Sandia National Laboratories

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Market Evaluation of Energy Storage Systems Incorporating Technology-specific Nonlinear Models

PRESENTED BY

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Outline

- Energy storage applications.
- Energy flow constant-efficiency model.
- Energy flow nonlinear models: Lead-acid/Li-ion battery, Vanadium Redox Flow Battery.
- Evaluation of energy storage for markets.
- Dynamic programming approach.
- Case studies.

Energy Storage Applications

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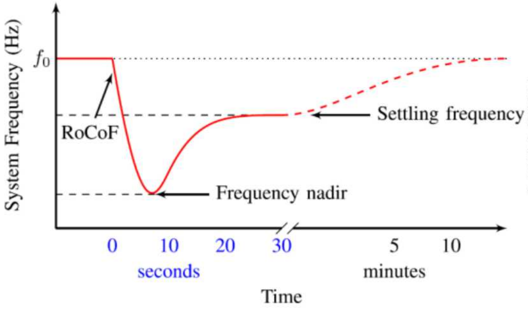
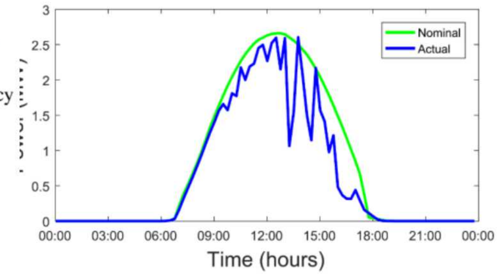
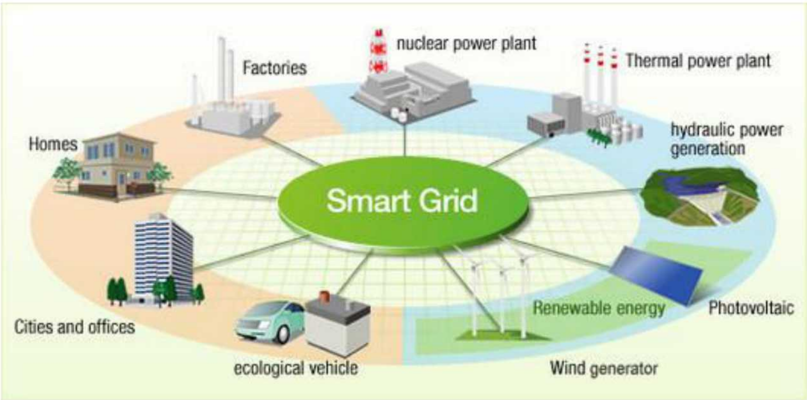
- **Power applications**
  - Frequency regulation
  - Voltage support
  - Small signal stability
  - Frequency droop
  - Renewable capacity firming
- **Energy applications**
  - Arbitrage
  - Renewable energy time shift
  - Customer demand charge reduction
  - Transmission and distribution upgrade deferral







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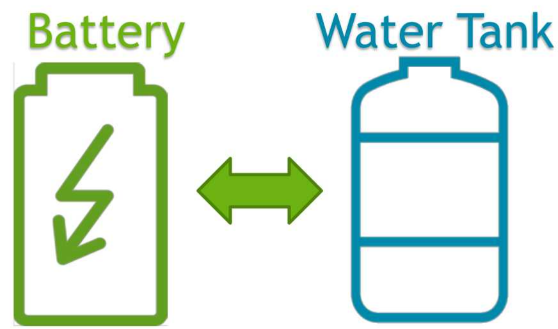
Energy Flow Constant-efficiency Model

- A generic constant-efficiency energy flow model is commonly used:

$$S_i = \eta_{\mathrm{s}} S_{i-1} + \eta_{\mathrm{c}} P_i^{\mathrm{c}} \tau - \frac{P_i^{\mathrm{d}} \tau}{\eta_{\mathrm{d}}}$$



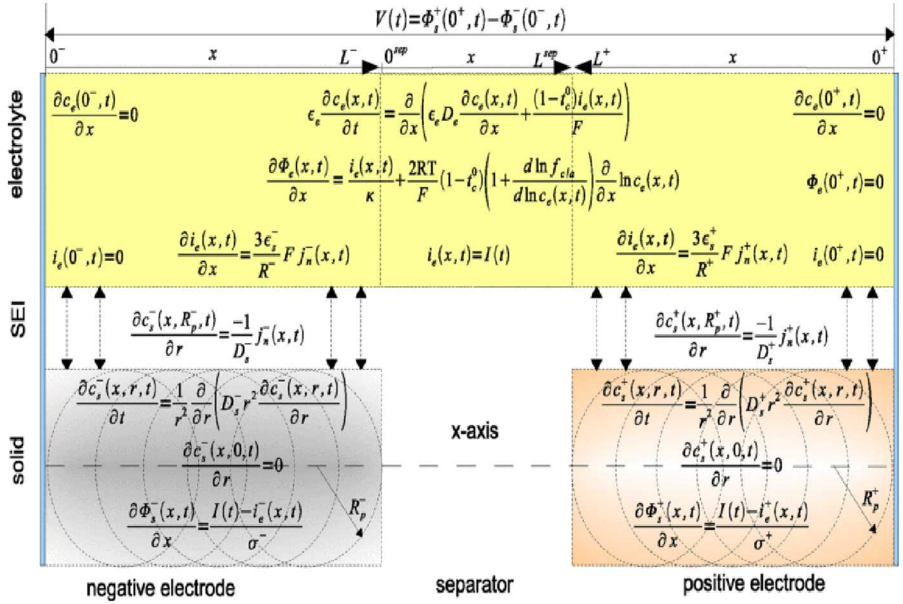
- **Technical Challenges:**
  - Modeling charge/discharge efficiencies as functions of operating states (SOC, Temp., Input/Output Power).

$$S_i = \eta_{\mathrm{s}} S_{i-1} + \underbrace{f^{\mathrm{c}}(P_i^{\mathrm{c}}, S_{i-1})}_{\text{Total charged power}} \tau - \underbrace{f^{\mathrm{d}}(P_i^{\mathrm{d}}, S_{i-1})}_{\text{Total discharged power}} \tau$$

  - Solving optimization problems incorporating those models.

Energy Flow Nonlinear Model

- The currently available technology-specific nonlinear models of energy storage only focus on the nonlinear fast dynamics
- These models use a set of partial differential equations (PDE) to precisely describe battery electrochemical processes.
- Therefore, they are not suitable for techno-economic analyses that examine long time periods (minutes to hours) given minimal knowledge of battery electrochemistry.



Lithium ion intercalation battery model [1]

[1] R. Klein, N. A. Chaturvedi, J. Christensen, J. Ahmed, R. Findeisen, and A. Kojic, "Electrochemical model based observer design for a lithiumion battery," IEEE Transactions on Control Systems Technology, vol. 21,no. 2, pp. 289–301, March 2013.

Energy Flow Nonlinear Model - VRFB

- The power loss of a VRFB includes two components: power for pumping the electrolytes and stack loss power [1].
- **During discharge:** $f^{\mathrm{d}} = \dfrac{P^{\mathrm{stackd}}}{\eta_{\mathrm{d}}}$

$$P^{\mathrm{stackd}} = a_{\mathrm{p}}^{\mathrm{d}} P^{\mathrm{d}}/\eta_{\mathrm{p}} + b_{\mathrm{p}}^{\mathrm{d}} S(S - \bar{S}) + c_{\mathrm{p}}^{\mathrm{d}}$$

$$\eta_{\mathrm{d}} = \frac{a_{\mathrm{v}}^{\mathrm{d}} P^{\mathrm{d}}/\eta_{\mathrm{p}} + b_{\mathrm{v}}^{\mathrm{d}} S + c_{\mathrm{v}}^{\mathrm{d}}}{a_{\mathrm{v}}^{\mathrm{o}} S + b_{\mathrm{v}}^{\mathrm{o}}}$$

- **During charge:** $f^{\mathrm{c}} = \eta_{\mathrm{c}} P^{\mathrm{stackc}}$

$$P^{\mathrm{stackc}} = (a_{\mathrm{p}}^{\mathrm{c}} S + b_{\mathrm{p}}^{\mathrm{c}})\eta_{\mathrm{p}} P^{\mathrm{c}} + c_{\mathrm{p}}^{\mathrm{c}} S + d_{\mathrm{p}}^{\mathrm{c}}$$

$$\eta_{\mathrm{c}} = \frac{a_{\mathrm{v}}^{\mathrm{o}} S + b_{\mathrm{v}}^{\mathrm{o}}}{(a_{\mathrm{v}}^{\mathrm{c}} S + b_{\mathrm{v}}^{\mathrm{c}})\eta_{\mathrm{p}} P^{\mathrm{c}} + c_{\mathrm{v}}^{\mathrm{c}} S + d_{\mathrm{v}}^{\mathrm{c}}}$$

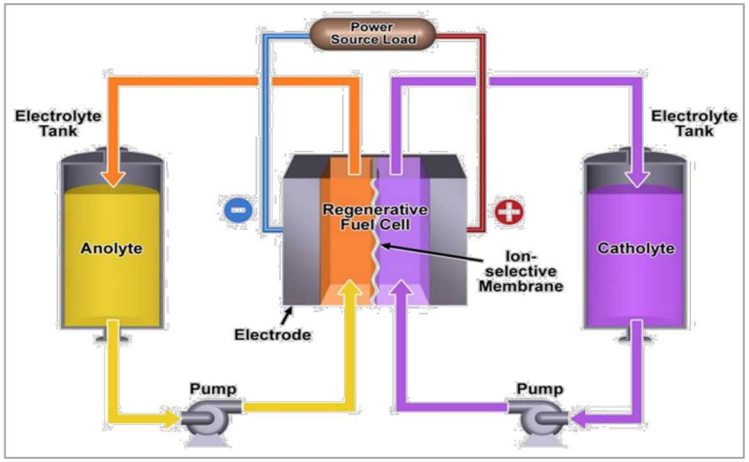


Table 1: VRFB Model Coefficients

$a_{\mathrm{v}}^{\mathrm{o}} = \frac{0.236}{\bar{S}}$	$b_{\mathrm{v}}^{\mathrm{o}} = 0.9989$	-	-
$a_{\mathrm{v}}^{\mathrm{d}} = \frac{-0.2833}{\bar{P}}$	$b_{\mathrm{v}}^{\mathrm{d}} = \frac{0.1325}{\bar{S}}$	$c_{\mathrm{v}}^{\mathrm{d}} = 0.9861$	-
$a_{\mathrm{p}}^{\mathrm{d}} = 1.0334$	$b_{\mathrm{p}}^{\mathrm{d}} = \frac{0.3454\bar{P}}{\bar{S}^2}$	$c_{\mathrm{p}}^{\mathrm{d}} = 0.1192\bar{P}$	-
$a_{\mathrm{v}}^{\mathrm{c}} = \frac{0.1974}{\bar{P}\bar{S}}$	$b_{\mathrm{v}}^{\mathrm{c}} = \frac{0.1617}{\bar{P}}$	$c_{\mathrm{v}}^{\mathrm{c}} = \frac{0.1421}{\bar{S}}$	$d_{\mathrm{v}}^{\mathrm{c}} = 0.9748$
$a_{\mathrm{p}}^{\mathrm{c}} = \frac{-0.128}{\bar{S}}$	$b_{\mathrm{p}}^{\mathrm{c}} = 1.05$	$c_{\mathrm{p}}^{\mathrm{c}} = \frac{0.038\bar{P}}{\bar{S}}$	$c_{\mathrm{p}}^{\mathrm{c}} = -0.118\bar{P}$

T. A. Nguyen, X. Qiu, J. D. Guggenberger II, M. L. Crow, and A. C. Elmore, “Performance characterization for photovoltaic-vanadium redox battery microgrid systems,” IEEE Transactions on Sustainable Energy, vol. 5, no. 4, pp. 1379–1388, 2014.

Energy Flow Nonlinear Model – Li-ion/Lead-acid

- The power losses during charging or discharging Lead-acid and Li-ion batteries are mainly caused by the heat loss due to ohmic and polarization effects.
- **During discharge:** $f^{\mathrm{d}} = P^{\mathrm{d}}/\eta_{\mathrm{p}} + P^{\mathrm{ld}}$

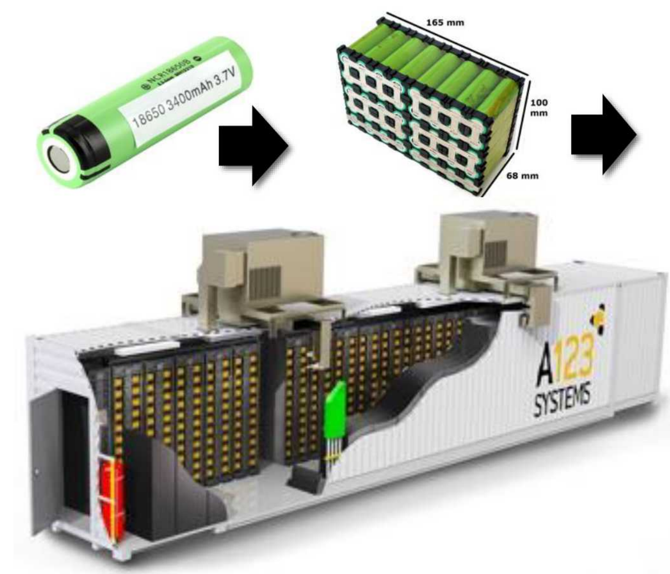
$$P^{\mathrm{ld}} = 10^{-6} n \left[\left(r + \frac{k\bar{s}}{s} \right) i_{\mathrm{cell}}^2 + \frac{k\bar{q}(\bar{s}-s)}{s} i_{\mathrm{cell}} \right]$$

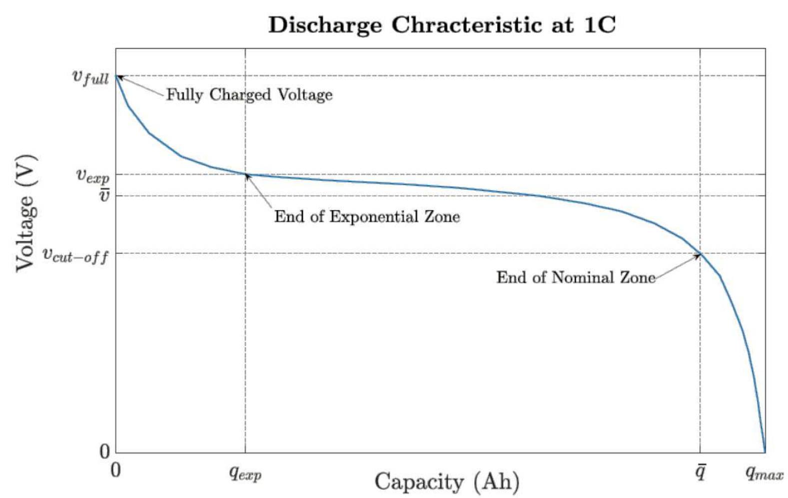
$$P^{\mathrm{ld}} \approx \frac{\bar{q}}{\bar{v}\bar{S}} \left[\left(r + \frac{k\bar{S}}{S} \right) \left(\frac{P^{\mathrm{d}}}{\eta_{\mathrm{p}}} \right)^2 + \frac{k\bar{S}\left(\bar{S}-S\right)}{S} \frac{P^{\mathrm{d}}}{\eta_{\mathrm{p}}} \right]$$

- **During charge:** $f^{\mathrm{c}} = \eta_{\mathrm{p}} P^{\mathrm{c}} - P^{\mathrm{lc}}$

$$P^{\mathrm{lc}} = 10^{-6} n \left[\left(r + \frac{k\bar{s}}{\bar{s}-s} \right) i_{\mathrm{cell}}^2 + \frac{k\bar{q}\left(\bar{s}-s\right)}{s} i_{\mathrm{cell}} \right]$$

$$P^{\mathrm{lc}} \approx \frac{\bar{q}}{\bar{v}\bar{S}} \left[\left(r + \frac{k\bar{S}}{\bar{S}-S} \right) \left(\eta_{\mathrm{p}} P^{\mathrm{c}} \right)^2 + \frac{k\bar{S}\left(\bar{S}-S\right)}{S} \eta_{\mathrm{p}} P^{\mathrm{c}} \right]$$





[1] O. Tremblay and L.-A. Dessaint, "Experimental validation of a battery dynamic model for ev applications," World Electric Vehicle Journal, vol. 3, no. 1, pp. 1–10, 2009

Evaluation of Energy Storage for Markets

- The objective is to maximize the revenue of an ESS when participating in multiple activities in a market area:

$$\max \sum_{i=1}^{N} \left(\sum_{j \in \mathrm{M}_e} \rho_i^j (P_i^{\mathrm{d}j} - P_i^{\mathrm{c}j})\tau + \sum_{k \in \mathrm{M}_p} \rho_i^k P_i^k \right)$$

- The state of charge can be calculates as:

$$S_i = \eta_{\mathrm{s}} S_{i-1} + \tau \sum_{j \in \mathrm{M}_e} [f^{\mathrm{c}}(P_i^{\mathrm{c}j}, S_{i-1}) - f^{\mathrm{d}}(P_i^{\mathrm{d}j}, S_{i-1})]$$
$$+ \tau \sum_{k \in \mathrm{M}_p} \underbrace{\frac{1}{N_k} \sum_{t=1}^{N_k} [f^{\mathrm{c}}(\sigma_{i,t}^{\mathrm{c}k} P_i^k, S_{i-1}) - f^{\mathrm{d}}(\sigma_{i,t}^{\mathrm{d}k} P_i^k, S_{i-1})]}_{f_i^k(P_i^{\mathrm{k}}, S_{i-1})}$$

- Example for energy arbitrage and frequency regulation:

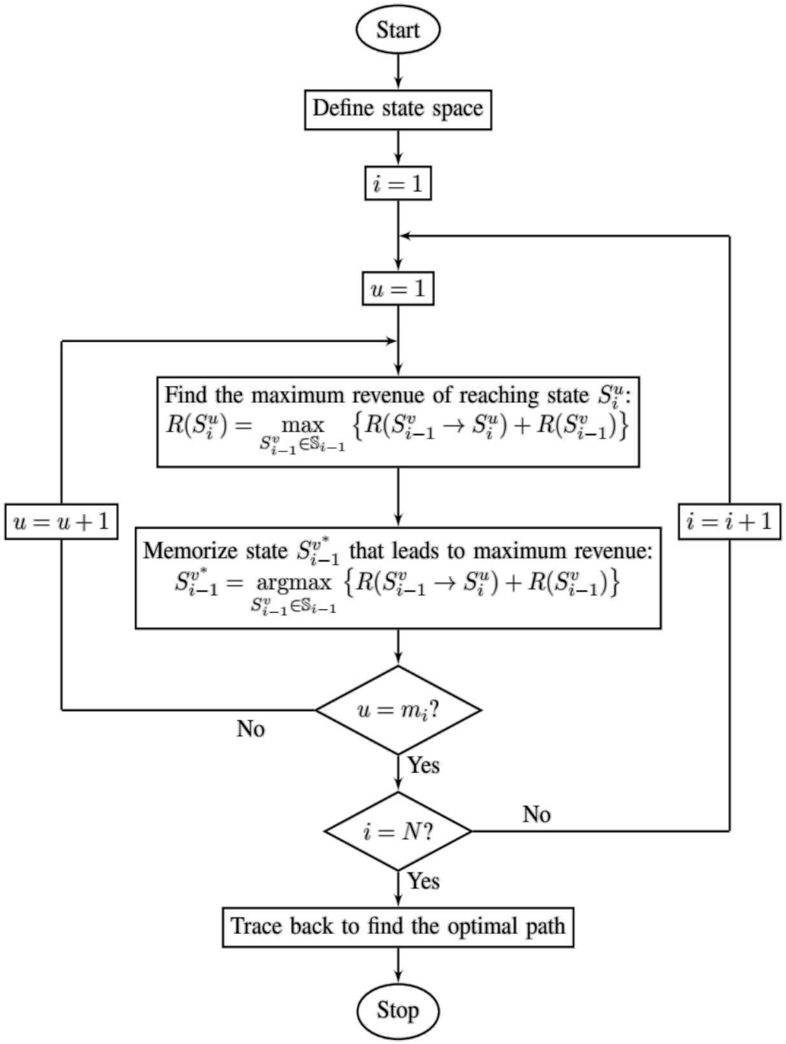
$$S_i = \eta_{\mathrm{s}} S_{i-1} + [f^{\mathrm{c}}(P_i^{\mathrm{c}}, S_{i-1}) - f^{\mathrm{d}}(P_i^{\mathrm{d}}, S_{i-1})]$$
$$+ \underbrace{\frac{1}{N_r} \sum_{t=1}^{N_r} [f^{\mathrm{c}}(\sigma_{i,t}^{\mathrm{RD}} P_i^{reg}, S_{i-1}) - f^{\mathrm{d}}(\sigma_{i,t}^{\mathrm{RU}} P_i^{reg}, S_{i-1})]}_{f_i^{\mathrm{reg}}(P_i^{\mathrm{reg}}, S_{i-1})}$$

Dynamic Programming Approach

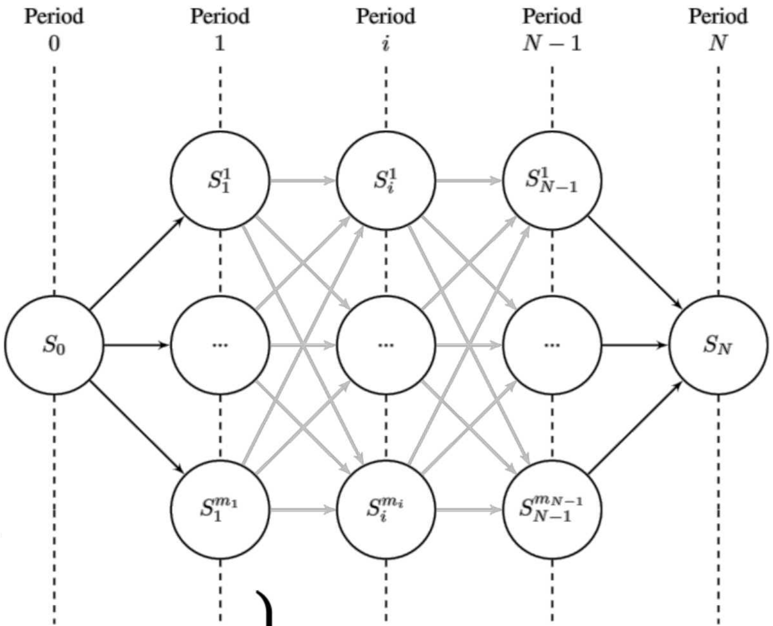
- Incorporating nonlinear storage model introduces nonconvexity and complex dynamics into the optimization problem.

- The problem becomes a sequential decision problem for which Dynamic Programming (DP) is well suited.

- The main advantage of DP is that it can find the global optimum by finding and memorizing the optimal subsequences.



Forward Dynamic Programming



- Define the state space:

$$\mathbf{S}_i = \{S_i \mid S_{min} \leq S_i \leq S_{max}\} \;\; \forall i \in [1, N-1]$$

- Run forward to find the maximum revenue reaching each state at each time step:

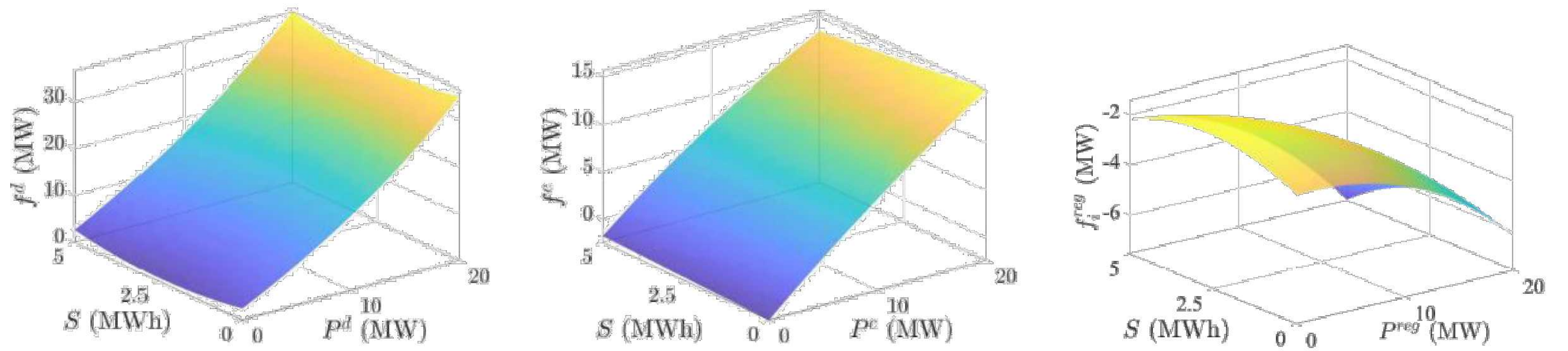
$$R(S_i^u) = \max_{S_{i-1}^v \in \mathbf{S}_{i-1}} \left\{ R(S_{i-1}^v \to S_i^u) + R(S_{i-1}^v) \right\}$$

$$R(S_{i-1}^v \to S_i^u) = \max \left\{ \sum_{j \in \mathbf{M}_e} \rho_i^j (P_i^{\mathrm{d}j} - P_i^{\mathrm{c}j})\tau + \sum_{k \in \mathbf{M}_p} \rho_i^k P_i^k \right\}$$

$$S_i^u - \eta_{\mathrm{s}} S_{i-1}^v = \tau \sum_{j \in \mathbf{M}_e} [f^{\mathrm{c}}(P_i^{\mathrm{c}j}, S_{i-1}^v) - f^{\mathrm{d}}(P_i^{\mathrm{d}j}, S_{i-1}^v)] + \tau \sum_{k \in \mathbf{M}_p} f_i^{\mathrm{k}}(P_i^k, S_{i-1}^v)$$

- Memorize optimal sub-paths and trace backward to find the optimal path

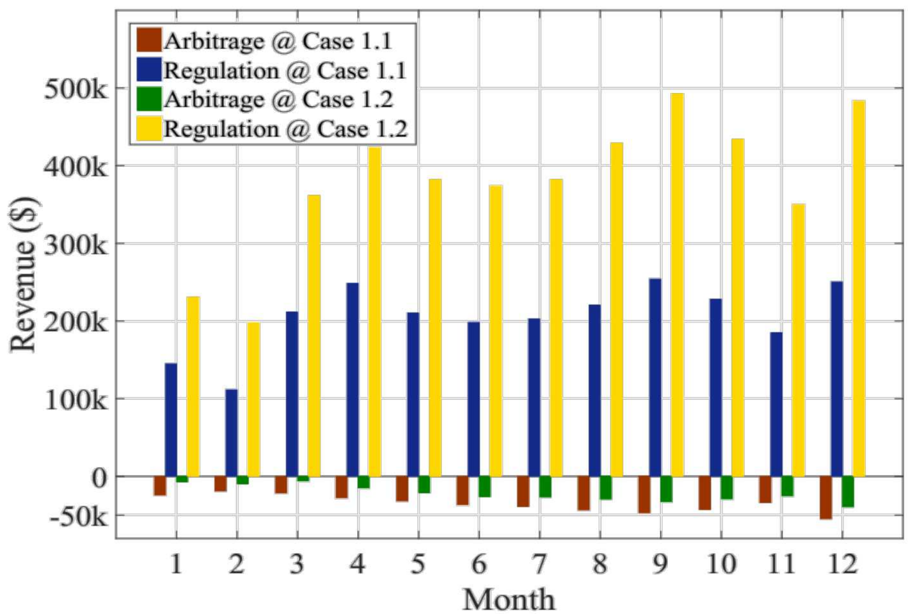
Case Study – 20MW/5MWh VRFB in PJM



(a) Discharge function f^d of the VRFB system

(b) Charge function f^c of the VRFB system

(c) Regulation function f_i^{reg} of the VRFB system during the first hour of June 2017



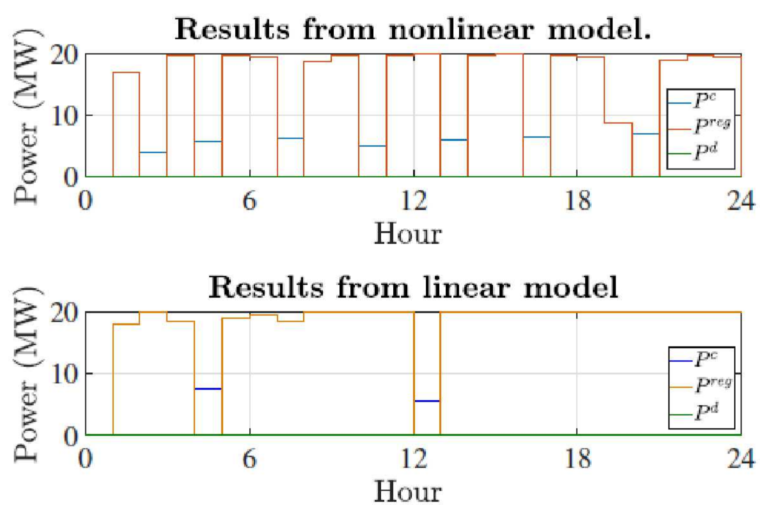
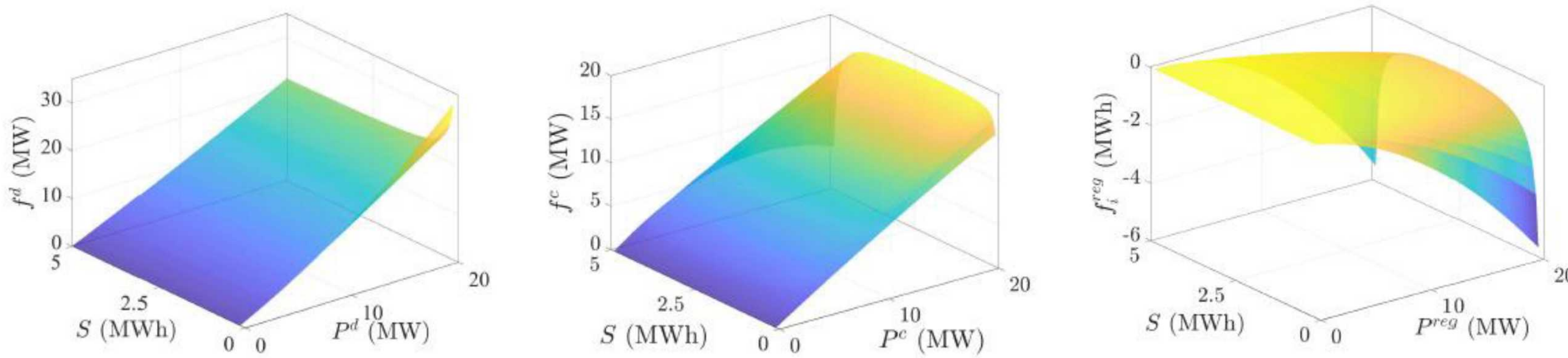


Fig. 5. Power output of the VRFB on June 1, 2017

Case Study – 20MW/5MWh Li-ion BESS in PJM



(a) Discharge function f^d of the Li-ion battery system (b) Charge function f^c of the Li-ion battery system (c) Regulation function f_i^{reg} of the Li-ion battery system during the first hour of June 2017

Fig. 3. Operating characteristics of a 20 MW / 5 MWh Li-ion system

Table 1: Case studies summary

Case	1.1	1.2	2.1	2.2
Model used	Nonlinear VRFB	70% constant efficiency	Nonlinear Li-ion	85% constant efficiency
2017 Arbitrage revenue ($)	−419,428.97	−265,567.55	−88,779.05	−17,552.31
2017 Regulation revenue ($)	2,463,602.39	4,537,275.94	3,963,421.31	4,658,817.18
2017 Total revenue ($)	2,044,173.42	4,271,708.39	3,874,642.25	4,641,264.88
2017 Total revenue (%)	44.04%	92.04%	83.48%	100.00%

Conclusions

- The nonlinear energy flow models for VRFB, Lead-acid and Li-ion battery systems have been derived to better capture technology-specific characteristics of energy storage.
- A DP-based approach is proposed to solve the nonconvex optimization when incorporating these nonlinear models.
- Future work in this area would involve the incorporation of market uncertainty into the energy storage revenue maximization problem as well as consider other analytical and numerical methods to solve the nonconvex optimization problem.

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