Health-Constrained Explicit Model Predictive Control Based on Deep-Neural Networks Applied to Real-Time Charging of Batteries

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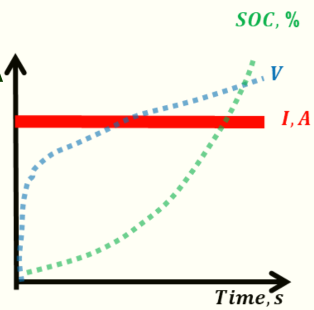
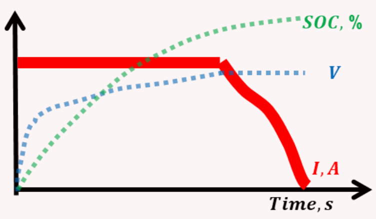
Importance of Battery Charging Protocols

- Batteries withstand **1000+s** of charging events
- **Charging manner** $\xLeftarrow{dependent}$ **degradation rate**
  - Heat generation, temperature rise, over voltage
  - Irreversible damage and capacity loss

Charging policy A



Charging Policy B



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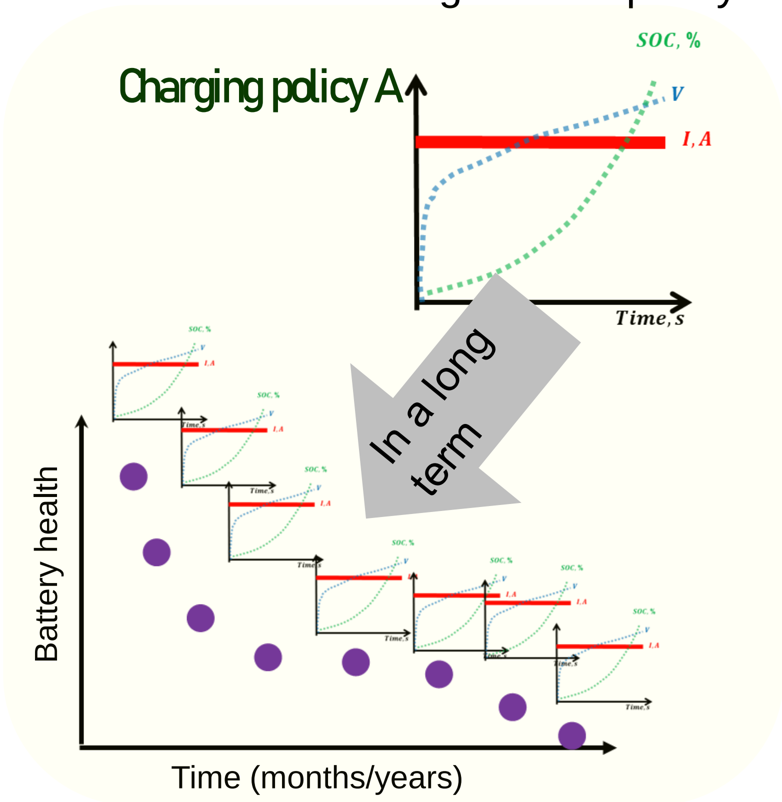
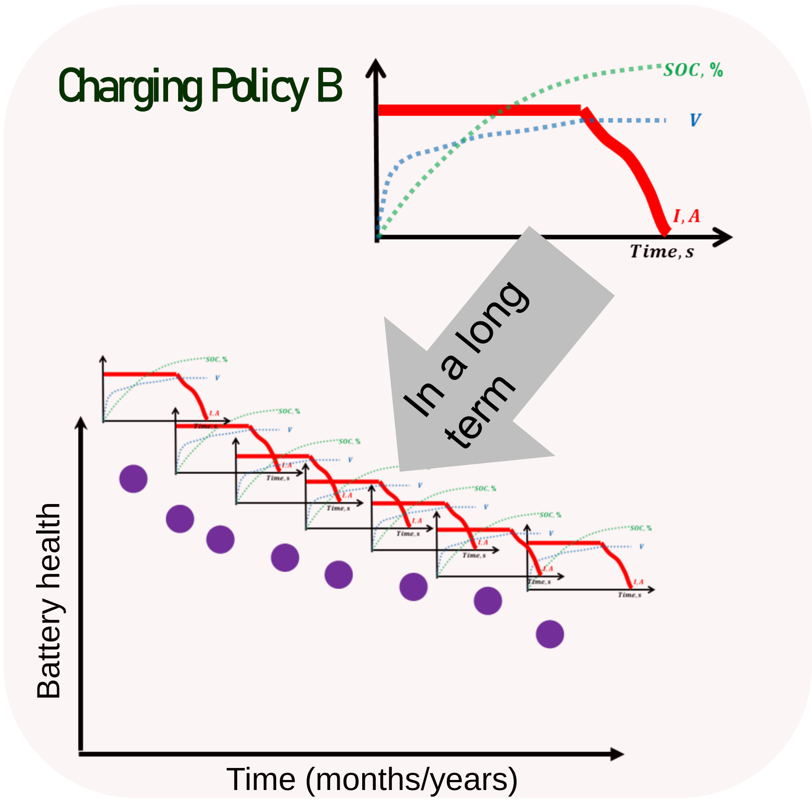
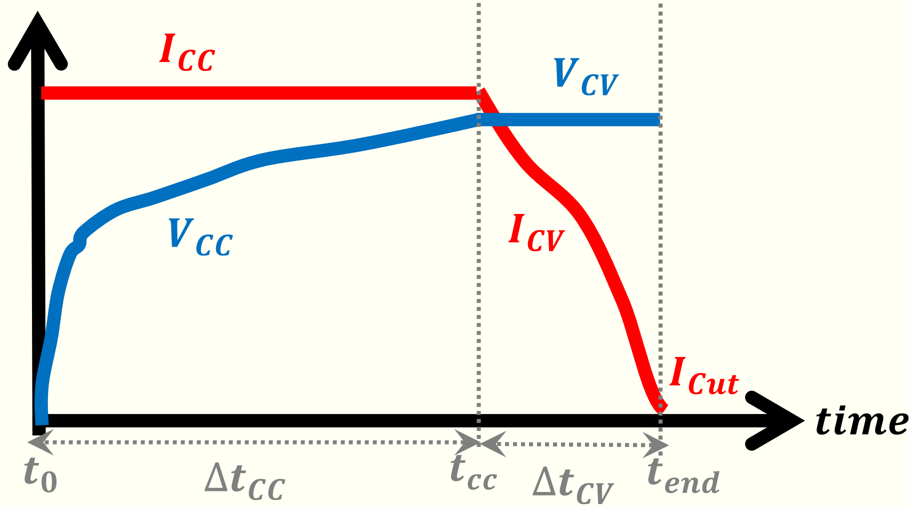




Battery Management Systems (BMSs) Rely on Empirical Protocols

For example:

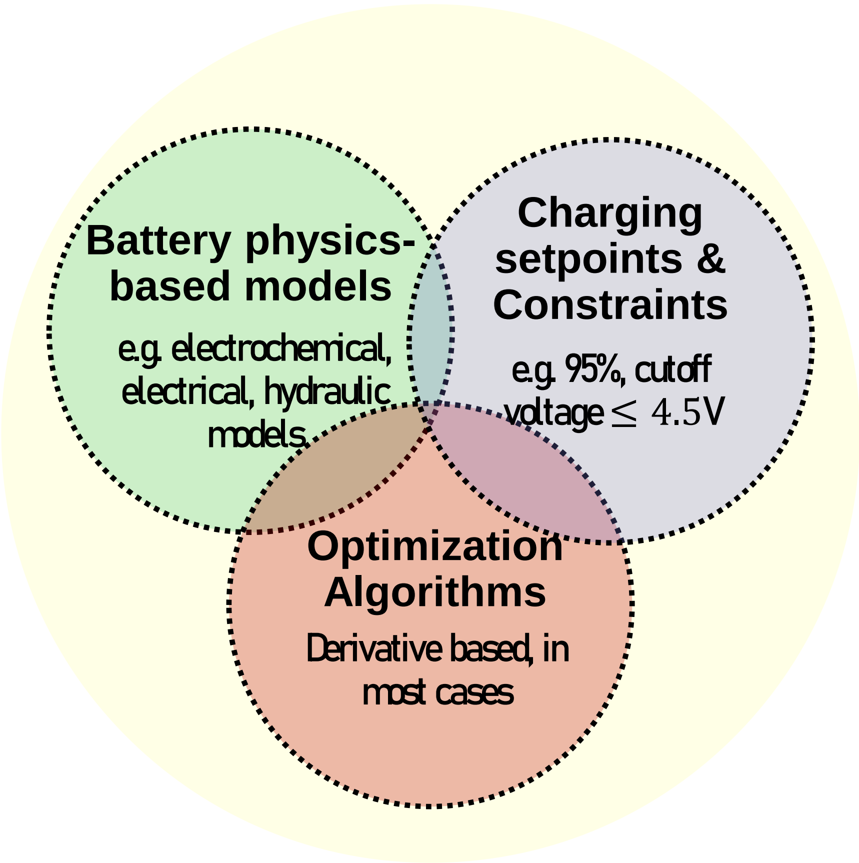
Constant Current-Constant Voltage (CC-CV)



- Experimentally designed, (i.e. offline)
- **Fair** performance (speed & safety), but **not optimal**, since
  - Do not exploit knowledge about battery dynamic (electrochemical, thermal, etc.)
  - Do not consider **varying** real-time conditions (initial SOC, temperature, etc.)
  - Do not consider evolving battery health

Recent Solution Attempts

- Advanced BMSs (ABMSs): Models + Optimization + Operation Requirements



1) Context of the Problem

Recent Solution Attempts

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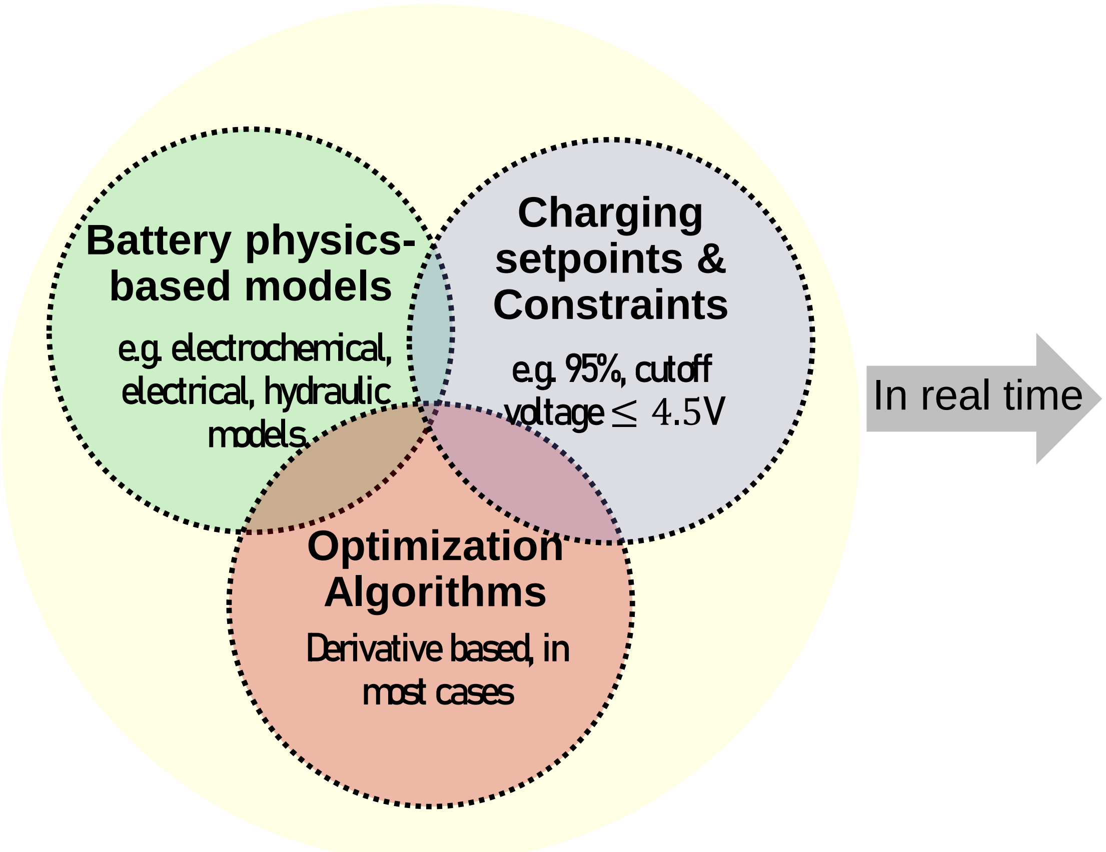


Model Predictive Control of charging

- Multivariate nonlinear systems
- Hard constraint on state/control
- **Perfectly suits for batteries:** highly nonlinear systems, implying operational, safety and health constraints

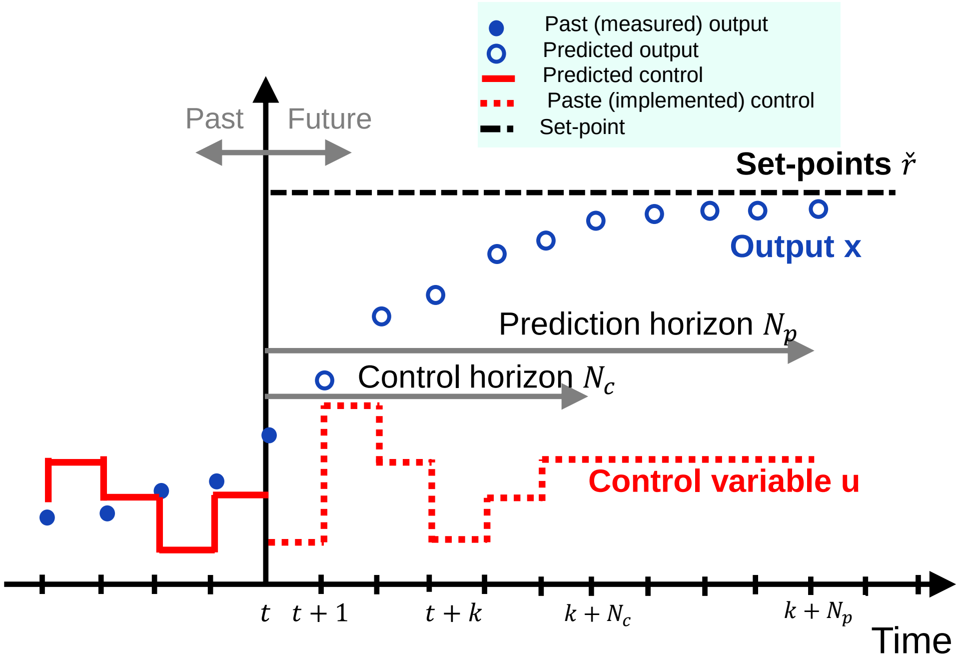
Model Predictive Control (MPC)

$$\min_{u_{t+1},\dots,u_{t+N_p}} J = x'_{t+N_p}\, P\, x_{t+N_p} + \sum_{k=1}^{N_p-1} \left[(x_{t+k} - \check{r})'Q\,(x_{t+k} - \check{r}) + \Delta u'_{t+k}\, \mathcal{R}\, \Delta u_{t+k}\right]$$

S.T.:

$$x_{k+1} = \boldsymbol{F}(x_k, u_k), \qquad x \in R^m, u \in R^v,$$
$$g_l(x_k, u_k) \le 0\,, \qquad l = 1,2, \dots L$$
$$x_{min} \le x_k \le x_{max},$$
$$u_{min} \le u_k \le u_{max},$$

- x_k: State/output variables
- u_k: Control variables
- $\check{r} \in R^m$: Setpoints
- Δu_k: Control increment $\Delta u_k = u_k - u_{k-1}$
- **$\boldsymbol{F}$: System model**
- g_l: Constraints
- $Q, P, \mathcal{R}$: coefficient matrices

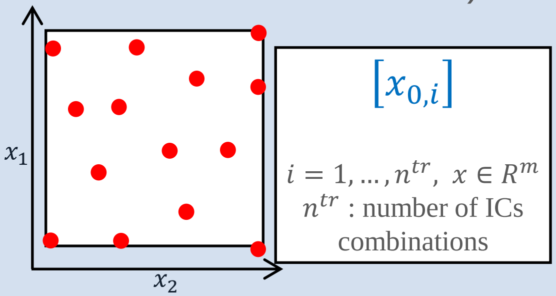


Shortcomings:

- Very demanding computations
  - Repeated solution of an optimal control optimization
- Infeasible for operational implementation in many practical cases

1-Sampling over State Domain

(generate different values of ICs)



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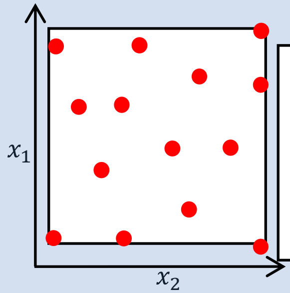

$[x_{0,i}]$

$i = 1, \dots, n^{tr}, \ x \in R^m$
n^{tr} : number of ICs combinations

2- Data Generation via MPC Solutions
(solving the MPC problem n^{tr} times)

$$\min_{u_{t+1},\dots,u_{t+N_p}} J = x'_{t+N_p} P\, x_{t+N_p} + \sum_{k=1}^{N_p-1} [(x_{t+k} - \check{r})\, Q\, (x_{t+k} - \check{r}) + \Delta u'_{t+k}\, \mathcal{R}\, \Delta u_{t+k}]$$

S.T.: …………..

Different closed-loop state-control trajectories for training

$[u^*_{1,i}, u^*_{2,i} \dots, u^*_{N^{trn},i}]$

$[x_{0,i}, x_{1,i}, \dots, x_{N^{trn}-1,i}]$

$i = 1, \dots, n^{tr}, \quad N^{trn} \le N^{fnl}$

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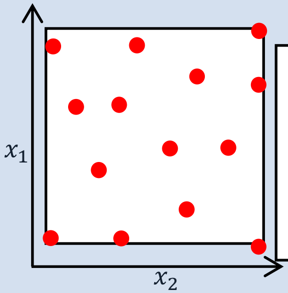

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3- Control Laws Development

Unfold training trajectories into input-output patterns

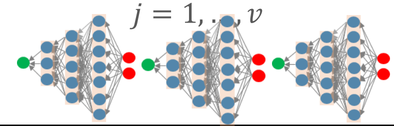
$[u^*_{t+1,i}] - [x_{t,i}]$

$i = 1, \dots, n^{tr} \times N^{trn}$

DNNs-based Control-Laws

$\hat{u}^*_{j,t+1} = \mathcal{F}_j(x_{1,t}, \dots x_{m,t})$

$j = 1, \dots, v$



Testing set

$[x^{ts}_{t,i}]$

$[u^{*ts}_{t+1,i}]$

$i = 1, \dots, n^{ts} \times N^{fnl}$

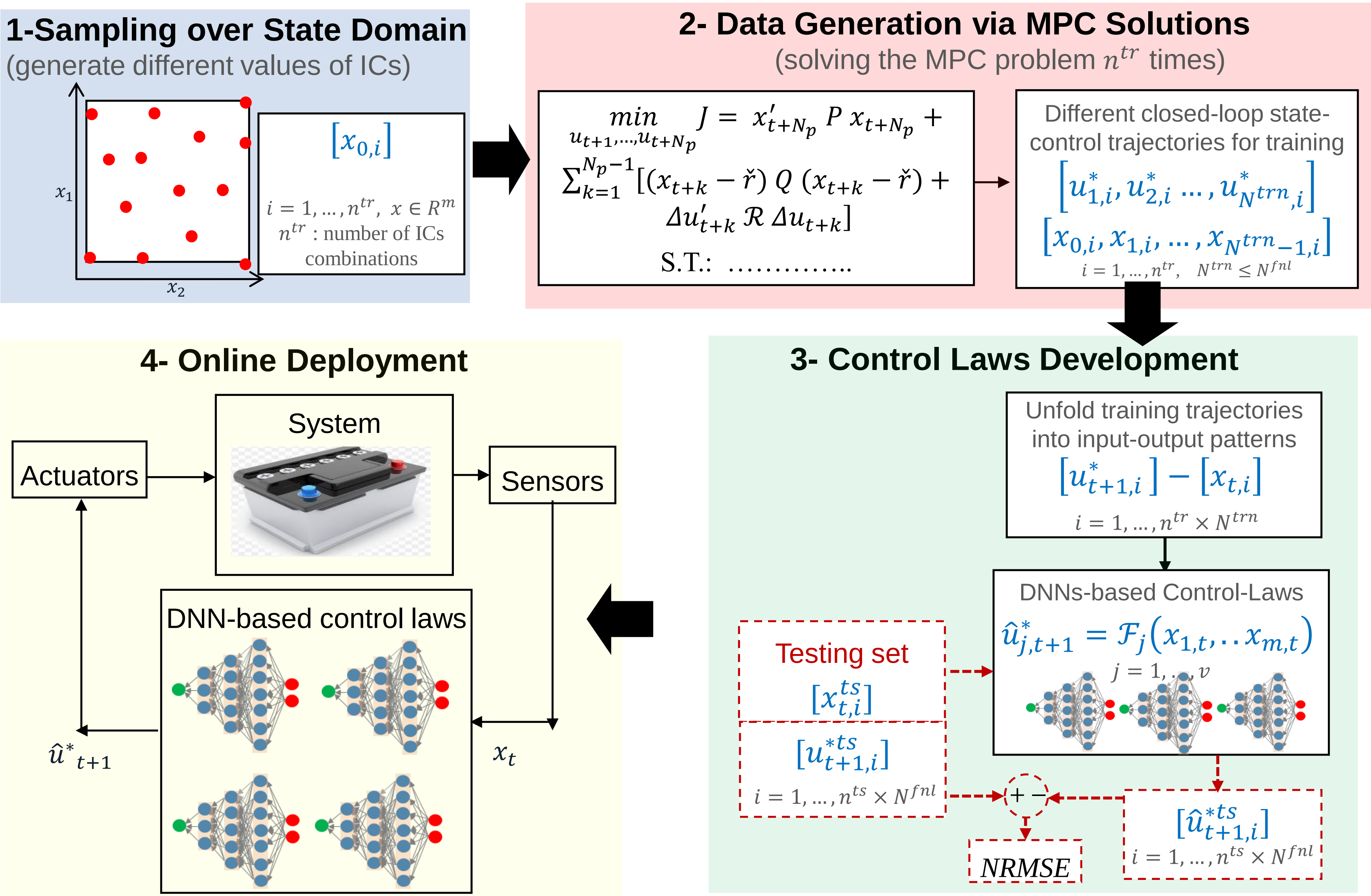
$+ \; -$

$[\hat{u}^{*ts}_{t+1,i}]$

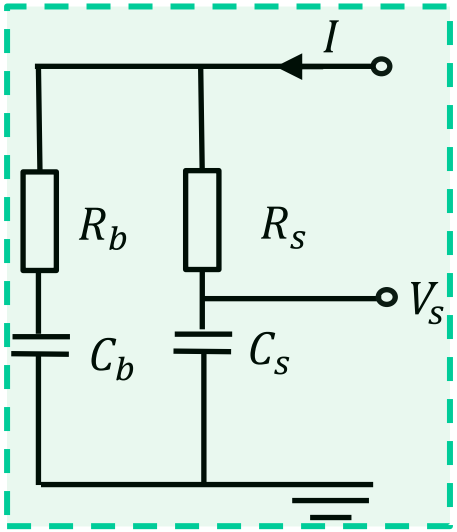
$i = 1, \dots, n^{ts} \times N^{fnl}$

$NRMSE$

2) Proposed Methodology

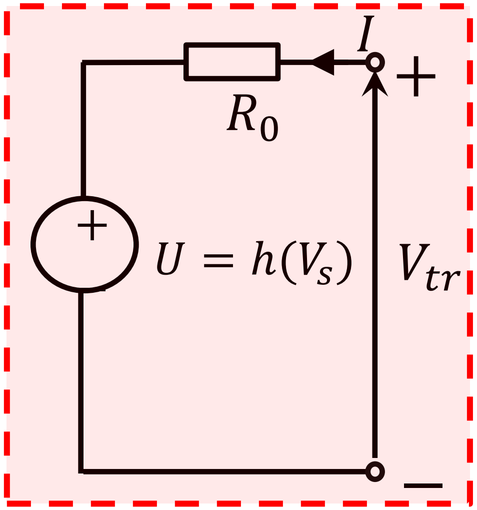


Battery Model: Nonlinear Double-Capacitors (NDC)



First circuit

- Two capacitor-resistor circuits
- $R_s - C_s$: electrode surface.
- $R_b - C_b$: electrode's inner bulk.
- Parallel link $\Longrightarrow$ migration of charge through the electrode
- V_s and V_b: voltages across C_s and C_b



Second circuit

- $U = h(V_s)$: is the open-circuit voltages
- R_0 : internal resistance
- V_{tr}: terminal voltage
- I : charging/discharging current

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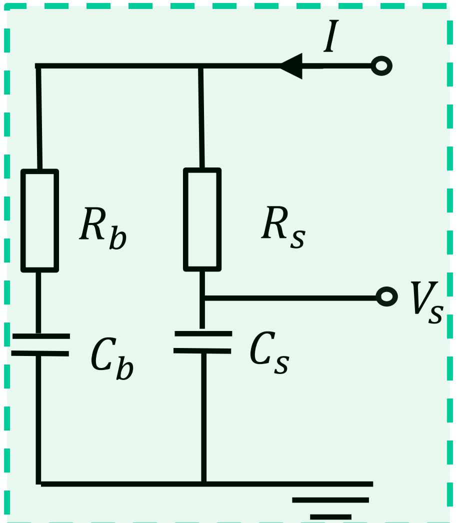

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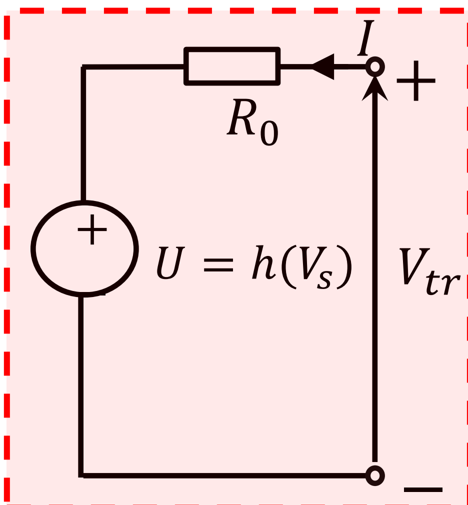

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Mathematical model

$$\begin{bmatrix} \dfrac{d\boldsymbol{V_b}(t)}{dt} \\ \dfrac{d\boldsymbol{V_s}(t)}{dt} \end{bmatrix} = A \begin{bmatrix} V_b(t) \\ V_s(t) \end{bmatrix} + B\, I(t)$$

$$\boldsymbol{SOC}(t) = \frac{C_b V_b(t) + C_s V_s(t)}{C_b + C_s}$$

$$\boldsymbol{V_{tr}}(t) = V_{oc}(t) + R_0\, I(t)$$

$$\boldsymbol{R_0}(t) = \beta_0 + \beta_1 \exp(-\beta_3(1 - SOC(t)))$$

$$\boldsymbol{U}(t) = h(V_s(t)) = \alpha_0 + \alpha_1 V_s(t) + \alpha_2 V_s(t)^2 + \alpha_3 V_s(t)^3 + \alpha_4 V_s(t)^4 + \alpha_5 V_s(t)^5$$

$$A = \begin{bmatrix} \dfrac{-1}{C_b(R_b + R_s)} & \dfrac{1}{C_b(R_b + R_s)} \\ \dfrac{1}{C_s(R_b + R_s)} & \dfrac{-1}{C_s(R_b + R_s)} \end{bmatrix}, B = \begin{bmatrix} \dfrac{R_s}{C_b(R_b + R_s)} \\ \dfrac{R_b}{C_s(R_b + R_s)} \end{bmatrix}$$

3) Applications: ML-E-MPC of Battery Charging

Charging MPC problem

$$\min_{I_{t+1},\ldots,I_{N_p}} J = \sum_{k=1}^{N_p-1} \left[(SOC_k - \check{r})' Q \, (SOC_k - \check{r}) + \Delta I_k' \, \mathcal{R} \, \Delta I_k \right]$$

S.T.:

Setpoint

$$SOC_0 = 20\% \, , \check{r} = 90\%$$

Safety constraints

$$0 \le I_k \le 3 \, A,$$
$$V_{tr,k} \le 4.2 \, V$$

Health constraints

$$V_{s,k} - V_{b,k} \le -0.04 \, SOC_k + 0.08$$

NDC Model

$$\dot{V}_{b,t}, \dot{V}_{s,t}, SOC_t, V_{tr,t} = \boldsymbol{F}(\ldots)$$

Coefficients

$$N_p = 10, \; N_u = 2, \; N_c = 1$$
$$Q = 1, \qquad R = 0.1$$

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Apply

Method parameters

Training data: $n^{tr} = 400 \, , N^{trn} = 5$

Testing data: $n^{ts} = 30, N^{fnl} = 150$

DNN: 7, 5 and 3 neurons

Training algorithm: Bayesian regularization backpropagation

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Charging control law

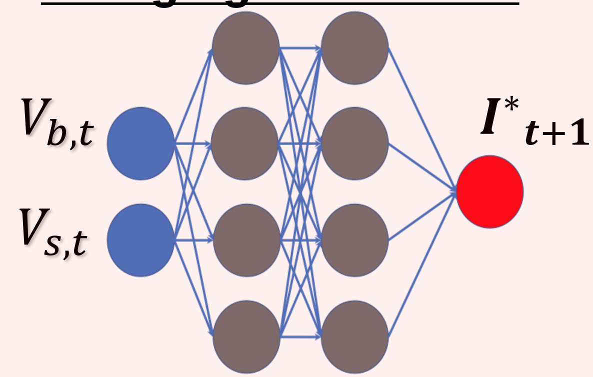
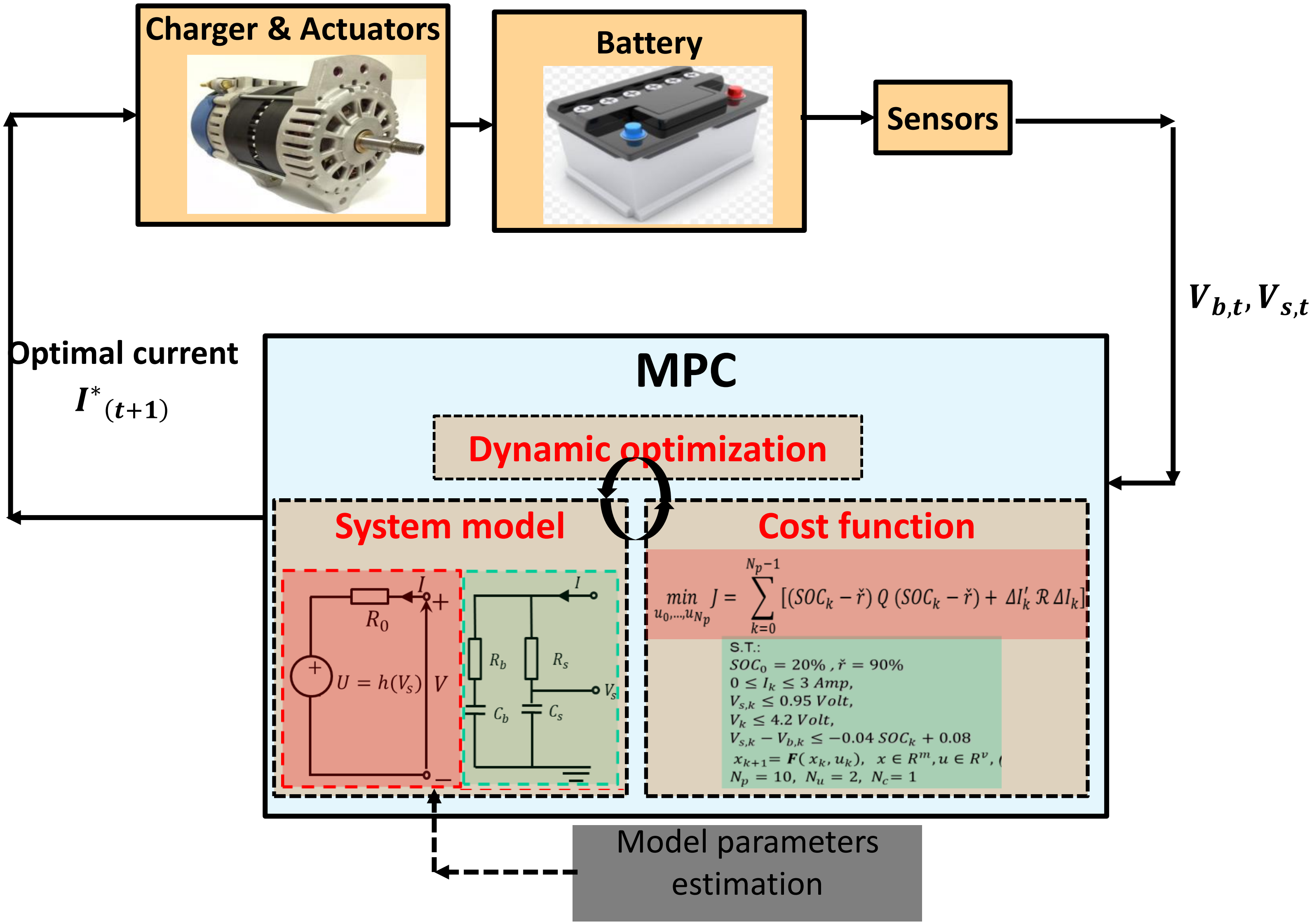


Table. Offline computational cost and open-loop accuracy.

**Intel core (TM) i7-8565U CPU@ 18 GHz, 12 GB RAM.*

Offline CPU time (s)*			Open-loop control accuracy (NRMSE (%))
Data generation		DANN fitting	
Training	Testing		
1834.9	2629.8	10.2	0.9

Testing of the DNN-based control law



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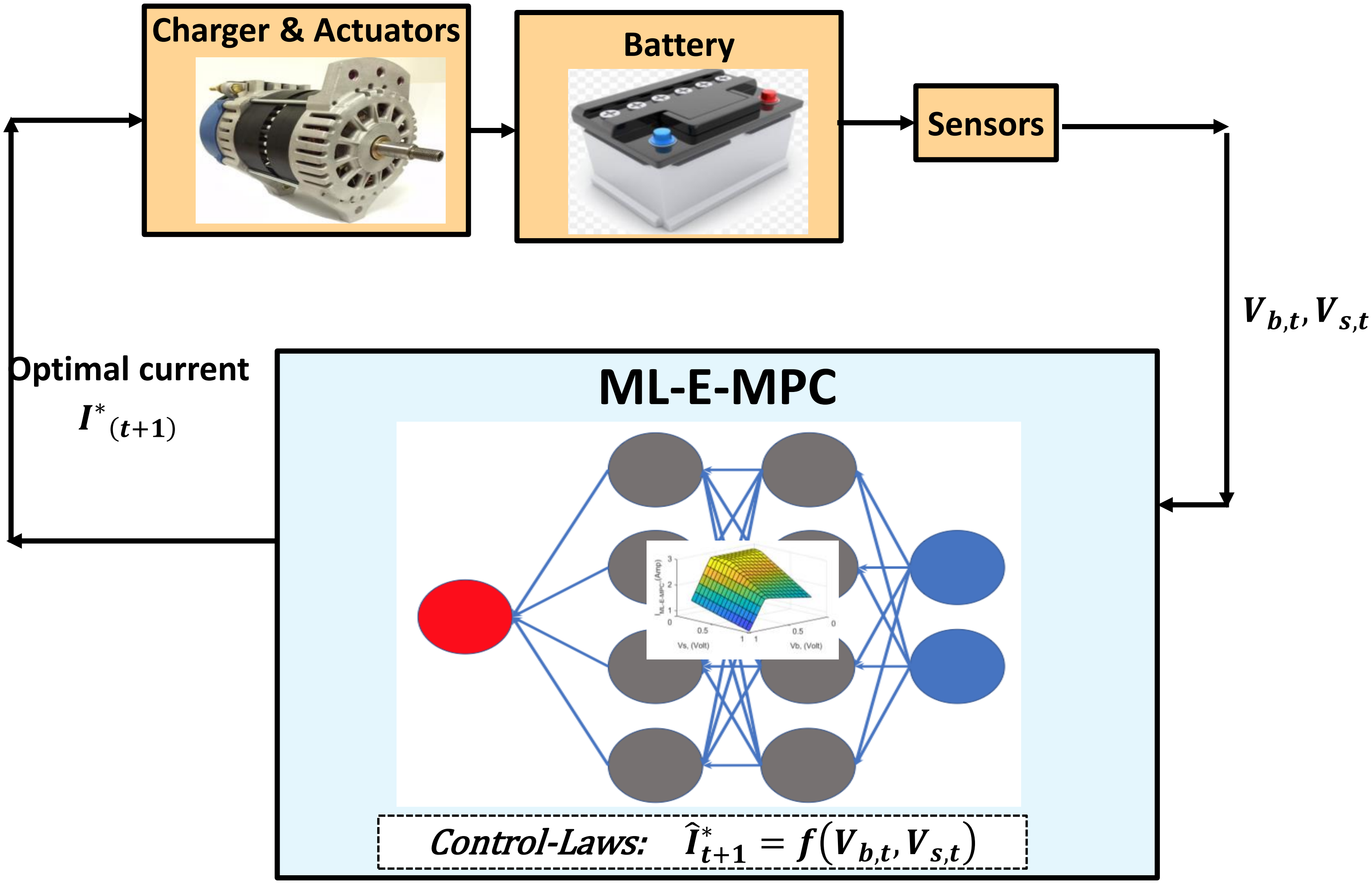

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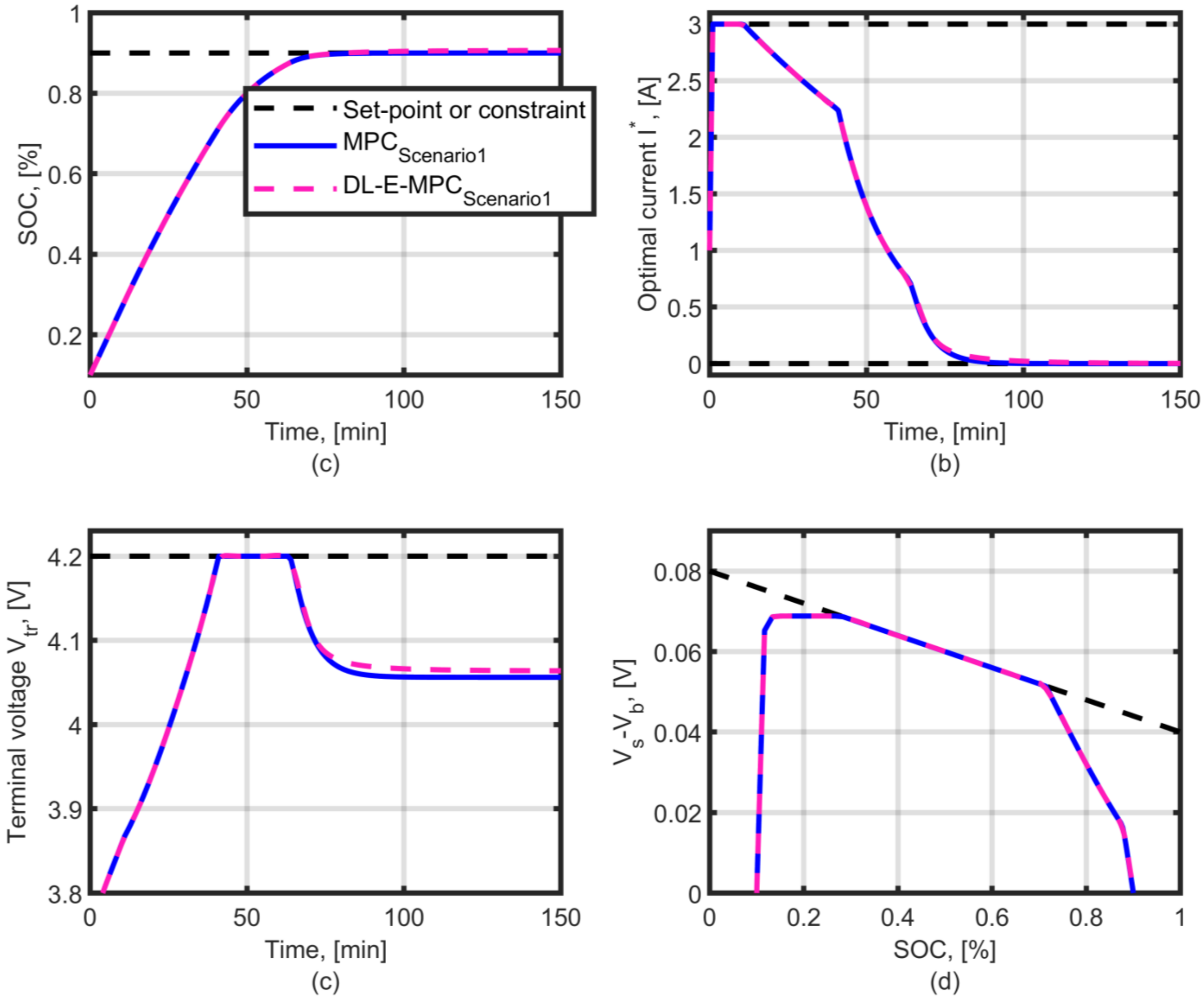
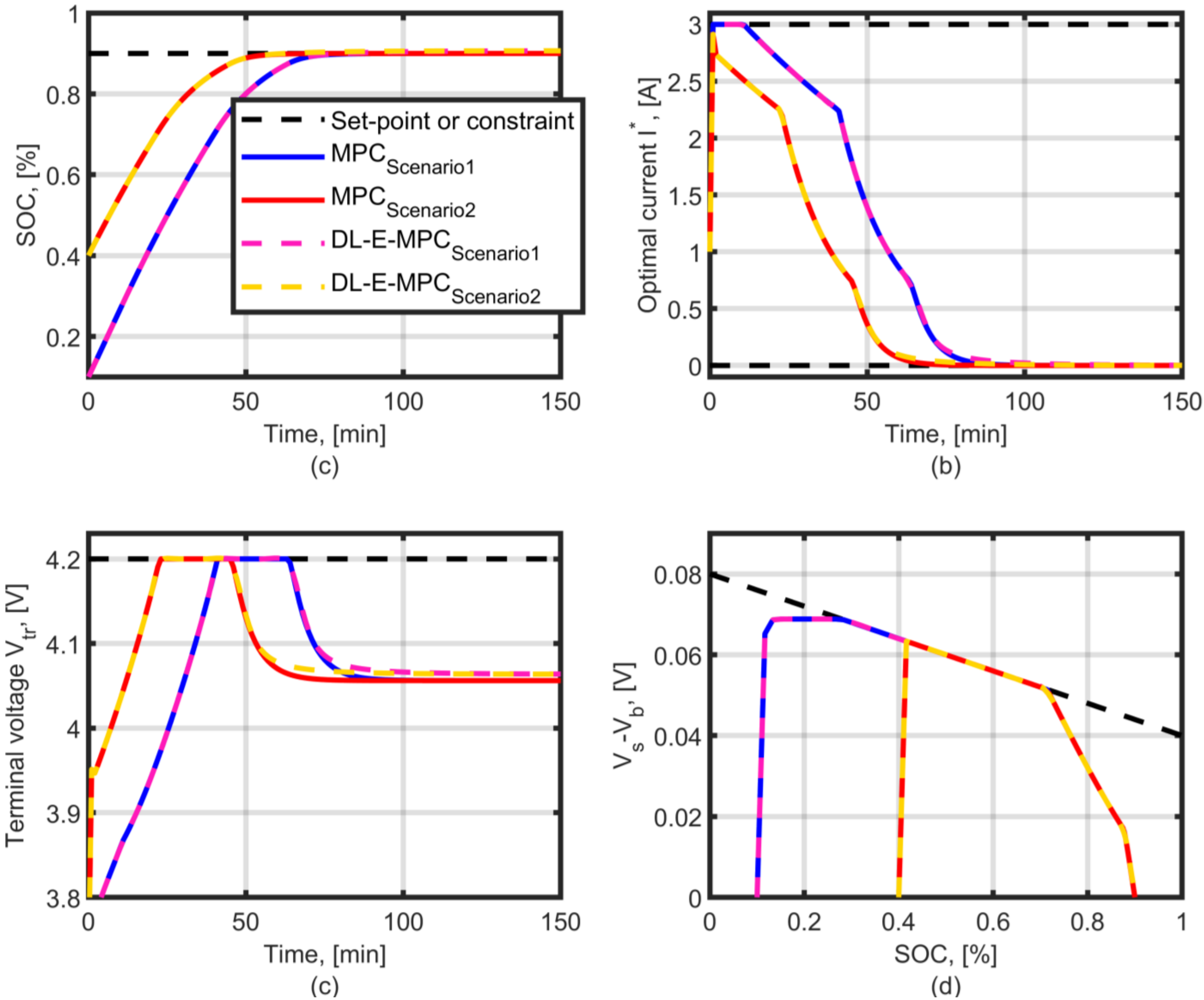
Testing of the DNN-based control law:

- Different initial SOC
    - Scenario 1



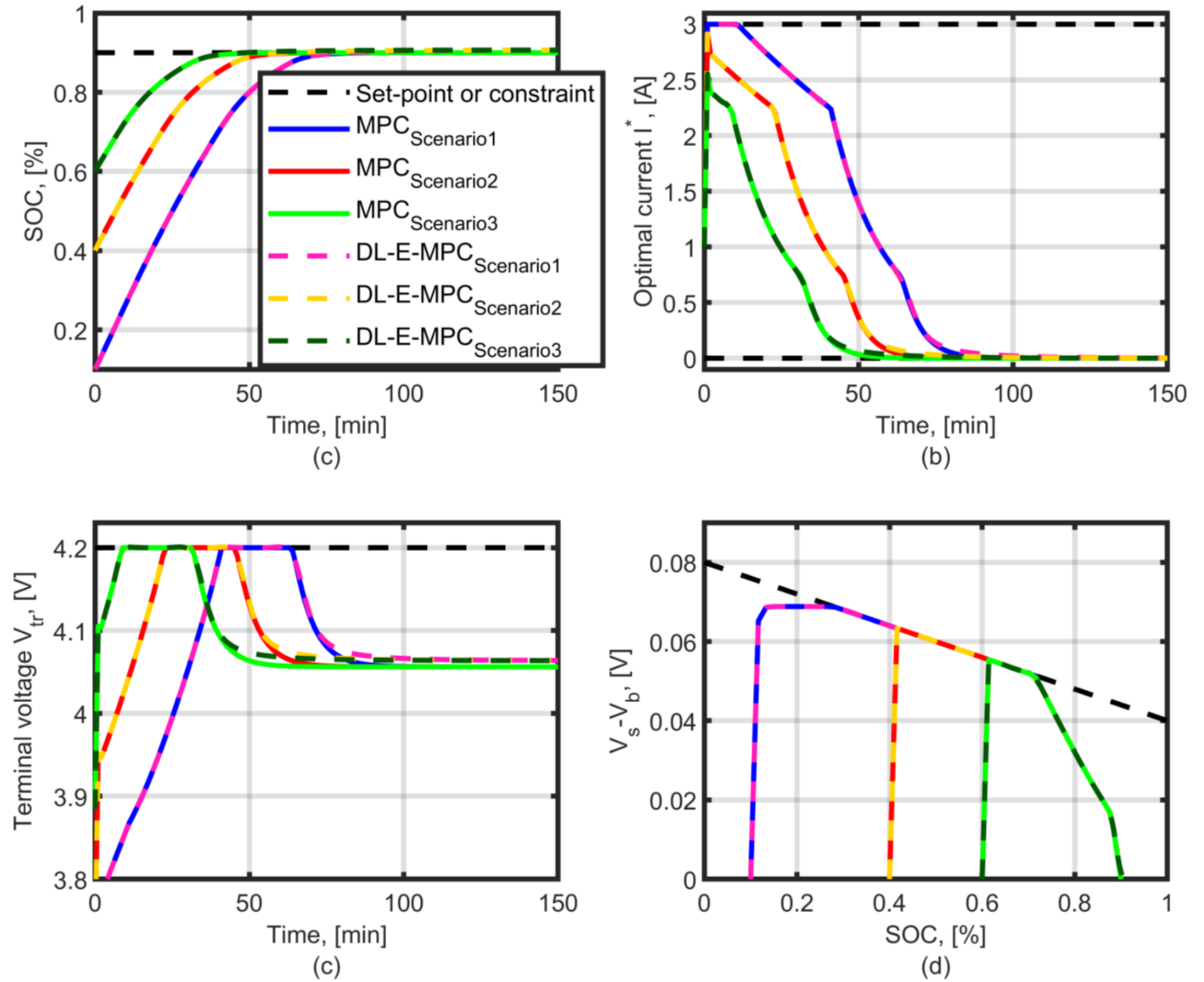
Testing of the DNN-based control law:

- Different initial SOC
  - Scenario 1
  - Scenario 2



Testing of the DNN-based control law:

- Different initial SOC
  - Scenario 1
  - Scenario 2
  - Scenario 3



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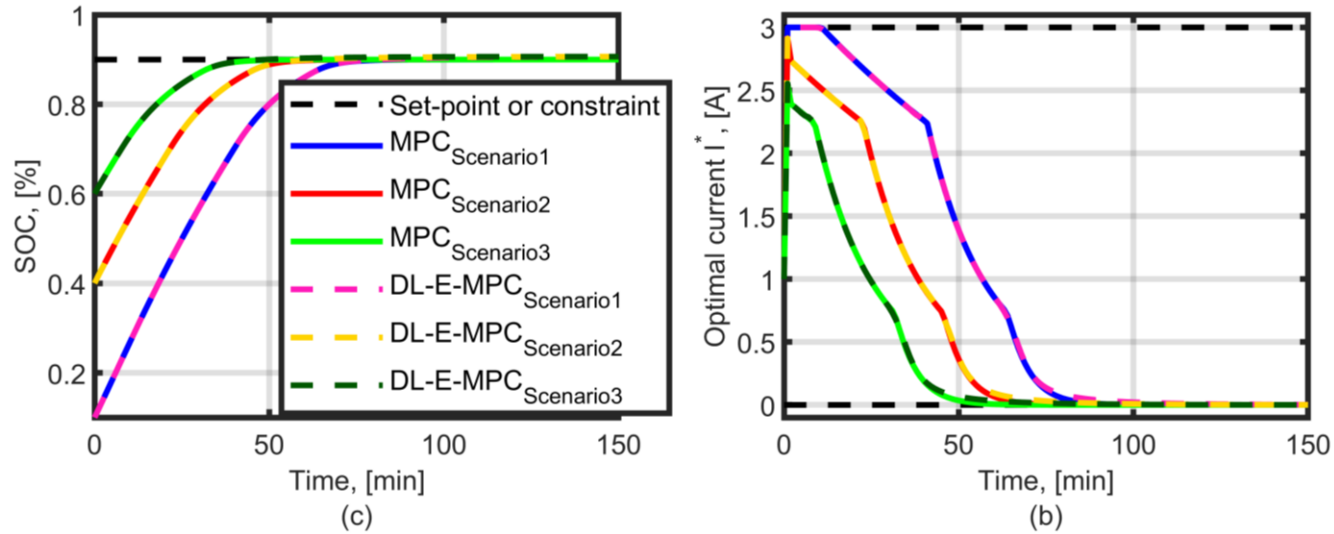


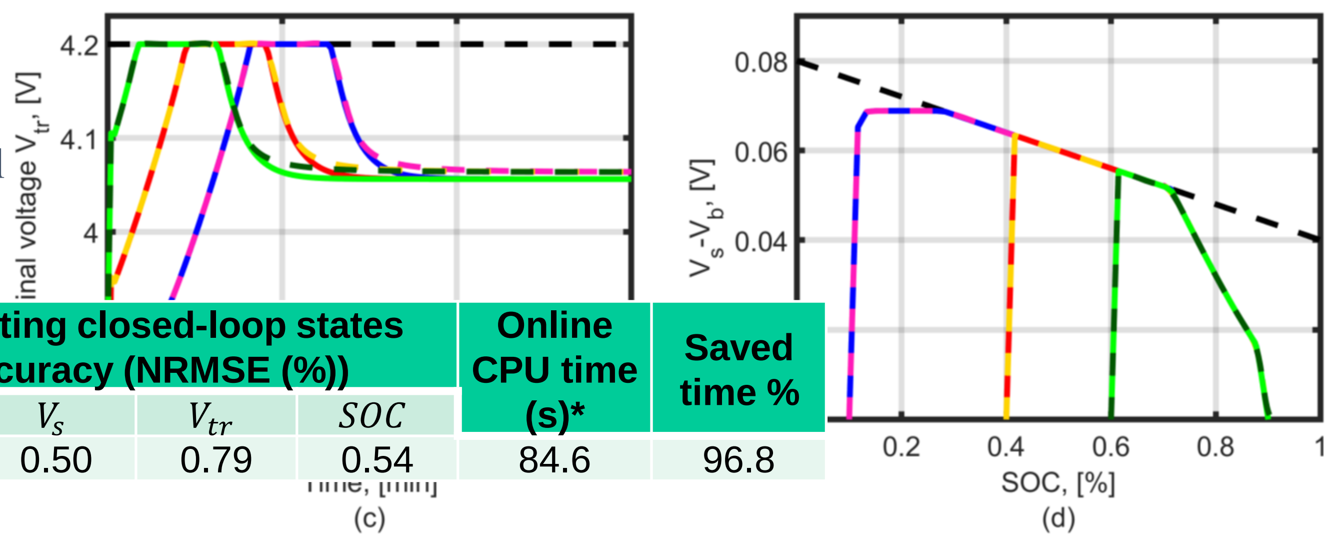
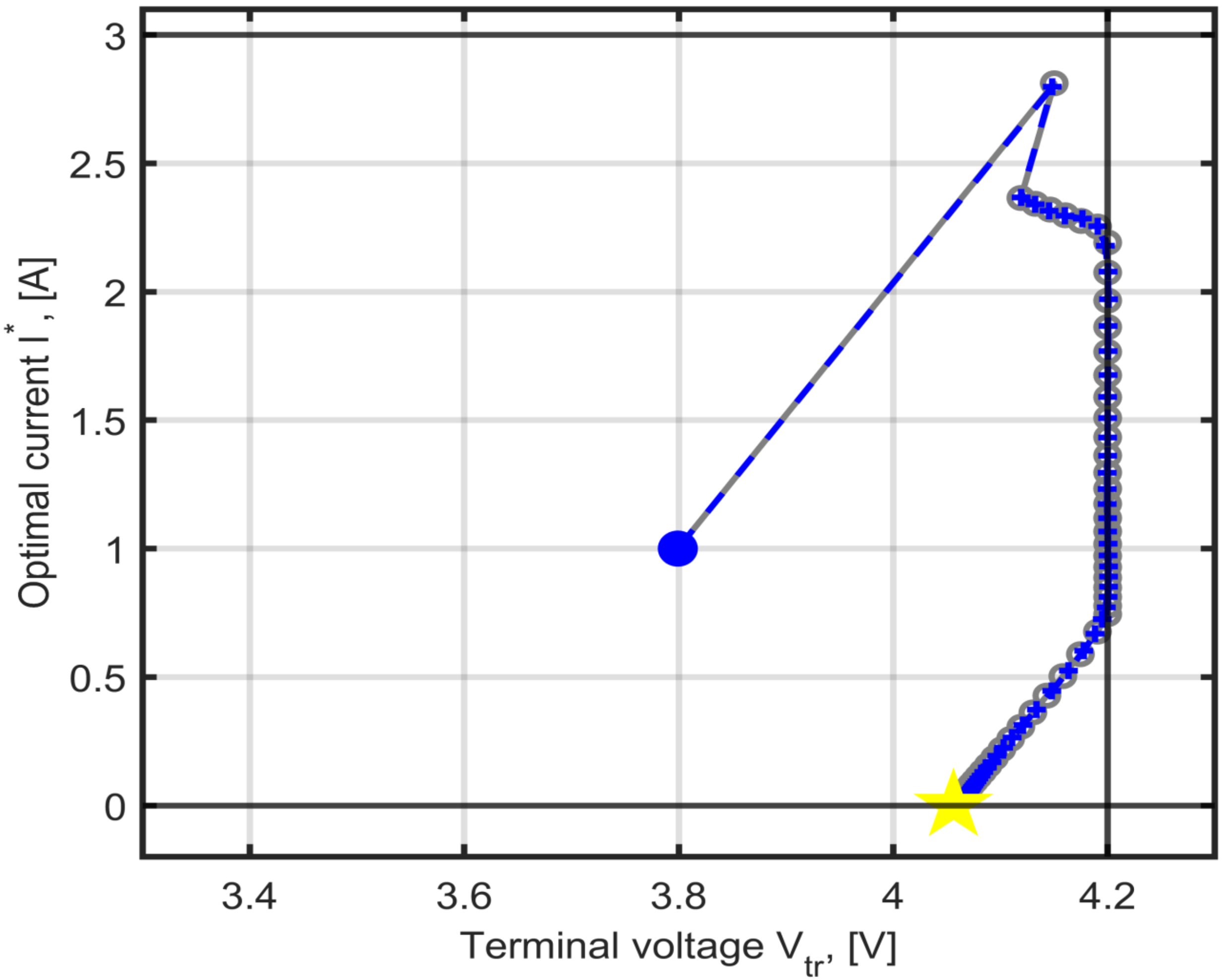


Table . Online computational cost and closed-loop accuracy.

Closed-loop control accuracy (NRMSE (%))	Resulting closed-loop states accuracy (NRMSE (%))				Online CPU time (s)*	Saved time %
	V_b	V_s	V_{tr}	SOC		
0.38	0.52	0.50	0.79	0.54	84.6	96.8

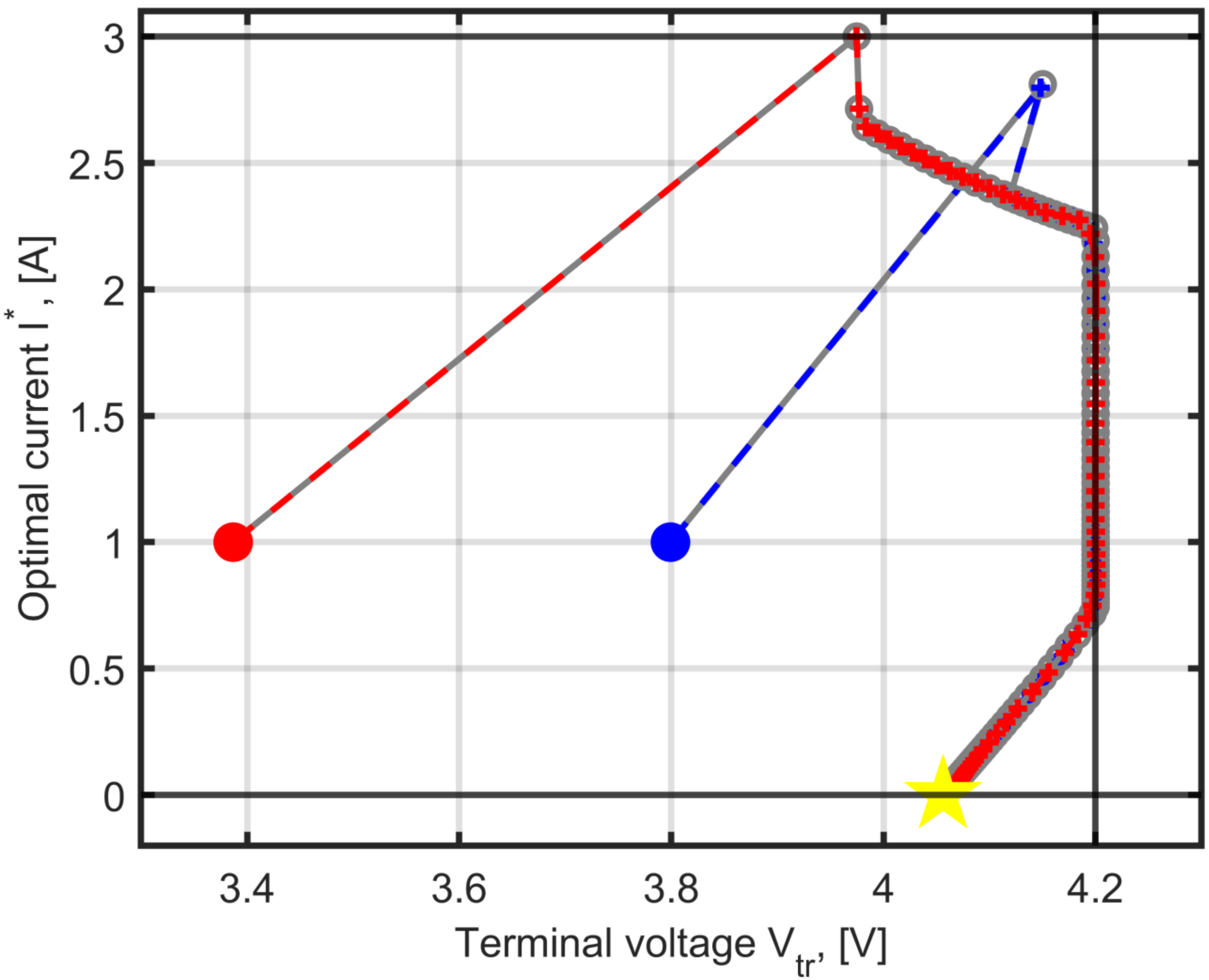
Testing of the DNN-based control law:

- Performance with respect to current and voltage constraints
    - Scenario 1



Testing of the DNN-based control law:

- Performance with respect to current and voltage constraints
  - Scenario 1
  - Scenario 2



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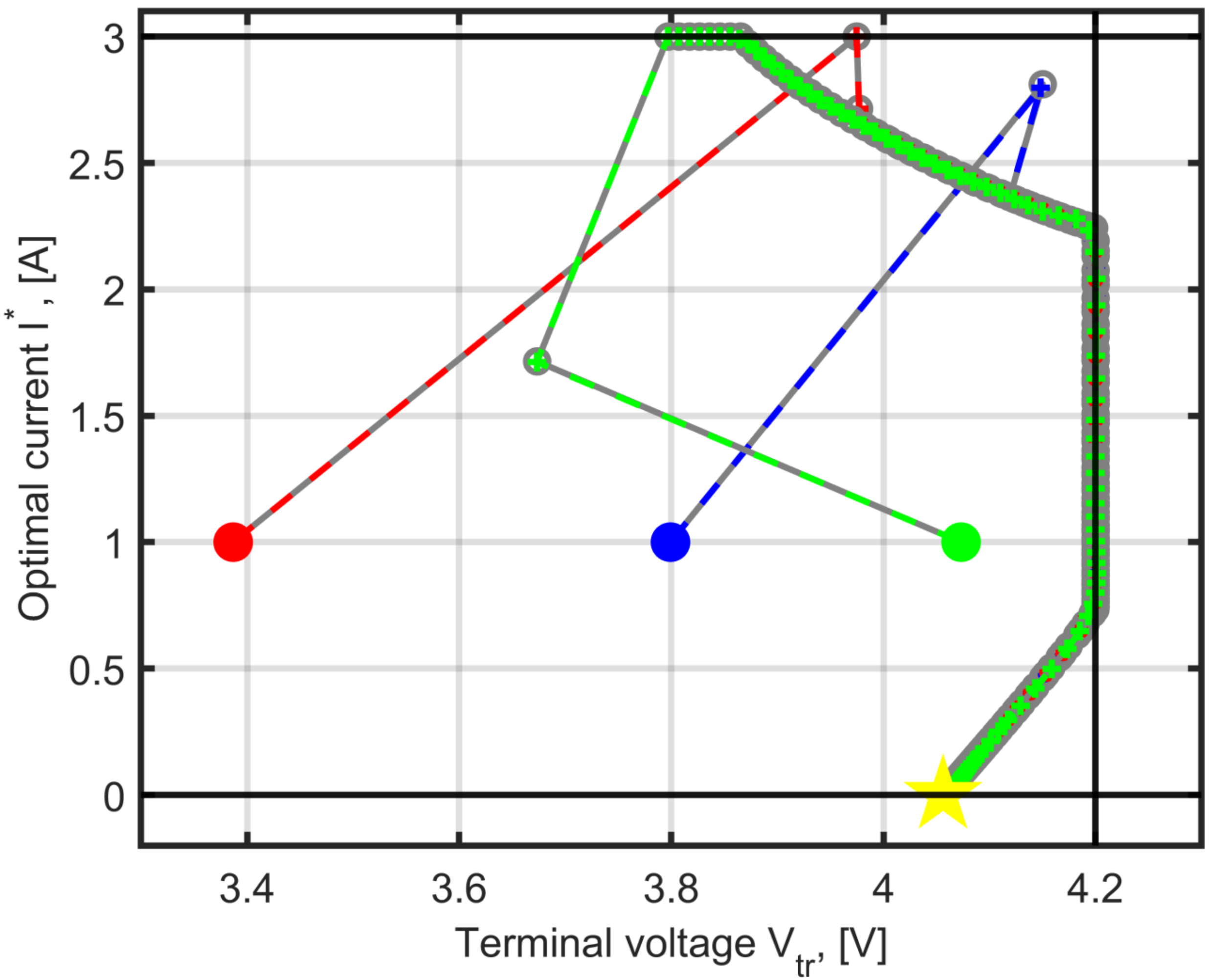
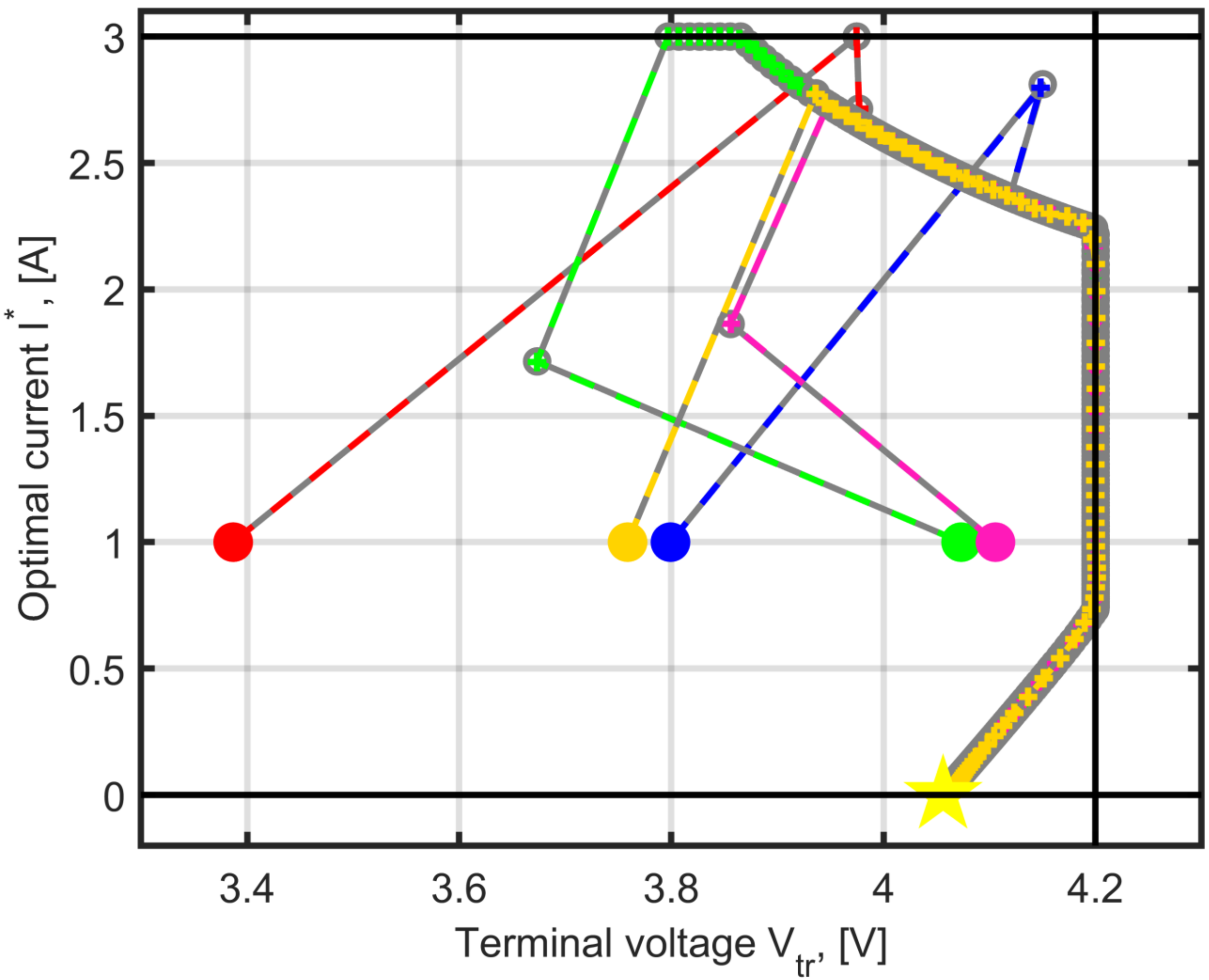


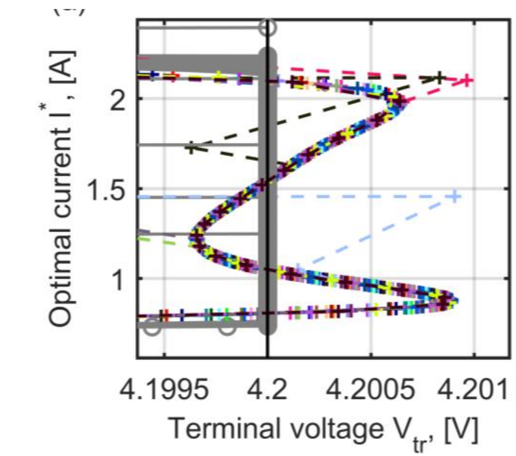
Testing of the DNN-based control law:

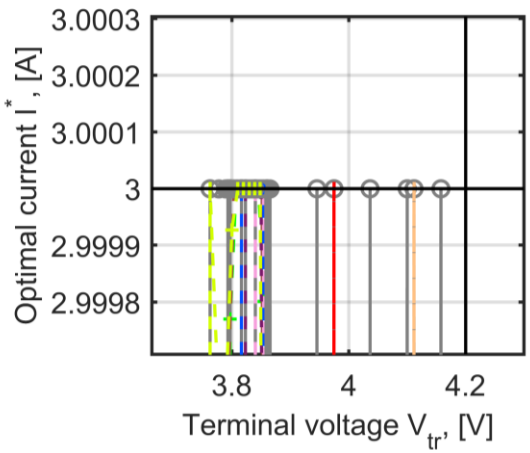
- Performance with respect to current and voltage constraints
  - Scenario 1
  - Scenario 2
  - Scenario 3
  - Scenario 4
  - Scenario 5

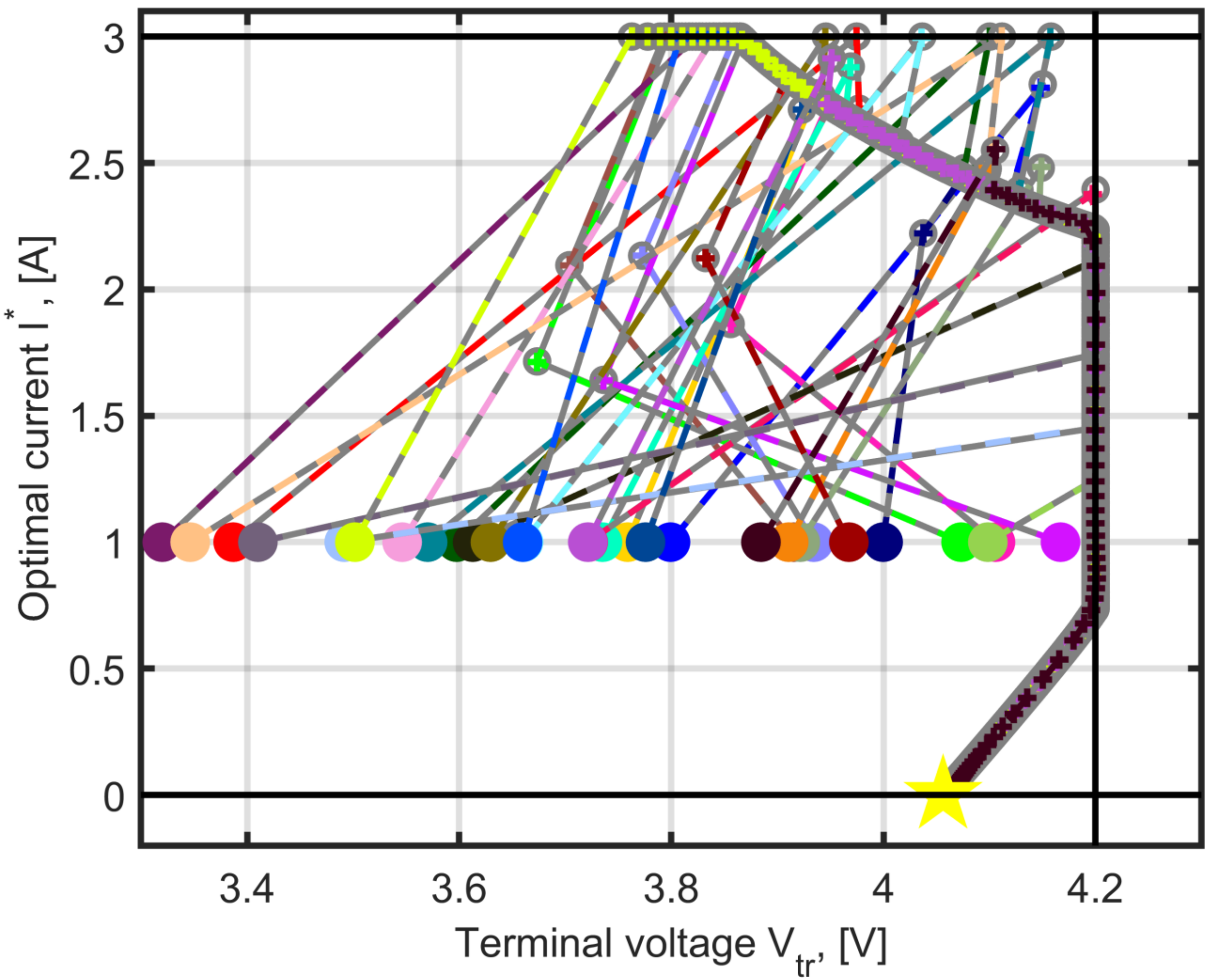


Testing of the DNN-based control law:

- Performance with respect to current and voltage constraints: all scenarios

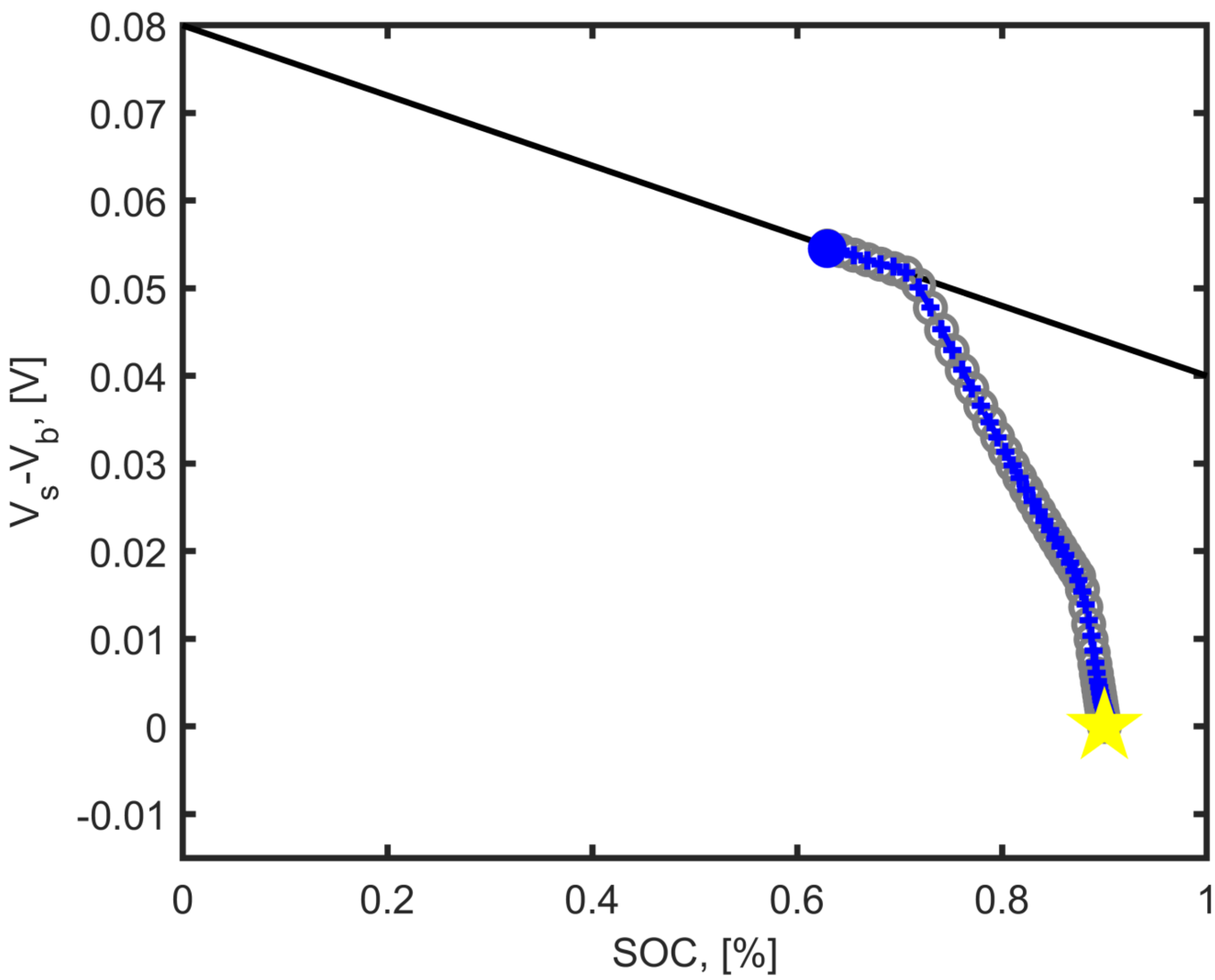






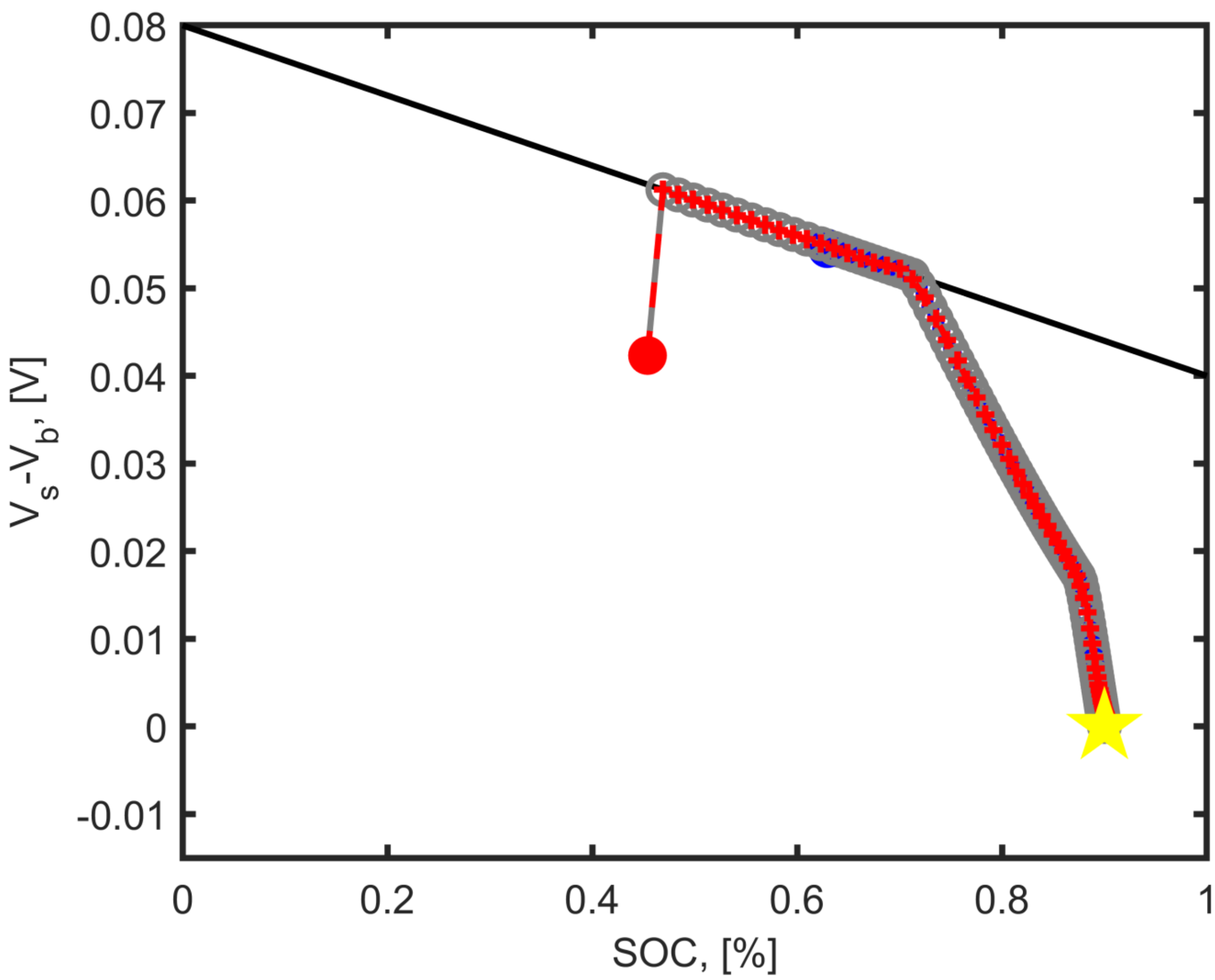
Testing of the DNN-based control law:

- Performance with respect to health constraint
  - Scenario 1



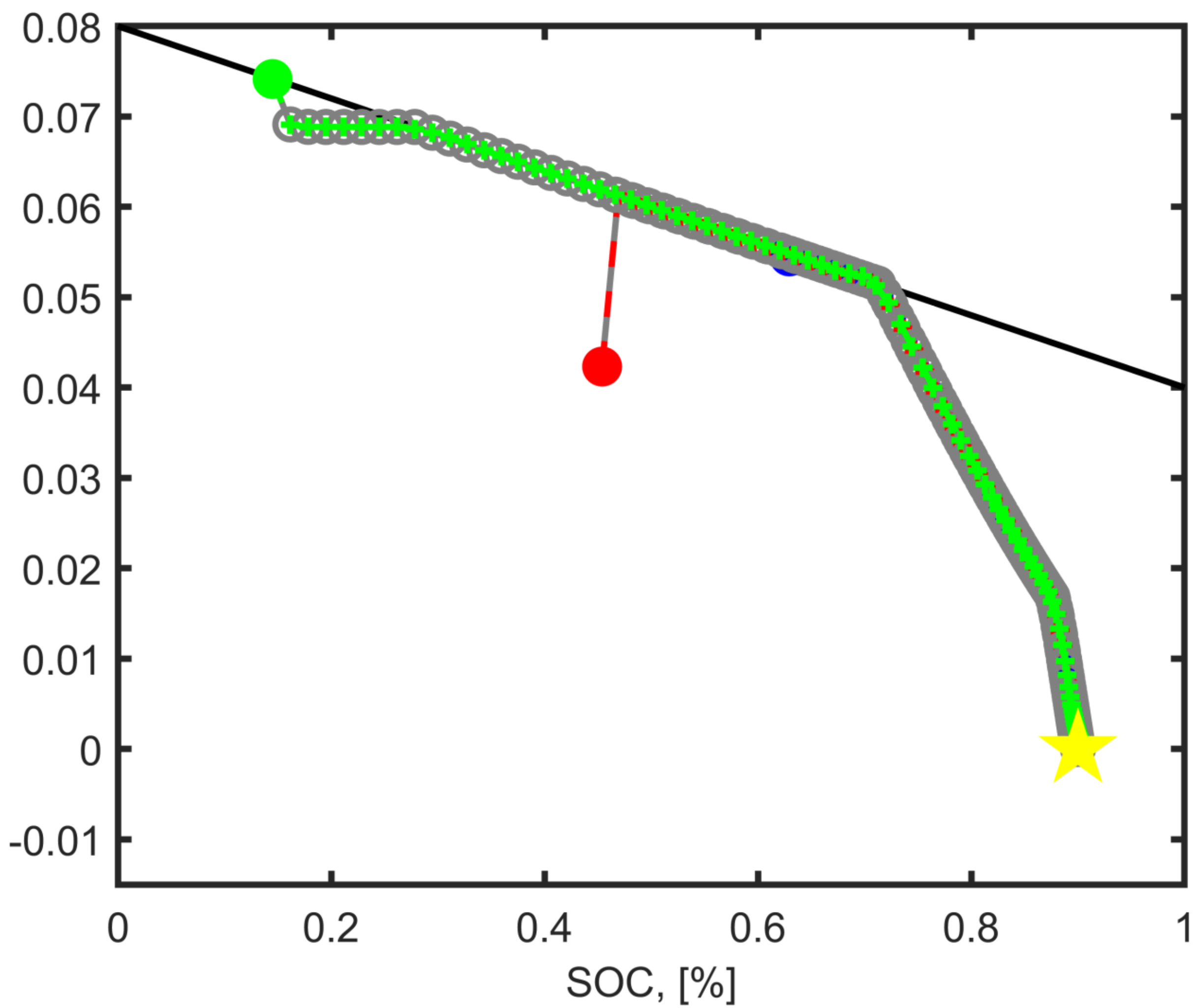
Testing of the DNN-based control law:

- Performance with respect to health constraint
  - Scenario 1
  - Scenario 2



Testing of the DNN-based control law:

- Performance with respect to health constraint
  - Scenario 1
  - Scenario 2
  - Scenario 3



Testing of the DNN-based control law:

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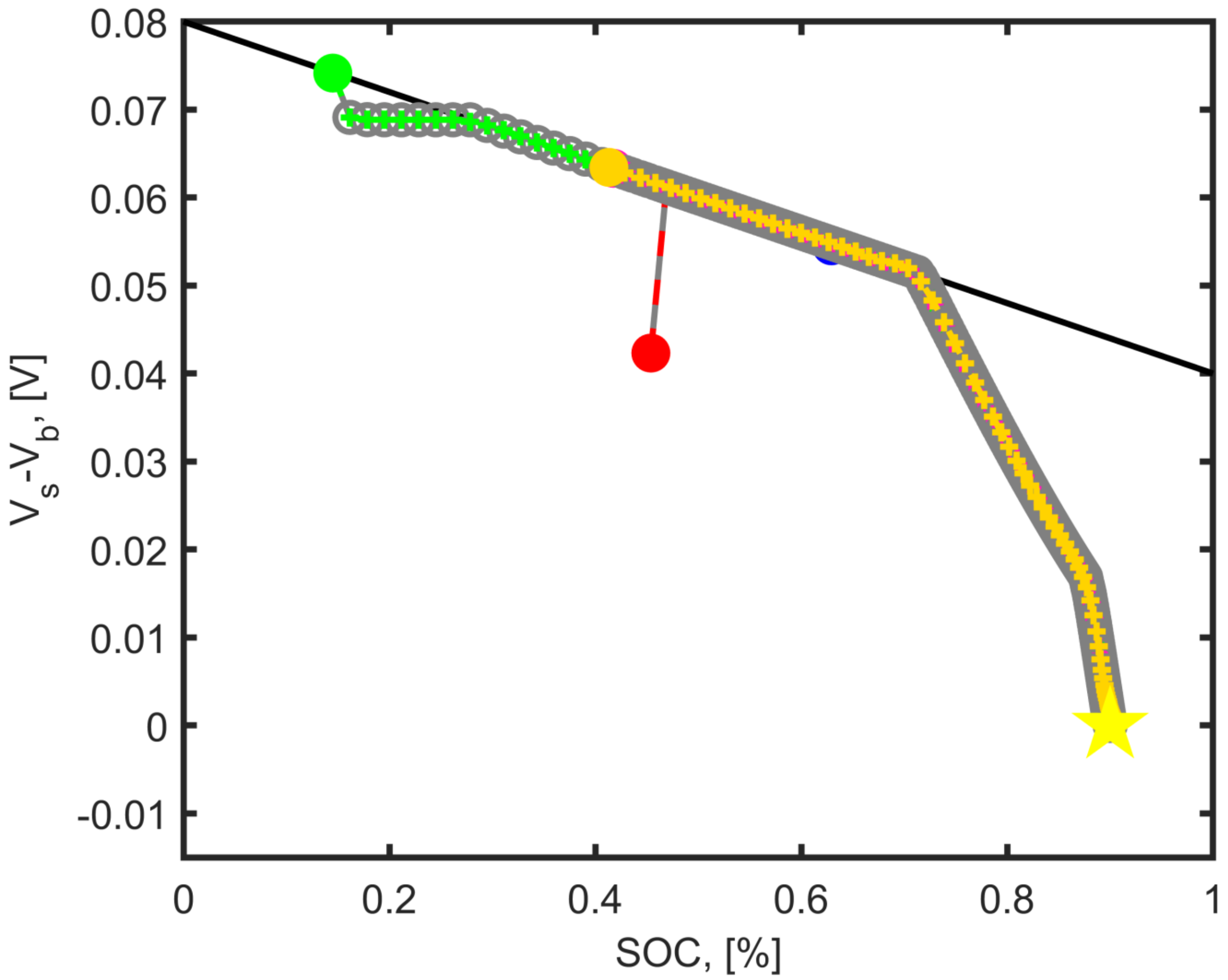
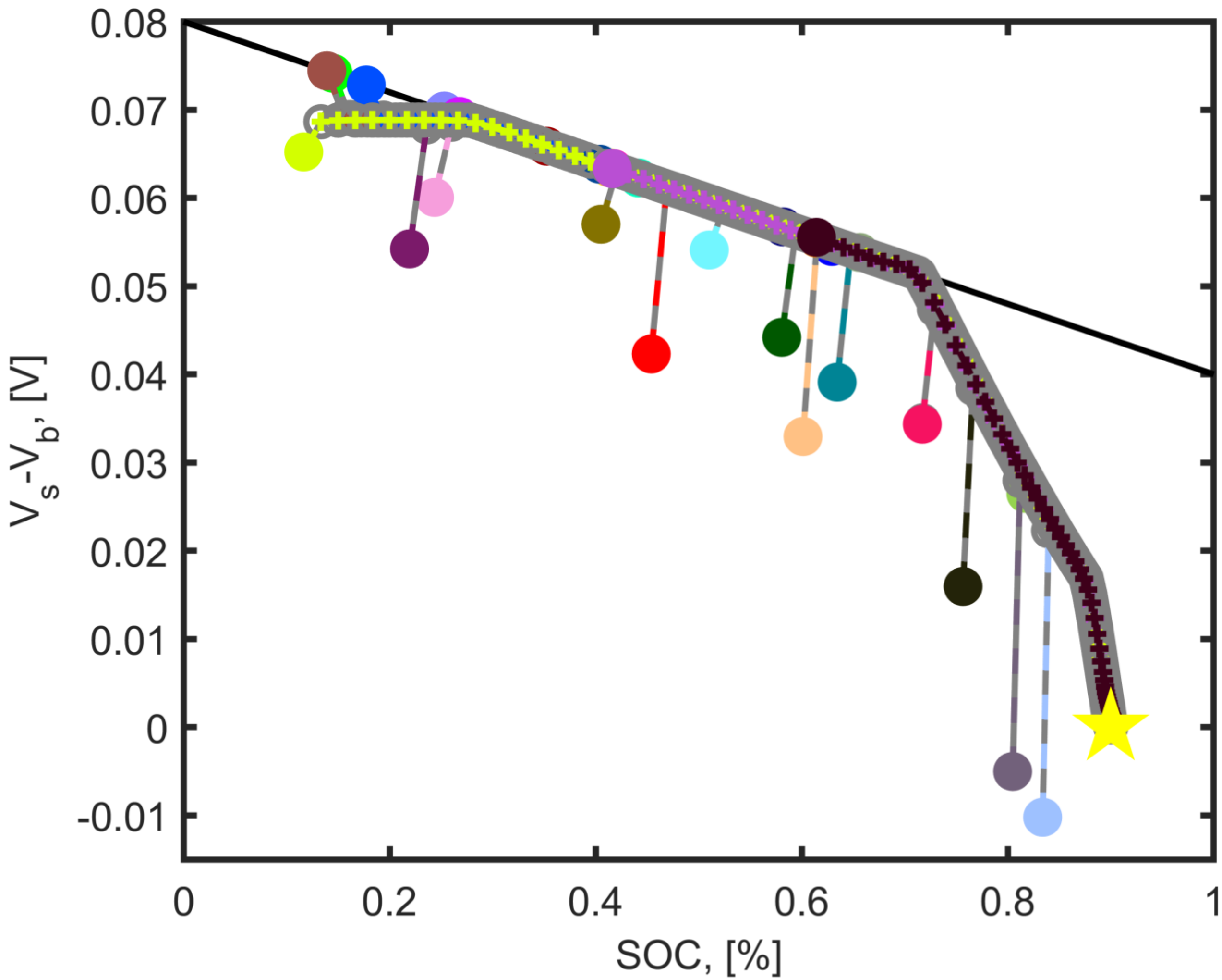
  - Scenario 1
  - Scenario 2
  - Scenario 3
  - Scenario 4
  - Scenario 5



Testing of the DNN-based control law:

- Performance with respect to health constraint
    - All scenarios



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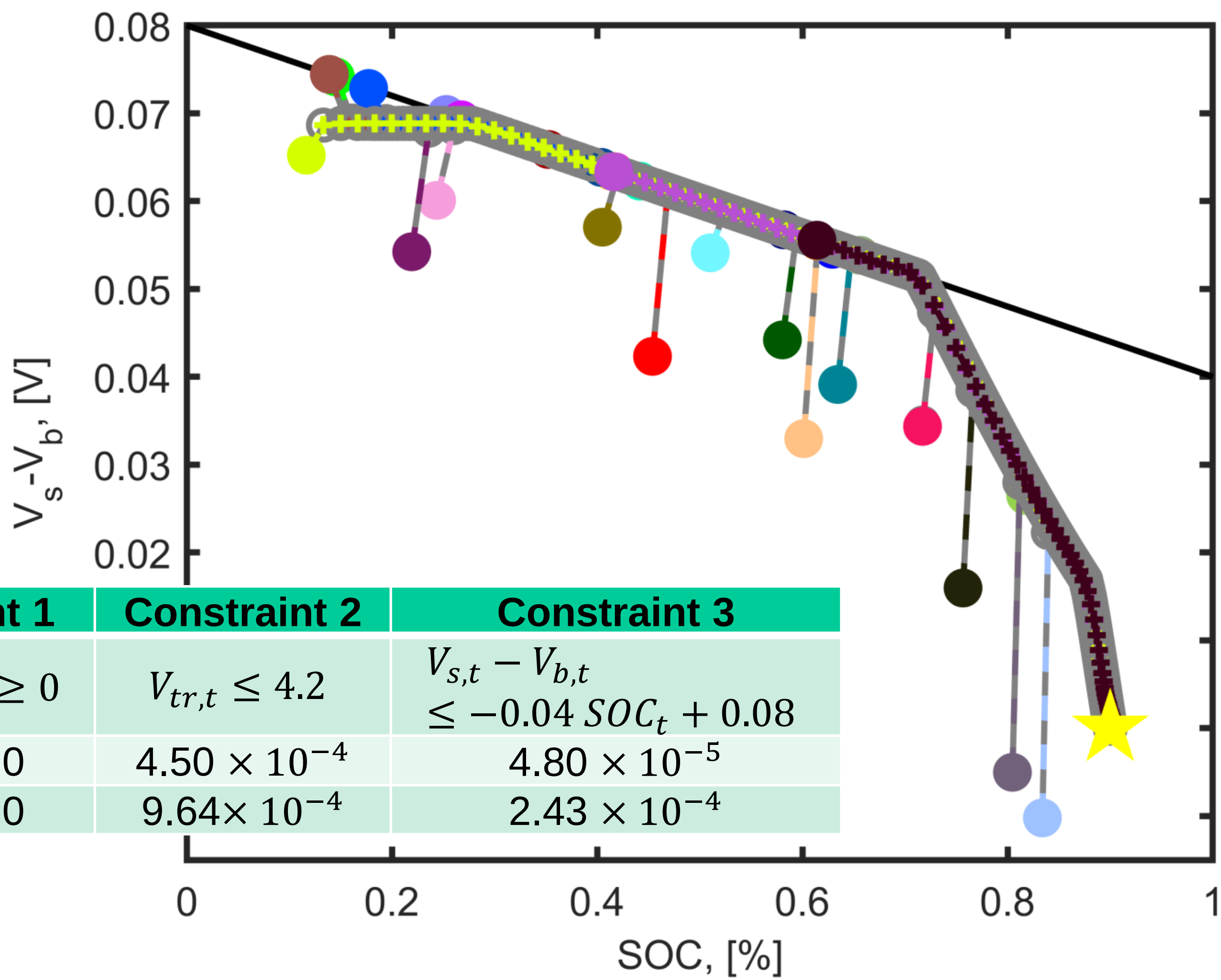

Table . Average and maximum constraint violations.

	Constraint 1		Constraint 2	Constraint 3
	$I_t \leq 3$	$I_t \geq 0$	$V_{tr,t} \leq 4.2$	$V_{s,t} - V_{b,t} \leq -0.04\, SOC_t + 0.08$
Average	0	0	4.50×10^{-4}	4.80×10^{-5}
Maximum	0	0	9.64×10^{-4}	2.43×10^{-4}

4) Conclusions and Future Work

- Classical charging is "online-blind", and can be suboptimal
- Charging MPC improves battery performance and prolong its life
  - Complexity of battery models, and modesty of BMSs computational capabilities hinders MPC application
- We developed a ML-based method for health-constrained E-MPC of battery charging
  - Accurate charging control laws **(NRMSE ⋘1%)**
  - Learn (safety and health) constraints from the data **(Max Violation 9.64$\times$ $\mathbf{10^{-4}}$)**
  - Significant reduction in computation time compared to mathematical solution of the MPC problem **(96.8% time saving)**
- Future Work
  - Developing formal guarantee of closed-loop feasibility and stability
  - Considering unknown disturbances, to develop robust charging control laws

Thank you !