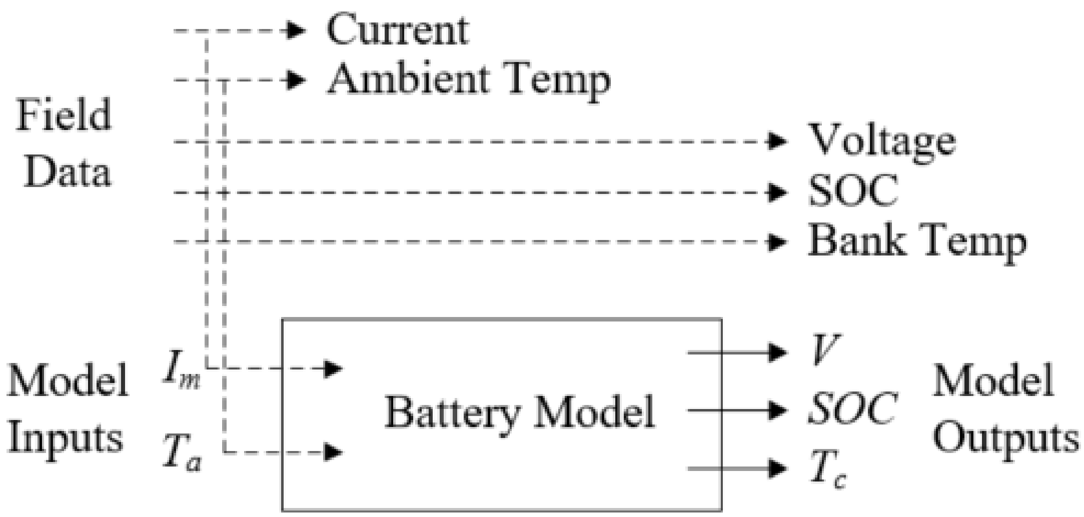
Battery Modeling

Take home messages:

- Equivalent circuit based model is simple enough to be executed in real-time with the timestep of a few microseconds.
- Battery model can simulate the battery dynamics of voltages and SOC.

Model Parameterization Method

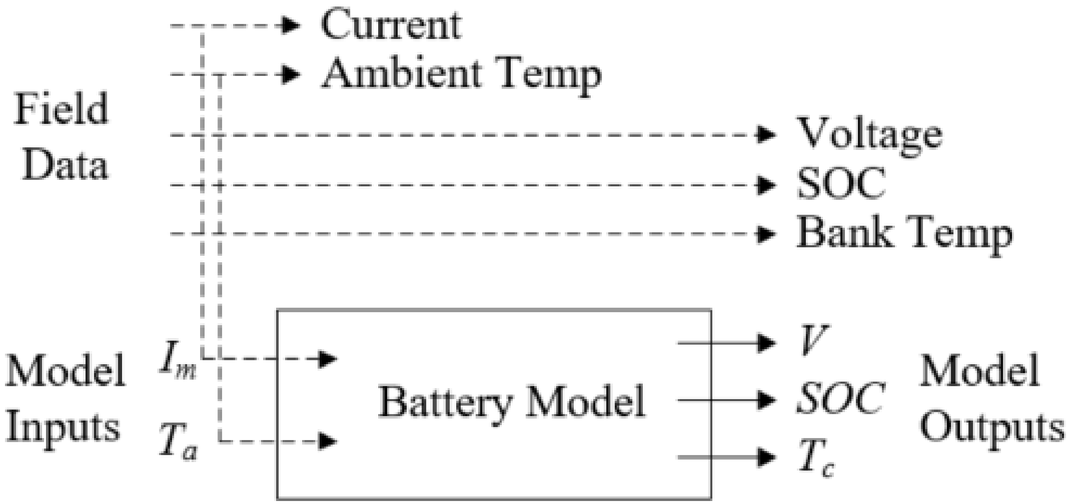
- Objectives:
  - To find an optimal set of model parameters so that the mismatch between simulation results and field measurements is minimized.



Model Parameterization Method

- Objective formulation:

$$\min_{\theta \in \mathbb{R}^N} \left\{ F(\theta) = \sum_{r=1}^{3} w_r \cdot f_r(\theta) : l \le \theta \le u,\ l, u \in \mathbb{R}^N \right\}$$



$$\sum_{r=1}^{3} w_r = 1$$

The weighting factor for different measurements.

Constraints on model parameters.

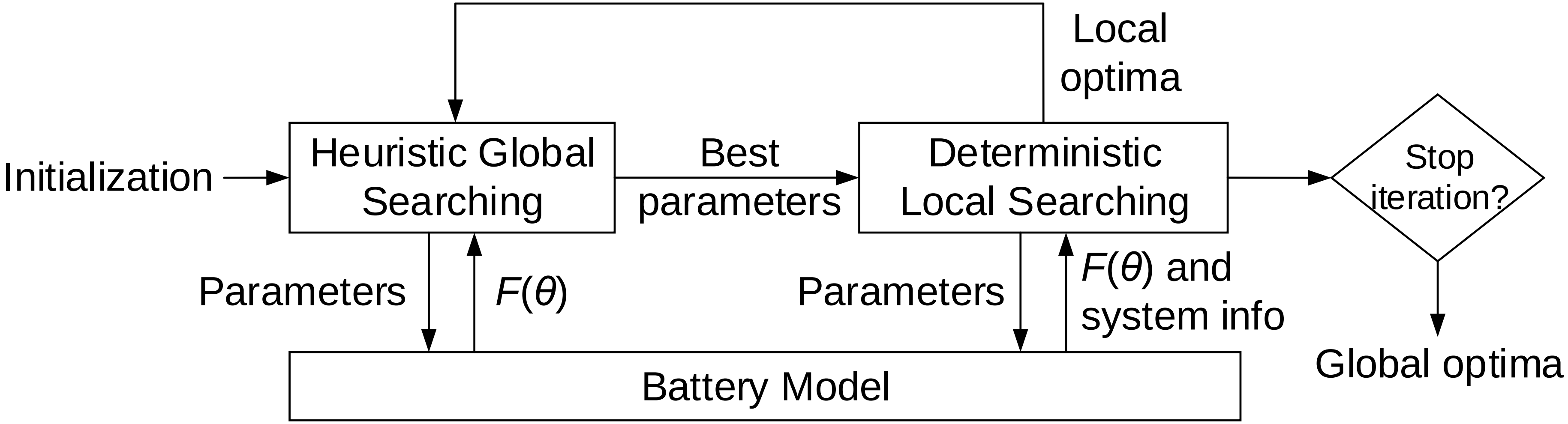
$$f(\theta) = \sum_{t=1}^{N_{sample}} \left(x(\theta, t) - \tilde{x}(t) \right)^2, \quad \theta \in \mathbb{R}^N$$

The mismatch between simulation results and field measurements.

Model Parameterization Method

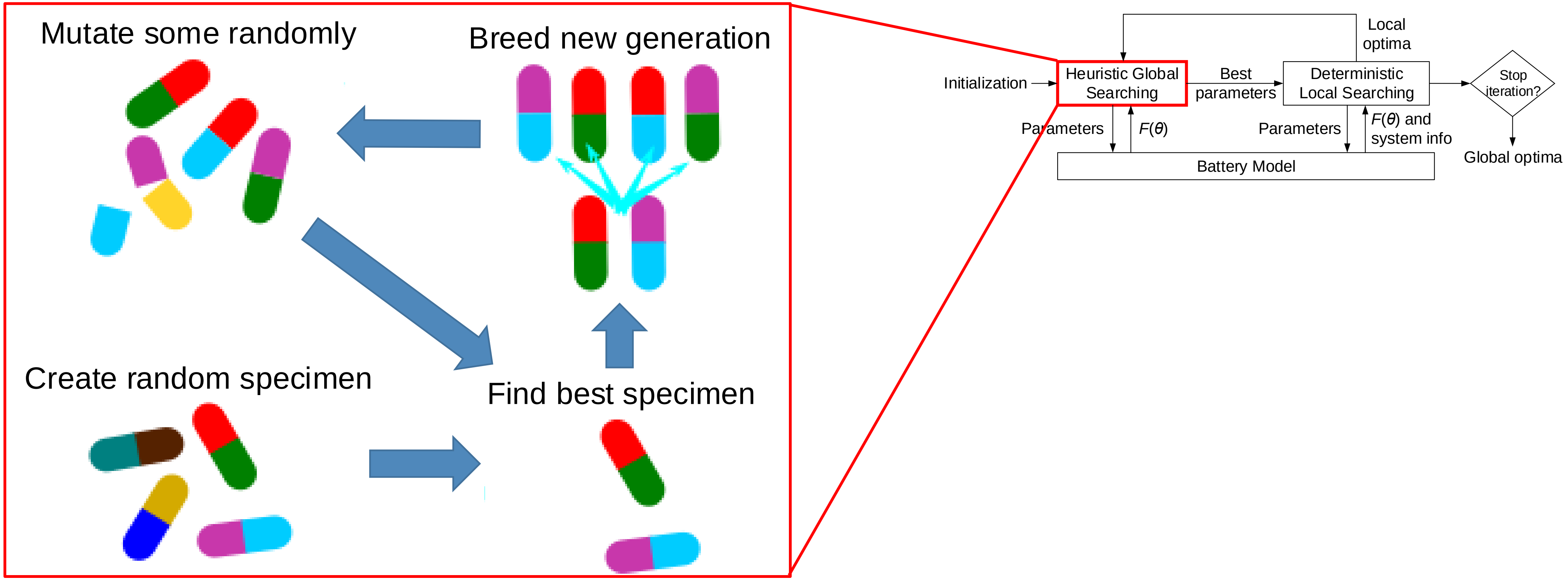
- Searching enhanced genetic algorithm (SEGA):

$$\min_{\theta \in \mathbb{R}^N} \left\{ F(\theta) = \sum_{r=1}^{3} w_r \cdot f_r(\theta) : l \le \theta \le u,\ l, u \in \mathbb{R}^N \right\}$$



Model Parameterization Method

- Searching enhanced genetic algorithm (SEGA):
  - Global searching: modified genetic algorithm (GA).



https://pastmike.com/what-is-a-genetic-algorithm/

Model Parameterization Method

- Searching enhanced genetic algorithm (SEGA):
  - Global searching: modified genetic algorithm (GA).
  - Local searching: trust region reflective algorithm.

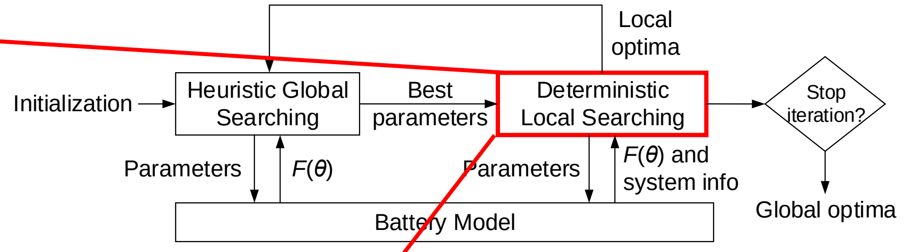
$$\min_{\theta \in \mathbb{R}^N} \left\{ F(\theta) = \sum_{r=1}^{3} w_r \cdot f_r(\theta) : l \le \theta \le u,\ l, u \in \mathbb{R}^N \right\}$$

Taylor expansion

$$\psi(\theta) = F(\theta_0) + \nabla F(\theta_0)^T \delta + \frac{1}{2}\delta^T \nabla^2 F(\theta_0)^T \delta, \quad \theta = \theta_0 + \delta$$

Subproblem of the original problem

$$\min_{\delta_k \in \mathbb{R}^N} \left\{ \psi(\delta_k) = J_k{}^T \delta_k + \frac{1}{2}\delta_k{}^T (H_k + C_k)\delta_k \right\}$$



Model Parameterization Method

- A simple and general example for SEGA (N_{GA} =6):

Step 1. Select 6 parent sets of θ values for GA algorithm based on the fitness Γ.

1	2	3	4	5	6
θ_1	θ_2	θ_3	θ_4	θ_5	θ_6

Model Parameterization Method

- A simple and general example for SEGA (N_{GA} =6):

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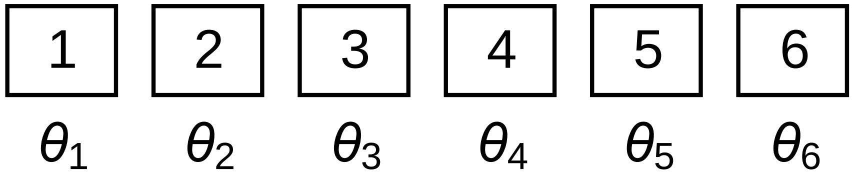


– Select the new population from the old population in last iteration based on the fitness.

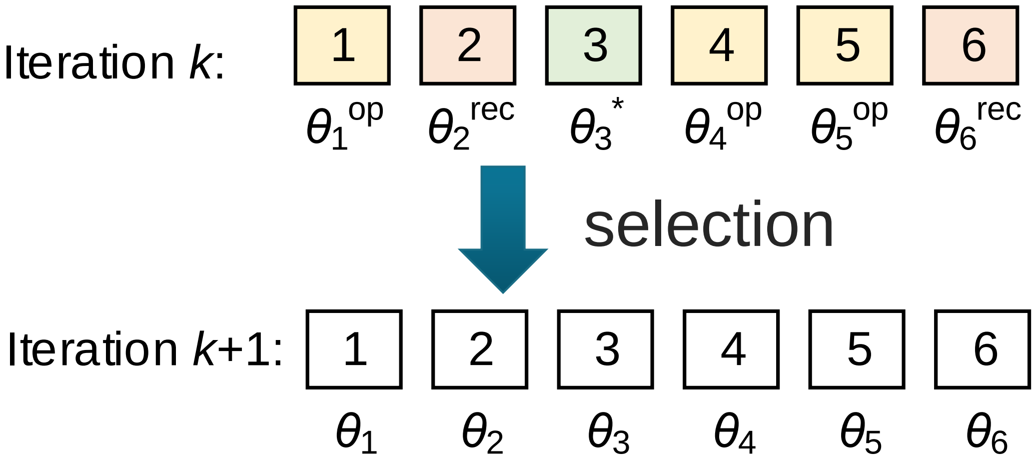
- Parameter fitness Γ(*F*)

$$F(\theta) = \sum_{r=1}^{3} w_r \cdot f_r(\theta)$$

$$\Gamma\left(F(\theta)\right) = \left(F(\theta)\right)^{-1}$$

- Selection possibility

$$p_i = \Gamma(\theta_i) \Big/ \sum_{i=1}^{N_{GA}} \Gamma(\theta_i),\ \theta \in \mathbb{R}^N$$



Model Parameterization Method

- A simple and general example for SEGA (N_{GA} =6):

Step 2. If set 1, 4, and 5 have the lowest fitness, they will be selected to mutate.

1	2	3	4	5	6
θ_1^{op}	θ_2	θ_3	θ_4^{op}	θ_5^{op}	θ_6

$$\Gamma(\theta_5) < \Gamma(\theta_4) < \Gamma(\theta_1) < \Gamma(\theta_2) < \Gamma(\theta_6) < \Gamma(\theta_3)$$

Model Parameterization Method

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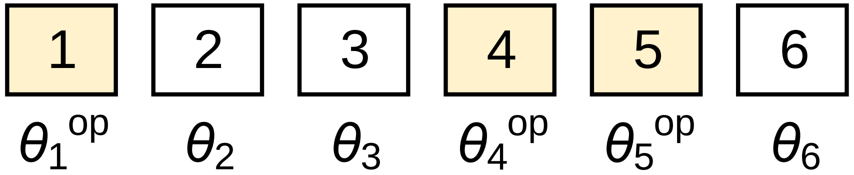
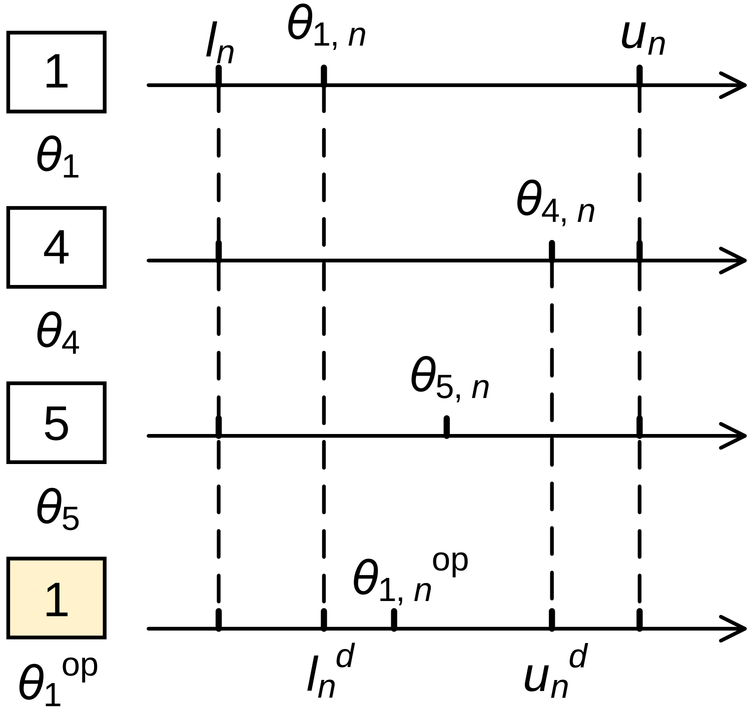


$$\Gamma(\theta_5) < \Gamma(\theta_4) < \Gamma(\theta_1) < \Gamma(\theta_2) < \Gamma(\theta_6) < \Gamma(\theta_3)$$

– The individual with relatively worse fitness will be transformed to the general opposite value.



Model Parameterization Method

- A simple and general example for SEGA (N_{GA} =6):

Step 3. Randomly select two sets of θ to recombine and if set 2 and 6 are selected.

1	2	3	4	5	6
θ_1^{op}	θ_2^{rec}	θ_3	θ_4^{op}	θ_5^{op}	θ_6^{rec}

$$\Gamma(\theta_5) < \Gamma(\theta_4) < \Gamma(\theta_1) < \Gamma(\theta_2) < \Gamma(\theta_6) < \Gamma(\theta_3)$$

Model Parameterization Method

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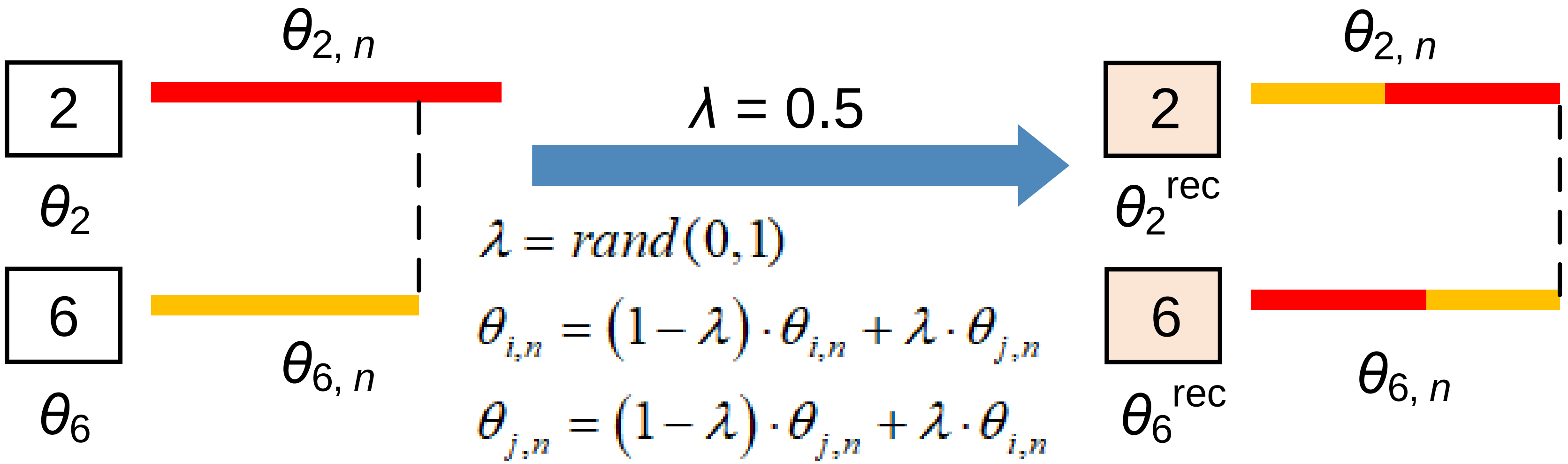
$$\Gamma(\theta_5) < \Gamma(\theta_4) < \Gamma(\theta_1) < \Gamma(\theta_2) < \Gamma(\theta_6) < \Gamma(\theta_3)$$

– The goal of recombination is to randomly generate new solutions from an existing individual pool.



$$\lambda = rand(0,1)$$

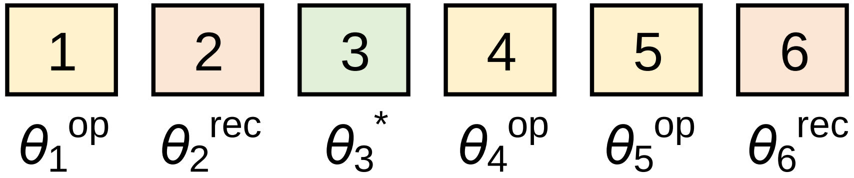
$$\theta_{i,n} = (1-\lambda)\cdot\theta_{i,n} + \lambda\cdot\theta_{j,n}$$

$$\theta_{j,n} = (1-\lambda)\cdot\theta_{j,n} + \lambda\cdot\theta_{i,n}$$

Model Parameterization Method

- A simple and general example for SEGA (N_{GA} =6):

  Step 4. Calculate the fitness Γ of the 6 sets of parameters. If set 3 has the highest fitness, set 3 (θ_3^{GA}) is selected as the one to proceed with the local exploitation for the θ_3^*.



  – Calculate the fitness again, best set of θ_i^{GA} from GA will be selected and used as θ_0 for the local exploitation algorithm.

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Model Parameterization Method

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Step 1. Select 6 parent sets of θ values for GA algorithm based on the fitness Γ.

1	2	3	4	5	6
θ_1	θ_2	θ_3	θ_4	θ_5	θ_6

Step 2. If set 1, 4, and 5 have the lowest fitness, they will be selected to mutate.

1	2	3	4	5	6
θ_1^{op}	θ_2	θ_3	θ_4^{op}	θ_5^{op}	θ_6

Step 3. Randomly select two sets of θ to recombine and if set 2 and 6 are selected.

1	2	3	4	5	6
θ_1^{op}	θ_2^{rec}	θ_3	θ_4^{op}	θ_5^{op}	θ_6^{rec}

Step 4. Calculate the fitness Γ of the 6 sets of parameters. If set 3 has the highest fitness, set 3 (θ_3^{GA}) is selected as the one to proceed with the local exploitation for the θ_3^*.

1	2	3	4	5	6
θ_1^{op}	θ_2^{rec}	θ_3^*	θ_4^{op}	θ_5^{op}	θ_6^{rec}

Step 5. Repeat step 1.

Model Parameterization Method

- Deterministic local searching - trust region reflective method:

$$\min_{\delta_k \in \mathbb{R}^N} \left\{ \psi(\delta_k) = J_k{}^T \delta_k + \frac{1}{2} \delta_k{}^T (H_k + C_k) \delta_k \right\}$$

s.t.

$J_k = \nabla F(\theta_k),\ H_k = \nabla^2 F(\theta_k)$ Jacobian matrix and Hessian matrix

$\left\| D_k \delta_k \right\| \le \Delta_k$ Constraints for trial steps of parameters

$D_k = diag\left(1 \big/ \sqrt{\left| v(\theta_k) \right|} \right)$ Diagonal scaling matrix

$C_k = D_k \cdot diag(J_k) \cdot J_k^v \cdot D_k$ Symmetric equivalence for Hessian matrix

Model Parameterization Method

- Deterministic local searching - trust region reflective method:

$$\min_{\delta_k \in \mathrm{R}^N} \left\{ \psi(\delta_k) = J_k^{\ T} \delta_k + \frac{1}{2} \delta_k^{\ T} (H_k + C_k) \delta_k \right\}, \quad \left\| D_k \delta_k \right\| \le \Delta_k$$

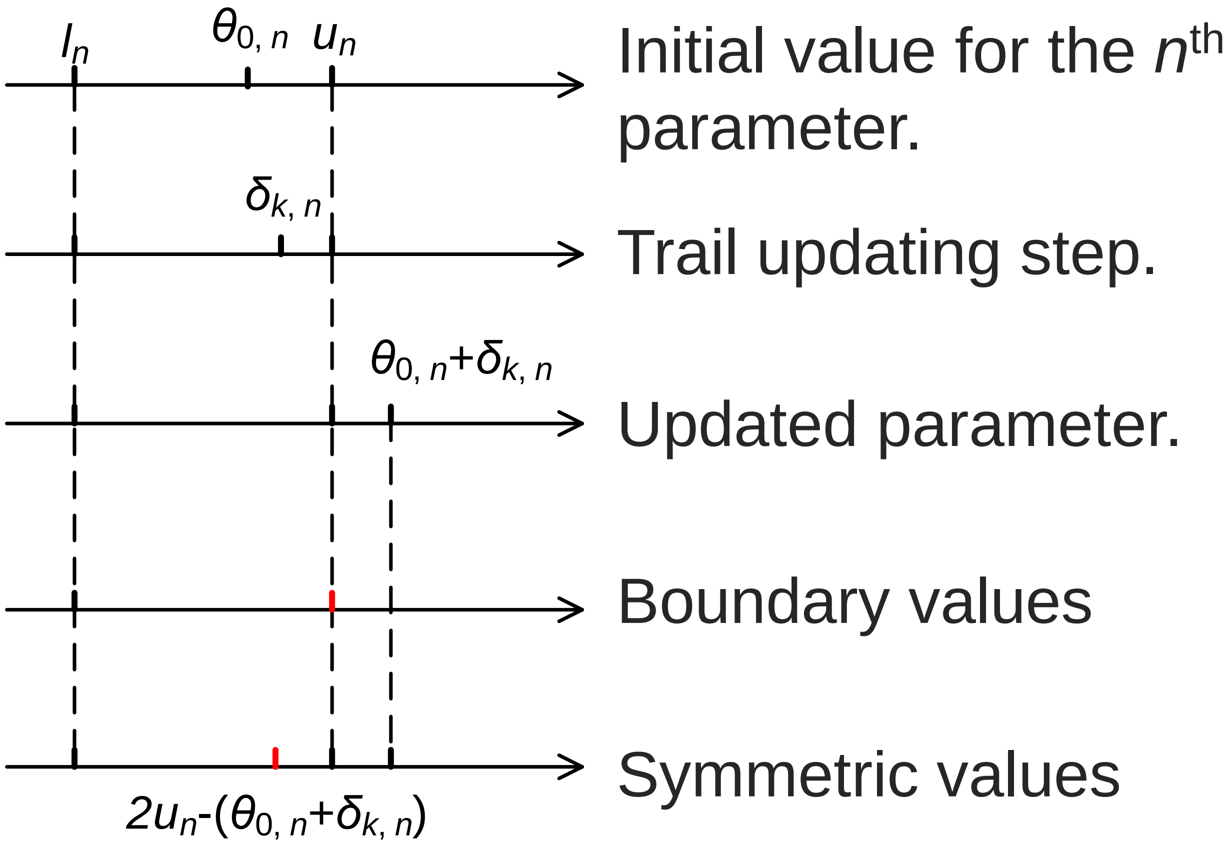
– One dimensional reflection.

- Boundary values.

$$\theta_n = u_n$$

- Symmetric values.

$$\theta_n = 2u_n - \left(\theta_{0,n} + \delta_{k,n} \right)$$



Model Parameterization Method

Take home message:

- Model parameters can be driven from field measurement data using automated methods.

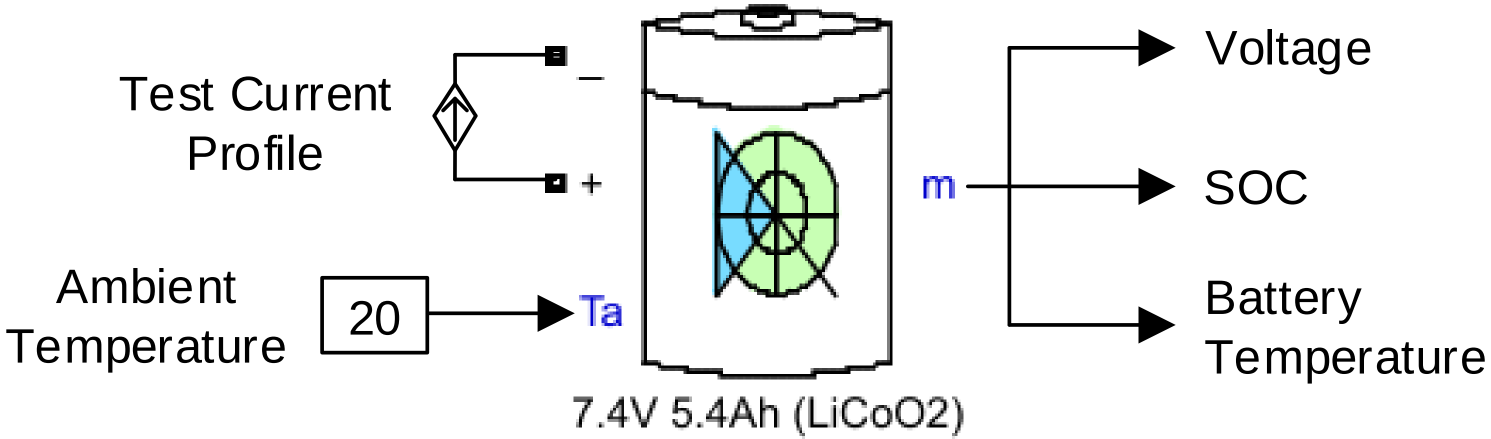
Case Studies

Summaries:

- Case 1: Benchmark test with known parameters
- Case 2: Li-ion battery cell with datasheet data
- Case 3: Lead acid battery bank with field measurements

Case Studies

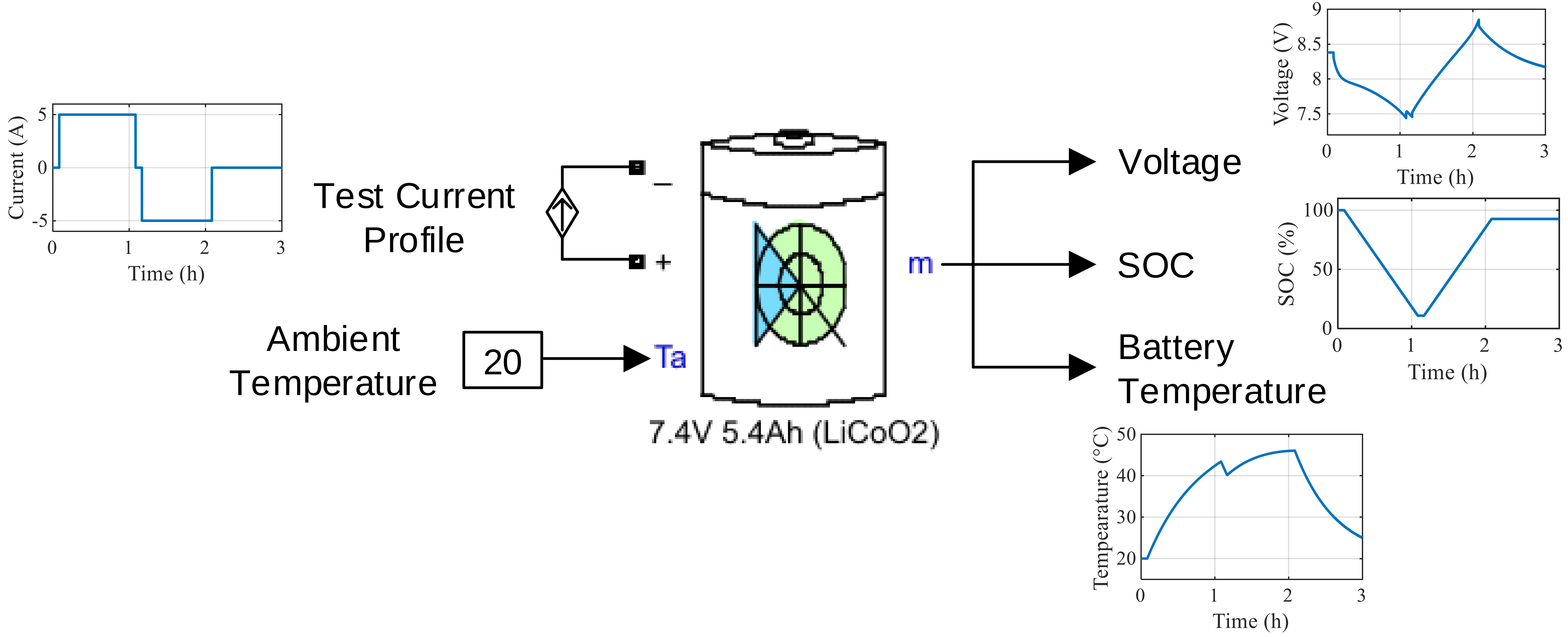
- Case 1: Benchmark Test



Definition	True Value	Unit	Search Range
Internal resistance R_{in}	0.0133	Ω	0.01 ~ 0.02
Thermal resistance R_{th}	0.6	°C/W	0 ~ 1
Maximum capacity C_{max}	5.6	Ah	0 ~ 10
Nominal Voltage E_n	7	V	0 ~ 7.9

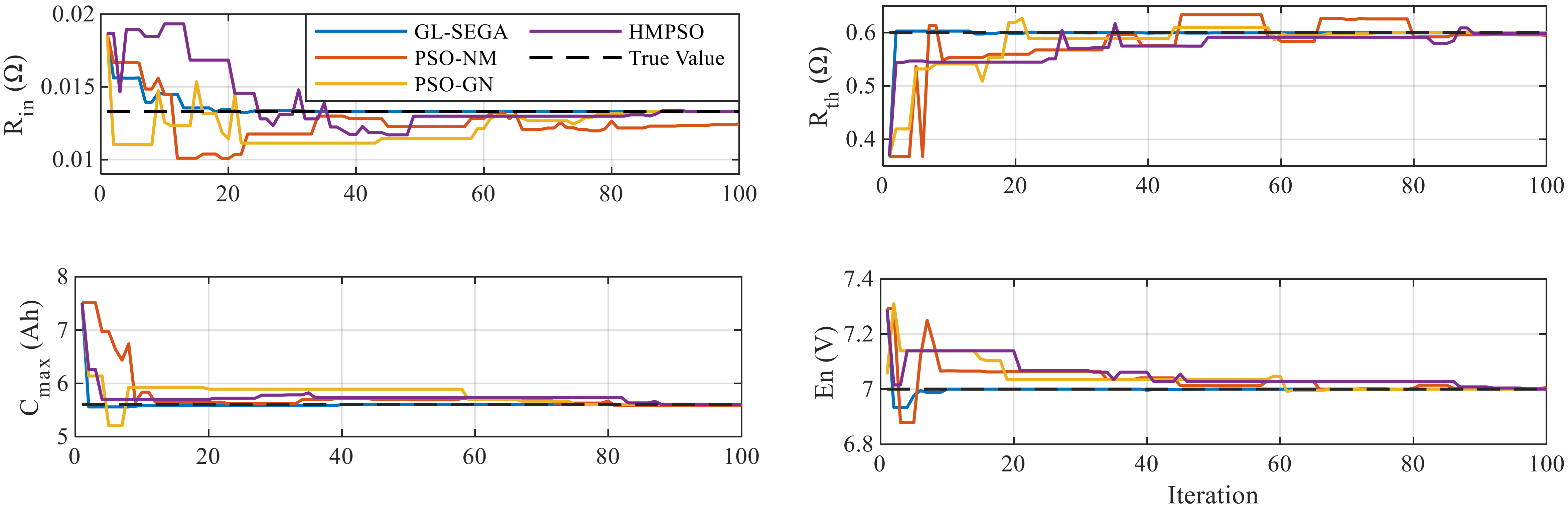
Case Studies

- Case 1: Benchmark Test



Backup 4

- Case 1: Benchmark Test



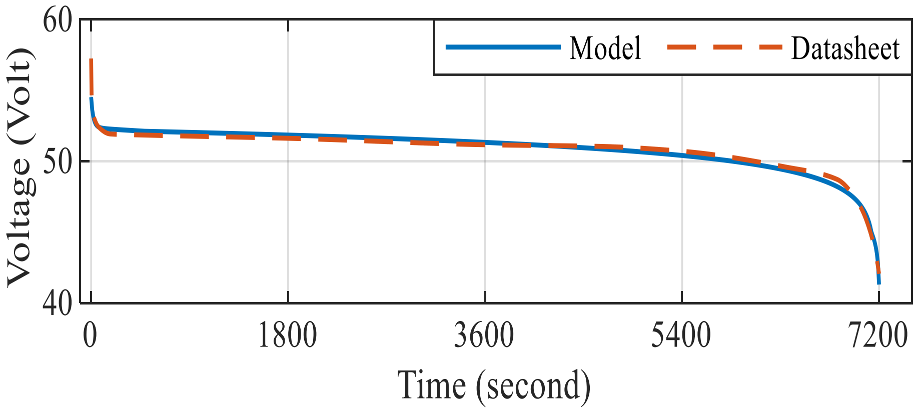
GL-SEGA: global-local searching enhanced genetic algorithm
HMPSO: hybrid multi-swarm particle swarm optimization
PSO-NM: hybrid modified particle swarm optimization and Nelder-Mead method
PSO-GN: hybrid particle swarm optimization and Gauss-Newton

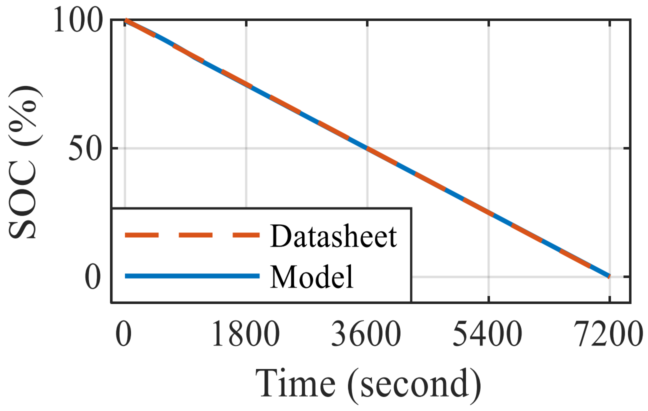
- Case 1: Benchmark Test

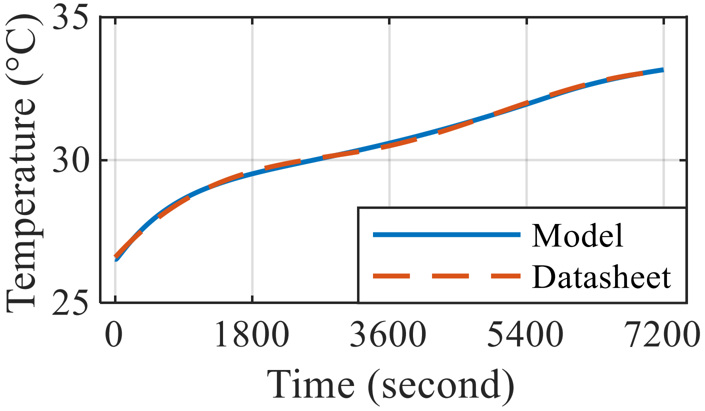
Metrics	Parameter	GL-SEGA	PSO-GN	HMPSO	PSO-NM
Converge Iteration	R_{in}	**35**	83	92	/
	R_{th}	**24**	75	89	88
	C_{max}	**40**	75	88	81
	E_n	**10**	78	91	86
Final Value	R_{in}	0.0133	0.0133	0.0133	0.01245
	R_{th}	0.6	0.6	0.5986	0.5947
	C_{max}	5.6	5.6	5.606	5.582
	E_n	7	7	7.003	7
Error	R_{in}	**0**	**0**	0	0.0009
	R_{th}	**0**	**0**	0.0014	0.0053
	C_{max}	**0**	**0**	-0.006	0.018
	E_n	**0**	**0**	-0.003	0

Case Studies

- Case 2: Li-ion Battery Cell
  - Model input: constant discharging current (32A) and ambient temperature.
  - Objective: minimize the mismatch between model output and datasheet data.



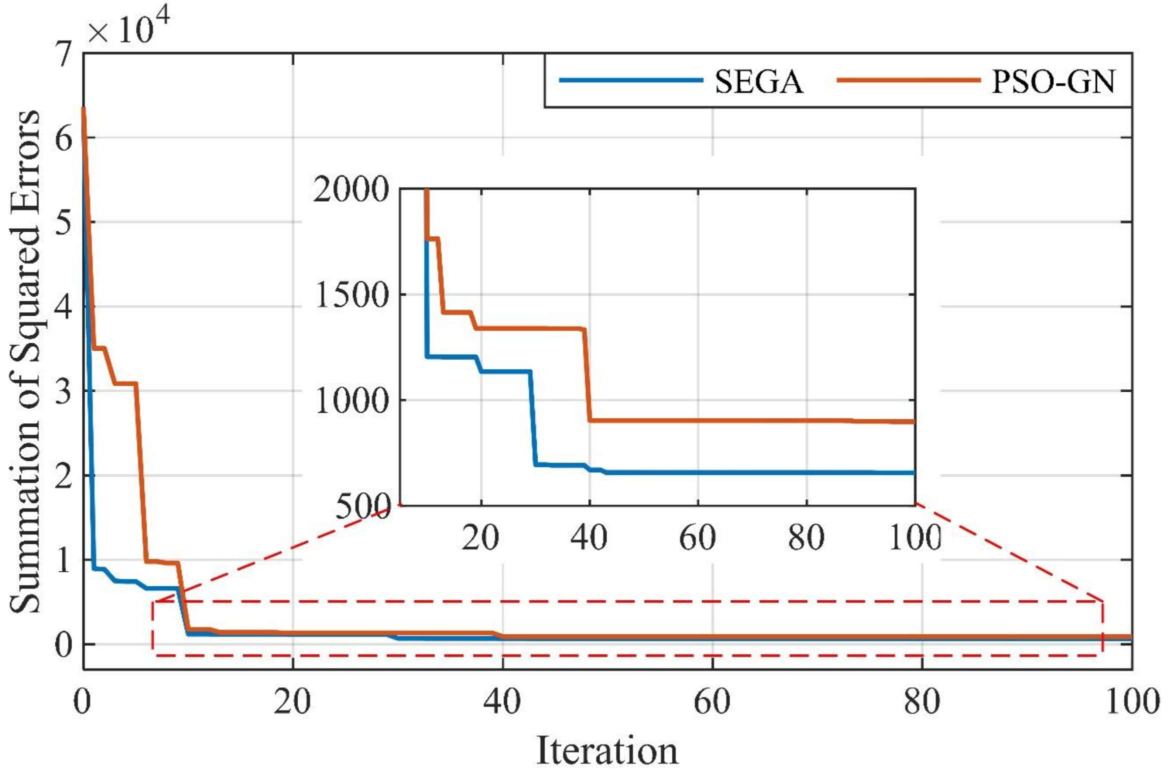




SimpliPhi 3.4kWh/48VDC Lithium Battery. [Online]. Available from: https://simpliphipower.com/product/phi-3-5-battery/.

Case Studies

- Case 2: Li-ion Battery Cell



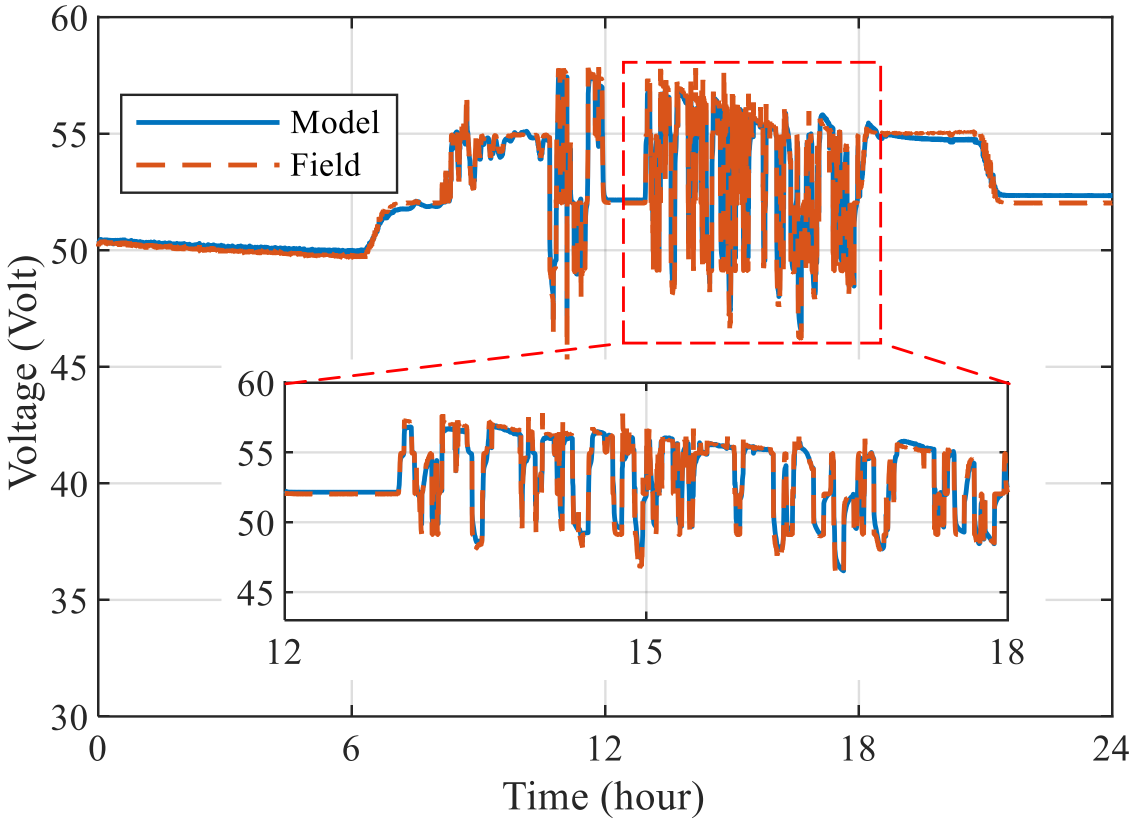
Case Studies

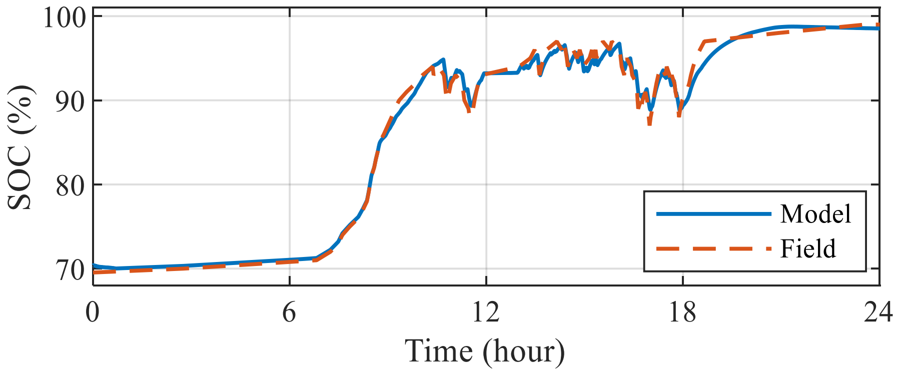
- Case 2: Li-ion Battery Cell

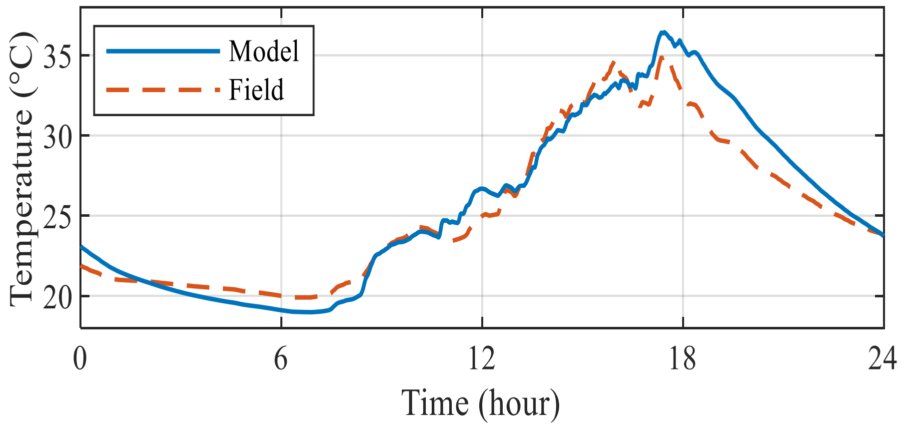
Metrics	Measurement	SEGA	PSO-GN *
Summation of squared errors	SOC	176.61	195.02
	Voltage	456.80	604.67
	Temperature	22.40	98.06
Mean square error	SOC	0.0273	0.0386
	Voltage	0.0721	0.0881
	Temperature	0.0031	0.0136
Normalized root mean square error	SOC	0.9943	0.9932
	Voltage	0.8014	0.7804
	Temperature	0.9660	0.9289
Normalized mean square error	SOC	1.0000	1.0000
	Voltage	0.9606	0.9518
	Temperature	0.9988	0.9949

Case Studies

- Case 3: Lead Acid Battery Bank
  - Model input: field measured current and ambient temperature from a microgrid testbed.



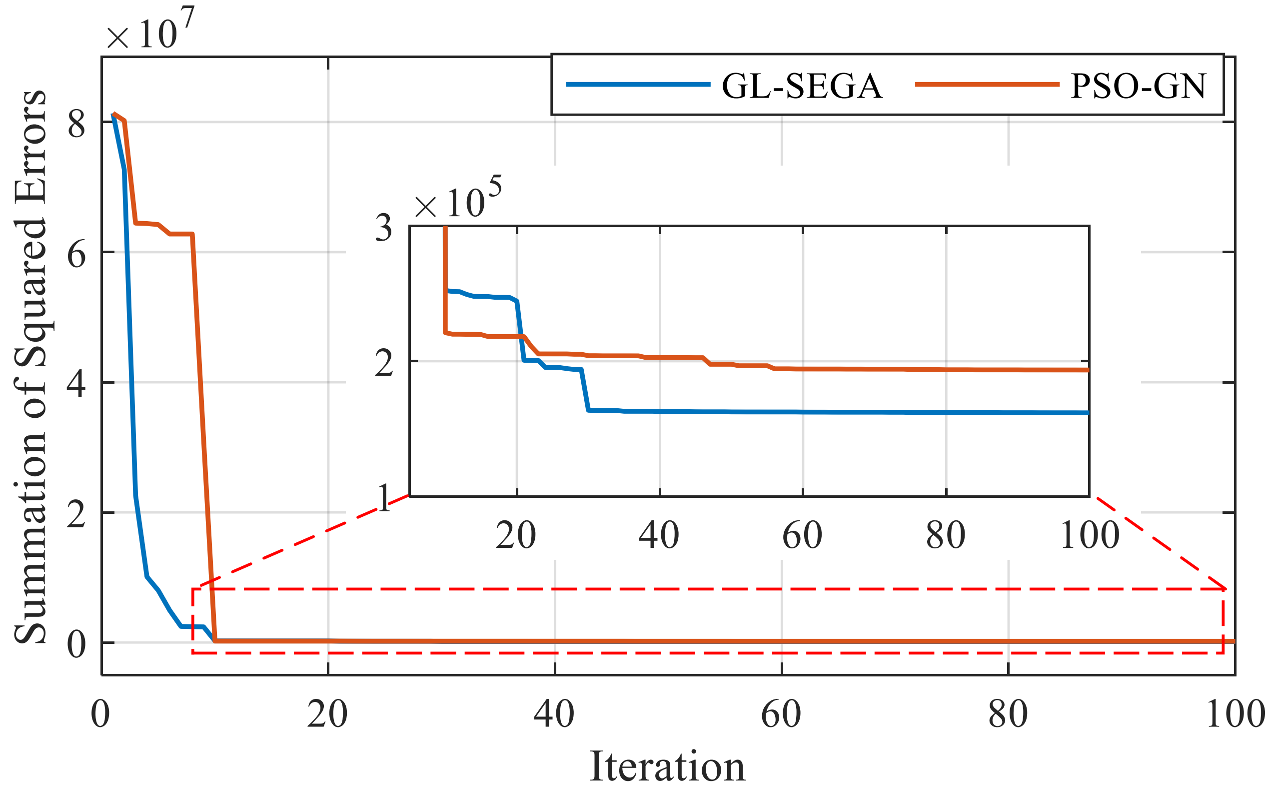




EnerSys 24 900Ah/2V Lead-acid Batteries. [Online]. Available from: https://www.enersys.com/Components/Templates/General.aspx?id=848

Case Studies

- Case 3: Lead Acid Battery Bank
  - Model input: field measured current and ambient temperature.



EnerSys 1.8kWh/2VDC Lead-acid Battery. [Online]. Available from: https://www.enersys.com/Components/Templates/General.aspx?id=848

Case Studies

- Case 3: Lead Acid Battery Bank

Metrics	Output	GL-SEGA	PSO-GN
Summation of squared errors	SOC	**43795.28**	70009.08
	Voltage	**8260.80**	10827.23
	Temperature	**109763.32**	112651.08
Mean square error	SOC	**0.5069**	0.8103
	Voltage	**0.0956**	0.1253
	Temperature	**1.2704**	1.3038
Normalized root mean square error	SOC	**0.8688**	0.8342
	Voltage	**0.9176**	0.9057
	Temperature	**0.7099**	0.7061
Normalized mean square error	SOC	**0.9828**	0.9725
	Voltage	**0.9932**	0.9911
	Temperature	**0.9156**	0.9136

Case Studies

Take home message:

- A hybrid optimization-based algorithm can improve and enhance the battery model parameterization.
- It balance the trade-off between efficiency and accuracy.

Summary

- Summary:
  - A hybrid optimization-based algorithm, SEGA, is presented to improve and enhance the battery model parameterization process for a single battery cell or a battery bank.
  - The proposed SEGA achieves a good balance among accuracy, convergence, and robustness requirements, which provides accurate simulations for battery studies.
  - The future works will focus on applying the proposed method to other microgrid components and online model parameterization.

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– Ph.D. Candidate at NC State (fxie2@ncsu.edu).

– Advisor: Prof. Ning Lu (nlu2@ncsu.edu).

- This research work is supported by Total S.A.

Backup 1

$$E_m(t) = E_{m0} - K_E T(t) \cdot (1 - SOC(t)) \quad (1)$$ → Simulate internal voltage source

$$R_0(t) = R_{00} \cdot [1 + K_0 (1 - SOC(t))] \quad (2)$$ → Calculate internal resistance

$$R_1(t) = -R_{10} \ln(SOC(t)) \quad (3)$$

$$C_1(t) = \tau_1 / R_1(t) \quad (4)$$

(3), (4) → Model battery dynamics branch

$$R_2(t) = R_{20} \frac{e^{K_{21} \cdot (1 - SOC(t))}}{1 + e^{K_{22} \cdot (I_m(t)/I_{m0})}} \quad (5)$$ → Simulate thermodynamic resistance

$$P_R(t) = (R_0(t) + R_2(t)) \cdot (I_m(t))^2 \quad (6)$$ → Calculate thermodynamic resistance

$$V(t) = E_m(t) + I_m(t) \cdot Z_{main}(t) \quad (7)$$ → Model terminal voltage

$$SOC(t) = \left[1 - \frac{1}{K_C K_T(T) C_0} \cdot \left(Q_{ini} - \int_0^t I_m(\tau) d\tau\right)\right] \times 100\% \quad (8)$$ → Estimate battery SOC

Backup 2

$$T(t) = T_{ini} + \frac{1}{C_T}\int_0^t \left[P_R(\tau) - (T(\tau) - T_a(\tau))/(R_T) \right] \cdot d\tau \quad (9)$$

→ Simulate battery internal temperature

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Backup 3

NC STATE UNIVERSITY

Algorithm 1: TRR for Model Parameterization

Initialization: Select the initial values for θ_0, Δ_0, Δ_{max}, k_{max}, and ε.

Output: optimal parameters set $\theta^* = \theta_k$.

1. **for** $k = 0, 1, \ldots, k_{max}$
2. Compute J_k, D_k, H_k, C_k and J_k^v.
3. Compute the trial step δ_k by solving

$$\min_{\delta_k \in \mathbb{R}^N} \left\{ \psi(\delta_k) = J_k^{\ T} \delta_k + \frac{1}{2} \delta_k^{\ T} B_k \delta_k : \|D_k \delta_k\| \le \Delta_k \right\}$$

4. **if** $\theta_k + \delta_k$ cross any bound constraint **then**

Recalculate δ_k using

$$\delta_{k,n}^R = \begin{cases} \delta_{k,n}, & n \neq m \\ -\delta_{k,n} - 2 J_{k,n}^v D_{k,n}^{-2}, & n = m \end{cases}$$

$$\delta_{k,n}^B = \begin{cases} \delta_{k,n}, & n \neq m \\ -J_{k,n}^v D_{k,n}^{-2}, & n = m \end{cases}$$

$$\delta_k = \arg \min_{\delta_k \in \mathbb{R}^N} \left\{ \psi\left(\delta_k^R\right), \psi\left(\delta_k^B\right) \right\}$$

end if

5. Compute the updating index ϕ_k using

$$\phi_k = \frac{1}{\psi(\delta_k)} \left(F(\theta_k + \delta_k) - F(\theta_k) + \frac{1}{2} \delta_k^{\ T} C_k \delta_k \right)$$

6. Calculate Δ_{k+1} using

$$\Delta_{k+1} = \begin{cases} \alpha_1 \cdot \Delta_k, & \phi_k < \mu_1 \\ \min\left(\alpha_2 \cdot \Delta_k, \Delta_{max}\right), & \phi_k > \mu_2 \\ \Delta_k, & \text{otherwise} \end{cases}$$

$$0 < \mu_1 < \mu_2 < 1$$

7. Calculate θ_{k+1} using

$$\theta_{k+1} = \begin{cases} \theta_k + \delta_k, & \phi_k > \mu_2 \\ \theta_k, & \text{otherwise} \end{cases}$$

8. **if** $\|J_k\|_2 \le \varepsilon$ **then**

Stop.

else

Go to step 2 until the maximum iteration number is reached.

end if

9. **end for**

Calculate system information.

Solve the equivalent TRR sub-problem.

Reflection scheme for updating parameters.

Update the trust region and model parameters based on the updating flag.

Converge criteria.