University of Houston

Department of Electrical and Computer Engineering

Optimal Energy Management for Battery Energy Storage System-Integrated Microgrids

PhD Candidate: Cunzhi Zhao

Committee Members:

- Dr. Xingpeng Li (Chair)
- Dr. Kaushik Rajashekara
- Dr. Hao Huang
- Dr. Zhu Han
- Dr. David R. Jackson

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UH RPG Lab

Overview

1. **Introductions**
    - Microgrid
    - Battery Energy Storage System
    - Energy management strategies
    - Contributions and organization
2. **BESS for Grid-Connected Microgrid**
    - Grid Friendly Microgrid
    - Grid Supporting Microgrid
3. **BESS for Isolated Microgrid**
    - Offshore Platform
    - Resilience
4. **Microgrid Energy Management with Battery Degradation Model**
    - Battery Degradation Data
    - Deep Neural Network
    - Microgrid Day-ahead Scheduling with NNBD
5. **Piecewise Linearized BDMDS Model**
    - Relu Activation Function
    - Linearization
6. **Computational Enhancement of BDMDS Model**
    - ReLu Approximation Methods
    - Sparse Neural Network
7. **Conclusions & Future Works**

3-D Trend of Power System

Decentralization
Decarbonization
Digitalization

Renewable Energy Resources
Integrated Microgrid

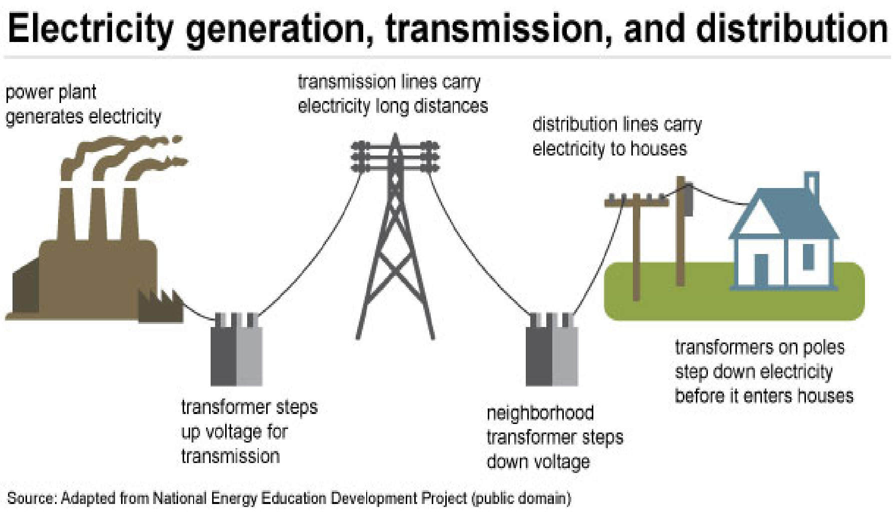


Figure. Traditional Power Generation

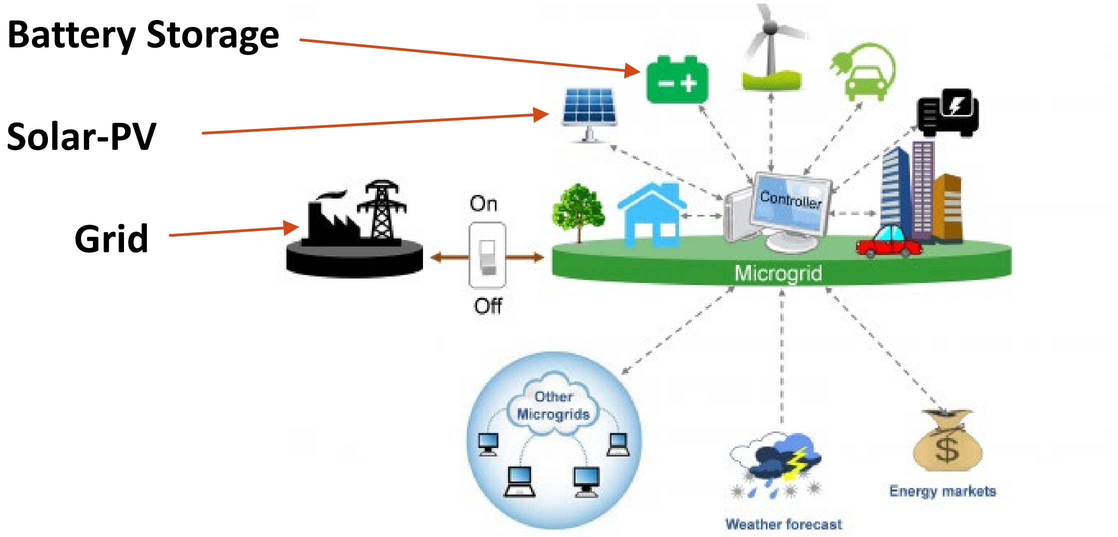


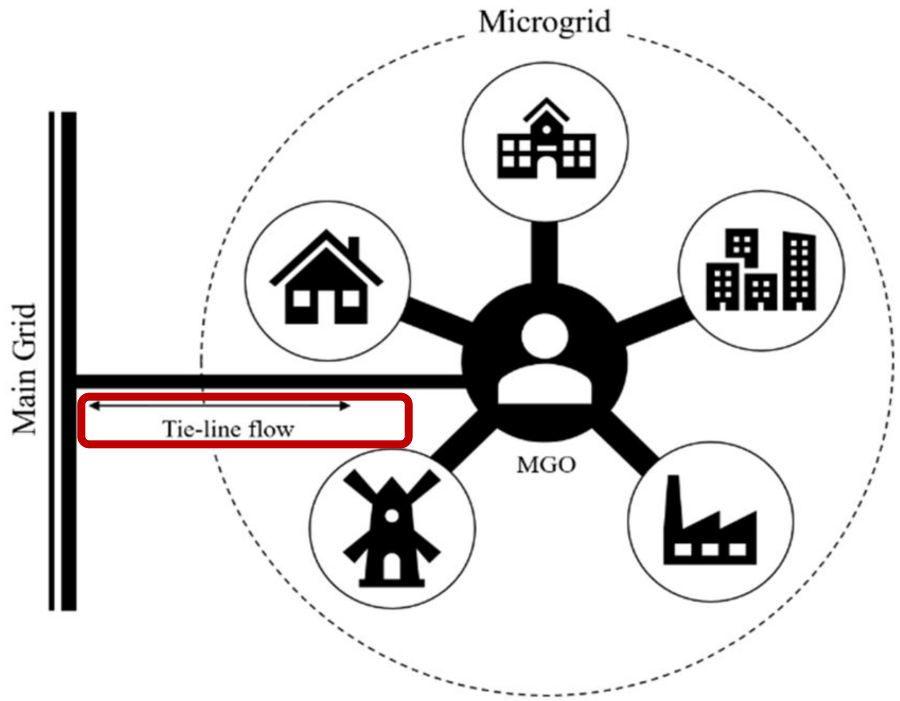
Figure. Microgrid Power Generation

[https://www.eia.gov/energyexplained/electricity/delivery-to-consumers.php]

The Elements of Microgrid

Microgrid are considered to be locally confined and independently controlled electric power grids in which a distribution architecture integrates loads and distributed energy resources.

- Generation
  - Diesel Generators
  - Microturbine
  - Renewable Energy Resources
- Energy Storage
  - Battery
  - Super capacitors
  - Flywheels
- Load
  - Community Loads
  - Main Grid
- Power Electronics
  - Converters
  - Inverters



Microgrid Energy Management

Microgrid management problems can be divided into a few groups based on time-scale:

- 5-25 years: microgrid design and optimal sizing
- 1-3 years: microgrid expansion planning
- 1 day to 1 week/month: maintenance scheduling
- 1 day: day-ahead scheduling (energy management)
- 5-30 minutes: economic dispatch (energy management)
- < 1 minute: for isolated microgrid , frequency regulation, stability
- < 1 minute: for networked microgrid , netload fluctuation control
- < 1 second: control of each microgrid asset (e.g., single PV/ESS)

[Li, Xingpeng (2022): ECE6327_SmartGrid. figshare. Online resource. https://doi.org/10.6084/m9.figshare.19761268.v1] c

Challenge with Increasing Renewable Energy Sources

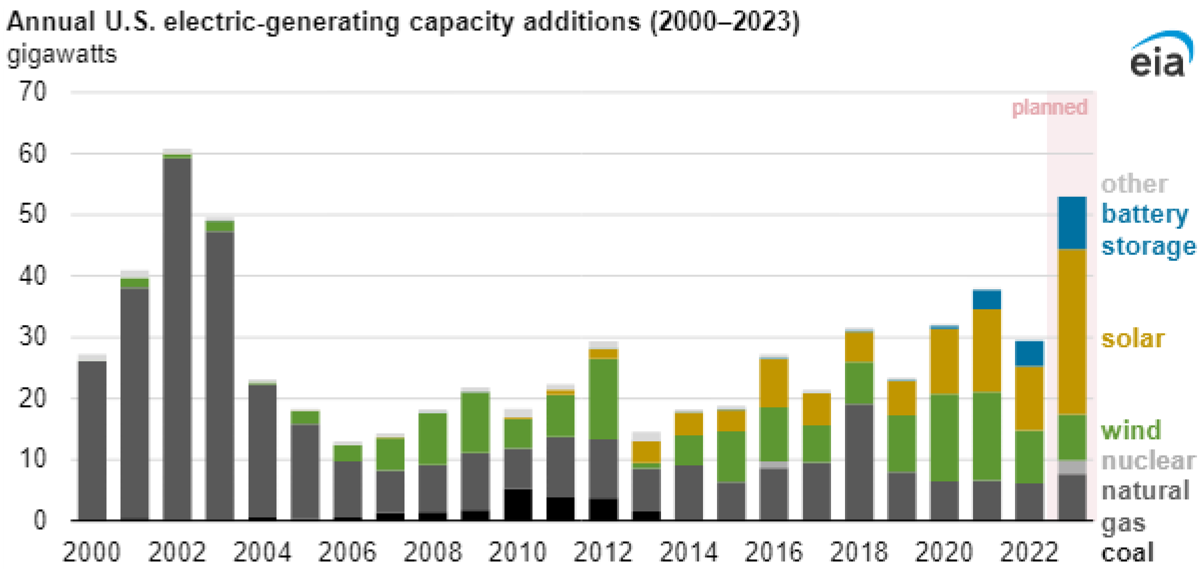


Figure. Generating Capacity Additions

- Increasing renewable generations may significantly weaken the system's reliability and resilience due to the stochastic and intermittent generation.

[https://www.eia.gov/todayinenergy/detail.php?id=55719]

Motivation for BESS

To reach 100% clean electricity goal by 2035:

- Generation capacity grows to roughly three times the 2020 level by 2035
- Estimated 2 terawatts of wind and solar.

Figure. 100 MW Gambit Energy Storage Park in Angleton, Texas.

- Renewable energy sources like wind and solar are intermittent and weather-dependent.
- Increasing demand of energy and clean energy policy require the large amount of BESS installation.

- Integration of BESS with these sources to provide reliable and continuous power supply, exploring advanced grid management strategies.
- Long-term performance and durability of BESS are limited by the impact of cycling, temperature variations, and other factors on their lifespan.

[https://www.nrel.gov/analysis/100-percent-clean-electricity-by-2035-study.html]

Contributions and Organization

BESS for Grid Connected Microgrid

- Grid Friendly: Provide fixed Tie-line exchange power
- Grid Supporting: Provide flexible Tie-line exchange power

BESS for Isolated Microgrid

- Offshore Microgrid Platform
- Resilience

Degradation Considered BESS

- Battery Data Analysis
- NN Based Battery Degradation Model
- Solving Algorithm
- Hierarchical Battery Degradation Model

Piecewise Linearized BDMDS Model

- “ReLU” Activation Function
- Linearization Model setup of the “Relu”
- L-BD-MDS Model

Computational Enhancement

- “ReLu” Approximation Methods
- Sparse Neural Networks

Conclusion & Future Work

Grid-Friendly Microgrid: Fixed Trade Power

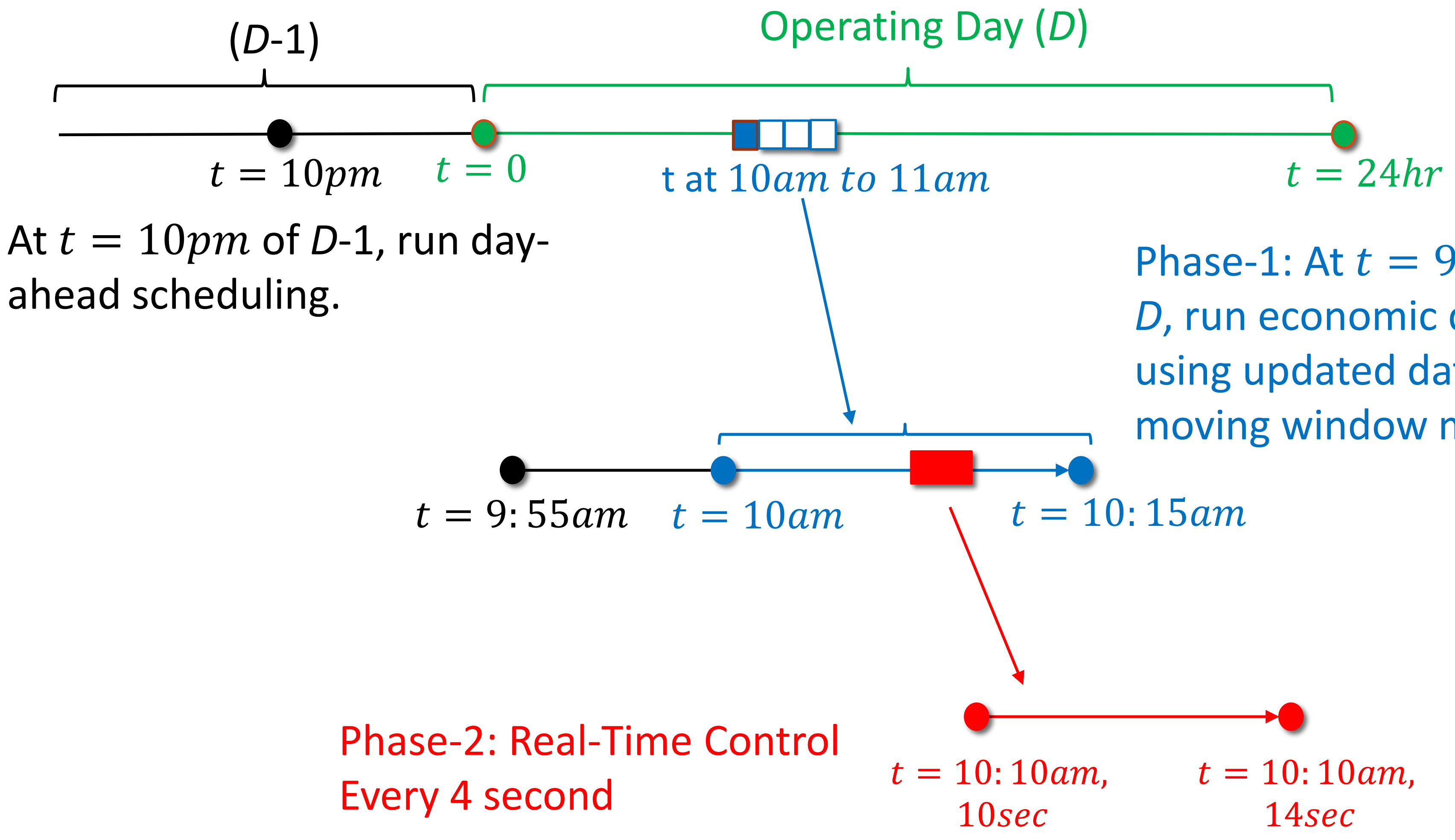
Objective:

- To maintain tie-line (point of common coupling) power at a less fluctuation level by employing both DERs and BESS to mitigate the fluctuation of microgrid net-load.

Proposed Strategy:

- A two-phase real-time energy management strategy for networked microgrid is proposed to address microgrid internal fluctuation internally.
    - *Real-time Dispatch Phase*: Solve a multi-interval microgrid economic dispatch problem.
    - *Real-Time control Phase*: Fast-acting Batteries will address the net-load fluctuation in real-time.

Timeline Summary



Results

- With the proposed two-phase energy management strategy, a microgrid can be considered as a grid-friendly microgrid from the perspective of a bulk grid operator.

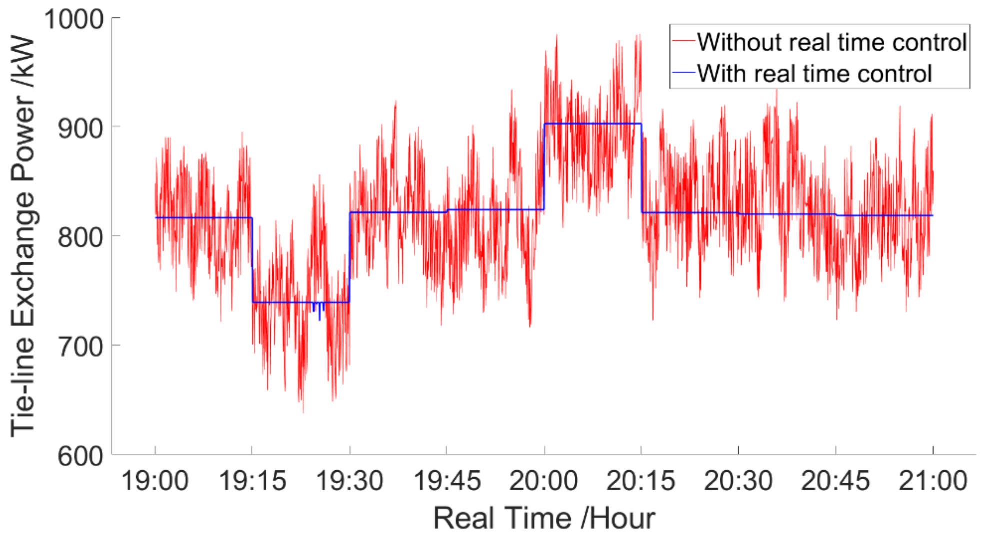


Figure. Tie-line exchange power at 5% prediction error

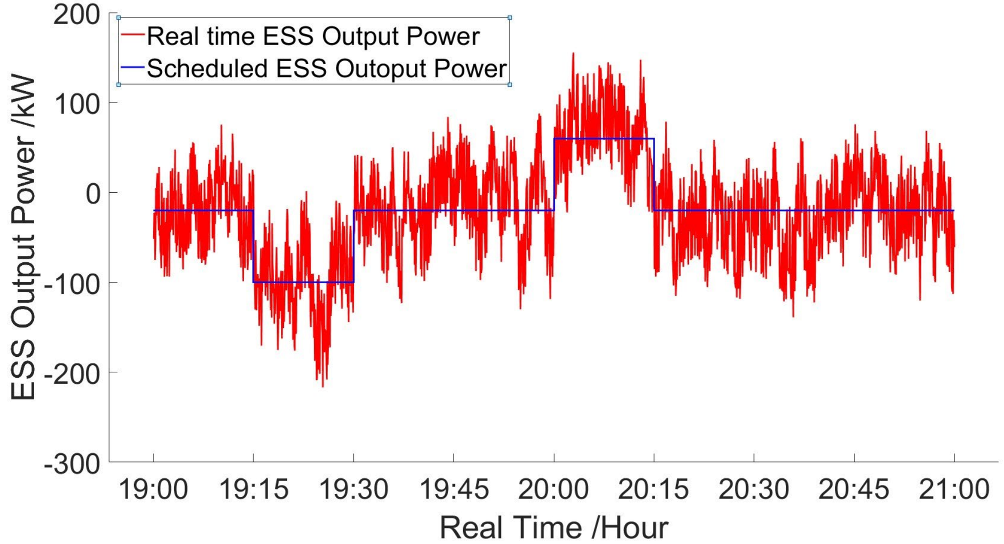


Figure. BESS Output at 5% prediction error

Grid Supporting Microgrid: Flexible Trade Power

Proposed Strategy:

- The proposed grid-supporting energy management (GSEM) strategy can not only properly manage DERs in a microgrid but also enable DERs to provide grid services, which enables a microgrid to be grid-supporting via flexible trading power.

Flexible trading power.

- Upper Bound: $Max\ \ P_{Exchange}^{t}$
- Lower Bound: $Min\ \ P_{Exchange}^{t}$

Adjustable Energy Sources:

- Diesel Generators
- Wind Turbine
- Battery Energy Storage System
- Roof-top Solar Panel System

Figure. Typical Wind Turbine

[Chatterjee, Debjyoti & Rather, Zakir. (2018). Modelling and Control of DFIG-based Variable Speed Wind Turbine.]

Result Analysis

Scenario A: Selling Power

- The target tie-line trading power for 15:15-15:30 is selling electricity to grid at a rate of 242.33 kW.
- BESS is on charging status with a power of 75 kW.

Scenario B: Purchasing Power

The target tie-line trading power for 19:45-20:00 is purchasing electricity from grid at a rate of 814.33 kW. BESS is on discharging status with a power of 20 kW.

Table Results of Scenario A

No.	α_g	α_s	α_w	Power Range (kW)
0	0	0	0	-242.33
1	0.05	0.01	0.05	(-247.33, -193.33)
2	0.05	0.02	0.05	(-252.33, -193.33)
3	0.05	0.02	0.08	(-252.33, -169.33)
4	0.08	0.02	0.08	(-252.33, -163.93)
5	0.08	0.05	0.1	(-267.33, -147.93)
6	0.1	0.05	0.1	(-267.33, -144.33)
7	0.1	0.08	0.1	(-282.33, -144.33)
8	0.12	0.08	0.1	(-282.33, -140.73)
9	0.15	0.08	0.1	(-282.33, -135.33)
10	0.15	0.1	0.1	(-292.33, -135.33)

Table Results of Scenario B

No.	α_g	α_s	α_w	Power Range (kW)
0	0	0	0	814.33
1	0.05	0.01	0.05	(809.33 , 863.33)
2	0.05	0.02	0.05	(804.33 , 863.33)
3	0.05	0.02	0.08	(804.33 , 887.33)
4	0.08	0.02	0.08	(804.33 , 892.73)
5	0.08	0.05	0.1	(789.33 , 908.73)
6	0.1	0.05	0.1	(789.33 , 912.33)
7	0.1	0.08	0.1	(774.33 , 912.33)
8	0.12	0.08	0.1	(774.33 , 915.93)
9	0.15	0.08	0.1	(774.33 , 921.33)
10	0.15	0.1	0.1	(764.33 , 921.33)

Summary

BESS-Integrated Grid-connected Microgrid:

- Able to provide a fixed and flexible tie-line exchange power.
- Enhances system's stability.
- Improves the quality performance of renewables.
- Reduces operational costs.
- Contributes to a cleaner and more reliable energy system.

1. **Cunzhi Zhao** and Xingpeng Li, "A Novel Real-Time Energy Management Strategy for Grid-Friendly Microgrid: Harnessing Internal Fluctuation Internally," *The 52nd North American Power Symposium (NAPS)*, Tempe, AZ, USA, Apr, 2021.
2. **Cunzhi Zhao** and Xingpeng Li, "A Novel Real-Time Energy Management Strategy for Grid-Supporting Microgrid: Enabling Flexible Trading Power," *IEEE PES General Meeting 2021*, Washington, DC, USA, Jul. 2021.

Offshore Rig Platforms Application

- Offshore loads: oil and natural gas rig platforms.
    - ~5 - 100 MW.
    - Most are powered by local diesel generators.
    - Some are powered by local gas generators.
    - Use 16 terawatt-hours (TWh) a year.
    - Heavy CO2 emissions.

- In 2019, gas and oil made up 55% of the world's CO2 emissions from fuel, and a significant proportion came from offshore O&G platforms.

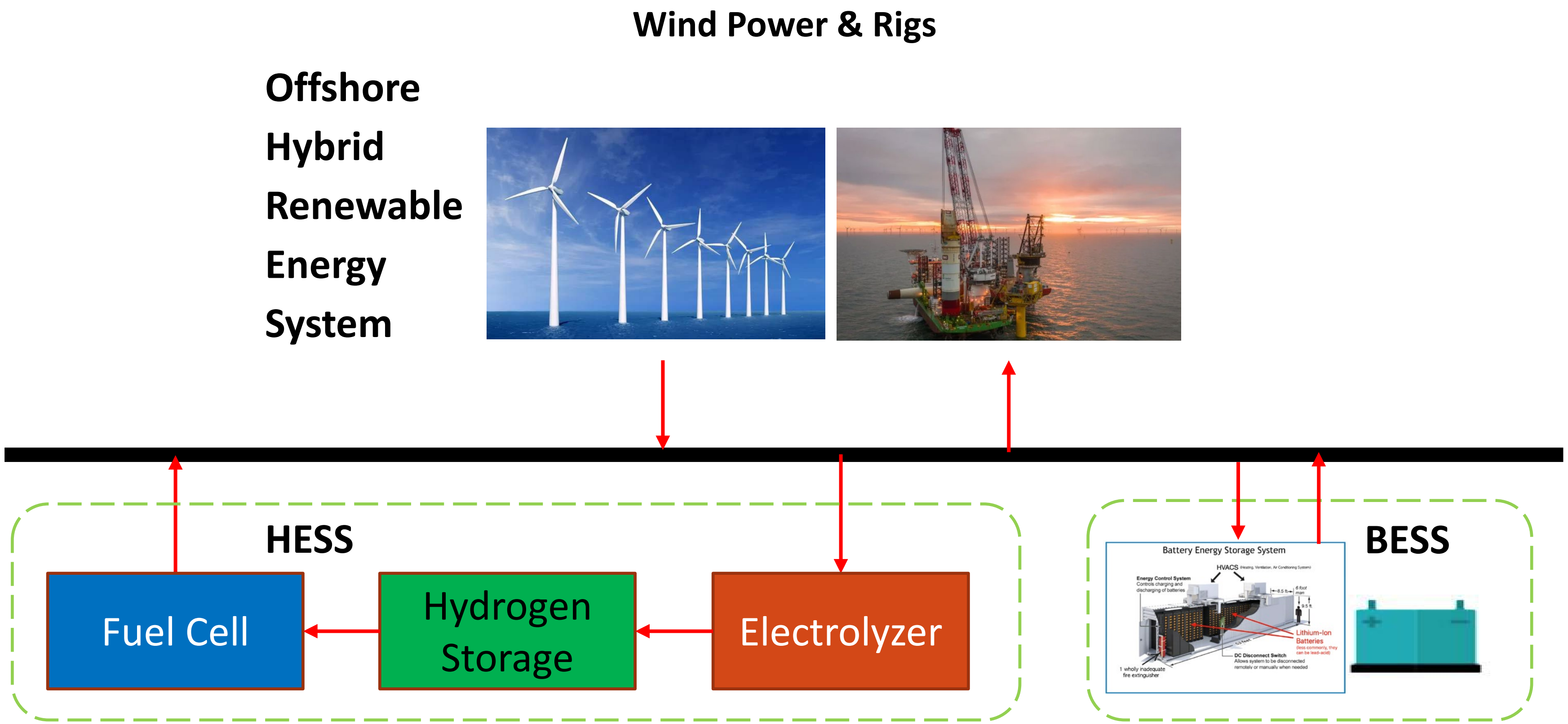
https://www.greentechmedia.com/articles/read/oil-and-gas-companies-can-power-offshore-platforms-with-renewables

A 100% renewable Offshore System

- Motivation:
    - Reduce CO2 emission; net-zero future.
    - Fast development of offshore wind power.
- Proposed Model:
    - A 100% Renewable Energy System which can enable zero CO2 emission for offshore platforms.
- Offshore hybrid Renewable energy system (OHRES) main components:
    - Battery energy storage system (BESS).
    - Hydrogen energy storage system (HESS).
    - Offshore wind power.

A 100% renewable Offshore Model

Illustration of the proposed Offshore Hybrid Renewable Energy Model for powering offshore loads with clean renewable energy.



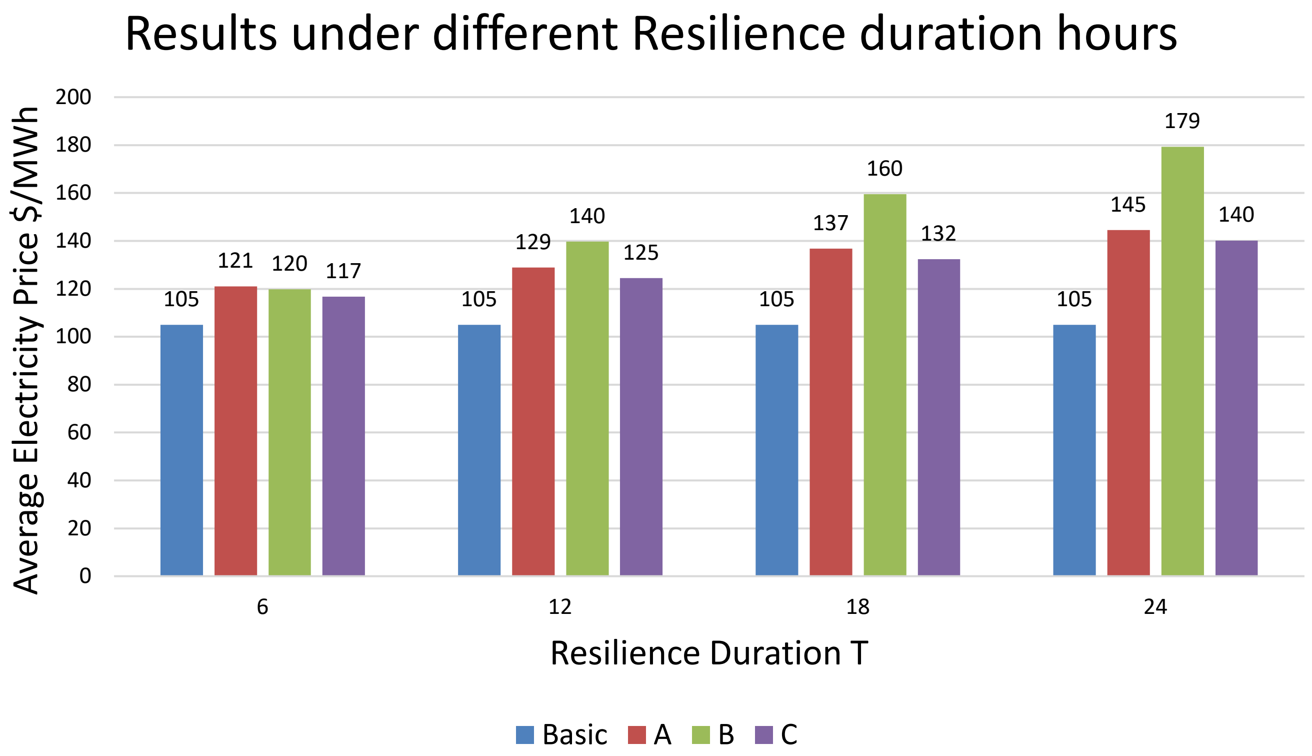
[https://atb.nrel.gov/electricity/2022/utility-scale_battery_storage]

Model of proposed Offshore System

- Three models:
  - A. HESS Resilience Model.
  - B. BESS Resilience Model.
  - C. Joint Resilience Model.

- A basic model that represents the traditional offshore system is demonstrated as a benchmark.

- Resilience duration T^R is defined as the time period that the system can survive without wind power.



Microgrid Resilience Operational Planning

Resilience Operational Planning (ROP) Algorithm

Motivation:

- Increase the resilience of microgrid.
- Prevent the system failure during extreme events.

Contribution:

- Resilience Index: Microgrid survivability rate *(SR)*
  - *Defined as the sum of the expected values of the successful scenarios where the power supplied by the microgrid never drops below a predefined percentage of critical load throughout the time period T.*
- Proposed Resilient Operational Planning (ROP) Algorithm.

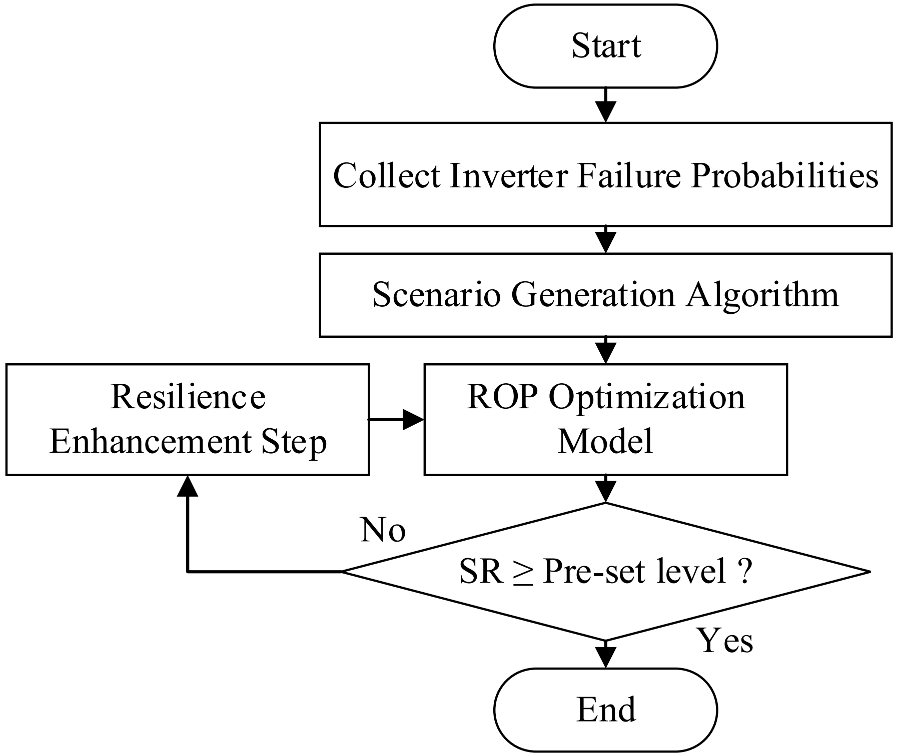


Figure. ROP algorithm flowchart.

ROP Case Studies

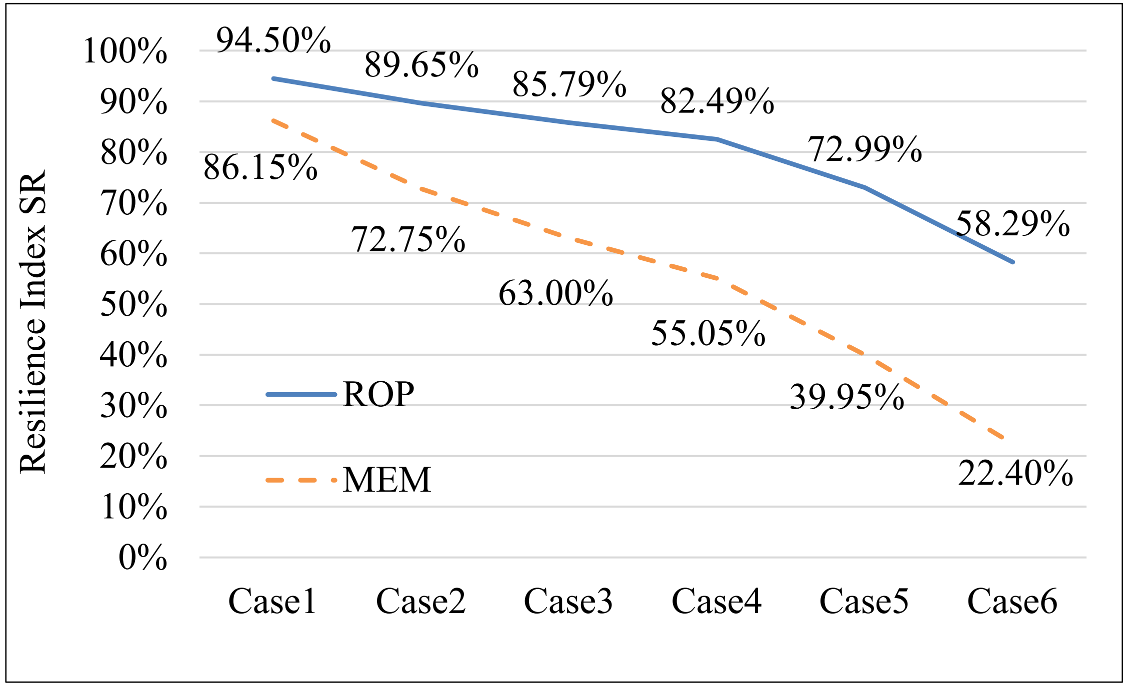


Figure. Plot of survivability rate.

Table Survivability Rate sensitivity test of α.

α	90%	95%	98%	100%	102%	105%
SR	100%	100%	99.5%	94.5%	94.2%	0%

α is defined as the minimum acceptable percentage of critical load supplied under extreme events.

Table Evaluation of ROP under different events.

SR	ROP	Add 1 DG	Add 2 DG
Non-emergency Event	96.2%	/	/
Moderate Event	36%	97%	/
Extreme Event	22.3%	94%	99.9%

Summary

BESS-Integrated Isolated Microgrid:

- Enables a zero carbon emission system for Offshore Platforms.
- Enhances the resilience against the extreme weather.

1. **Cunzhi Zhao** and Xingpeng Li, "A 100% Renewable Energy System: Enabling Zero CO2 Emission Offshore Platforms", *54th North American Power Symposium*, Salt Lake City, UT, USA, Oct. 2022.
2. **Cunzhi Zhao**, Jesus Silva-Rodriguez and Xingpeng Li, "Resilient Operational Planning for Microgrids Against Extreme Events", Hawaii International Conference on System Sciences, Maui, Hawaii, USA, Jan. 2023.

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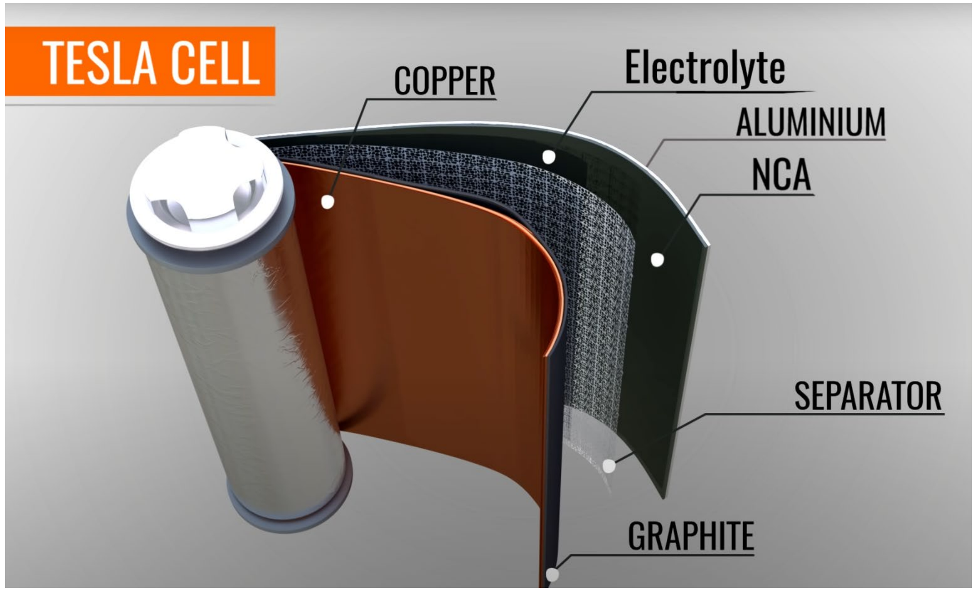
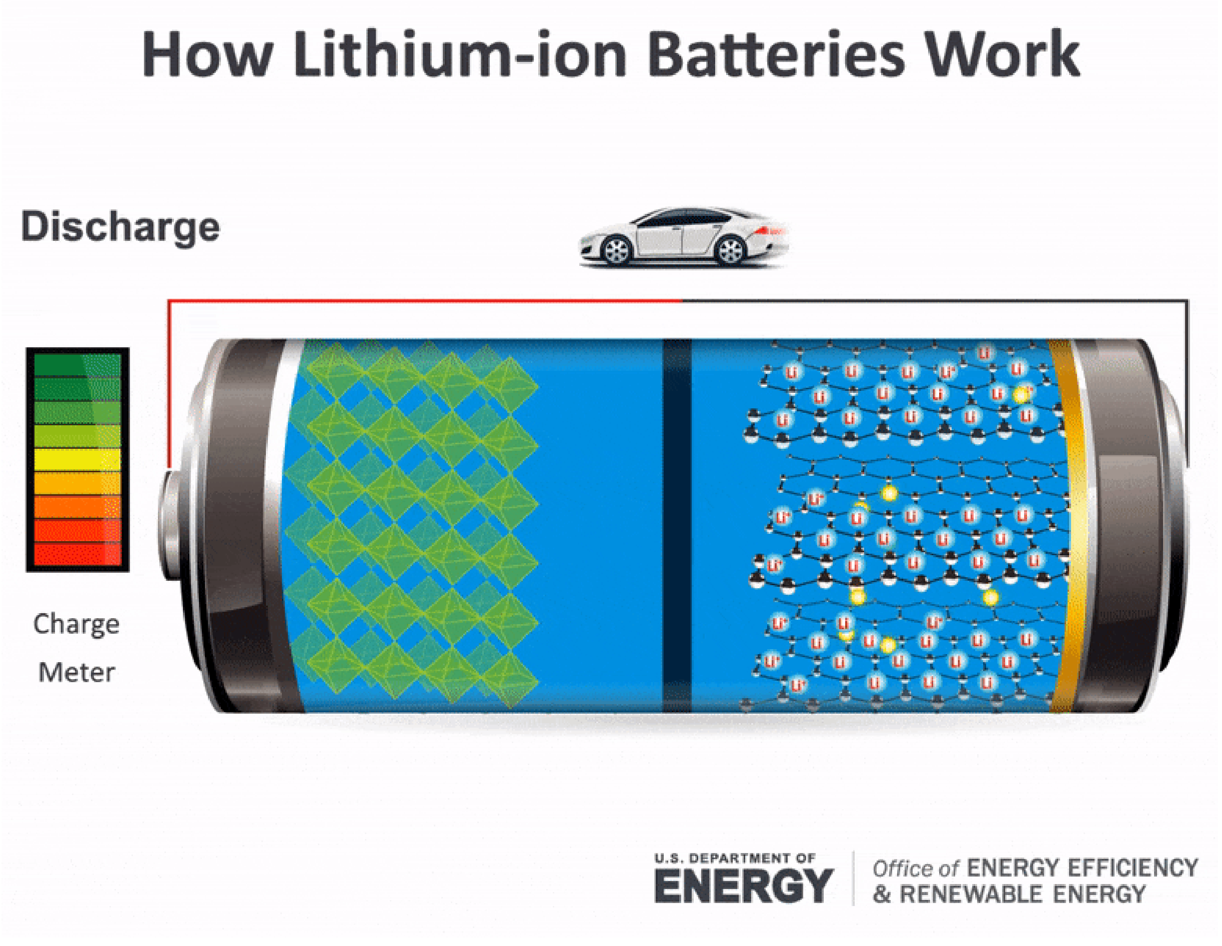
Introduction of Battery Degradation

Main Component of BESS: Lithium-ion Battery

Main Reason of Degradation:

- Loss of Li-ions
- Loss of Electrolyte
- Internal Resistance





[https://www.levyelectric.com/post/the-newest-battery-technologies-we-re-excited-about-for-electric-scooters]

Real Battery Data

Battery capacity curve

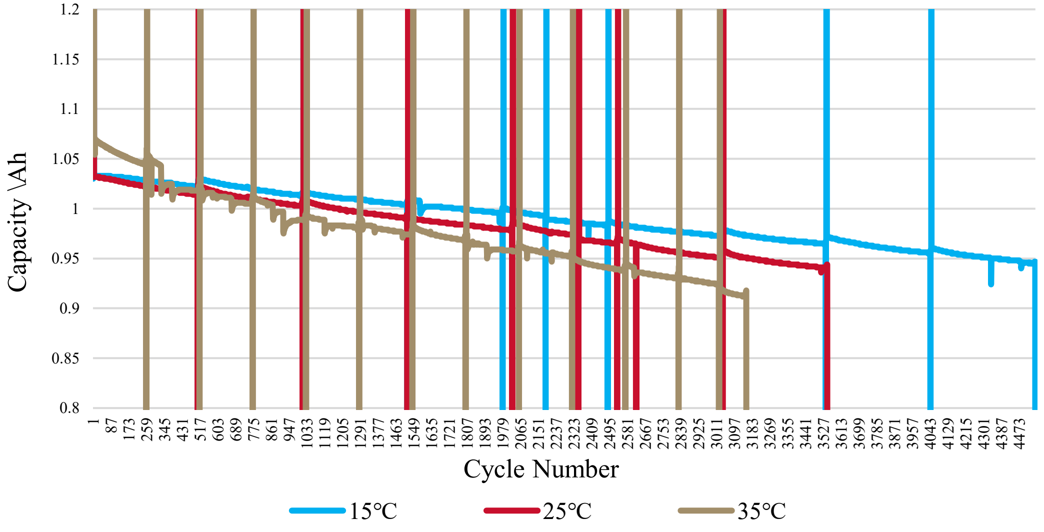


Fig. SNL LFP 0-100 1C.

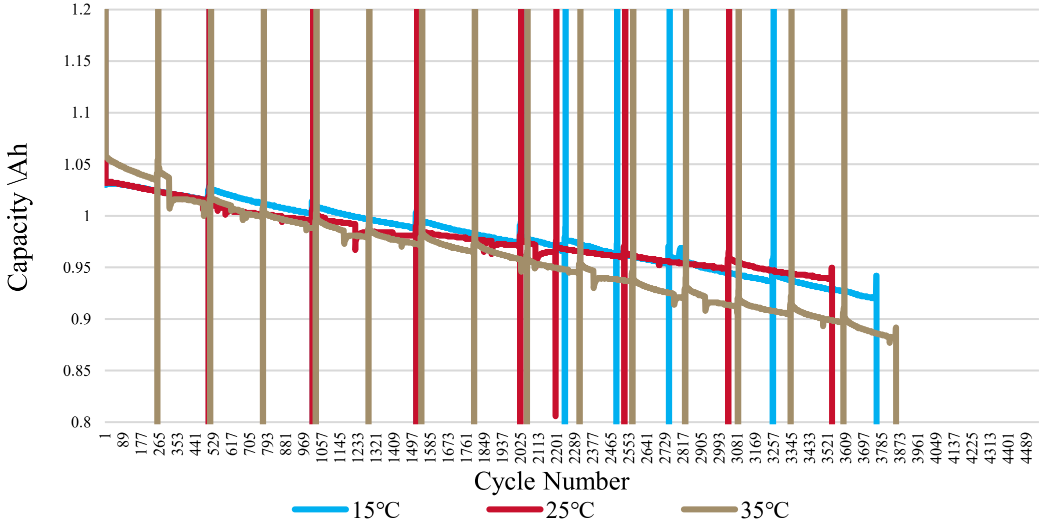


Fig. SNL LFP 0-100 2C.

SNL: Sandia National Lab

LFP: Lithium iron phosphate

C rate: charging/discharge rate

1C represents the battery can be fully charge/discharge in 1 hour.

2C represents the battery can be fully charge/discharge in 0.5 hour.

[https://www.batteryarchive.org/]

Motivations

Heuristic Battery Degradation Models

- **Linear Degradation Model (1)**

$$f(BDC) = \sum_t c_{BD} * (P_{BESS}^{Charge,t} + P_{BESS}^{Discharge,t})$$

- **DOD based Degradation Model (2)**

$$f(BDC) = \sum_t c_{BD}^{DOD,t}$$

BDC represents Battery Degradation Cost

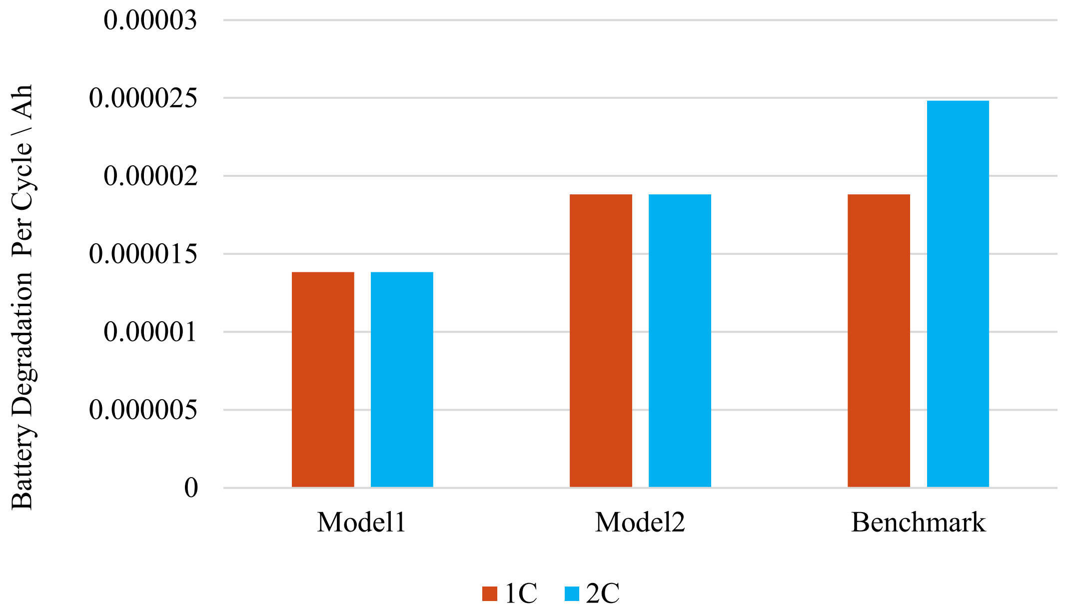


Figure. Degradation comparison under different discharge rates

Research Gap: Heuristic Battery Degradation Models cannot accurately predict the degradation values caused by different operating conditions, and the degradation prediction error is high for both models.

Neural Network based Battery Degradation (NNBD)

Battery Variables:

- Charge/Discharge Rate
- Initial State of Charge (SOC)
- Depth of Discharge (DOD)
- Ambient Temperature (T)
- Capacity (SOH)

Structure of the NN model

- Input Layer :5
- Hidden Layer 1: 20
- Hidden Layer 2: 10
- Output Layer:1

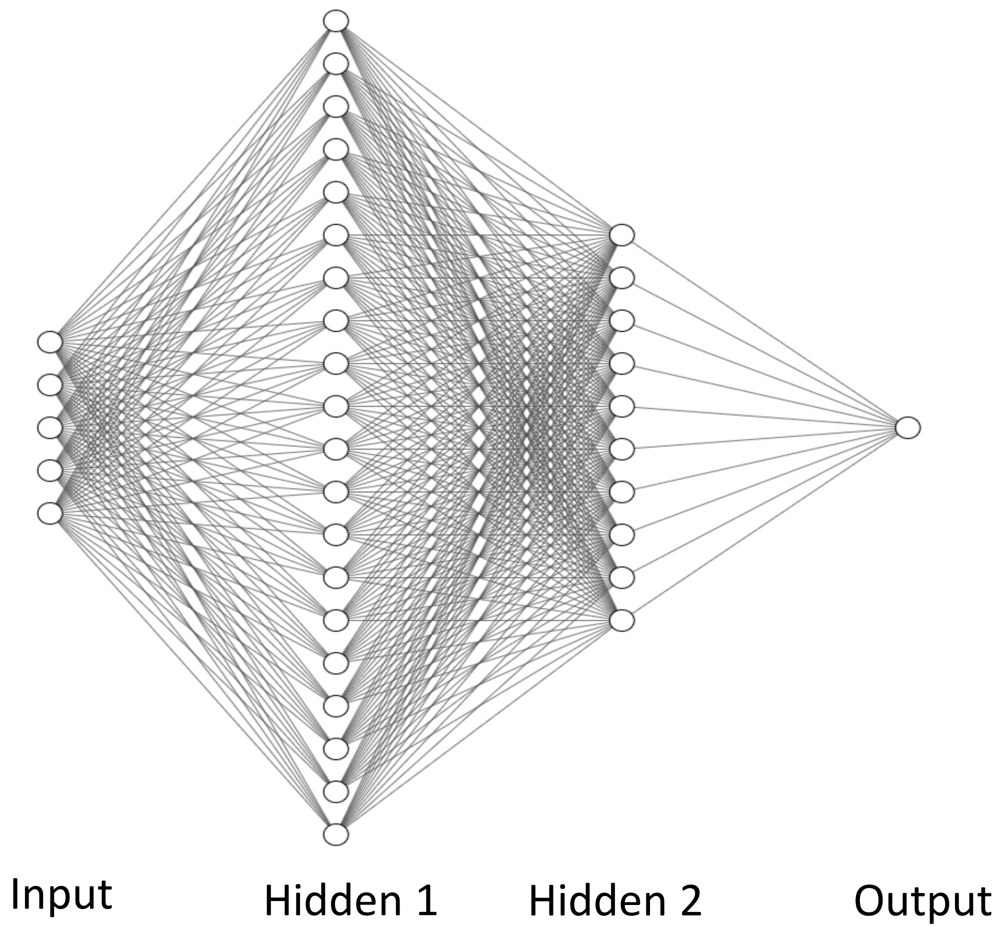


Fig. Structure of NNBD Model

Training Dataset

MATLAB Simulink

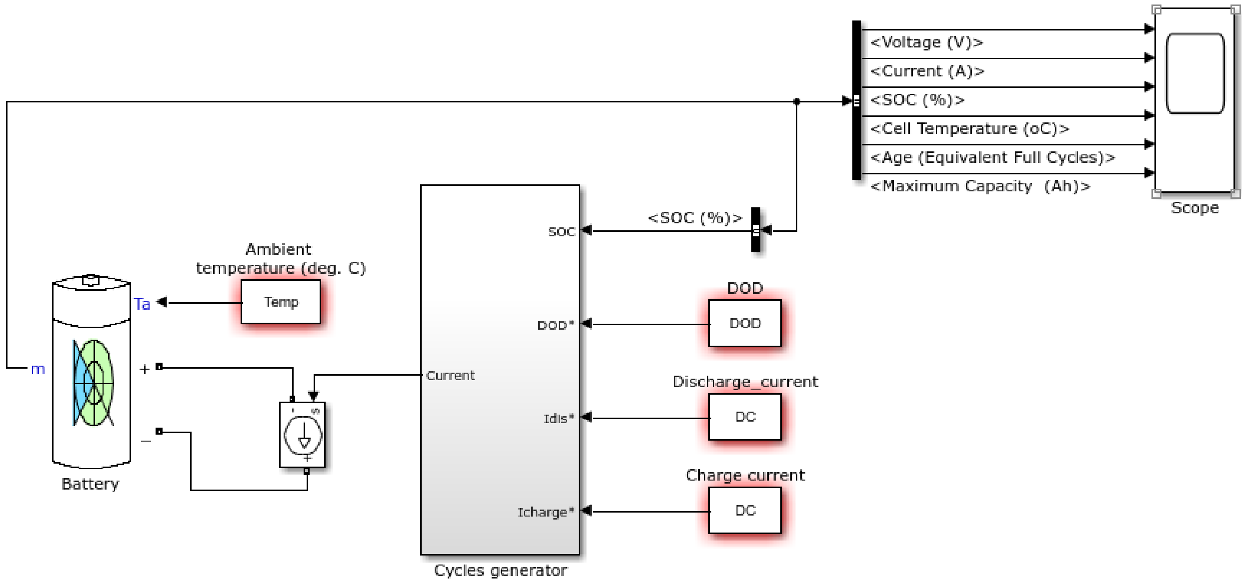


Fig. Simulink file for data collection

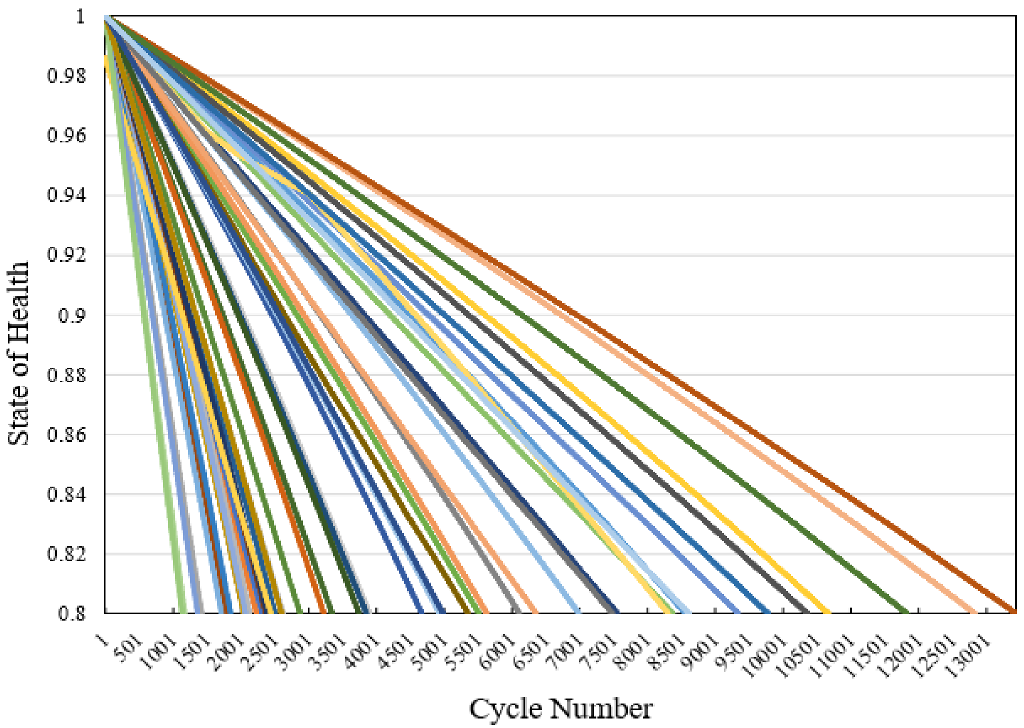


Fig. State of Health versus Cycle Number

The training dataset includes 945 different battery aging tests with different values of degradation factors.

BESS Integrated Microgrid Day-ahead Scheduling (MDS)

Objective:

$f^{MG} = \sum\sum(P^t_{Gi}c_{Gi} + U_{Gi}c^{NL}_{Gi} + V_{Gi}c^{SU}_{Gi}) + P^t_{Buy}c^t_{Buy} - P^t_{Sell}c^t_{Sell}\ (i \in S_G, t \in S_T)$ (1)

Objective function

Constraints are as follows:

$P^t_{Buy} + \sum_{i \in S_G} P^t_{Gi} + \sum_{i \in S_{WT}} P^t_{WTi} + \sum_{i \in S_{PV}} P^t_{PVi} + \sum_{i \in S_S} P^{t,i}_{Disc} = P^t_{Sell} + \sum_{i \in S_L} P^t_{Li} + \sum_{i \in S_S} P^{t,i}_{Char}$ (2)

Power balance equation for microgrid

$P^{Min}_{Gi} \le P^t_{Gi} \le P^{Max}_{Gi}\ (i \in S_G, t \in S_T)$ (3)

$P^{t+1}_{Gi} - P^t_{Gi} \le \Delta T \cdot P^{Ramp}_{Gi}\ (i \in S_G, t \in S_T)$ (4)

$P^t_{Gi} - P^{t+1}_{Gi} \le \Delta T \cdot P^{Ramp}_{Gi}\ (i \in S_G, t \in S_T)$ (5)

Controllable Generation

$U^t_{Buy} + U^t_{Sell} \le 1\ (i \in S_G, t \in S_T)$ (6)

$0 \le P^t_{Buy} \le U^t_{Buy} \cdot P^{Max}_{Grid}\ (t \in S_T)$ (7)

$0 \le P^t_{Sell} \le U^t_{Sell} \cdot P^{Max}_{Grid}\ (t \in S_T)$ (8)

Power trading with main grid

$U^{t,i}_{Disc} + U^{t,i}_{Char} \le 1\ (i \in S_G, t \in S_T)$ (9)

$U^{t,i}_{Char} \cdot P^{Min}_{Si} \le P^{t,i}_{Char} \le U^{t,i}_{Char} \cdot P^{Max}_{Si}\ (i \in S_S, t \in S_T)$ (10)

$U^{t,i}_{Disc} \cdot P^{Min}_{Si} \le P^{t,i}_{DiscS} \le U^{t,i}_{Disc} \cdot P^{Max}_{Si}\ (i \in S_S, t \in S_T)$(11)

$SOC^t_{Si} = E^t_{Si}/E^{Max}_{Si}\ (i \in S_S, t \in S_T)$ (12)

$E^t_{Si} - E^{t-1}_{Si} + \Delta T \cdot (P^{t-1,i}_{Disc}/\eta^{Disc}_{Si} - P^{t-1,i}_{Char}\eta^{Char}_{Si}) = 0\ (i \in S_G, t \in S_T)$ (13)

$E^{t=24}_{Si} = E^{Initial}_{Si}\ (i \in S_S)$ (14)

Battery energy storage system

$P^{Max}_{Grid} - P^t_{Buy} + P^t_{Sell} + \sum_{G \in S_G}(P^{Max}_{Gi} - P^t_{Gi}) \ge R_{percent}(\sum_{i \in S_L} P^t_{Li})\ (t \in S_T)$ (15)

Backup Constraint

Traditional objective function does not consider the equivalent battery degradation cost

Battery Degradation Considered MDS (BDMDS)

New objective cost: $f = f^{MG} + f^{BESS}$

Equation (1)

Battery Degradation Cost Calculation:

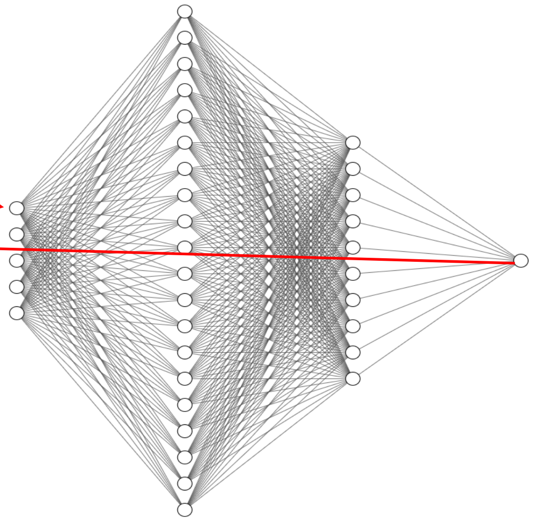
$$f^{BESS} = \frac{c_{BESS}^{Capital} - c_{BESS}^{SV}}{1 - SOH_{EOL}} BD$$

Cycle based Battery Usage Processing Method:

- For any continuous time intervals, if the operation status (charging or discharging) does not change, they will be aggregated as a single charging or discharging cycle.

$$\overline{x}_c = (T, C, SOC, DOD, SOH)$$

$$BD = \sum_{c \in AC} f^{NN}(\overline{x}_c)\, SOH$$



NNODH Solving Algorithm

Motivation:

- BDMDS optimization problem is hard to solve directly due the non-linear and non-convex of the NNBD model.

Proposed Algorithm:

- A neural network and optimization decoupled heuristic (NNODH) algorithm is proposed to effectively solve this neural network embedded optimization problem.

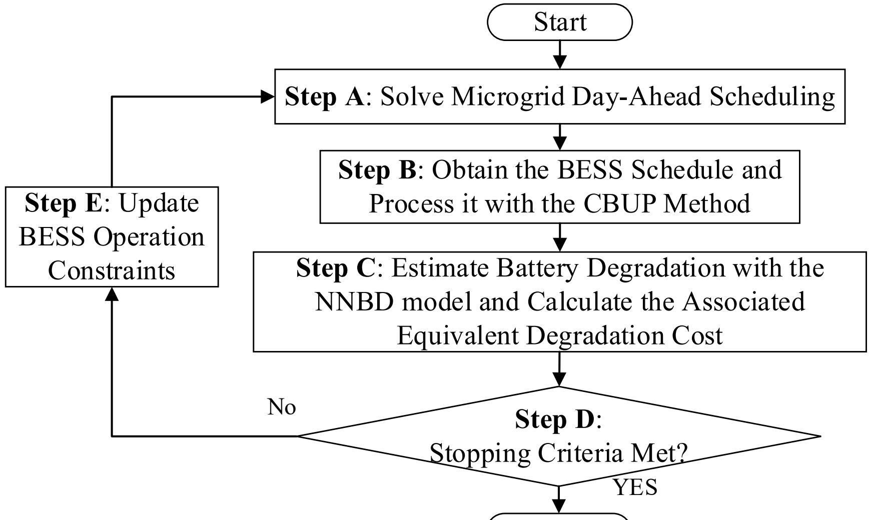


Fig. Flowchart

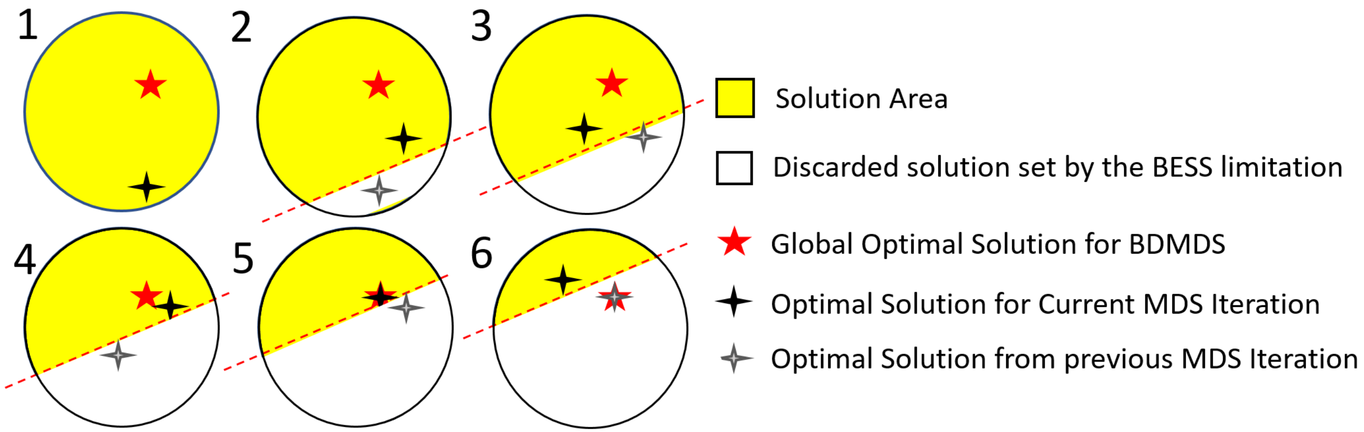


Fig. Illustration of the proposed NNODH algorithm.

Result Analysis

- The proposed iteration (NNODH) algorithm can obtain the optimal solution efficiently.
- Compared with the traditional MDS models, the total cost can be reduced significantly by 5.82% with the proposed BDMDS model.
- The proposed model can reduce the daily BESS degradation significantly from 0.02% to 0.0045%.

Table Model comparison

Model	Daily BESS Degradation	Annual Degradation Cost ($)	Annual Cost Saving ($)	Expect Lifetime (years)
MDS	0.02%	18,301.1	N/A	4.1
Cycle Limit	0.012%	12,540.8	6,205	6.8
Linear BDC	0.01%	8,832.5	6,935	8.2
BDMDS	0.0045%	3,920.1	11,151	18.3

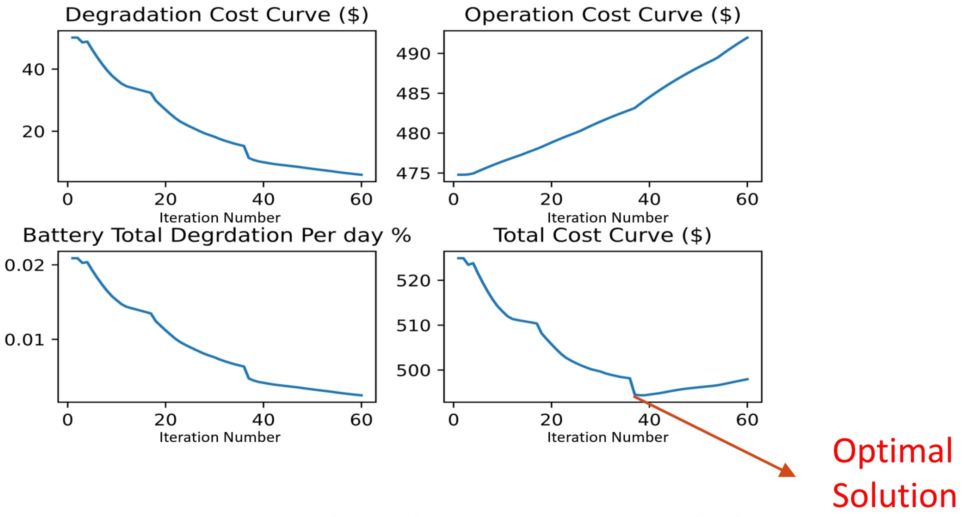


Fig. BDMDS Results of the NNODH-BCL method.

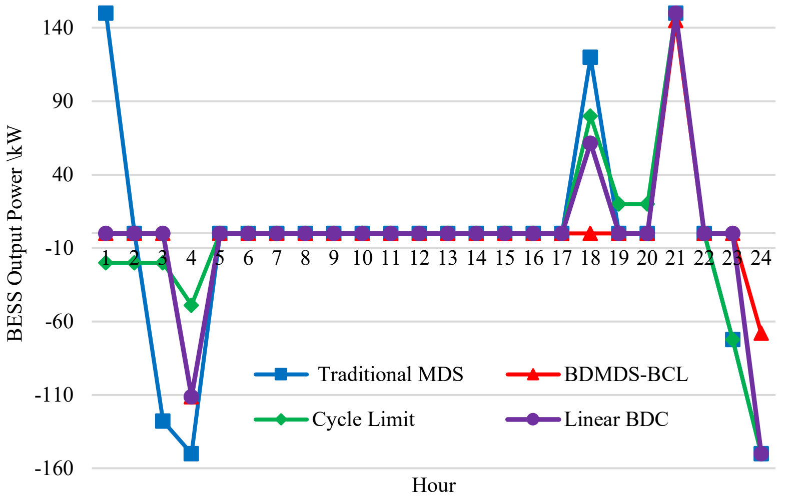


Fig. BESS scheduled operations comparison.

Hierarchical Deep Learning (HDL) Model

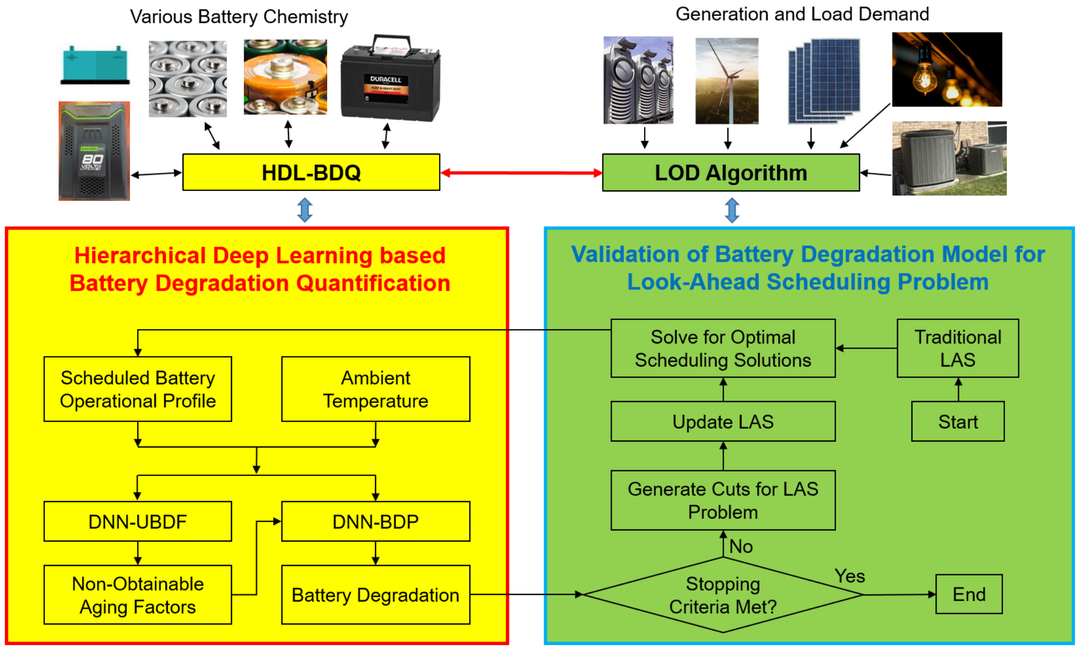
Motivation

- Previous NNBD model works well under different scenarios and have an accuracy of 94.5% on the degradation prediction at a 15% error tolerance.
- However, the input of the NN only consist the ambient temperature, charging/discharging rate, SOC, DOD and SOH.
- The internal features such as internal temperature and internal resistance that are more likely to affect the battery degradation are ignored in the previous NN model.

Proposed HDL model

Includes two sequential and cohesive deep neural networks:

- DNN for unobtainable battery degradation features (DNN-UBDF)
- DNN for battery degradation prediction (DNN-BDP)



Hierarchical Deep Learning Model

Potential models for (DNN-UBDF)

Model #	Inputs	Outputs
1	SOC, DOD, Temp, C Rate, SOH	IT
2	SOC, DOD, Temp, C Rate, SOH	IR
3	SOC, DOD, Temp, C Rate, SOH	IT, IR
4	SOC, DOD, Temp, C Rate, SOH	IT, ELCN
5	SOC, DOD, Temp, C Rate, SOH	IR, ELCN
6	SOC, DOD, Temp, C Rate, SOH	IT, IR, ELCN

Training results of proposed models for DNN-UBDF

Error Tolerance	5%	10%	15%	20%
DNN-UBDF Model 1	45.25%	77.33%	88.63%	89.74%
DNN-UBDF Model 2	48.66%	78.37%	89.21%	90.59%
DNN-UBDF Model 3	37.96%	69.14%	85.47%	87.19%
DNN-UBDF Model 4	48.82%	73.86%	88.58%	91.23%
DNN-UBDF Model 5	51.05%	75.12%	89.90%	90.11%
DNN-UBDF Model 6	39.78%	65.61%	81.31%	83.74%

Potential models for (DNN-BDP)

Model #	Inputs	Outputs
1	IT, ELCN	Degradation
2	IR, ELCN	Degradation
3	SOC, DOD, Temp, C Rate, IT	Degradation
4	SOC, DOD, Temp, C Rate, IR	Degradation
5	SOC, DOD, Temp, C Rate, IT, ELCN	Degradation
6	SOC, DOD, Temp, C Rate, IR, ELCN	Degradation
7	SOC, DOD, Temp, C Rate, IT, SOH	Degradation
8	SOC, DOD, Temp, C Rate, IR, SOH	Degradation
9	SOC, DOD, Temp, C Rate, IT, SOH, ELCN	Degradation
10	SOC, DOD, Temp, C Rate, IR, SOH, ELCN	Degradation

Training results of proposed models for DNN-BDP

Error Tolerance	5%	10%	15%	20%
DNN-BDP Model 1	45.30%	77.57%	93.94%	97.89%
DNN-BDP Model 2	48.80%	82.16%	97.23%	99.89%
DNN-BDP Model 3	48.76%	82.04%	97.41%	99.91%
DNN-BDP Model 4	50.82%	79.37%	94.20%	99.91%
DNN-BDP Model 5	34.38%	65.57%	86.15%	95.91%
DNN-BDP Model 6	25.99%	59.11%	88.12%	97.76%
DNN-BDP Model 7	15.67%	21.66%	30.81%	45.85%
DNN-BDP Model 8	12.17%	18.85%	23.66%	30.82%
DNN-BDP Model 9	56.39%	88.87%	96.67%	97.07%
DNN-BDP Model 10	58.36%	91.56%	99.36%	99.99%

Results Analysis

- Results show the HDL-BDQ is more advanced than the single stage NNBD model since it requires less training data and achieves higher training accuracy (91.7% versus 83.1% & 79.2%, with an error tolerance of 15%).
- The HDL-BDQ has also been validated in the microgrid look ahead scheduling optimization problem using the iteration method.
- The proposed model creates a framework for battery degradation model. It can be extend to any types pf battery other than the lithium ion batteries.

Overall Efficiency Comparison

Error Tolerance	5%	10%	15%	20%
HDL-BDQ	37.4%	73.4%	91.7%	97.3%
NNBD	31.4%	57.0%	83.1%	97.3%

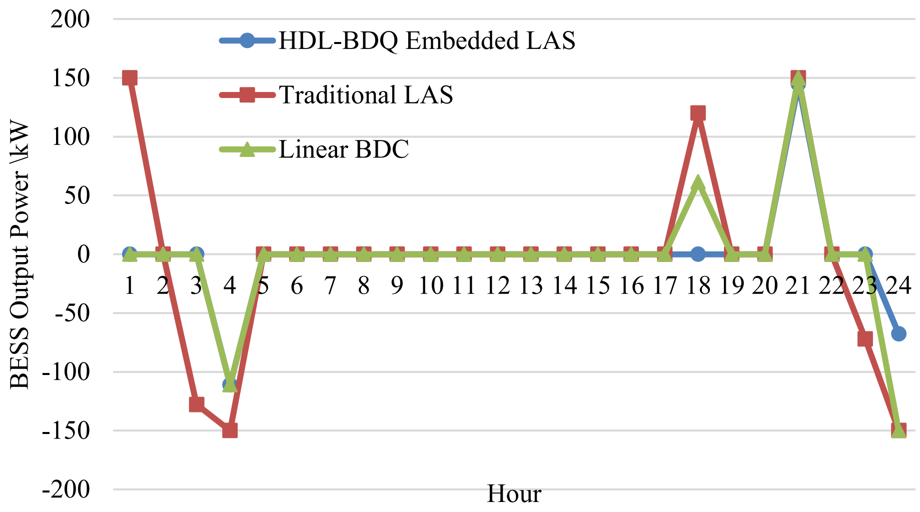


Fig. BESS scheduled operations comparison.

Summary

- A set of battery cycle generators is designed to simulate battery degradation under different battery operational profiles.
- A neural network based battery degradation model is proposed to accurately predict the degradation.
- An NNODH algorithm is proposed to efficiently solve the battery degradation based MDS model that is hard to solve directly.
- Hierarchical Deep Learning Model is proposed to enhance the performance of the battery degradation prediction.

1. **Cunzhi Zhao**, Xingpeng Li, and Yan Yao, “Quality Analysis of Battery Degradation Models with Real Battery Aging Experiment Data”, *Texas Power and Energy Conference*, College Station, TX, USA, Feb. 2023.
2. **Cunzhi Zhao** and Xingpeng Li, “Microgrid Optimal Energy Scheduling Considering Neural Network based Battery Degradation”, *IEEE Transactions on Power Systems*, early access, Jan. 2023.
3. **Cunzhi Zhao** and Xingpeng Li, “Hierarchical Deep Learning Model for Degradation Prediction per Look-Ahead Scheduled Battery Usage Profile”, *IEEE Transactions on Smart Grid*. (In preparation)

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    - Sparse Neural Network
7. **Conclusions & Future Works**

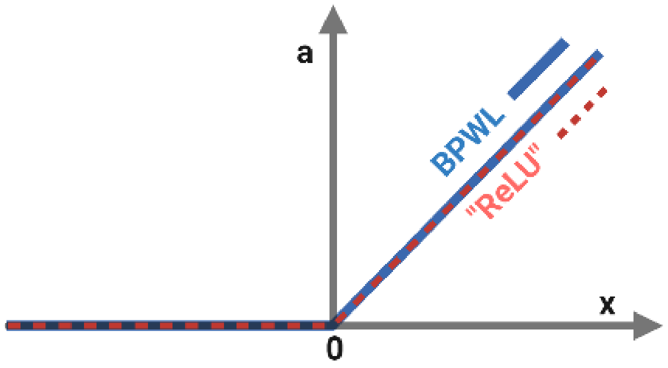
Non-linearity of BDMDS Model

Motivation:

- Previous work shows the iteration (NNODH) algorithm is feasible for the BDMDS model.
- However, only 1 BESS is considered in the previous test cases.
- If we increase more BESS in the test case, we found the iteration (NNODH) algorithm can not find the optimal solution anymore.

Proposed Piecewise Linearized BDMDS Model:

- The non-linear part in the BDMDS model is the NNBD model.
  - “Relu” activation function
- Linear the non-linear “Relu” activation function.



$$ReLU(x) = \max(x, 0)$$

Piecewise Linearized BDMDS Model

Proposed L-BD-Energy Scheduling method:

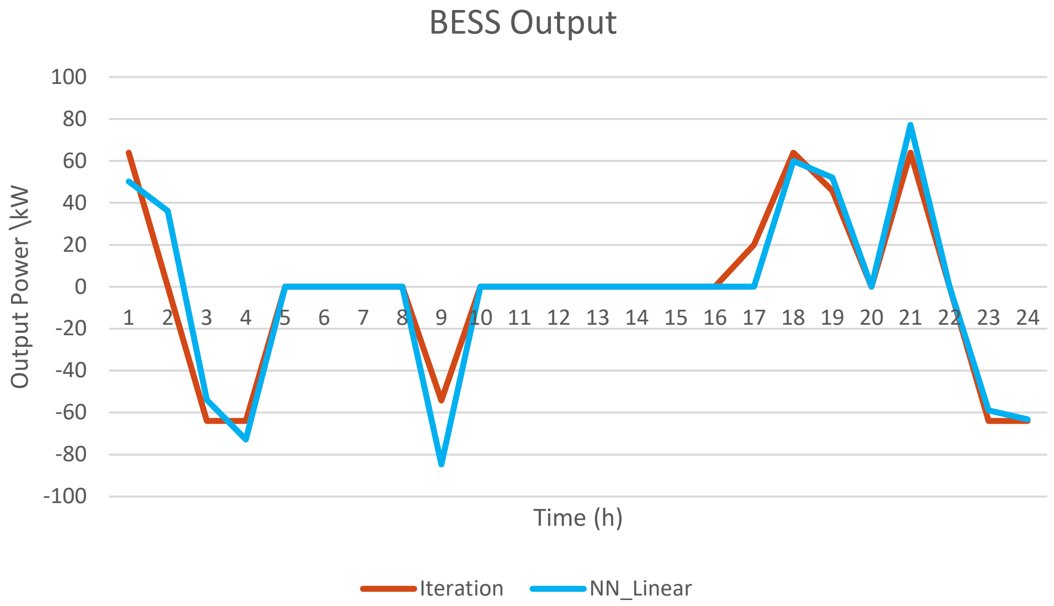
- Linearized BD-Energy Scheduling Problem
- The non-linear activation function "relu" is linearized by the proposed formulations.

Neural Network Calculation $x_h^i = \sum x_{h-1}^i * W + Bias$

"relu" activation function $a_h^i = relu(x_h^i) = max(0, x_h^i)$

"relu" linearization
$$\begin{cases} a_h^i \le x_h^i + BigM * (1 - \delta_h^i) \\ a_h^i \ge x_h^i \\ a_h^i \le BigM * \delta_h^i \\ a_h^i \ge 0 \end{cases}$$

Validation in Microgrid Test Case



Cost for Iteration (NNODH) Method is $529.52
Cost for Linearization method is $529.50

Multi-BESS System Result

The proposed model can also be applied in the bulk power system.

Table Results for IEEE-24 bus system.

IEEE 24-bus test systems with 5 BESSs			
	Fuel Cost ($)	BD Cost ($)	Total Cost ($)
Traditional-Energy Scheduling	256,404.60	34,643.80	291,048.40
L-BD-Energy Scheduling	258,448.90	20,348.10	278,797.00
Reduction	-0.80%	41.30%	4.21%

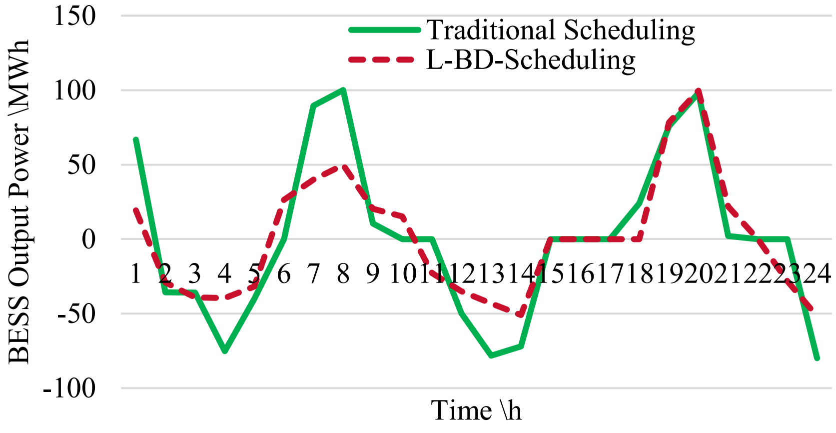


Figure. Output power of BESS #4 at bus 14.

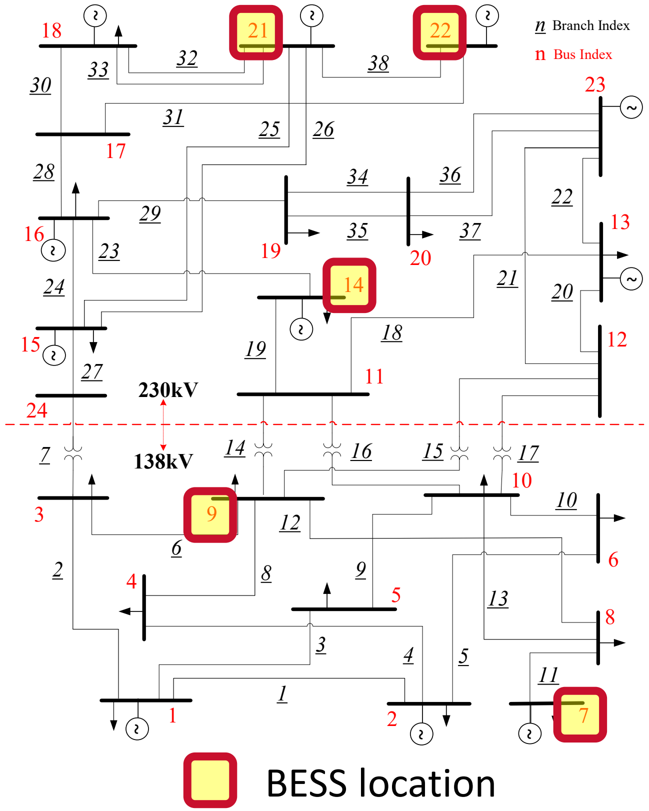


Table Relative mipgap tests on 5-BESS system.

Optimization Mipgap	Total Cost ($)	Degradation Cost ($)	Solving Time (s)
0.1	302,843.2	19,515.2	47.2
0.01	278,797.0	20,348.1	357.2
0.001	278,777.4	20,338.3	3600
0.0001	278,774.5	20,338.5	3600
0	278,774.5	20,338.5	3600

Summary

- Linearized L-BD-Energy Scheduling model

  - The “ReLU” activation function is reformulated to be linear.
  - The proposed L-BD-Energy Scheduling model that considers the equivalent battery degradation cost is directly solvable.

1. **Cunzhi Zhao** and Xingpeng Li, “An Alternative Method for Solving Security-Constraint Unit Commitment with Neural Network Based Battery Degradation Model”, *54th North American Power Symposium*, Salt Lake City, UT, USA, Oct. 2022.

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ReLu Approximation Methods

Motivation:

- The solving time take too long due to the heavy computing burden for L-BDMDS model.

Proposed Methods:

- Convex triangle area relaxation (CTAR)
- Penalized CTAR (P-CTAR)
- Penalized convex area relaxation (PCAR).

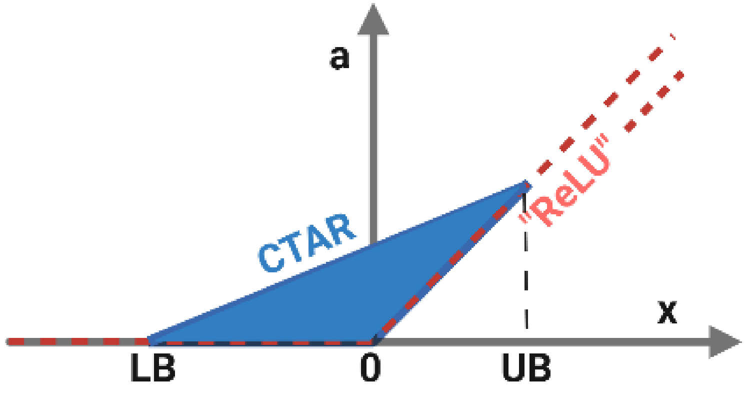


Figure. CTAR Illustration.

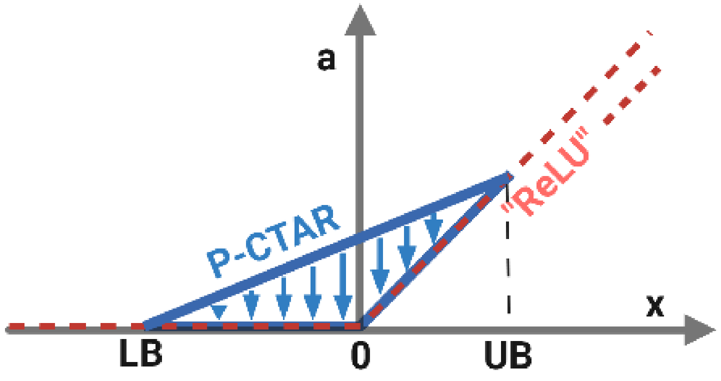


Figure. P-CTAR Illustration.

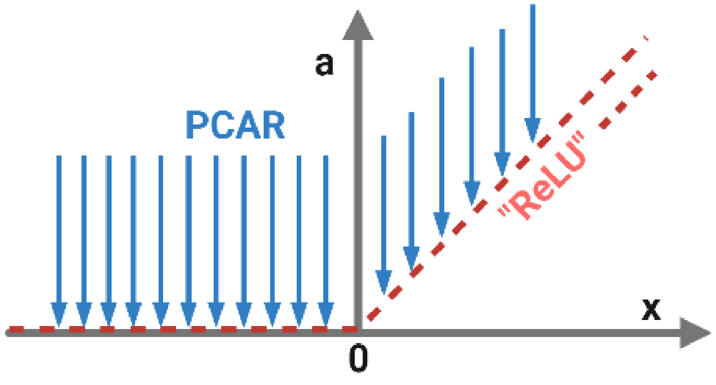


Figure. PCAR Illustration.

ReLu Approximation Methods Formulation

$$a_{\mathrm{h}}^{i} \leq x_{\mathrm{h}}^{i} + BigM * (1 - \delta_{\mathrm{h}}^{i})$$

$$a_{\mathrm{h}}^{i} \geq x_{\mathrm{h}}^{i}$$

$$a_{\mathrm{h}}^{i} \leq BigM * \delta_{\mathrm{h}}^{i}$$

$$a_{h}^{i} \geq 0$$

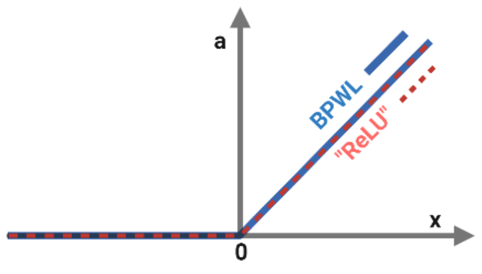


Figure. Linear “Relu”.

$$a_{\mathrm{h}}^{i} \leq \frac{UB}{UB - LB} x_{\mathrm{h}}^{i} - \frac{UB \cdot LB}{UB - LB}$$

$$a_{\mathrm{h}}^{i} \geq x_{\mathrm{h}}^{i}$$

$$a_{h}^{i} \geq 0$$

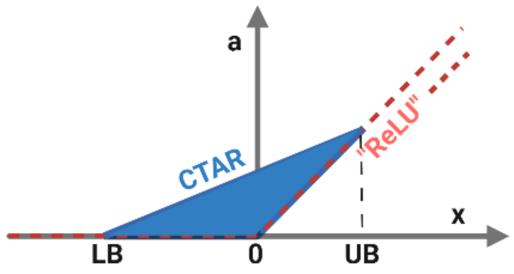


Figure. CTAR.

$$f^{c} = \sum a_{\mathrm{h}}^{i} c_{h}$$

$$a_{\mathrm{h}}^{i} \leq \frac{UB}{UB - LB} x_{\mathrm{h}}^{i} - \frac{UB \cdot LB}{UB - LB}$$

$$a_{\mathrm{h}}^{i} \geq x_{\mathrm{h}}^{i}$$

$$a_{h}^{i} \geq 0$$

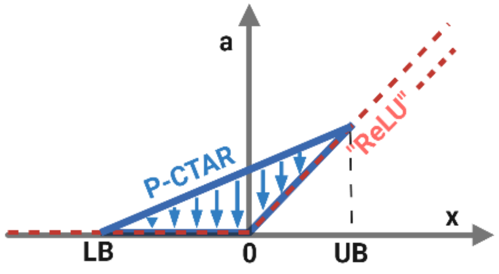


Figure. P-CTAR.

$$f^{c} = \sum a_{\mathrm{h}}^{i} c_{h}$$

$$a_{\mathrm{h}}^{i} \geq x_{\mathrm{h}}^{i}$$

$$a_{h}^{i} \geq 0$$

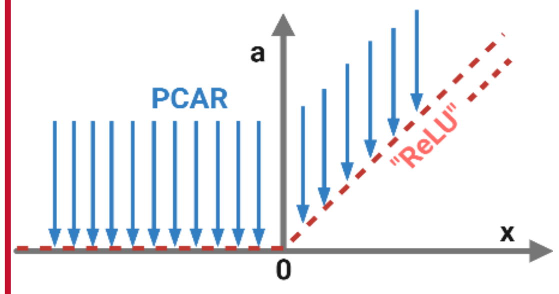


Figure. PCAR.

Results Analysis

The proposed model can also be applied in the bulk power system.

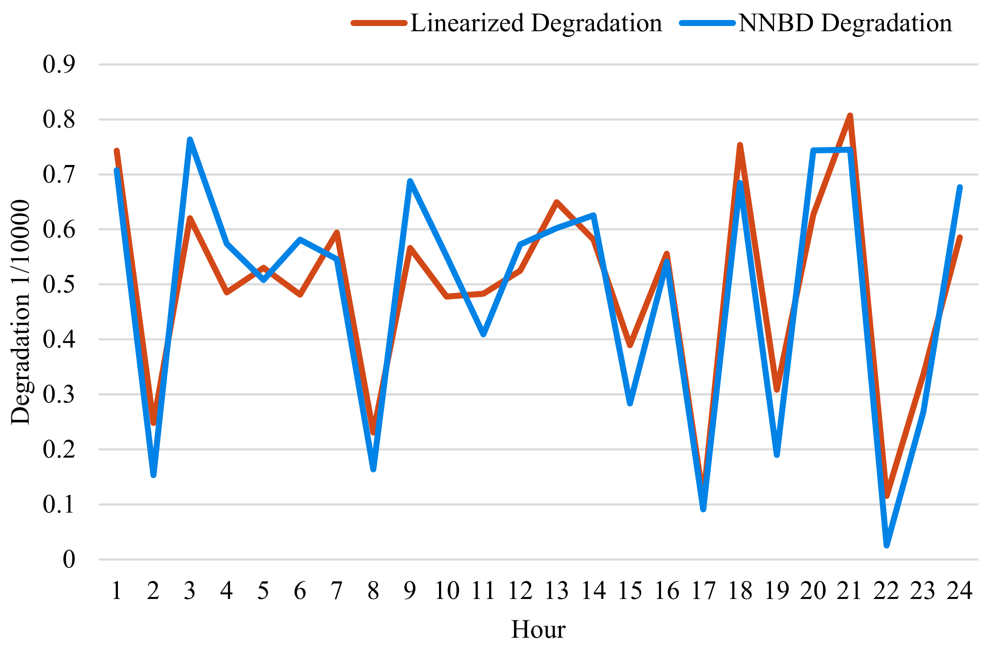


Figure. P-CTAR model degradation comparison.

Table MDS Results.

MDS	Basic	CTAR	P-CTAR	PCAR
Degradation	0.0368%	0%	0.0344%	0.094%
Real Degradation	0.037%	0.0487%	0.0348%	0.15%
Error %	0.543%	100%	1.14%	37%
Total Cost	$530	$489	$530	$651
Real Total Cost	$530	$543	$530	$719
Solving Time	28 s	0.9 s	8.75 s	0.58 s

Sparse Neural Network Assisted BDMDS

Motivation:

- The L-BD-MDS model in previous chapter is proved to be a feasible model for multi-BESS problems.
- The solving time take too long due to the heavy computing burden.

Proposed Sparse Neural Network Assisted BDMDS

- Train the Sparse Neural Network base on the existing NNBD model.
- Pruning method.
- Reduce the computing burden.

Increase the sparsity level of ***W***

$$x_h^i = \sum x_{h-1}^i * \boxed{W} + Bias$$

Linearization Sets

$$a_h^i = relu(x_h^i) = max(0, x_h^i)$$

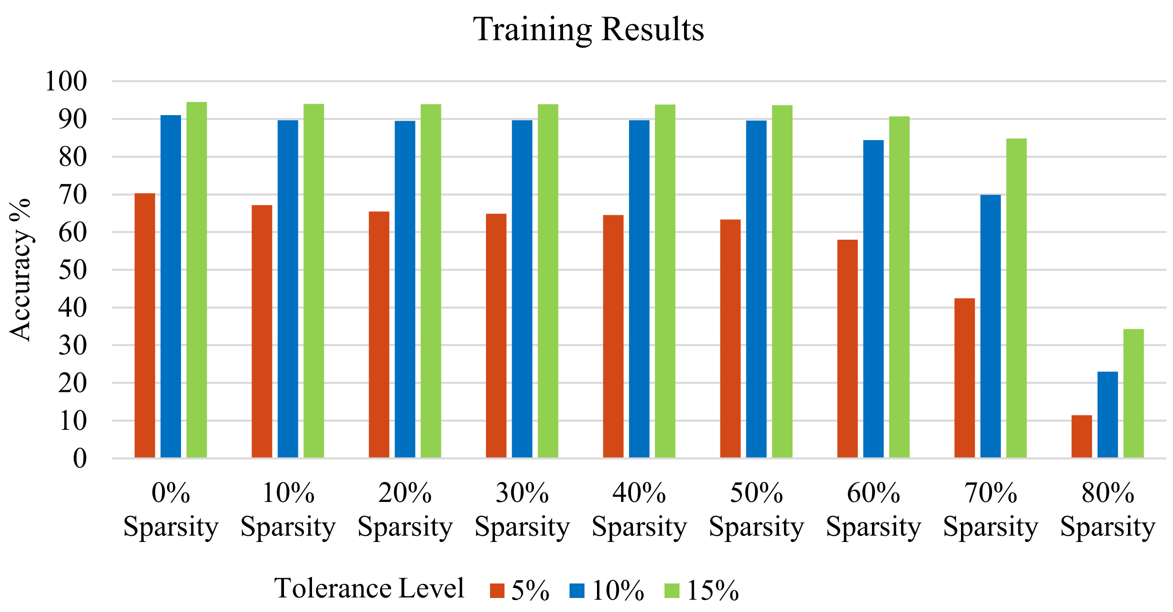
$$a_h^i \le x_h^i + BigM * (1 - \delta_h^i)$$

$$a_h^i \ge x_h^i$$

$$a_h^i \le BigM * \delta_h^i$$

$$a_h^i \ge 0$$

Results Analysis



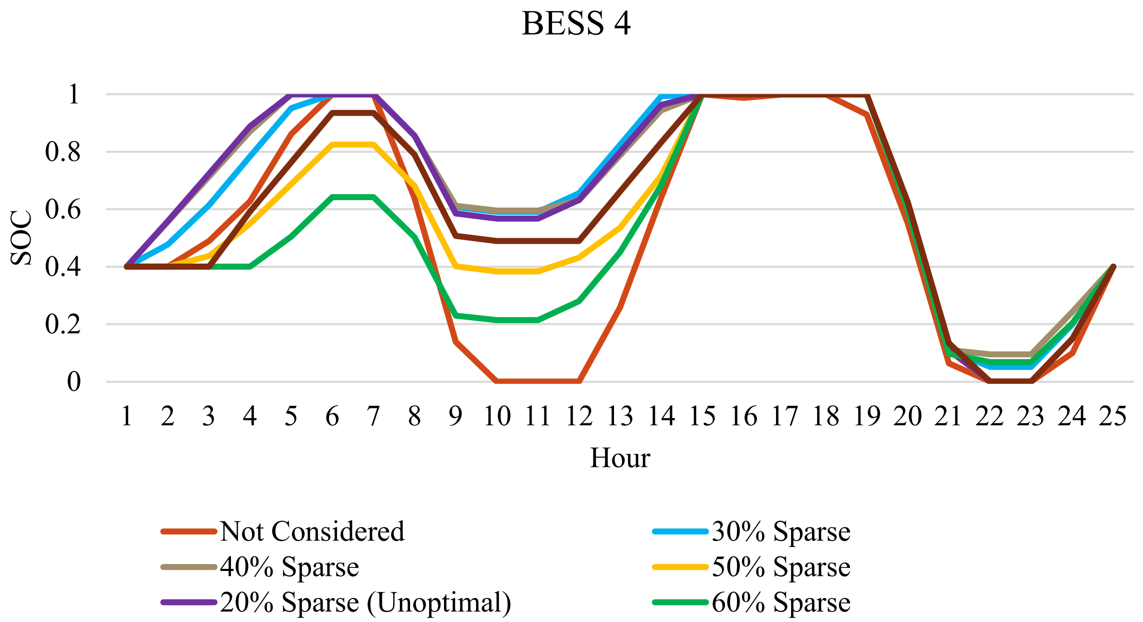


Table Training accuracy comparison

Error	0	10%	20%	30%	40%	50%	60%	70%	80%
5%	70.3	67.2	65.5	64.9	64.5	63.3	58.0	42.4	11.4
10%	91.0	89.7	89.5	89.7	89.7	89.6	84.4	69.9	23.0
15%	94.5	94.0	93.9	93.9	93.8	93.7	90.7	84.8	34.3

Table Solving efficiency comparison

Sparsity	10%	20%	30%	40%	50%
Operation Cost	/	259435	259848	260186	259472
Time	/	72000 (TO)	4383 s	1858 s	455 s

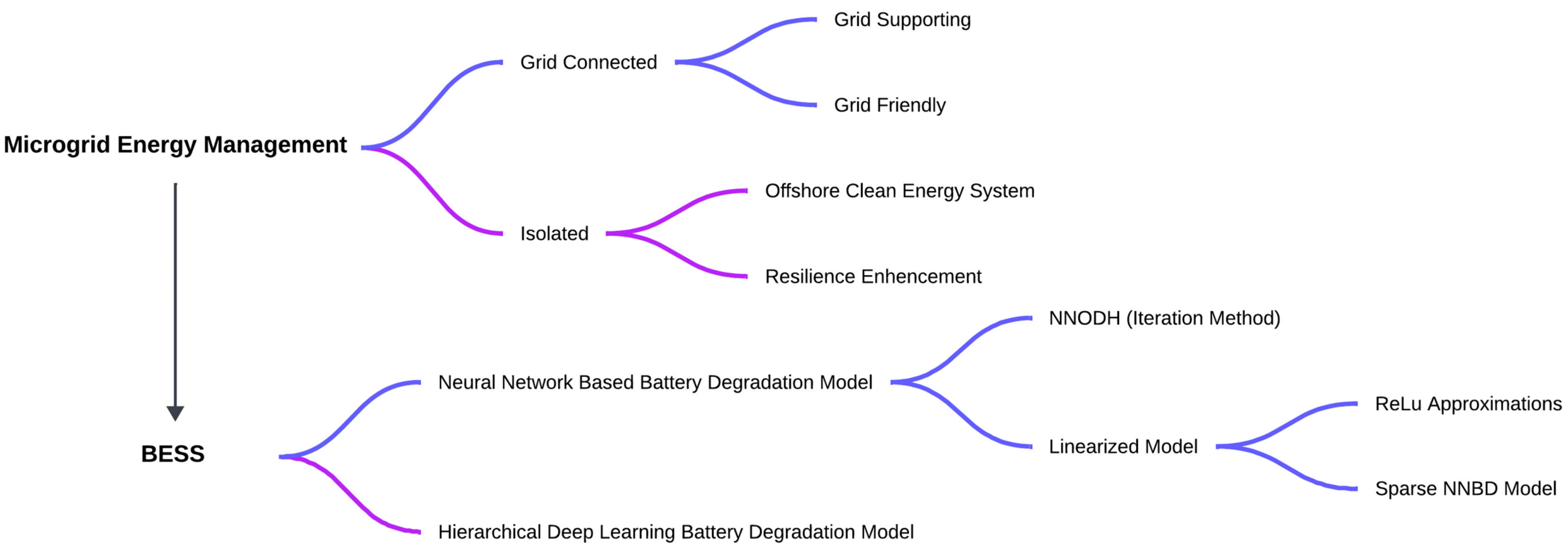
Summary

- Relu Linearization Approxiamtion Method:
  - Improve the computation efficiency for NNBD embedded optimization problem.

- Sparsity Neural Network
  - Reduce the complexity of the NNBD model.
  - Improving computational efficiency.

1. **Cunzhi Zhao** and Xingpeng Li, “Sparsity Neural Network Assisted Microgrid Day-ahead scheduling Considering Battery Degradation” *IEEE Transactions on Power Systems*, Sep. 2023 (Under Review).
2. **Cunzhi Zhao** and Xingpeng Li, “Linearization of ReLU Activation Function for Neural Network-Embedded Optimization: Optimal Day-Ahead Energy Scheduling” *Electric Power System Research (PSCC special issue)*, Sep. 2023 (Under Review).

Conclusions



Future Works

- Grid-integrated battery operational profile-based aging test; model: LSTM.
- Transfer learning for different types of battery.
  - Train a ML model (M1) for a given type of battery.
  - Use M1 as the starting model for training other types of battery: less data are required for training and testing process.
- Hydrogen Energy Storage System:
  - Develop the HESS model that can be integrated into the MDS problem.
  - Degradation model for HESS can be formulated using similar strategies.
- Continue working on the Impact of BESS on power energy markets:
  - LMP, load payment, generator cost, generator revenue, congestion cost, generator uplift payment, reserve cost.

Publications

1. **Cunzhi Zhao** and Xingpeng Li, “A Novel Real-Time Energy Management Strategy for Grid-Friendly Microgrid: Harnessing Internal Fluctuation Internally,” *The 52nd North American Power Symposium (NAPS),* Tempe, AZ, USA, Apr, 2021.
2. **Cunzhi Zhao** and Xingpeng Li, “A Novel Real-Time Energy Management Strategy for Grid-Supporting Microgrid: Enabling Flexible Trading Power,” *IEEE PES General Meeting 2021*, Washington, DC, USA, Jul. 2021.
3. Praveen Dhanasekar, **Cunzhi Zhao** and Xingpeng Li, “Quantitative Analysis of Demand Response Using Thermostatically Controlled Loads”, *IEEE PES Innovative Smart Grid Technology*, New Orleans, LA, USA, Apr. 2022.
4. **Cunzhi Zhao** and Xingpeng Li, “An Alternative Method for Solving Security-Constraint Unit Commitment with Neural Network Based Battery Degradation Model”, *54th North American Power Symposium*, Salt Lake City, UT, USA, Oct. 2022.
5. **Cunzhi Zhao** and Xingpeng Li, “A 100% Renewable Energy System: Enabling Zero CO2 Emission Offshore Platforms”, *54th North American Power Symposium*, Salt Lake City, UT, USA, Oct. 2022.
6. **Cunzhi Zhao**, Jesus Silva-Rodriguez and Xingpeng Li, “Resilient Operational Planning for Microgrids Against Extreme Events”, *Hawaii International Conference on System Sciences*, Maui, Hawaii, USA, Jan. 2023.
7. **Cunzhi Zhao** and Xingpeng Li, “Microgrid Optimal Energy Scheduling Considering Neural Network based Battery Degradation”, *IEEE Transactions on Power Systems*, early access, Jan. 2023.
8. Ali Siddique, **Cunzhi Zhao**, and Xingpeng Li, “Microgrid Optimal Energy Scheduling with Risk Analysis”, *Texas Power and Energy Conference*, College Station, TX, USA, Feb. 2023.
9. **Cunzhi Zhao**, Xingpeng Li, and Yan Yao, “Quality Analysis of Battery Degradation Models with Real Battery Aging Experiment Data”, *Texas Power and Energy Conference*, College Station, TX, USA, Feb. 2023.
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UH RPG Lab

Thank you!

Cunzhi Zhao