Optimal, Reliable Building-Integrated Energy Storage

Cooperative Research and Development Final Report

CRADA Number: CRD-17-00723

NREL Technical Contacts: Aron Saxon and Partha Mishra

NREL is a national laboratory of the U.S. Department of Energy
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Technical Report
NREL/TP-5700-82454
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Cooperative Research and Development Final Report

Report Date: March 18, 2022

In accordance with requirements set forth in the terms of the CRADA agreement, this document is the CRADA final report, including a list of subject inventions, to be forwarded to the DOE Office of Scientific and Technical Information as part of the commitment to the public to demonstrate results of federally funded research.

Parties to the Agreement: Eaton Corp.

CRADA Number: CRD-17-00723

CRADA Title: Optimal, Reliable Building-Integrated Energy Storage

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Sponsoring DOE Program Office(s):

U.S. Department of Energy Office of Technology Transitions (OTT)

U.S. Department of Energy Grid Modernization Laboratory Consortium (GMLC)

Joint Work Statement Funding Table showing DOE commitment:

Estimated Costs	NREL Shared Resources a/k/a Government In-Kind
Year 1 Year 2	$250,000.00 $275,000.00
TOTALS	$525,000.00

Executive Summary of CRADA Work:

The team will advance the commercial readiness of behind-the-meter (BTM) energy storage (ES) systems by employing health-conscious controls that guarantee lifetime and optimize the ES system's value stream when integrated with onsite renewable energy generation. Specifically, the team will develop ES controls that increase the net present value (NPV) of photovoltaics (PV) by 50% in markets where net-metering policies are being replaced by variable electricity pricing structures. The team will also reduce the risk of achieving a 10-year ES warranty lifetime by at least one order of magnitude. The successful two-year project will develop the controls and system enabling Eaton to commercialize the technology by 2021. The developments achieved through this project may enable wide scale adoption of stationary energy storage benefitting the public.

Summary of Research Results:

Recent trends of elimination or modification of net-metering policies by utilities combined with time-of-use rate structures have created financial incentives for facilities to better manage loads and store renewable energy onsite, thus catalyzing the BTM energy storage market. The following tasks outlined in this report illustrate the steps taken within this project scope to further the adoption of this BTM energy storage solution developed by Eaton.

Task 1: Develop a health-conscious energy storage **supervisory controller that guarantees** energy storage **lifetime in excess of 10 years and maximizes overall system performance to increase penetration of renewables such as PV in distributed residential and commercial applications.**

Under Task 1, a degradation-aware algorithm was developed to incorporate battery state of health monitoring and battery operation into the economic optimization of the battery system. The current standard approach in lifetime techno-economic modeling is to assume a useful battery life. This approach does not capture the battery energy storage system (BESS) being greatly dependent on depth and number of cycles, cell temperatures, and time-weighted states of charge. The 10-year life assumption may be overly conservative or optimistic depending on the dispatch of the system. To make an informed decision of the dispatch of the BESS the model should cover the optimum size while considering the degradation impact of the system. To address this information process, NREL developed a novel process to incorporate non-linear battery degradations into a linear program. The addition of the degradation model ensures the BESS sizing and dispatch balance avoided utility costs with state-of-health impacts, so the usage cost does not exceed revenue.

To evaluate the impact of the inclusion of a degradation model, the Los Angeles tariff used in the business case analysis was modeled. However, since the load for the California site described in the previous section were so small, and resulted in small battery sizes, the load was increased. Three separate runs were made for this site: (1) without the degradation model included, (2) with the degradation model included but forcing in the optimal system sizes from the first run, (3) with the degradation model and having the model size the cost-optimal components. Model results are presented Table 1. It is shown that by accounting for degradation in the system, the lifetime in years is increased from 4.8 year to 19.9 years without impacting the overall system cost. This equates to a reduction of degradation costs by a factor of four. This reduces the overall lifecycle cost and retains most of the battery’s value. If the model is able to select the size of the system, it selects a larger system and reduces the total lifecycle cost even further.

Table 1. Comparing system sizes, battery life as calculated using the degradation surface in REopt, and degradation costs.

	No Degradation (assumes 10-yr life)	Degradation – Fixed Sizes	Degradation – Optimized Sizes
Battery power [kW]	108	108	136
Battery storage [kWh]	126.7	126.7	166
PV Size [kW-DC]	401	401	408
Life (as calculated by REopt) [yrs]	4.8	19.9	19.9
Cost of Degradation	$ 84,800	$ 22,620	$ 29,600
Lifecycle Cost	$ 2,496,360	$ 2,482,090	$ 2,479,700

Figure 1 presents a representative week of dispatch comparing the state of charge (SOC) profiles of the no-degradation and degradation cases (with fixed sizes from the no-degradation case). One can note that the degradation-aware results limit the maximum depth of discharge (DOD) component (in this case not going after full charge/discharge for time-of-use energy arbitrage) and maintain a moderate resting SOC. Important peak shaving events (such as seen on July 5th) are still addressed with the degradation aware case, but the SOC is raised and lowered quickly to achieve the peak shaving required.

Figure 1: Comparing the state of charge for a representative week between the no-degradation case and the degradation-aware case (with the optimal size from the no-degradation case)

Task 2: Integrate a learning ability for the controller to adjust to uncertain battery initial health and degradation. This technology enables (1) the use of low-cost second-life electric vehicle (EV) batteries such as in the Eaton xStorage system, and (2) reduces the need to conduct slow and expensive cell-aging tests when adapting the system to future battery technologies.

In this task, the learning ability is imparted to the controller by developing an estimation framework which can update battery life model parameters from usage data thereby enabling auto-tuning of a nominal battery life model to adjust for uncertain battery initial health and degradation rates. Traditionally, battery life models, that involve capacity decay and resistance growth models, are developed by fitting rapid aging experimental data to semi-empirical battery life models. These models use simple proxy models for various degradation mechanisms that occur in Lithium-ion batteries. However, as with any empirical model, the accuracy of these models is limited to the quality of the training data used to develop these models and these models need updating as the battery ages with different usage patterns. This task develops a hierarchical estimation framework (see Figure 2) that continuously monitors the operation and various measurements from the battery (pack/cell) to update the underlying models for estimation.

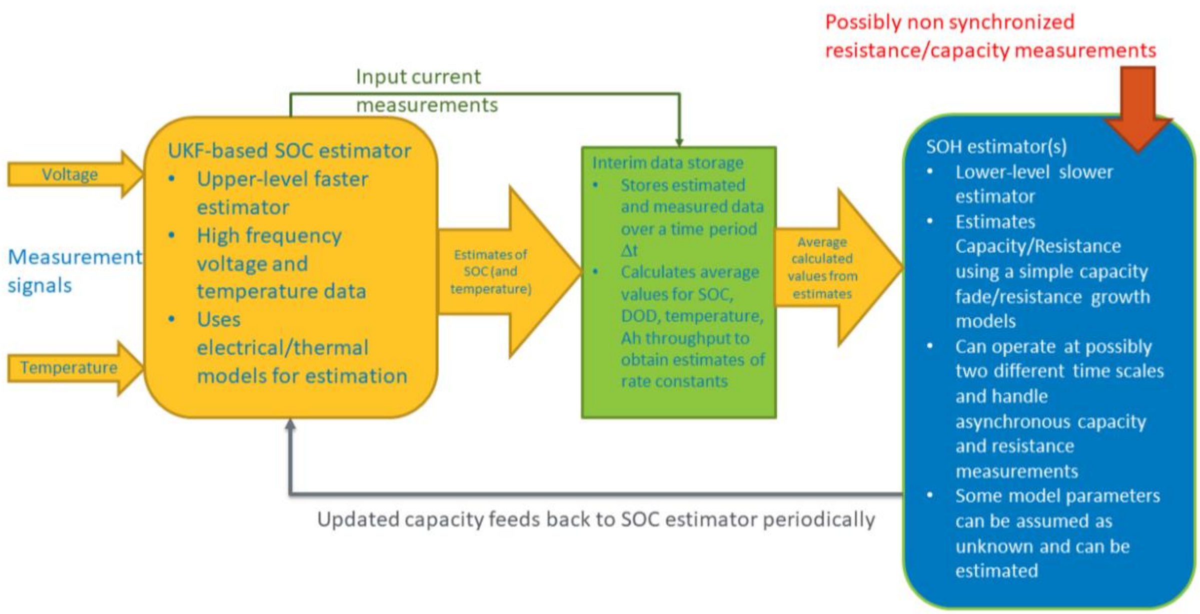
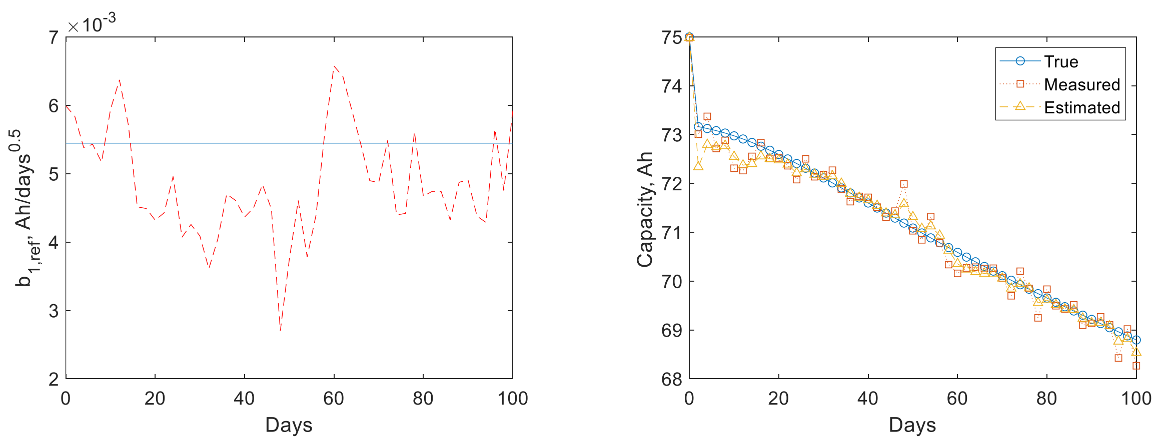


Figure 2: Flowchart of the hierarchical auto-tuning battery state of charge and state of health estimator

The framework consists of the following steps:

1. Faster upper level estimator – This estimator (hereby called the performance estimator) is setup to estimate battery internal states such as SOC and temperature that changes at a faster rate as the battery is being used. The estimator, operating at time samples ranging from seconds to minutes, uses an underlying electro-thermal model and measurement signals such as current, voltage, and temperature to estimate these internal states.
2. Interim data storage step – In this step, the estimated (e.g. SOC) and measured (e.g. temperature) signals are stored over a period such as a day or two. From this data, derived quantities such as average SOC, maximum (DOD), amp-hour throughput etc. are calculated to be used in the underlying life model(s).
3. Slower low level estimator(s) – The derived quantities are used in these low level estimators to: (a) estimate battery health degradation rates, and (b) tune health-related parameters as new measurements become available over the life of the battery (hereby called the SOH estimator). These unscented Kalman filter (UKF) based estimators use capacity degradation and resistance growth nominal models which are developed from rapid aging experimental data. Model parameters which show significant impact on resultant capacity and resistance can be assumed to be unknowns and whose values are continuously tuned to improve the estimation.

Simulation based analysis using a simplified life model shows how the estimation framework estimates and modifies life model parameters (one parameter in this example) to estimate capacity of the cell.



(a) Auto-tuning of model parameter $b_{1,ref}$

(b) Capacity estimation as an indicator of state of health

Figure 3: Simulation based case study result showing auto-tuning of degradation model parameter that can be used by the health-conscious controller

Task 3: Use techno-economic analysis to identify target markets for commercialization of the technology and quantify its value in terms of payback period, NPV, reduction of monthly utility bills, self-consumption of onsite renewable generation and resilience to grid outages or fluctuations.

NREL's REopt tool [1] was used to perform the techno-economic analysis for three cases (1) baseline case without energy storage, (2) addition of business-as-usual energy storage, and (3) addition of energy storage with the battery health-conscious supervisory control (Task 1). REopt is a rapid screening and component sizing tool that identifies and optimizes renewable energy projects at a single site, or across a portfolio of sites, to meet techno-economic objectives. Figure 4 shows REopt simulation results for a scenario in Hawaii where feeding excess photovoltaic (PV) power to the grid is prohibited. Without energy storage (top), much of the available PV resource (dictated by roof area available) goes unused, undercutting the value of PV. With energy storage and with some shifting of air conditioning (AC) and domestic hot water (DHW) loads, the entire PV resource is used.

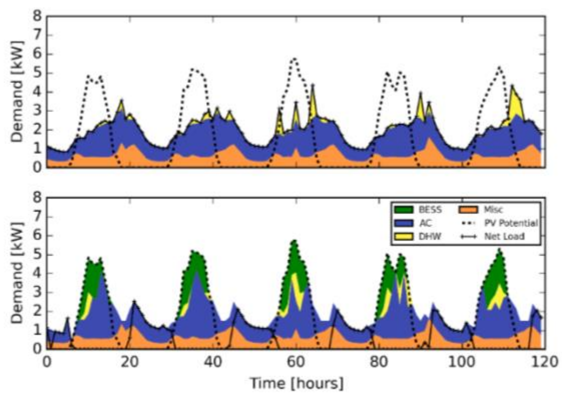


Figure 4: PV potential overlaid with site loads for a facility in Hawaii (to). Optimal strategy for onsite PV self-consumption using combination of energy storage and shifting of heating/cooling loads (bottom)

Based on these analyses, Eaton identified the target markets and products in energy storage and microgrid controller as follows:

- Eaton UPS (North America) and xStorage (Europe, Middle East, Africa (EMEA)): Datacenters are increasingly adopting Li-ion backed servers and Eaton's UPS product line now offers Li-ion batteries to the industry. The UPS product line has been adopted in EMEA (commercialized as xStorage) for microgrid and BTM applications. Battery degradation is based on supplier data and the controls are based on rule-based dispatch.
- Eaton microgrid controller Power Xpert Energy Optimizer (PXEO): Eaton also offers a microgrid and DER controller in which the energy storage degradation status is derived based on a simple estimated linear projection based on cell supplier. The DER dispatch algorithm currently mainly addresses power quality and resiliency with strategies for focusing on reducing operating expenses.

Task 4: Integrate and demonstrate the health-conscious supervisory controls on Eaton's xStorage energy storage **system in a residential hardware-in-the-loop (HIL) environment at NREL.**

The original project plan was to implement and evaluate Eaton's controls in HIL experiments. Due to delays in sourcing a testing article and delays due to lab shutdown during the pandemic, the hardware testing plan was shifted to focus on battery life testing of xStorage pack to 1) evaluate and further tune the life model developed on Nissan cell data and 2) gather data for training and improving the SOC/SOH estimator. For the life testing, the xStorage pack sat in a chamber set to 25°C and was cycled using a compressed profile based on Eaton's field data. After the life testing, there was minimal degradation on the pack, less than 2%. The life model prediction was compared to the testing data which showed good match in the middle but errors at the beginning and the end. This was due to the too little degradation and too few testing data points, causing large uncertainty in life model parameters identification. As a result of this, Task 5 and Task 6 were included to provide more insight into the pack degradation and life model fitting. These two tasks were completed using plus-up funding from Eaton.

Task 5: Perform at least 3 months of xStorage life cycling at TTF with monthly RPT and HPPC.

Under Task 5, NREL performed life cycling of the Eaton xStorage system. This task required a minimum of three months cycling degradation and NREL was able to perform 16 months of life tracking which include blocks of four months cycling, six months calendar aging, and six months of cycling. Figure 5 illustrates the cycling and rest conditions of the xStorage unit at the TTF. The six months of calendar aging resulted from a contract modification to gather additional data for higher model validity. Under this task, NREL successfully performed ten RPTs to map the system degradation over this time. Figure 6, Figure 7, and Figure 8 outline the experimental setup.

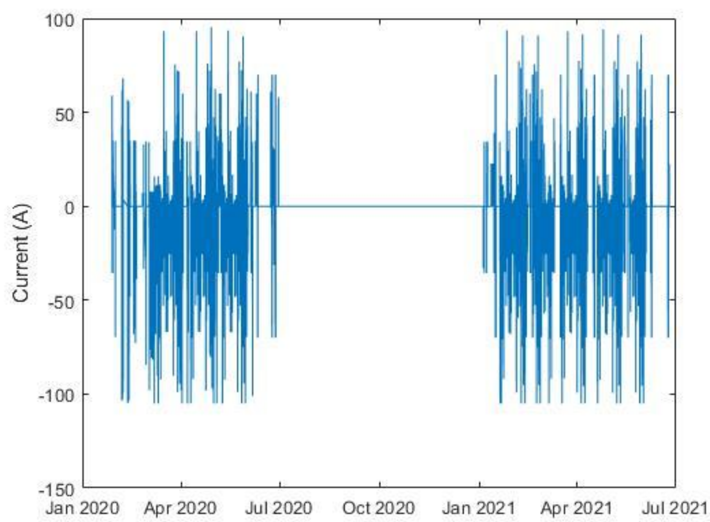


Figure 5: Life Cycling of Eaton xStorage System

Figure 6: xStorage pack in the CSZ environmental chamber

Figure 7: ABC-150 Battery Cycler

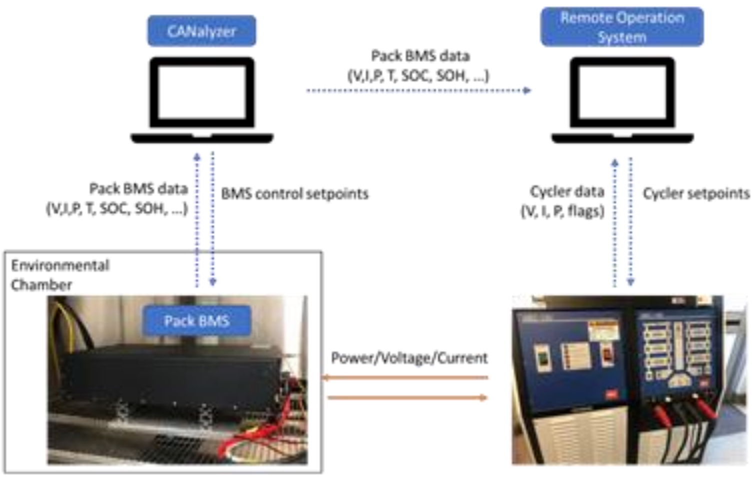


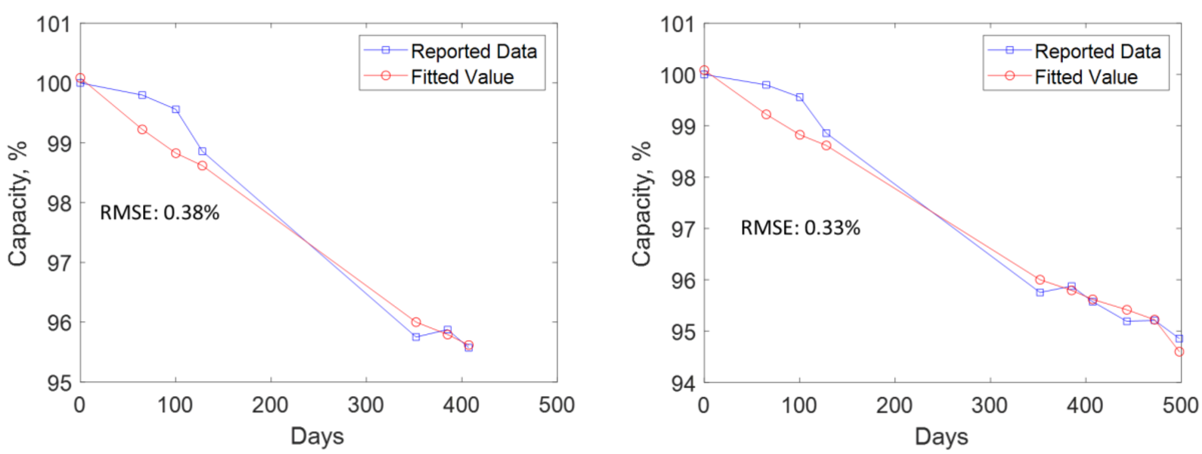
Figure 8: Schematic of Experiment Setup

Task 6: Modify the Nissan life model to best fit the xStorage test data. NREL will generate the best model prediction degradation curve and error bounds to demonstrate life model prediction capability with key parameters affecting prediction accuracy.

In this task, the Kokam cell model [2] and modified it to best fit the experimental degradation data for the Nissan xStorage battery pack was adopted. The battery pack is cycled using an Eaton developed custom cycling profile. Between July 2020 to almost January 2021, the battery was kept in storage conditions due to cycling interruptions. Overall trend observed after more than a year of degradation testing alluded to a Lithium (Li)-limited capacity loss as the dominant degradation mechanism. The Li-limited capacity loss model from [2] is modified to fit the experimental data in this project as:

$$Q_{Li} = b_0 - b_1 t^p - b_2 N - b_3(1 - \exp(-t/\tau_{b_3})) \quad (1)$$

In Eq. (1), b_0 is the relative battery capacity at beginning of life (BOL), b_{1-3} are rate constants that are dependent on cycling conditions, t, N are calendar time and number of cycles, and p, τ_{b_3} are exponentials and time constants dictating the dependency of capacity degradation with time and duration of the break-in mechanism term. We selected a subset of the model parameters (affecting the rate constants b_{1-3} and the exponent p) provided in [2] and tuned those parameters such that error between the model predicted capacities and measured capacities is minimized. Several iterations of model tuning are carried out during the project. The final list of tuned parameters is identified by using data from over 400 days of testing (Figure 9(a)). Tuned model is used to predict the relative capacity for the rest of the duration of testing (i.e. 400-500 days), thereby validating the identified model. Root mean square error (RMSE) for both model fitting and model validation was found to be <1%.



(a) Model parameters are tuned using >400 days of testing data

(b) Identified model parameters are used to predict degradation between 400-500 days of testing.

Figure 9: Model parameters are tuned using part of the experimental data while rest of the data is used to validate the tuned model

Conclusion

In this project, NREL analyzed business cases using the REopt model and data provided by Eaton to investigate how the utility tariff, site load, and battery degradation impact the optimal battery sizing, operation, and lifetime benefit in BTM applications. The team compared model results of cases with no-degradation, degradation with fixed system sizes, and degradation-based optimal system sizes. The team found that an assumed BESS life of 10 years can be a poor assumption. This is because dispatch decision-making process without considering battery state-of-health information can result in much shorter useful life of BESS than a 10-year rule-of-thumb. The team found an accurate battery degradation-based dispatch decision-making process can improve overall system economics with extended battery service life. From simulation, the degradation-aware results limit some deep DOD events and maintain a moderate resting SOC. Important peak shaving events are still addressed with the degradation-aware case, but the SOC is raised and lowered at each event to achieve the peak shaving while simultaneously minimizing extended periods of time where battery is at high SOC, which negatively impacts battery life.

From the business case analysis, it became clear that control decisions need to be determined by considering both the potential revenue that could be gained (demand savings) and the impact on battery SOH. Therefore, it is key to add a battery life model into control decision-making process. One challenge in battery life modeling is that it is highly sensitive to varied battery technology and availability of real testing data, which is perquisite to develop an accurate life model conventionally in advance. To make the battery life model technology-agnostic, a hierarchical SOC/SOH estimator has been developed to automatically tune key life model parameters on-the-fly. The UKF-based two-stage estimator works with one stage running on a faster timescale to estimate SOC while the other running on a slower timescale to estimate SOH. The estimator was trained and evaluated using synthetic data from an electrical-thermal model and able to converge to the true values of SOC and SOH in this project.

Eaton has reviewed different controls before incorporating battery SOC/SOH estimator developed by NREL team. Several control options, including average SOC, time-selected charging and energy arbitrage, are shown to affect the energy storage life quite differently while providing very similar operation savings in the BTM applications. These control options not only help determine how a system should be designed and operated for any particular user scenario, but also enable great potentials to suggest real-time control opportunities during the practical operation under the uncertain load characteristics. Coupled with an agnostic and hierarchical SOC/SOH estimator developed and validated on Eaton xStorage systems, an intelligent Eaton DERM controller software framework is ready to be implemented and commercialized soon.

Two software records were submitted out of this project:

- NREL SWR-20-22 Battery State of Health Linear Model
- NREL SWR-20-24 Hierarchical Real-time State-of-health and State-of-charge Estimator

References

[1] https://reopt.nrel.gov/, Accessed 8/1/2021

[2] K. Smith, A. Saxon, M. Keyser, B. Lundstrom, Ziwei Cao and A. Roc, "Life prediction model for grid-connected Li-ion battery energy storage system," 2017 American Control Conference (ACC), 2017, pp. 4062-4068, doi: 10.23919/ACC.2017.7963578.

Subject Inventions Listing:

None

ROI #:

None