INL/EXT-21-65443-Revision-1

# A Technical and Economic Assessment of LWR Flexible Operation for Generation and Demand Balancing to Optimize Plant Revenue

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Light Water Reactor Sustainability Program

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**Dylan McDowell, Anna Wrobel, Paul W. Talbot, Konor Frick, Haydn Bryan, Jason Hansen, Richard D. Boardman (INL)**

**John Taber, Chad Boyer (EPRI)**

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# EXECUTIVE SUMMARY

With increased penetration of variable renewable energy (VRE) resources that are often subsidized and competition from low natural gas prices, existing light water reactor (LWR) nuclear power plants (NPPs) are struggling to remain economically competitive. This work examines the potential economic competitiveness of various thermal energy storage (TES) technologies when coupled directly or indirectly with an NPP. To highlight their relative economic competitiveness, we contrast several energy storage solutions in stochastic dispatch optimization.

We leverage data from recent work analyzing a range of TES technologies with varying capital costs, performance, and technology readiness level (TRL) to establish our case. We explore inserting these technologies into an electricity market with existing nuclear generation and large projected variable renewable energy (VRE) penetration. Although the project capital costs of these technologies may make them unlikely candidates in their current state, this analysis demonstrates a high-fidelity techno-economic analysis of energy storage. Furthermore, as the projected cost of energy storage technologies evolves, this analysis sets a precedent for similar future investigations.

One region with projected trends that may be unfavorable for existing nuclear capacity is the New York Independent System Operator (NYISO) market. New York state's baseload generation has been historically provided by fossil-fired, nuclear, and hydro assets. However, amid economic pressures from subsidized VREs and low natural gas prices, Indian Point nuclear power plant units 2 and 3 have recently shut down. Furthermore, the state plans to meet its zero-emission generation target by 2040 by replacing fossil-fired capacity with significant investments in VRE resources like wind and solar photovoltaic (PV) and battery storage. Increased intermittent resource penetration lowers the baseload power requirement, adding further economic pressure to the state's three remaining NPPs still in operation. This work analyzes potential economic benefits to the three remaining NPPs on the New York grid when directly or indirectly coupled with various TES technologies.

This work requires two modeling steps to analyze the potential economic benefits of various system configurations of the TES directly or indirectly coupled with nuclear. First, this analysis leverages capacity expansion modeling by experts at the Electric Power Research Institute (EPRI) who are authors on this study. Using their deterministic capacity expansion model, U.S. Regional Economy, Greenhouse Gas, and Energy (US-REGEN), EPRI analysts evaluated the capacity and generation evolution of the New York state energy market under four projection scenarios. These four projection scenarios were developed to represent the potential evolution of the capacity and generation in NYISO from 2015 to 2050 under various economic, technology, and policy constraints. The results from these capacity expansion models are then used as boundary conditions in the second modeling step.

The second modeling step, performed by the INL authors, uses the Holistic Energy Resource Optimization Network (HERON) for a set of stochastic techno-economic analyses (STEAs) to investigate the potential increase in the economic viability of various configurations of the TES. With no current capacity expansion capabilities, HERON takes the data generated from US-REGEN for 2050 to generate synthetic load, solar, and wind data. Then HERON economically optimizes the capacity and dispatch of the various TES configurations. The potential economic benefit is the differential net present value (NPV) of the TES configurations from the no-TES baseline. As a stochastic techno-economic analysis package, HERON introduces uncertainty into the economic metrics, while US-REGEN trades resolution for reduced computational complexity. Using HERON also allows the modeling of direct thermal coupling, a feature not common in capacity and dispatch models.

As expected, with high capital costs, the costs of introducing energy storage for all the technologies considered outweighed the potential economic benefit of this strategy for flexible plant operation under Reference scenarios. However, for scenarios with elevated electricity prices, due to implementation of a nationwide clean energy standard, there is a clear benefit from introducing TES to provide NPP flexibility. Further, in the clean energy standard cases, new NPP can be profitably introduced when coupled to TES to further increase profitability, demonstrating a complementary balance between VRE generation and NPP coupled with TES.

And additional benefit of this analysis is primarily in demonstrating a workflow that examines innovative solutions to increase NPP revenue via TES coupling. HERON's stochastic capacity and dispatch optimization process used in this work has proven an effective tool in observing and evaluating the impact of introducing storage technologies in a grid energy system.

## ACKNOWLEDGEMENTS

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# ACRONYMS

| | |
|---|---|
| ARMA | Auto-regressive moving-average |
| CAPEX | Capital expenditures |
| CCS | Carbon capture and sequestration |
| CES | Clean Energy Standard |
| CLCPA | Climate Leadership & Community Protection Act |
| EPRI | Electric Power Research Institute |
| EST | Eastern Standard Time |
| ETES | Electro-Thermal Energy Storage |
| FARMA | Fourier Auto-Regressive Moving-Average |
| FORCE | Framework for Optimization of Resources and Economics |
| FPOG | Flexible Plant Operation and Generation |
| GMT | Greenwich Mean Time |
| HERON | Holistic Energy Resource Optimization Network |
| IES | Integrated Energy Systems |
| INL | Idaho National Laboratory |
| LCOS | levelized cost of storage |
| LWR | Light-water reactor |
| NGCC | Natural gas combined cycle |
| NGCCS | Natural gas with carbon capture and sequestration |
| NGCT | Natural gas combustion turbine |
| NPP | Nuclear power plant |
| NPV | Net present value |
| NYCA | New York Control Area |
| NYISO | New York Independent System Operator |
| PTC | Production Tax Credit |
| PV | Photovoltaic |
| RAVEN | Risk Analysis Virtual Environment |
| RPS | Renewable Portfolio Standard |
| RTE | round trip efficiency |
| SHS | sensible heat storage |
| SOEC | Solid oxide electrolysis cell |
| STEA | Stochastic techno-economic analysis |
| TES | Thermal energy storage |

| | |
|---|---|
| TRL | Technology readiness level |
| US-REGEN | U.S. Regional Economy, Greenhouse Gas, and Energy Model |
| VRE | Variable renewable energy |

# A TECHNICAL AND ECONOMIC ASSESSMENT OF LWR FLEXIBLE OPERATION FOR GENERATION/DEMAND BALANCING TO OPTIMIZE PLANT REVENUE

## 1. INTRODUCTION

As the global energy landscape transitions toward grid decarbonization and strives to meet clean energy targets, there has been renewed interest in the role of nuclear energy to provide clean and reliable baseload power generation. Currently, nuclear power provides $1/5^{th}$ of the total electricity generation and roughly half of the total carbon-free energy produced in the United States. Furthermore, nuclear power plants (NPPs) provide carbon-free and reliable baseload generation 24 hours a day, seven days a week. However, power generation mixes are undergoing rapid changes driven by technological advancements, emissions targets, and market factors.

Over the last decade, grid decarbonization efforts and technological advancements have driven the sharp impetus towards investment in variable renewable energy (VRE) resources, like wind and solar photovoltaic (PV) generation. Furthermore, government subsidies for wind and solar PV have pushed the expansion of VRE portfolios in many areas of the U.S. Increased penetration of weather-dependent, intermittent resources creates challenges in both hourly and seasonal balancing of intermittency and maintaining grid reliability. Increased capacity investment in VRE resources creates over-generation in times of high availability, decreasing baseload generation requirements during those times. Furthermore, historically low natural gas prices have increased investment in gas turbine generation. With increased competition in the electricity grid from low natural gas prices and low-cost VREs, NPPs are under increasing pressure to remain economically competitive.

Operating NPPs flexibly is a potential solution. In a flexible plant operation, the nuclear power plant varies power output to meet market demands, ramping up in times of low VRE production and down in times of high VRE production. Although flexible plant operation has been successfully applied in France for more than 30 years [1], this operation method is not in practice in the U.S. With fixed refueling contracts, existing license limitations, and fixed dollar per megawatt-hour operations and maintenance costs, the economic benefits of load-following to U.S. based NPP operators remains unproven [2].

Another potential solution to increase the economic competitiveness of nuclear is by operating NPPs as a part of an integrated energy system (IES). For example, NPPs coupled with energy storage could supply power to the grid during times of scarcity and store energy during periods of oversupply. The stored energy is later converted back to electricity to supply the grid in a power-storage-power scenario. Integrating energy storage with existing NPPs would reduce curtailment, allowing plants to maintain high-capacity factors.

Much of the focus on energy storage technology in the past decade has been on lithium-ion (Li-ion) battery storage, despite its high costs [3], challenges in cold climates [4], and recent problems with facility fires and explosions [5] [6]. Another promising energy storage technology that is being explored by both academia (e.g., [3] [7] [8]) and industry [9] for potential NPP coupling is thermal energy storage (TES). Since nuclear reactors produce heat, coupling TES with an NPP allows the plant to operate at full power without sacrificing efficiency lost in the conversion. While the capital costs of TES are generally projected to be lower than Li-ion, they are still significant. To be economically beneficial, the flexibility introduced must be sufficient to overcome the capital costs of TES. Although high capital costs may deny practical TES deployment, this analysis demonstrates a high-fidelity techno-economic analysis of energy storage.

One energy market in the U.S. facing challenges in balancing intermittency and maintaining grid reliability is the New York state electricity market. The New York state grid, operated by New York

Independent System Operator (NYISO), plans to meet its zero-emissions climate target by 2040 through significant investment in VRE resources, battery storage, and phasing out of fossil-fired generation [10]. Among challenges to remain economically competitive with subsidized VRE resources and low natural gas prices, two nuclear units at Indian Point Energy Center have been deactivated, a loss of roughly 2,000 MW of baseload capacity. With three NPPs of about 3,200 MW of capacity still in operation, this analysis is interested in the potential increase in economic benefit to the existing NPPs on the NYISO grid when coupled with one of several TES technologies compared with more common electrical storage mediums such as Li-ion and hydrogen. Leveraging previous work analyzing storage technologies with the potential to be coupled with existing light water reactors (LWRs) [11], three different TES technologies were chosen for our analysis, Electro-Thermal Energy Storage (ETES), Thermal Hitec XL, and Thermal Dowtherm A. More on the TES technologies considered in our analysis can be found in Section 4.

This work focuses on proving the effectiveness of state-of-the-art INL software tools in observing and evaluating the impact of introducing storage technologies in a grid energy system. The software Holistic Energy Resource Optimization Network (HERON) is a tool for capacity and dispatch optimization. As a representative case to prove the effectiveness of HERON, this analysis performs Stochastic Techno-Economic Analyses (STEA) of several different TES technologies in the NYISO energy market. The STEA aims to investigate the potential increase in the economic viability of an NPP when coupled with TES, considering several different TES technological varieties. First, under varying assumptions and policies, four capacity expansion possibilities for New York state are established as baselines for comparison. The impact is then determined by comparing the system's economic viability in the no-TES baseline to an NPP coupled with TES technology. The analysis also examines the optimal configuration of the system and how much of each technology can benefit the system.

## 1.1 Simulation Tools Review and Design Overview

To demonstrate the effectiveness of HERON's stochastic capacity and dispatch optimization process on energy storage, this analysis investigates the potential increase in the economic viability of existing NPPs coupled with TES in the NYISO market. Laying the groundwork for the STEA requires first creating a baseline of capacity and generation evolution in the NYISO projected into 2050. To create this baseline, capacity expansion modeling was performed using the Electric Power Research Institute (EPRI) U.S. Regional Economy, Greenhouse Gas, and Energy Model (US-REGEN). Experts at EPRI applied and adjusted economic drivers and assumptions in US-REGEN to create four different scenarios, discussed in Section 3.1; these scenarios reflect possible outcomes on NYISO capacity, generation, and system costs from 2015 to 2050.

We then use this baseline information as boundary conditions for a set of STEA that includes TES. As a part of the Framework for Optimization of Resources and Economics (FORCE), Risk Analysis Virtual ENvironment (RAVEN) framework plugin HERON is used to perform the STEA. RAVEN takes the baseline data in 2050 from the four
US-REGEN scenarios and generates synthetic load, solar, and wind data. A STEA introduces uncertainty into the economic metrics and models the synthetic data in a time-continuous fashion. HERON then economically optimizes both the capacities and dispatch of TES configurations. Furthermore, traditional capacity and dispatch tools focus on electricity. HERON, however, is designed to treat all resources (e.g., heat and electricity) equally during the modeling process.

## 1.2 Report Purpose and Organization

The primary purpose of this analysis is to demonstrate the effectiveness of HERON's workflow as used to examine innovative solutions for increasing NPP revenue. This work achieves that purpose through analyzing the potential benefits of several different TES technologies to NPP economic viability in the NYISO market. Coupling TES with an NPP allows a plant to operate flexibly while continually producing energy, potentially creating an opportunity to increase NPP revenue in the face of decreasing baseload requirements. We investigate this potential solution by first leveraging the capacity expansion capabilities of EPRI's US-REGEN and then performing a set of STEA on TES technologies using

HERON software. The results from the STEA are then compared to the baseline, allowing us to investigate the optimal TES technology and what capacity of each system leads to the most significant economic benefit for the NPPs in the NYISO market under several scenarios.

This report is structured as follows. Following the Introduction, Section 2 gives a brief overview of the current and planned NYISO market. Next, Section 3 discusses how the baseline for comparison is created using the US-REGEN capacity expansion model and explains the outlooks produced in the four model runs. The outlooks provide the boundary conditions needed to run the STEA of several TES technologies. Section 4 then gives a brief overview of the specific TES technologies considered. In Sections 5 and 6, we discuss the capacity and dispatch optimization performed by HERON and the results from the HERON runs, respectively. Finally, Section 7 summarizes the analyses performed, results, conclusions and suggests potential future work from the lessons learned.

# 2. NYISO ELECTRICITY MARKET

## 2.1 Market Structure

NYISO operates a deregulated market, providing real-time and day-ahead electricity auctions, ancillary services, and a longer-run capacity auction. Competitive wholesale electricity markets characterize a deregulated market for buying and selling electricity. In this market structure, generators bid their production costs ($/MW) and capacity available in advance in each production cycle. After the bids are submitted, the grid operator, NYISO in this case, assembles the bids based on the bid price and capacity of each retail supplier. NYISO then dispatches the capacity from the least to most expensive until the load is met. When the market clears (i.e., supply matches demand), the bidding price of the most expensive generation unit to successfully clear the market becomes the “clearing price.” This is then the dollar per megawatt paid to each generator dispatched during the cycle. Each generator aims to maximize profit by submitting bids at marginal cost and dispatching to receive revenue greater than or equal to marginal cost. This competitive market incentivizes and rewards efficient and innovative generation (i.e., low marginal costs).

## 2.2 Current and Future Generation Mix

New York state’s generation mix has undergone significant changes over the last two decades. Under decarbonization objectives and the eroding economics of oil and coal-fired generation, the state’s resource mix has shifted toward lower or zero-carbon emission generation sources. Over the last decade, driven by policy efforts and technological advancements, the state’s investment in VRE resources like wind and solar PV has increased [12]. With increased penetration of relatively inexpensive VRE resources that reduce baseload requirements and competition from low natural gas prices, New York deactivated two of its nuclear reactors in the last two years [13]. The NYISO grid of today is representative of these trends over the previous two decades.

In 2020, 55% of energy production in the New York Control Area (NYCA) was zero-emissions resources. Nuclear energy provided 53% of the zero-emissions generation, hydro provided 41%, and wind provided the remaining 6% [14]. New York saw an increase in fossil-fired generation and a decrease in zero-emissions generation following the closure of Indian Point Unit 2, a nuclear reactor in downstate New York, in April of 2020. Zero-emissions generation is expected to fall even further in 2021 after the closure of Indian Point Unit 3 in April [15]. Without Indian Point Units 2 and 3, the remaining nuclear power was expected only to comprise 9% of NYCA’s installed capacity available in summer 2021 [14].

With support from government subsidization, technological advancements, and climate policy pressures, many markets in the U.S. are expanding their VRE portfolios, including NYISO. Under their 2019 Climate Leadership and Community Protection Act (CLCPA), the investment targets for the new generation envisioned by NYISO consist of 6000 MW of solar, 9000 MW of wind, and 3000 MW of battery storage. These investment targets, among others, will help the NYISO achieve a zero-emissions grid by 2040, as called for in the CLCPA [14].

As the state's energy grid transitions, NYISO acknowledges potential challenges in maintaining grid reliability and balancing intermittency. Historically, fossil-fired, nuclear, and hydro generation has supplied most of the state's baseload requirements. With the retirement of Indian Point Units 2 and 3 and the phasing out of fossil-fired generation, NYISO recognizes the challenge of maintaining a reliable grid with increased penetration of weather-dependent, intermittent resources. NYISO is considering how dispatchable and flexible resources can help meet these challenges [14].

# 3. CAPACITY EXPANSION MODELING IN US-REGEN

HERON is not currently designed for capacity expansion modeling. As such, to create the no-TES baseline, this analysis leverages work performed by experts at EPRI using their US-REGEN model [16] on four potential decarbonization scenarios in the NYISO market. As a deterministic model, US-REGEN sacrifices some of the uncertainty analysis and resolution present in HERON to consider long-term projection modeling of grid energy system development. Leveraging this capability, HERON can then use US-REGEN outputs and introduce changes in the predicted outcomes. Specifically, HERON can introduce new technologies, optimizing capacity and enabling analysis of TES coupled with nuclear.

US-REGEN is a regional energy-economy model that combines dispatch and capacity expansion models and dynamic computable general equilibrium models of the U.S. As a regional energy-economy model, US-REGEN explores the impacts of sub-region differences in policy, costs, technology, demand, and electricity transmission on the evolution of capacity, generation, and system costs over the modeling time horizon. For this analysis, US-REGEN uses two operation modes. The first operation mode is a dynamic long-run formulation, producing the economically optimal capacity portfolios for each year in the modeling time horizon, a thirty-five-year period from 2015 to 2050. In the dynamic mode, to reduce computational complexity and improve run time, each year is represented by roughly 100 segments instead of modeling every hour. Each time slice represents anywhere from one to two hundred hours of the 8760 hours in a given year, and the hours within each time slice are not usually contiguous. These time slices are chosen to be representative of different periods throughout a given year, such as peak demand in the summer or several hours in shoulder months. Together, these time slices capture the intra-annual renewable resource availability and load profile.

The second operation mode US-REGEN uses for this analysis is a static hourly formulation for the year 2050. Modeling storage requires the sequential 8,760 hours. Since the temporal granularity of the dynamic model is reduced to 100 segments per year, US-REGEN is unable to model storage in this mode. To include storage, the outputs from the dynamic long-run mode of US-REGEN are then used as inputs to the static hourly formulation. The static hourly formulation mode enables full 8,760 hourly resolution. For this analysis, US-REGEN dynamic model data for the year 2050 are used to seed the static model. See US-REGEN model documentation [16] for more information on the differences in characteristics of US-REGEN's dynamic and static models.

## 3.1 Scenarios and Assumptions

The capacity expansion portion of this analysis examines the market and grid energy system development of the NYISO for four possible decarbonization scenarios. The design of these scenarios includes a combination of pricing structures, New York state and national policies, and technology constraints. The matrix of US-REGEN model runs is shown in Table 1. It is essential to keep in mind that the scenarios presented are not projections of the future, but rather descriptions of possible systems given the inputs. While each of the four scenarios are under the same state policy, they allow for differing assumptions on U.S. policy, nuclear costs, renewable costs, and Li-ion storage allowance. Note that the inclusion or omission of storage from the scenarios is in EPRI's US-REGEN baseline-defining cases only, and doesn't reflect on HERON's inclusion of storage in subsequent analyses.

Table 1. US-REGEN EPRI scenario descriptions.

| | State Policy | U.S. Policy | Nuclear Cost Assumptions | Renewable Cost Assumptions | Other Assumptions |
|---|---|---|---|---|---|
| Reference | Current (70% RPS in NYS by 2030) | Current | Default | Reference | No Li-ion Storage |
| Reference + Storage | Current | Current | Default | Reference | Li-ion Storage |
| CES | Current | 100% CES in 2035 | Lower Nuclear Costs | Smaller Declines in Wind and Solar PV | No Li-ion Storage |
| CES + Storage | Current | 100% CES in 2035 | Lower Nuclear Costs | Smaller Declines in Wind and Solar PV | Li-ion Storage |

### 3.1.1 Policy Assumptions

For this analysis, the US-REGEN model implements a state and national policy for each of the four capacity expansion scenarios. All the scenarios considered in this analysis are under the same state policy: a 70% Renewable Portfolio Standard (RPS) in New York state by 2030. The US-REGEN model requires the New York state RPS target to be met as a binding constraint. The reference cases implement current national policy. The clean energy standard (CES) cases implement a national policy of meeting 100% CES in 2035.

### 3.1.2 Nuclear and Renewable Cost Assumptions

The US-REGEN model takes in nuclear and renewable cost assumptions. These cost assumptions are shown in Figure 1 below. Both reference scenarios use a default capital cost for any new nuclear construction of \$4,000/kW. The two CES scenarios use lower nuclear costs of \$3,000/kW, a capital cost reduction of 25%. The lower nuclear cost of \$3,000/kW was chosen to reflect the ambition of some advanced nuclear designers and serves as a lower, or cheapest, boundary cost. Note that existing nuclear in the NYISO is assumed to continue operating without capital cost until end of foreseeable license extensions. For renewable cost assumptions, the two reference scenarios use the US-REGEN reference renewable costs, and the two CES scenarios use a higher (but still decreasing) renewable cost assumption. Compared to the reference, the high-cost renewable assumption is represented by smaller declines in renewable costs over time.

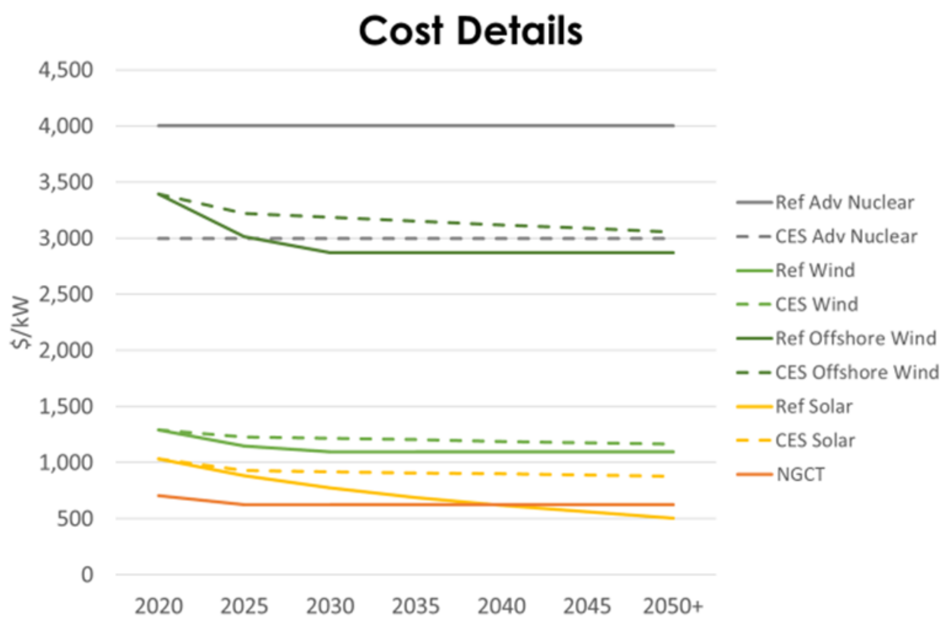


Figure 1. Time-dependent cost of generation resources.

Lastly, these four scenarios are under a Li-ion storage assumption. The US-REGEN model implements this assumption for each of the four cases, either allowing or prohibiting Li-ion storage capacity build-out. As shown in Table 1, the reference and CES scenarios with storage allow Li-ion storage capacity to be built out. In contrast, the reference and CES scenarios without storage prohibit Li-ion storage from building out in their capacity expansion forecasts.

## 3.2 Capacity Expansion Results

Table 2. Generator acronyms for Figure 2–Figure 7.

| Legend Name | Generator Name |
|---|---|
| Storage | Battery, pumped hydro, and other |
| Rooftop Solar | Rooftop solar photovoltaic |
| Solar CSP | Concentrating solar power |
| Solar PV | Solar photovoltaic |
| Off. Wind | Offshore wind |
| On. Wind | Onshore wind |
| Hydrogen | Hydrogen used for electricity production |
| NGCC | Natural gas combined cycle |
| NGCT | Natural gas combustion turbine |
| Gas CCS/NGCCS | Natural gas with carbon capture and sequestration |
| New Gas | All new natural gas without CCS |
| Ex. Gas | All existing natural gas without CCS |
| Coal CCS | Coal carbon capture and sequestration |
| Coal | All types of coal that do not have CCS |
| Bio CCS/BECCS | Biomass with carbon capture and sequestration |
| Other/Bio | Oil, diesel, and minor generation methods that do not fit other categories |

| Legend Name | Generator Name |
|---|---|
| Hydro | All hydroelectric |
| Geothermal | All geothermal facilities |
| New Nuclear | All new nuclear facilities |
| Ex. Nuclear | All existing nuclear facilities |

The US-REGEN tracked generation technology's capacity and generation evolution in the NYISO from 2015 to 2050 for the four scenarios described above. The outputs of the four US-REGEN runs are displayed in Figure 2-Figure 7. The outputs are displayed in two types: dynamic results and static results. The dynamic results, shown in Figure 2-Figure 7, indicate the projected capacity and generation evolution over the modeling time horizon in New York for the reference and CES scenarios. The last two figures show the static results, displaying the projected capacity and generation of New York in the final modeling year of 2050 under each of the four scenarios, respectively.

Note that only the static model results show the capacity and generation of the Reference + Storage and CES + Storage scenarios. This is because modeling storage requires the sequential 8,760 hours, temporal granularity only available in the static model. To generate the static model results in 2050, first, the dynamic model results of the Reference and CES without storage scenarios were generated to capture the long-run additions and retirements. Then, using the dynamic model results as inputs, the static model optimized capacity for short-build time assets by considering both the endowments of those long-lived assets and the sequential 8,760 hours.

Consistent with the current generation mix discussed in Section 2.2, Figure 2 and Figure 3 show that natural gas is the largest source of capacity in the NYISO at the beginning of the modeling time horizon. In both the reference and CES scenarios under a 70% RPS by 2030, significant retirements in existing natural gas assets occur. In the CES scenario, minimal new natural gas investment occurs due to the 100% nationwide CES starting in 2035. However, there is no restriction on the capacity for fossil-fired assets in the reference scenario. As a result, there is a significant new natural gas investment in the reference scenario from 2030 to 2050, as shown in Figure 2.

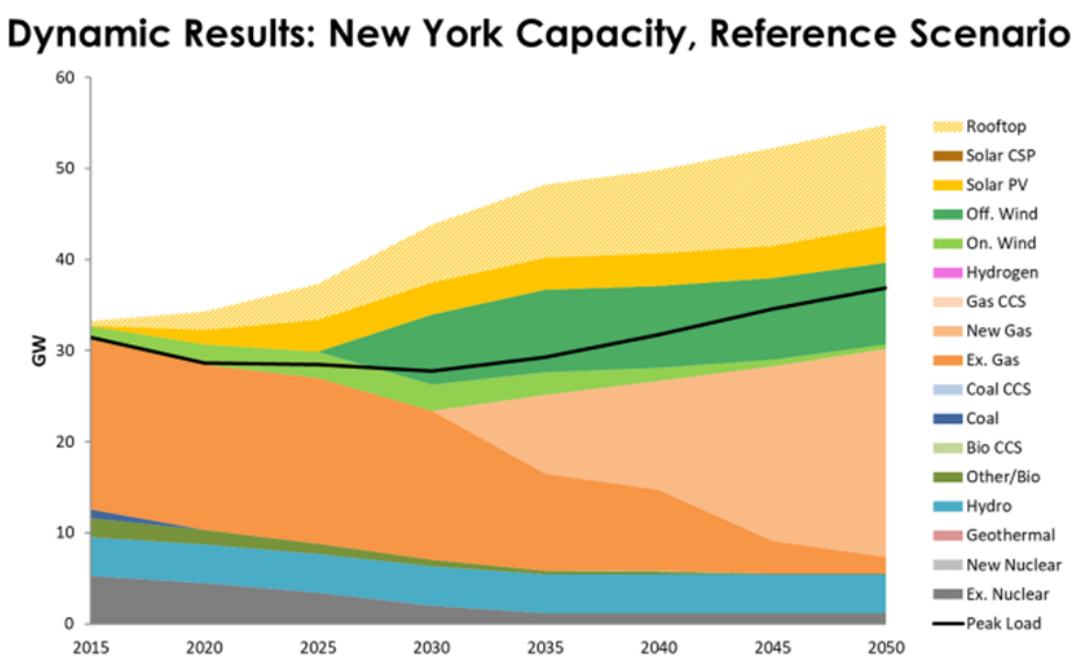


Figure 2. New York Capacity Evolution in the Reference Scenario.

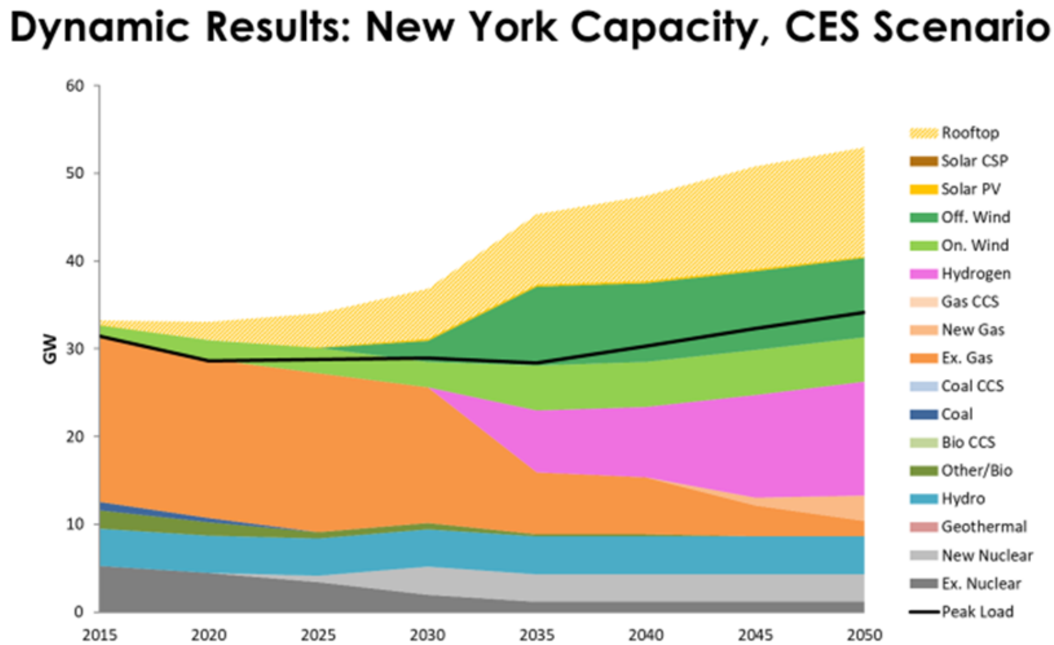


Figure 3. New York Capacity Evolution in the CES Scenario.

In the capacity evolution of both scenarios, we see increased investment in VRE resources starting notably in 2030. This is unsurprising given that both scenarios are under the state's 70% RPS by 2030. The effects of the high-cost renewable constraint on the CES scenario seem to be modest, with similarly significant increases in rooftop solar and offshore wind relative to the reference scenario. Both scenarios see a similar decline in existing nuclear over the modeling time horizon. However, the CES scenario sees new nuclear capacity investment under a low nuclear cost assumption. Under a nationwide CES, hydrogen capacity builds out for storage as VRE capacity grows and fossil-fired investment declines.

Figure 4 and Figure 5 display the generation evolution of various technologies in the reference and CES scenarios, respectively. In the reference scenario, under a state 70% RPS and the current national policy, we see net imports from outside New York (the gap between in-state generation and load) increase by over 150% from 2015 to 2050. The regions surrounding New York state have less ambitious RPS or CES targets than New York state. For example, three states that border NY - Massachusetts, Connecticut, and New Jersey - all have RPS targets of around 50% by 2030 [17]. With lower RPS targets than New York state and without a nationwide CES, the reference scenario sees NYISO import cheaper, and potentially fossil-fired, electricity from its neighbors. In the CES scenario, however, which is under a national 100% CES in 2035, we see net imports in New York decrease by roughly 50%.

In terms of the portion of generation provided by in-state resources, from 2015 to 2050, we see a significant decline in fossil-fired generation and an increase in VRE generation, most notably from offshore wind. This is the same in both the reference and CES scenarios. In the reference scenario, nuclear generation sees curtailment due to renewable overproduction cutting into the baseload operation. In the CES scenario, under a lower nuclear cost assumption, NYISO maintains current nuclear energy generation throughout the entire modeling time horizon. In the reference case, there was negative feedback pushing consumers to use less electricity due to electrification, so the overall demand is lower in the reference case than in the CES case due to high electricity costs.

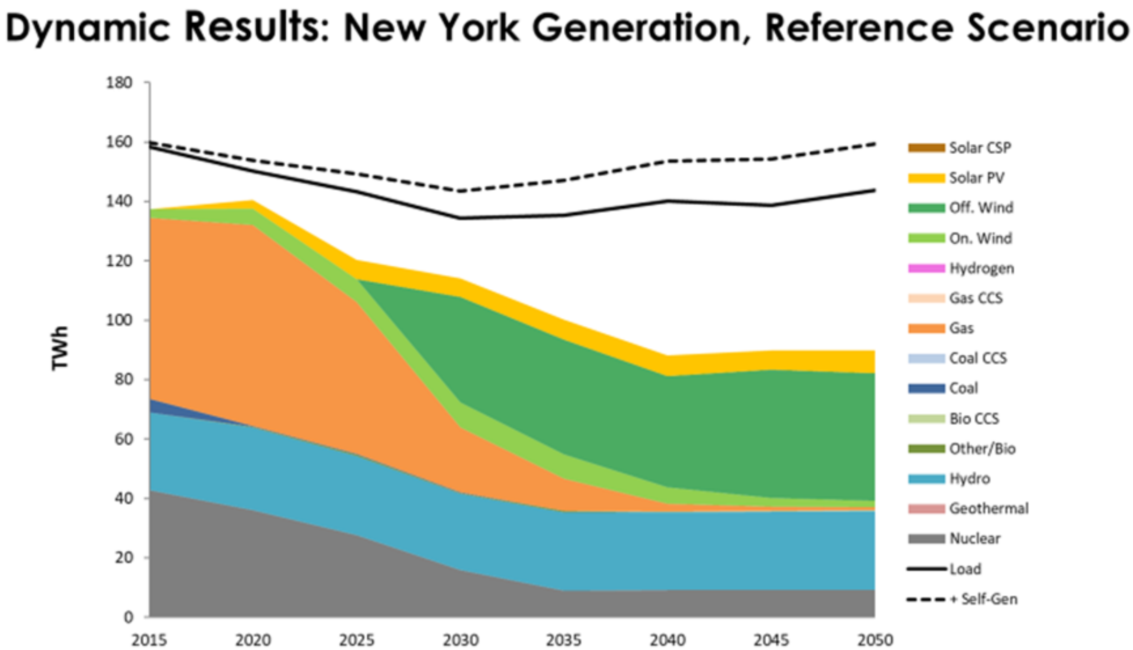


Figure 4. New York Generation Evolution in the Reference Scenario.

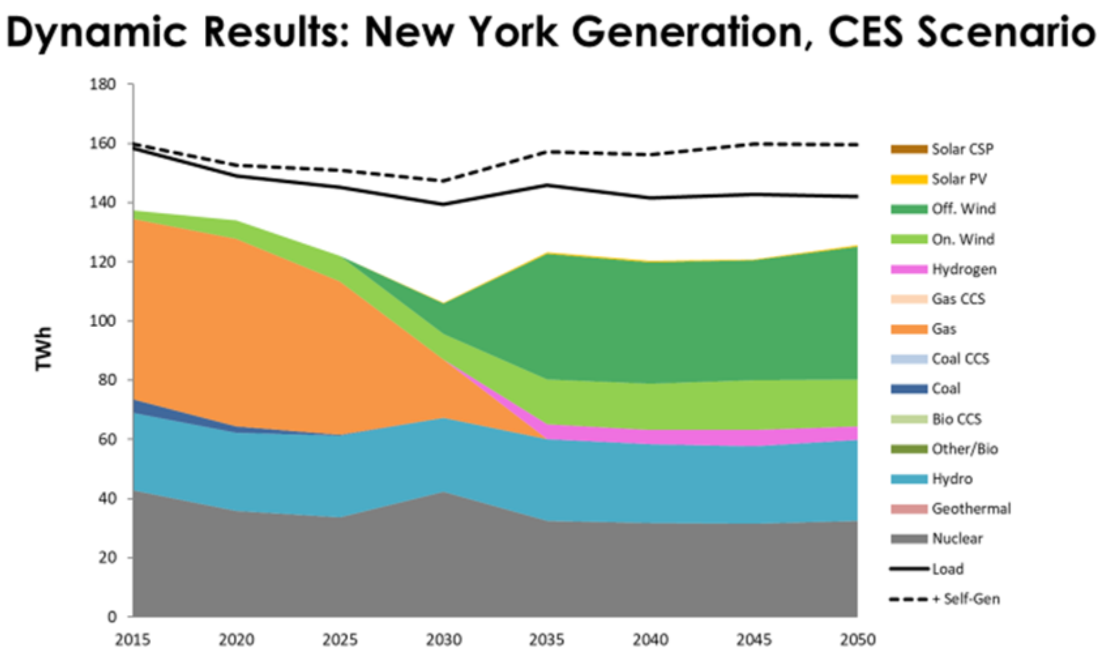


Figure 5. New York Generation Evolution in the CES Scenario.

As shown in Figure 6, the addition of storage reduces NGCT capacity and slightly increases Solar PV capacity in the reference scenario. In the CES scenario, the addition of storage reduces the capacity of hydrogen, which is used as long-duration storage, by roughly the same amount of capacity added by storage. Expansion of storage does not impact the capacity of nuclear in either scenario. Even though some fossil-fired capacity was retained in all scenarios, Figure 7 shows that it is rarely dispatched and is only retained to meet the NYCA-wide reserve requirements. In both the reference and CES scenarios, the impact of adding storage on net generation is the storage generation itself. The addition of storage in both the reference and CES scenarios increases total generation slightly and lowers VRE curtailment. Consistent with the dynamic model results for the evolution of generation, in-state generation is higher in the CES scenarios than the reference scenarios in 2050. Figure 7 shows NY imports less in the CES scenarios due to higher quality and lower costs of renewables in-state relative to neighboring regions and because there is less cheap, fossil-fired generation available for import.

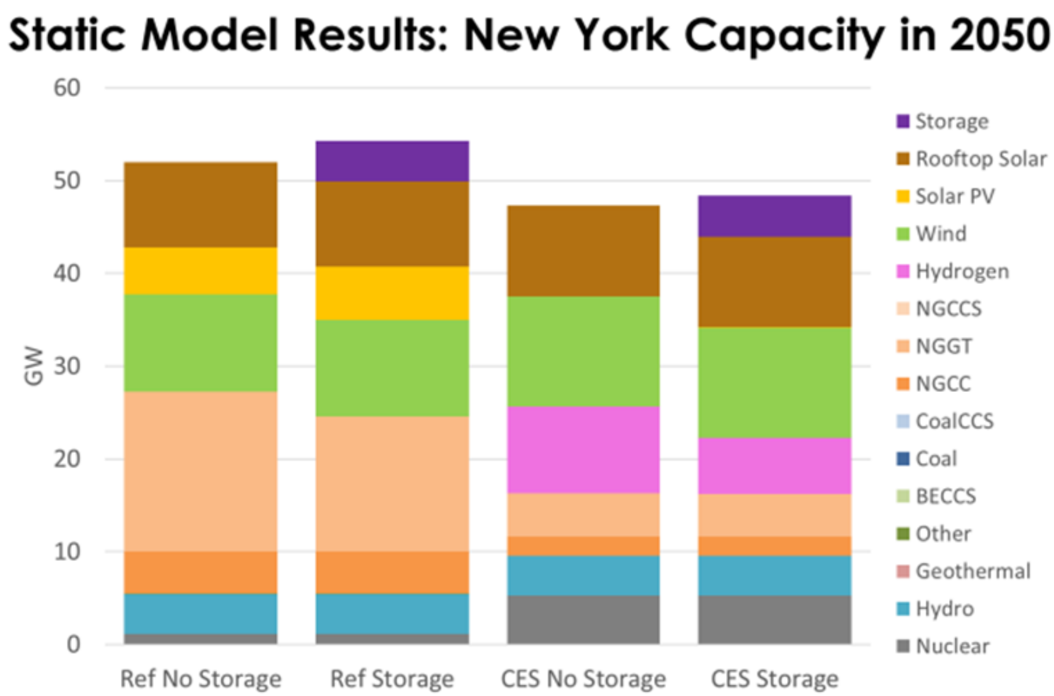


Figure 6. New York Capacity in 2050 for All Four Scenarios.

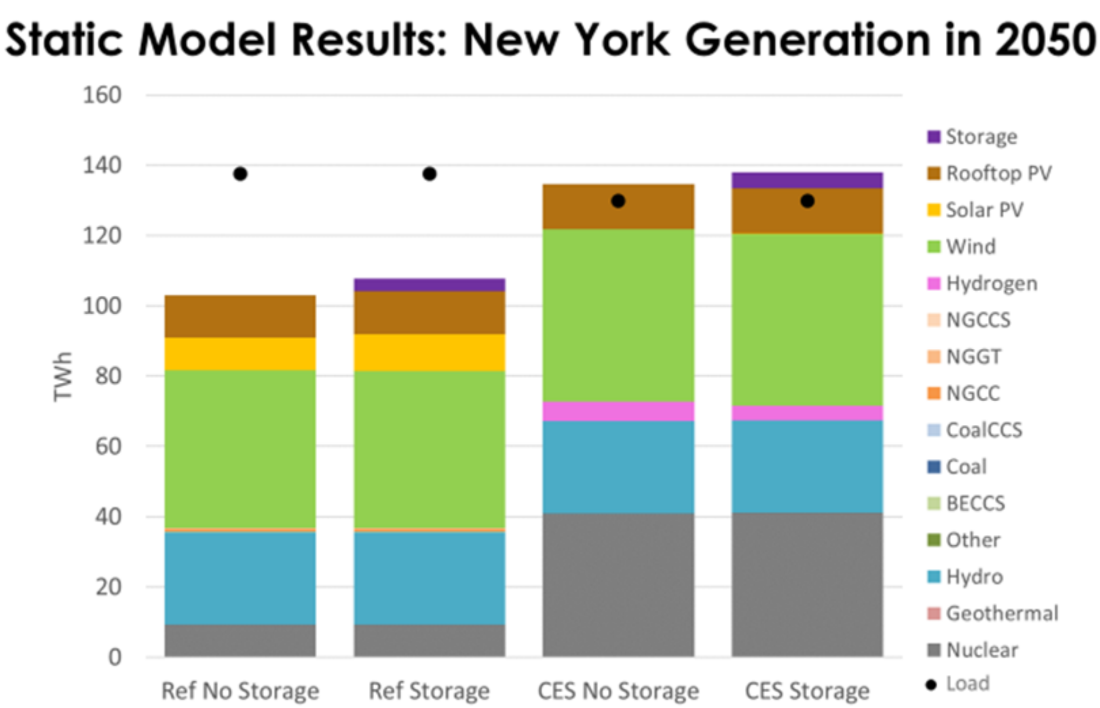


Figure 7. New York Generation in 2050 for All Four Scenarios.

# 4. ENERGY STORAGE TECHNOLOGIES AND CONSIDERATIONS

Existing NPPs are struggling to remain economically competitive in the face of increasing intermittent resource adoption and cheap natural gas. Coupling energy storage with NPPs is one potential solution to increase NPP revenue. Such a coupling allows the NPP to operate flexibly, supplying the grid in periods of scarcity and storing power in times of oversupply. One energy technology being considered for NPP coupling is TES. Since thermal power plants like NPPs produce heat, TES can directly store energy in the form of heat without the loss of efficiency from conversion. Furthermore, with low-cost potential and high technology readiness levels for some technologies, TES is a promising option for integration with existing NPPs.

As mentioned above, our analysis leverages some previous work analyzing energy-storage technologies that can be integrated with existing LWRs. The authors of a previous INL study on energy arbitrage for NPPs the leveraged work compare a variety of TES, hydrogen, and Li-ion technologies [10]. From those nine technologies considered, we select three TES technologies, ETES, Thermal Hitec XL, and Thermal Dowtherm A, to compare to hydrogen and Li-ion. Table 3 displays the five energy storage technologies compared in this analysis. This study does not include, however, a potential leading option of burning hydrogen in an existing natural gas turbine, or in a peaking turbine dedicated to hydrogen production. Nor does this evaluation consider a reversible solid-oxide electrolysis/fuel cell option. These options could alter the outcomes of the present evaluation, because both would have lower capital costs, and high round-trip efficiencies that the $H_2$ Physical Storage SOEC / PEM FC case.

Table 3. Thermal energy storage technology characteristics.

| Storage Option | Input Operating Temperature Range | Capital Cost per unit of stored energy ($/kWh-e) | Capital Cost ($M) | Cost of Debt ($M/yr) | RTE (%) | Total Revenue ($M/yr) | LCOS (breakeven) ($/MWh-e) | TRL |
|---|---|---|---|---|---|---|---|---|
| Li-ion LFP Batteries | NA | 828 (6 & 12 h) | 2484 (6h) 4967 (12h) | 119 (6h) 239 (12h) | 88 | 300 (6h) 600 (12h) | 357 (6 & 12 h) | 9 |
| $H_2$-Physical Storage, SOEC / PEM FC | NPP heat to SOEC | 548 (6h) 296 (12h) | 1644 (6h) 1777 (12h) | 79 (6h) 86 (12h) | 38 | 209 (6h) 253 (12h) | 248 (6h) 151 (12h) | 2-3 |
| Thermal (ETES) | -3°C to 390°C | 417 (6h) 247 (12h) | 1250 (6h) 1483 (12h) | 60 (6h) 71 (12h) | 55 | 204 (6h) 297 (12h) | 194 (6h) 141 (12h) | 5-6 |
| Thermal (sensible / Hitec XL) | 120°C to 500°C | 199 (6h) 171 (12h) | 598 (6h) 2912 (12h) | 28 (6h) 49 (12h) | 82 | 212 (6h) 202 (12h) | 105 (6h) 96 (12h) | 9 |
| Thermal (sensible / Dowtherm A) | -3°C to 359°C | 373 (6h) 347 (12h) | 1120 (6h) 2086 (12h) | 54 (6h) 100 (12h) | 82 | 167 (6h) 317 (12h) | 159 (6h) 151 (12h) | 9 |

Since this analysis considers the potential economic benefit of TES coupled with existing NPPs, the technologies selected to compare to Li-ion and $H_2$ were chosen based on Technology Readiness Level (TRL) and commercial interests. High TRLs indicate a capability for near-term LWR coupling. Two of the TES technologies analyzed in this work, Thermal Hitec XL and Thermal Dowtherm A, are sensible-heat storage (SHS) systems. SHS systems are currently commercially available and have been widely deployed with thermal plants, like concentrated solar power and coal. With a high TRL and commercial deployment, the two SHSs were deemed attractive candidates for this analysis. Thermal ETES was chosen based on commercial interests as well as high TRL. While ETES is considered a TES technology, it differs from the other two TES systems in input. ETES operates stand alone on the grid, meaning the system does not need to be connected to a heat source. Instead, an ETES system takes power from the grid, converts it into heat energy, and then converts the heat energy back into electricity for the grid in a peaking manner. Li-ion and $H_2$ were chosen as the comparison storage mediums because of historical precedent and increased focus on a hydrogen economy, respectively.

Round trip efficiency (RTE) can be assessed in a variety of ways: AC to AC power, thermal to AC power, thermal to thermal, each of which is defined as the fraction of energy taken out of the storage to the energy put into storage. The higher the RTE, the more efficient the system. All storage systems lose power during the power conversion process, and the RTE aggregates the net losses of this process. The RTE values for Li-ion, $H_{2,}$ and Thermal ETES were established in [13] and correspond to AC to AC power conversion. However, the RTE values for Thermal Hitec XL and Thermal Dowtherm A storage options were recalculated for our analysis as for a fair comparison with a nuclear power plant, a thermal to thermal conversion is needed. The RTE values found in [13] for these two storage mediums is 27%, corresponding to AC to AC power.

Since NPPs have around a 33% thermal to electric conversion efficiency, the power being stored in the Li-ion battery coupled with an NPP has already gone through a 33% transition from the nuclear heat. This was not accounted for in [13]. Therefore, to do a fairer comparison with Li-ion, we divided 27% by 33%, the thermal efficiency of an NPP. This recalculation gives Thermal Hitec XL and Thermal Dowtherm A an RTE of 82%. The RTE for hydrogen already accounts for the NPP heat to storage process, and ETES takes electricity as its input.

As can be seen from Table 3, Li-ion has the highest levelized cost of storage (LCOS) for both the 6-hour and 12-hour storage durations, followed by $H_2$. Even with the heat-to-heat RTE values for Thermal Hitec XL and Thermal Dowtherm A, Li-ion has the highest RTE of 88%. Thermal Hitec XL and Thermal Dowtherm A have the next highest RTE values of 82%, followed by ETES with an RTE of 55%.

# 5. HERON DISPATCH ANALYSIS DESCRIPTION

## 5.1 System Description

Figure 8 displays the energy flow of the market simulated in HERON. This diagram shows the combination of thermal and electrical storage technologies used as optimizing components in the analysis. It also includes the energy produced by VREs and the turbines that convert thermal storage into electricity.

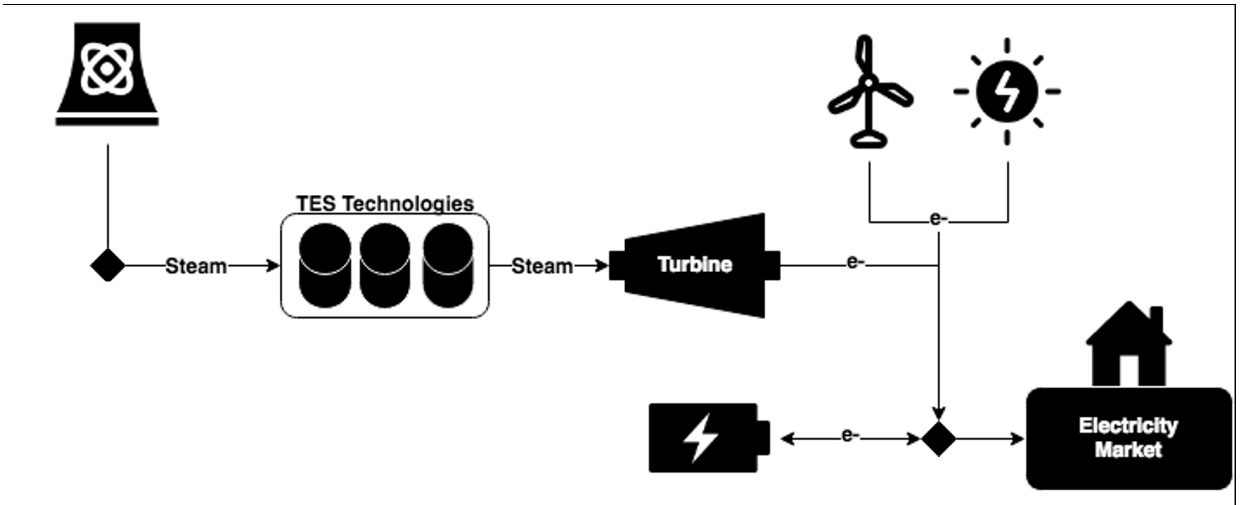

Figure 8. Diagram of HERON dispatch analysis.

### 5.1.1 Synthetic History Training and Validation

A series of synthetic histories were generated using data from US-REGEN. These histories represent the total load (demand), wind capacity utilization, and solar capacity utilization throughout the year. Since wind and solar were only provided for one year by US-REGEN, the synthetic histories were generated for the first and last year of the project lifetime. All the years in between were interpolated with a constant factor. This establishes an assumption used in HERON that load, wind, and solar behavior will not significantly change over 20 years. It is also important to note that the solar generation was reported using Greenwich Mean Time (GMT) and not Eastern Standard Time (EST). This explains why there are peaks in solar in the latter part of the day when the peaks would be expected during the early and middle parts of the day. Since the dispatch window is 24 hours, this does not significantly affect the dispatching results.

Specifically, two synthetic histories were generated using a Fourier Auto-Regressive Moving-Average (FARMA) model. Each FARMA model requires four parameters: the auto-regressive order (p), the moving-average order (q), the detrending Fourier bases, and the number of clusters to group by.

For the Reference case, a model order of (1,0) was chosen for p and q, respectively. The Fourier bases were: 8760, 4380, 2920, 2190, 438, 168, 24, 12, 6, 3 for the wind and load values, and 24, 12 for the solar values. The FARMA was then clustered with eight representative groups, meaning that the year of data can be represented using eight distinct days. This clustering reduces some of the computational complexity of the optimization and allows for a more generalized behavior of the stochastic history. Figure 9 shows the synthetic history in comparison to the original US-REGEN data.

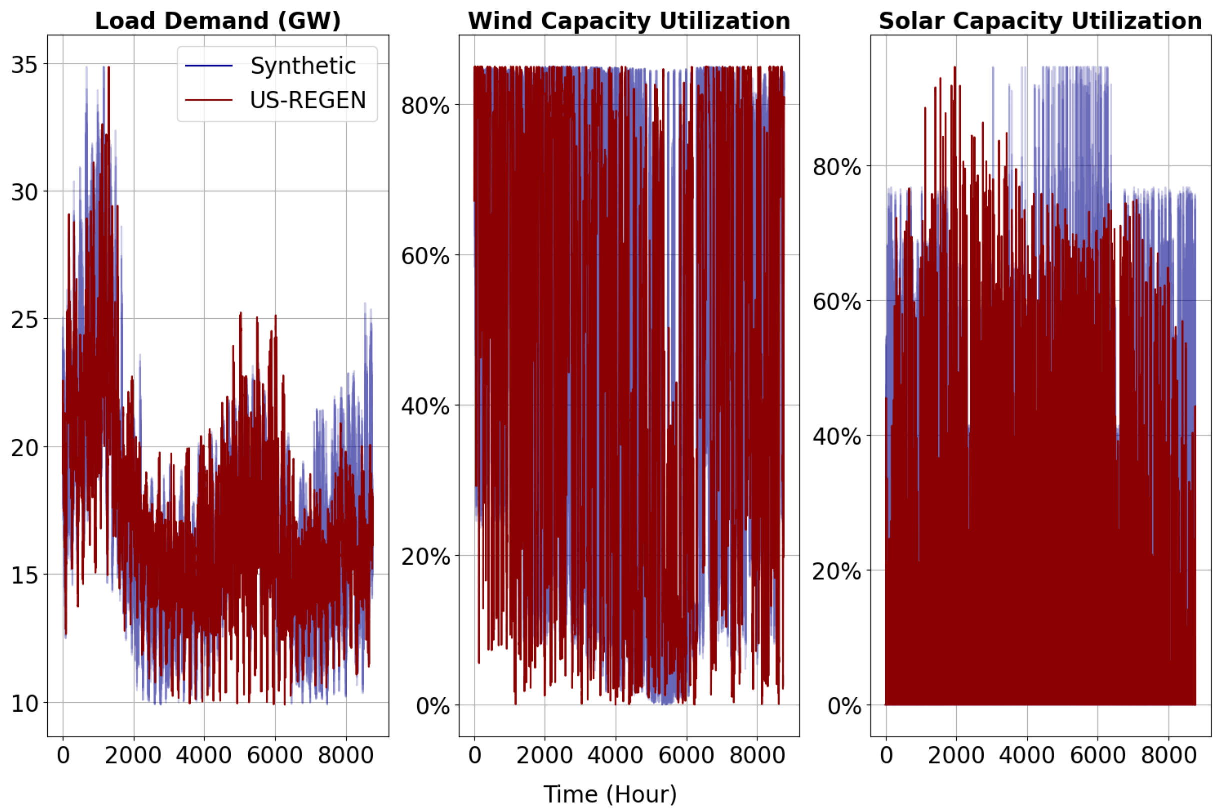


Figure 9. Reference Case - Synthetic History compared to US-REGEN.

A model order of (1,0) was chosen for the CES case. The Fourier bases were specified as 8760, 4380, 2920, 2190, 438, 168, 24, 12, 6, 3 for wind and load and 24, 12, 6, 3 for solar. The clustering was performed in the same manner as the Reference case. Figure 10 shows the synthetic history in comparison to the original US-REGEN data. More information on this model and its formulation can be found in [19] and [20].

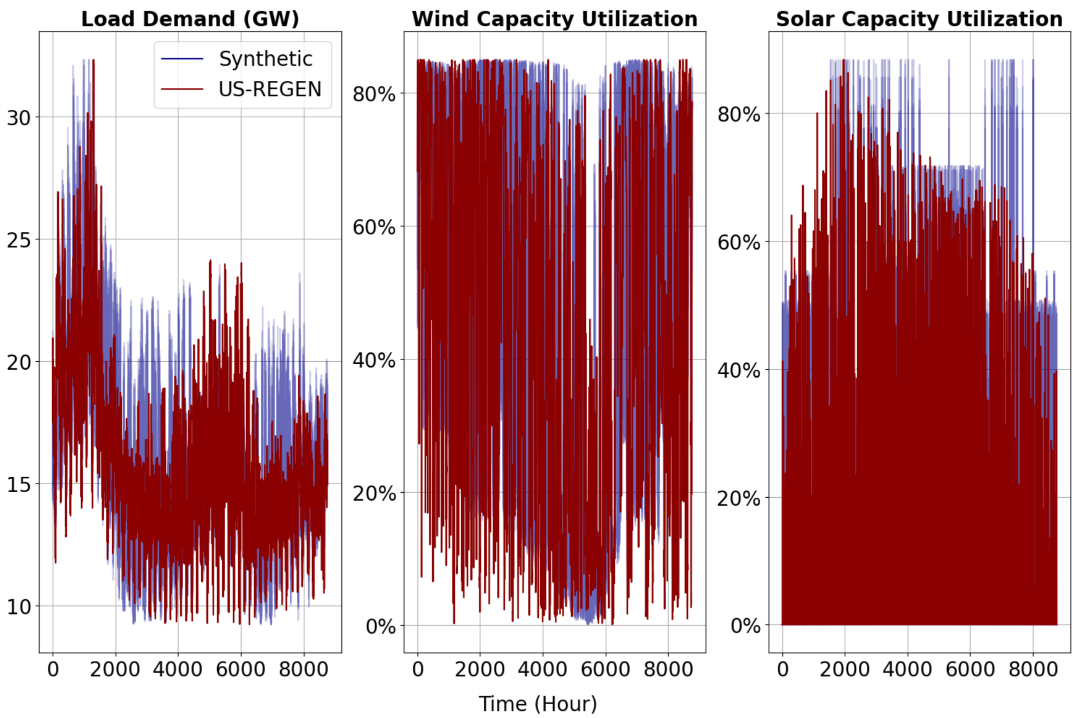


Figure 10. CES Case - Synthetic History compared to US-REGEN.

### 5.1.2 Dispatch Optimization

Optimizing the dispatch of these cases is relatively straightforward. For this study, the additional NPP, unused NPP, grid demand, and the different storage technologies define the system of components. The grid and unused NPP are both required demands; both must be completely satisfied during the simulation each hour. Since the NPP is assumed to be operating as a non-flexible generator, there may be hours in which thermal energy from the NPP is generated but not used to satisfy electricity demand, and some portion of that may not always be stored. In these instances, lacking other alternatives in the model, in order to use the un-dispatched heat, the NPP must bid the electricity generated from the unused heat under the Production Tax Credit (PTC) [17] of the VREs, resulting in an associated cost-for-unused-heat of $17,000/GWe. During optimization, this cost acts as a penalty to prevent the NPP from producing an overabundance of heat with nowhere to store or use it. The unused NPP also has a flat demand whose quantity is determined in the outer optimization and remains constant in the inner. The synthetic history provides the grid demand.

Table 4 displays the capacity constraints and marginal cost for each component in each scenario in our analysis. The combination of the capacity and cost creates the stack that will be used to drive cashflows and guide the dispatch strategy. Note that Solar and Wind are not a part of the marginal-cost-sorted list of energy generators (or “stack”) as the energy produced by VRE is subtracted from the total load to yield a net demand to be met by the generators, with a VRE marginal cost of $0.00/GWe. Also, the increasing marginal cost of each component must be observed; depending on the amount of capacity represented by each marginal cost in the stack, the step function that computes clearing price will become either elongated or abbreviated.

Table 4. Component capacity and costs.

| Case | Strategy | Component | Capacity (GW) | Marginal Cost ($) |
|---|---|---|---|---|
| Reference | Storage | Hydro | 4.28 | $- |
| Reference | Storage | Nuclear | 1.14 | $12.69 |
| Reference | Storage | NGCC | 4.53 | $25.11 |
| Reference | Storage | NGGT | 17.22 | $32.70 |
| Reference | Storage | Overflow | 35.00 | $169.68 |
| Reference | No Storage | Hydro | 4.28 | $- |
| Reference | No Storage | Nuclear | 1.14 | $12.69 |
| Reference | No Storage | NGCC | 4.53 | $25.11 |
| Reference | No Storage | NGGT | 14.52 | $32.70 |
| Reference | No Storage | Overflow | 35.00 | $169.68 |
| CES | Storage | Hydro | 4.28 | $- |
| CES | Storage | Nuclear | 5.24 | $12.69 |
| CES | Storage | NGCC | 2.10 | $25.11 |
| CES | Storage | NGGT | 4.64 | $32.70 |
| CES | Storage | Overflow | 35.00 | $169.68 |
| CES | No Storage | Hydro | 4.28 | $- |
| CES | No Storage | Nuclear | 5.24 | $12.69 |
| CES | No Storage | NGCC | 2.10 | $25.11 |
| CES | No Storage | NGGT | 2.10 | $32.70 |
| CES | No Storage | Overflow | 35.00 | $169.68 |

Using the marginal costs in Table 4 and the synthetic histories discussed in Section 5.1.1, we constructed visualizations of the demand levels observed as well as the corresponding marginal costs to meet that demand. To visualize the demand levels, we sampled 50 synthetic time histories of load, wind, and solar data, then subtracted wind and solar generation from load to get net load (which may sometimes be negative; in practice we curtail these to zero but show them in the visualization for reference). This net load was then placed into a histogram, showing the frequency of occurrence for each bin of demand levels. These are shown in orange for each scenario in Figure 11 and Figure 12.

On the same figures, we show the evolution of the clearing price as a function of demand in blue. That is, the blue line sits over top of the net demand histogram at precisely the corresponding point. We calculate clearing price as the lowest-cost way to meet demand based on the marginal cost and available capacity of each generating component in the system. Each level in the blue step function is labeled with the new technology that must be brought online to meet demand at that level of demand, with corresponding clearing price. Thus, for initial demand, Hydro and Nuclear technologies , while at more infrequent, higher levels of demand, higher cost NGCC and NGGT must be brought online. For the most infrequent levels of demand (right tails of the distributions), the highest-possible clearing price results due to the high costs of the technology clearing price (either NGCC or NGGT). However, we can observe from the demand histograms that the most expensive "Overflow" technologies, meet no instances of demand and the "Overflow" clearing price is never realized.

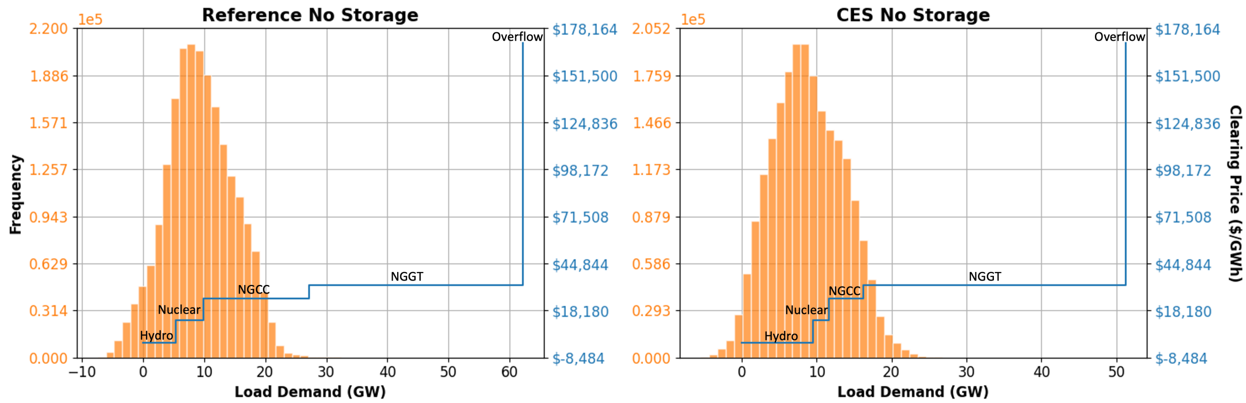


Figure 11. Net Demand and Clearing Price, EPRI-No-Storage Baseline

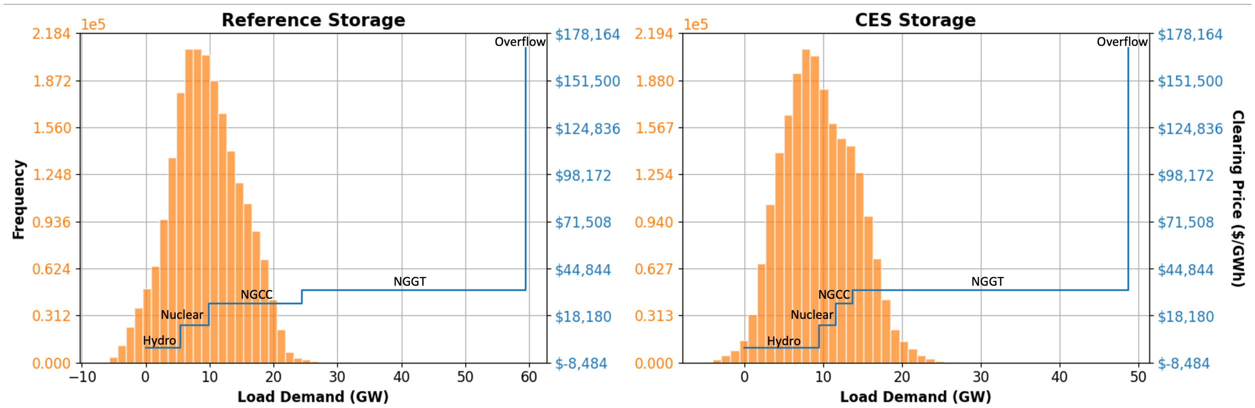


Figure 12. Net Demand and Clearing Price, EPRI-Storage Baseline

The distribution of clearing prices can be obtained by considering the histogram of net demand levels with clearing prices in Figure 11 and Figure 12. In the Reference cases, the bulk of the histogram falls below the level of demand at which the NGGT determines the clearing price, resulting in cheaper prices of electricity when compared to the CES cases. In CES cases, the tail of the histogram is significantly into the NGGT portion of the clearing price plot, which in practice means more instances of higher cost of electricity. This increase in frequency of high-cost electricity demands leads to more opportunity for TES profit through NPP coupling with TES, as the NPP can store energy when demand is low and clearing prices are low, while providing stored energy when demand and clearing prices are high.

In the past, HERON analyses would employ a round-about way to construct the objective function for the optimization, often employing price-taker assumptions. Since the clearing price stack can be described as a non-linear, non-differentiable function, its implementation would sometimes lead to intractable formulations of the objective function for dispatch optimization.

To approximate the non-differentiable behavior with a suitable algebraic representation, an exponential function was fit to the stack. While an approximation of the true behavior, the exponential function provides two conveniences: first, an analytical way to formulate the optimization problem, which cuts down on computational complexity, and second, a way to guide the storage dispatch while still using the stack in the computation of cash flows. Figure 13 displays the given fits for each case. Note the previously mentioned dynamic step sizing across the cases. We emphasize that the piecewise constant clearing price function is used for evaluating dispatch cost as part of the stochastic dispatch optimization; the algebraic exponential fit is only used to emulate clearing price in dispatch optimization.

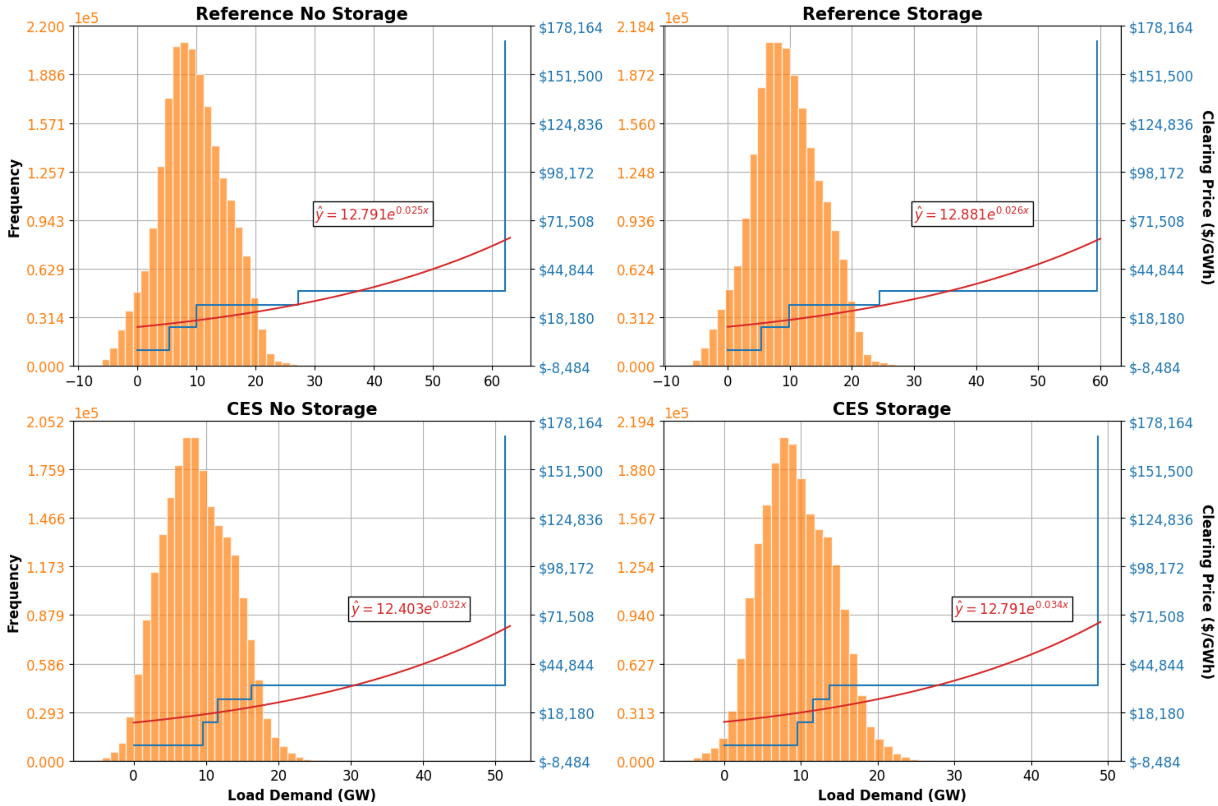


Figure 13. Clearing price formulation.

### 5.1.3 Capacity Optimization

While the dispatch optimization happens during the inner loop of a HERON run, capacity optimization occurs during the outer loop. This is where the optimizer bids to find the proper combination of storage capacities to maximize NPV for a given market scenario. For a meaningful conclusion to be drawn, a set of baseline cases that purposefully build out zero capacity for all storage technologies must be completed. This allows for a comparison in NPV between a scenario with no storage capacity and a scenario that has found specific technologies profitable. Barring the optimizer getting stuck in a local minimum, the difference between the baseline and optimized case NPV should converge to a non-negative value.

Table 5 displays the total system cost NPV statistics gathered from the baseline cases. Note the extreme difference in cost across all the cases. This disparity in prices can be explained by the restrictive policies assumed in the CES scenarios. When a CES policy is in place, we can expect to see higher electricity costs due to utilities having to purchase energy from clean generators from neighboring ISOs. Also, as a rule, any differential NPV that falls within one standard deviation of the baseline NPV would be suspect of any improvement due to the observed variation of the baseline mean.

Table 5. Baseline NPV statistics.

| Scenario | Mean NPV ($MM) | Std. Dev. NPV ($MM) |
|---|---|---|
| **Reference - No Storage** | $2,347.88 | $41.43 |
| **Reference - Storage** | $2,034.58 | $46.83 |
| **CES - No Storage** | $42,662.58 | $962.60 |
| **CES - Storage** | $43,054.78 | $517.59 |

# 6. MARKET SIMULATION RESULTS

## 6.1 Dispatching

Figure 14Figure 12 is a sample of dispatch optimization mechanics seen throughout the optimizing runs in HERON. Since each dispatch is part of the solution for one year, within one sample, within a single optimization cycle, we only display a cross-sectional overview of the dispatch system. This view provides insight into how the model treats energy demand during specific hours of the day. Note in reading the dispatch optimization figures that "absorbed quantities" (such as electricity consumed at the grid) are shown to have a negative value by convention in HERON; that is, when demand is high, the electricity absorbed at the grid is a large negative value. Conversely, when demand is low, the electricity absorbed at the grid is a small negative value. Note also that solid-line generation and consumption rates (such as GW) use the left y-axis, while dotted-line energy quantities (such as GWh, e.g., for energy storage levels) use the right y-axis.

In Figure 14Figure 14, we can see that Dowtherm A chooses to build up storage while electricity is cheap during low-demand hours, so it will be able to sell it off when electricity becomes more expensive. Similarly, the same behavior can be seen in Li-ion battery storage when the grid demands are near zero. What is particularly interesting is the lagging factor seen in lithium-ion storage level and the threshold for when it decides to start building up storage levels.

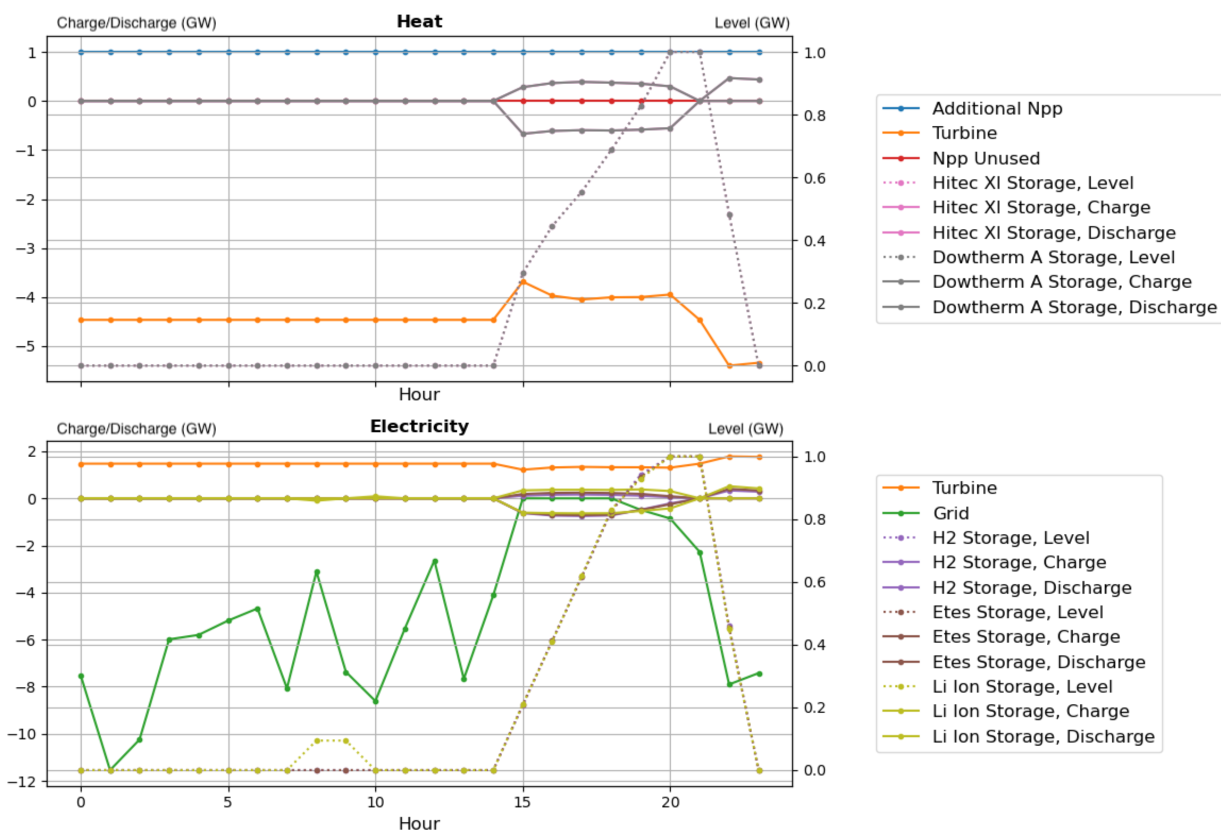


Figure 14. Example dispatch strategy.

Figure 14 becomes more interesting when looking at it combined with Figure 15. This figure shows the solar and wind availability as a percentage of installed capacity along with total load demand taken from each respective stochastic history. We can see that as the variable renewable energies peak in the day, it reduces the net amount of energy the grid demands. The storage technologies see this as an opportunity to build up storage since the clearing price of electricity is low, due to high VRE production. Also, once the VREs drop off, the storage technologies sell off much of its level since demands are higher without the VREs satisfying the load, leading to higher clearing prices.

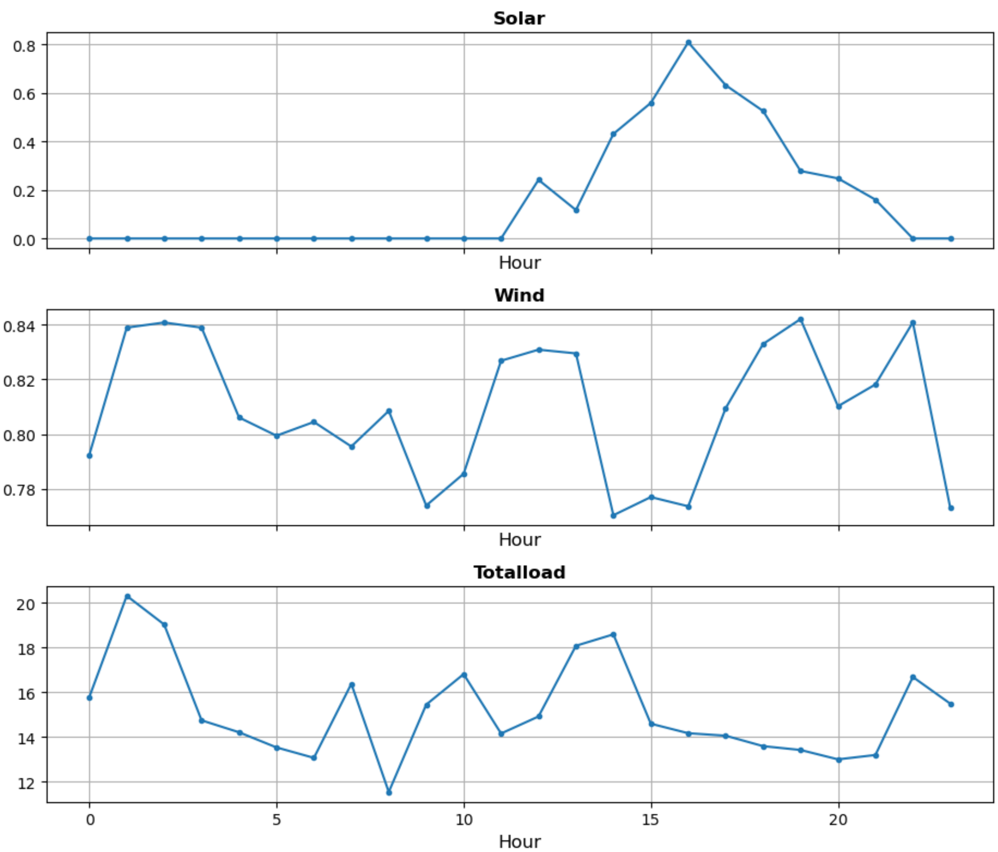


Figure 15. Example Synthetic History in Dispatch Window.

Also note in Figure 14 that frequently the dispatch optimization both charges and discharges storage technology simultaneously. In this specific dispatch scenario, the net demand after VRE generation requires less than the NPP full capacity, and there is not enough storage built to absorb all the excess generation. To avoid underbidding the PTC and curtailing VREs, the dispatch optimization instead uses the inefficiencies of the storage technology, represented in the RTE, to sink excess heat. While it is unlikely a storage owner would choose to remove excess energy through this process, it is indicative of the quantity of unused heat in some dispatch hours due to baseload NPP operation and high-variance VRE generation.

## 6.2 Optimization Results

As expected, the results of the HERON optimization analyses display a tendency to minimize storage technology capacity across the Reference scenarios. This result becomes quite clear when looking at the projected capital costs per unit of energy for each technology in Table 3. The current costs of these technologies act as a barrier to entry in deregulated markets, where electricity prices rarely rise high enough to justify the capital costs required to invest in TES. However, many of these technologies are currently low TRL, suggesting large uncertainty in actual capital costs. Some of these newer low-TRL technologies may have significantly lower capital costs, and therefore lower electricity costs required before installation may be profitable.

In CES scenarios, however, electricity prices often higher than in the Reference scenarios. This allows additional opportunity for TES to capitalize on buy-low sell-high dynamics, storing energy from the NPP during low demand (and low prices) and providing that energy during high-demand high-price time. This demonstrates that small changes in the projected price of electricity can have large impact on the viability of storage. The profitability of storage does not lead to a continuum of solutions; rather, if storage is net profitable, enough storage should be built to capitalize on price fluctuations. Inversely, if storage is not net profitable, no storage should be built. The decision variable for building storage or not is binary. The question of how much storage to build is a secondary question that can be answered once the profitability of storage is determined.

Furthermore, the CES scenarios represent NPP with a low capital cost, lower than some predictions but within the bounds of current estimates. While existing NPP in NYISO are assumed incur no capital cost for inclusion in the simulation, we allowed HERON to consider installing additional nuclear at $3000/kW in CES scenarios and $4000/kW in Reference scenarios, as discussed in Section 3.1.2. In Reference scenarios, HERON optimized no additional nuclear installation. In CES scenarios, however, significant nuclear is installed, up to 100% more than the amount predicted in the baseline models. This additional nuclear installation is enabled through the direct coupling of the TES, allowing nuclear to act in response to the volatility of the VREs that are dominant in the CES scenarios.

Another noteworthy result in the optimization processes is the speed with which some technologies are embraced or rejected. This speed of rejection is indicative of strong sensitivity in the expected NPV with respect to the construction of that TES technology; the higher the negative impact due to introducing the technology, the more readily the optimization process will reject the technology. Generally, we observe the electricity-based storages being minimized first. Among heat storage technologies, we observe Hi-Tec XL to be the last storage minimized, suggesting the most positive effect from this heat storage. These results correlate well with the capital costs of the technologies.

Table 6 summarizes the optimization results achieved by HERON for each case. As shown in the following sections, the Reference scenarios struggled to fully realize any TES installation; however, the result was not as profitable as the baseline case (in which no TES at all was installed). We attribute this lack of convergence to difficulties in the topology of the problem, which we discuss in Section 7.2. In the CES cases, however, notable improvements in the NPV are shown by introducing TES, especially in the No-Storage baseline case from US-REGEN. We discuss each of these optimizations in the following sections.

Table 6. Optimization Results

| Scenario | H2 $GWh_e$ | ETES $GWh_e$ | Hitec XL $GWh_t$ | Dowtherm A $GWh_t$ | Li-ion $GWh_e$ | Mean NPV $MM | Baseline NPV $MM | Δ NPV $MM | Change % |
|---|---|---|---|---|---|---|---|---|---|
| **Reference – No Storage** | 0.00 | 0.00 | 0.10 | 1.53 | 0.00 | $2,273 | $2,347 | -$74 | -3.16% |
| **Reference - Storage** | 0.25 | 0.26 | 0.41 | 0.25 | 0.45 | $1,511 | $2,034 | -$523 | -25.73% |
| **CES - No Storage** | 0.23 | 0.00 | 0.00 | 4.64 | 0.00 | $49,368 | $42,662 | $6,706 | 15.72% |
| **CES - Storage** | 0.54 | 0.50 | 0.45 | 0.43 | 0.46 | $43,835 | $43,054 | $780 | 1.81% |

Figure 16 through Figure 19 in the following sections show the evolution of optimization decisions made by HERON as a function of the number of iterations. We define an iteration as each successive step

HERON makes in determining the optimal component sizing. At each iteration, HERON evaluates the expected value of the configuration's NPV by sampling many synthetic histories and optimizing dispatch to each. HERON evaluates this expected NPV both at a proposed new optimal point as well as neighbor points. These evaluations are then used to locally estimate a gradient, pick a new direction to move to maximize NPV, and choose a step size to take in that direction. In the event the new proposed optimal point is an improvement over the old point, the new point is accepted (green dot). If the new point is not an improvement, it is rejected (red dot), and HERON returns to the previously accepted point to reconsider the gradient and step size (blue dot). Eventually as HERON falls into a profit-maximization point, it is unable to find any beneficial movements and reports convergence. This convergence is reached much more quickly near a boundary (such as when all storages are zeroed out) than on the interior of the problem.

### 6.2.1 Reference – EPRI-No-Storage

The Reference – No Storage case represents a scenario that maintains current state and national policies, along with default nuclear costs and the assumption that no new lithium-ion batteries would be built during the projected window of our analysis. It can be observed in Figure 16 that all storage technologies are driven toward 0 GWh of capacity, and the mean difference between optimized NPV and baseline NPV approaches 0 as the TES are removed from the system. This, in effect, drives the differential NPV towards zero since the resultant capacities mirror the capacities found in the baseline case.

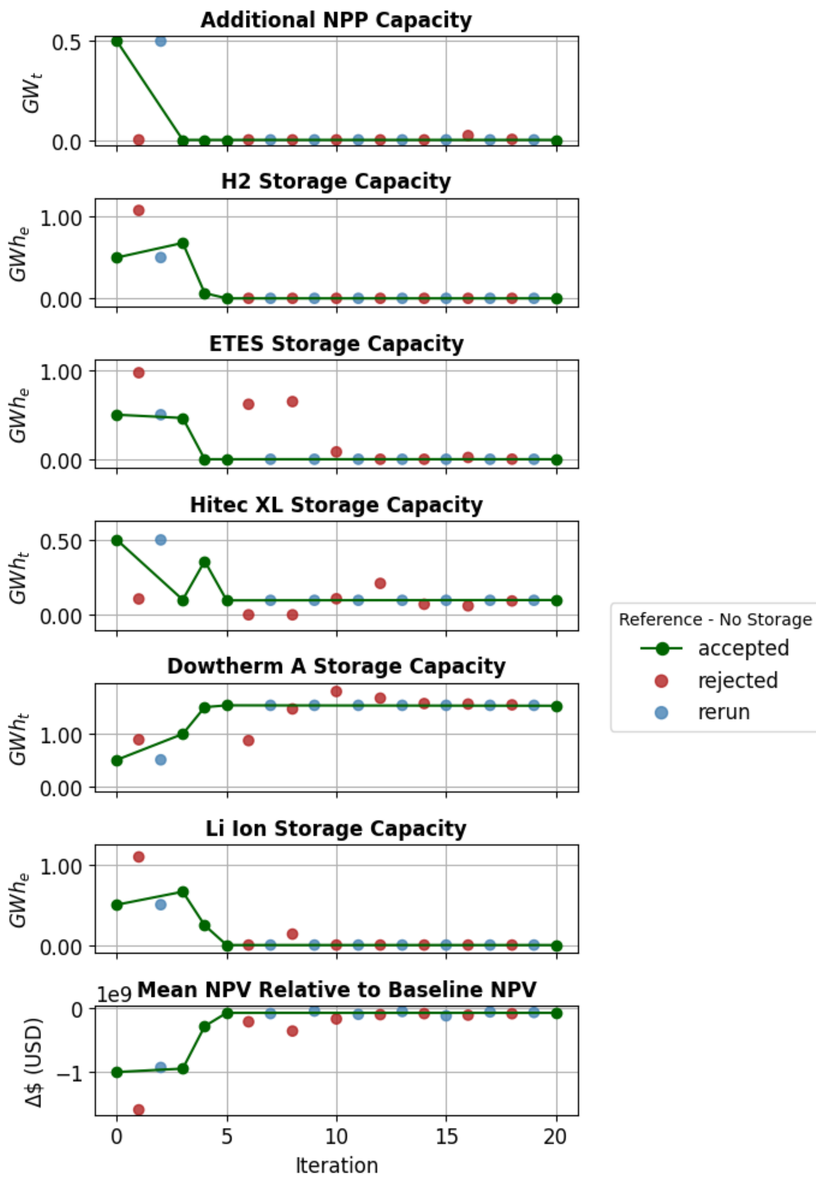


Figure 16. Optimization results of Reference – EPRI-No-Storage scenario.

### 6.2.2 Reference – EPRI-Storage

Similar to the previous case, the Reference – Storage case makes all the same assumptions about state and national policies as well as nuclear costs. The primary difference from the previous case is that Li-ion storage is allowed to be built and used throughout the project lifetime. As shown in Figure 17, HERON struggled to find an optimization path after minimizing the size of the additional nuclear installation. It is likely that the sensitivity of the NPV to this parameter dwarfs the sensitivity to other parameters, and the optimizer struggles to minimize the size of storages. With additional work on the HERON optimization parameters, we expect this optimization process would improve. However, no optimization iterations approach the profitability of the baseline case, leading us to doubt the options for profitable TES inclusion in this scenario.

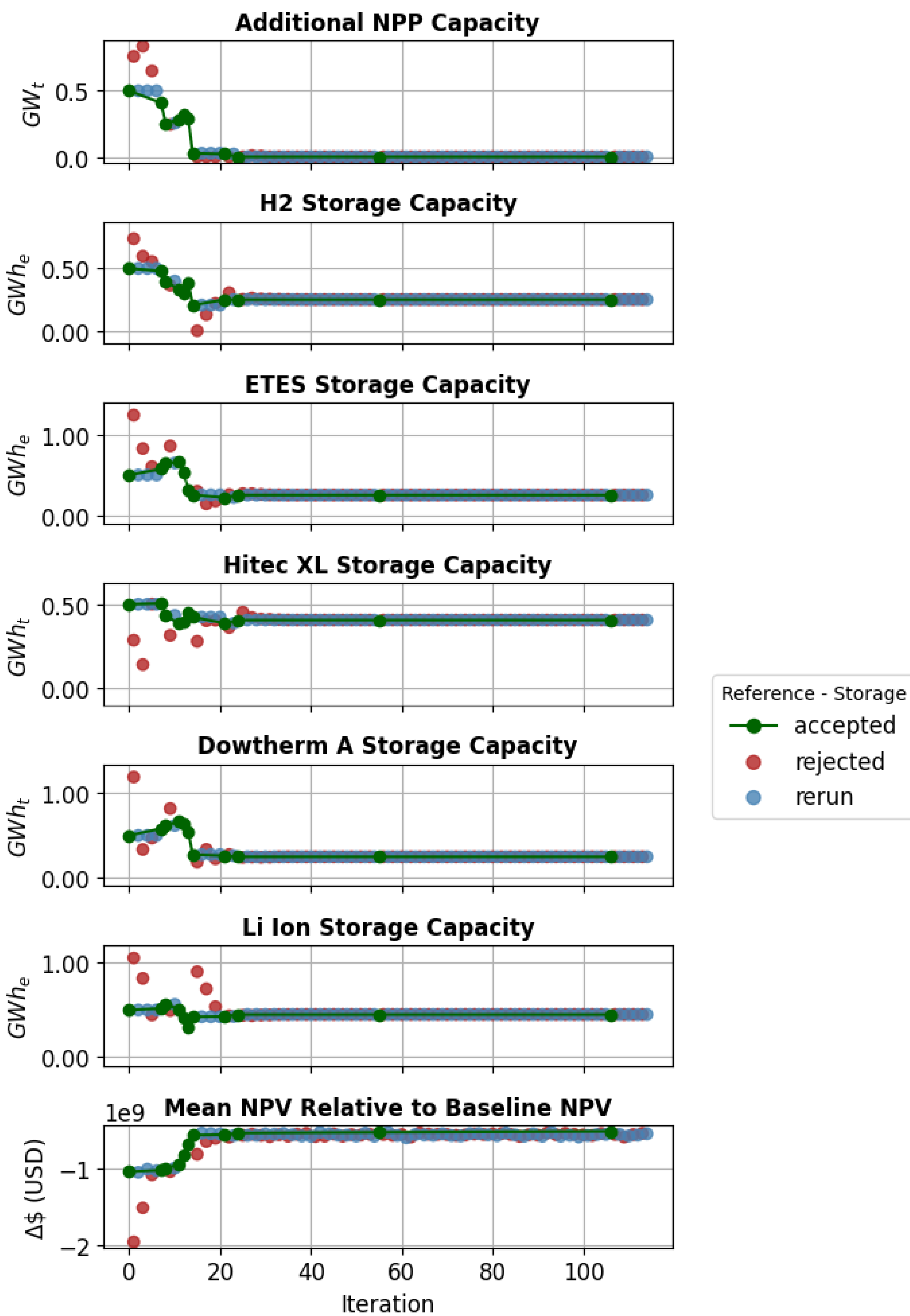


Figure 17. Optimization Results of Reference – EPRI-Storage scenario.

### 6.2.3 CES – EPRI-No-Storage

The CES – No Storage scenario operates under the assumption that the US will implement a CES policy by 2035. It also assumes reduced cost in nuclear power generation capital costs. As shown in Figure 18, while HERON minimizes the sizes of other TES, it elects to profitably build 5 $GWh_t$ Dowtherm A storage. Furthermore, it also elects to install nearly 4 $GW_t$ (1.3 $GW_e$) of additional nuclear capacity to capitalize on the TES coupling. These combined choices lead to a $6 billion in expected NPV over the baseline case, a 15% increase.

Interestingly, the capital cost of Dowtherm A is higher than Hitec XL, and both technologies have a similar RTE and mechanical interaction with the NPP and grid. Thus, we expect Hitec XL to be a superior choice in the optimization. We attribute the optimizer's choices to the dominance of two dimensions, Additional NPP and *total* installed storage, in NPV sensitivity when compared to the choice of any one storage technology. We discuss this behavior more in Section 7.2. We expect that, were the Additional NPP and total storage fixed, the optimizer would be able to navigate the problem to select Hitex XL over Dowtherm A.

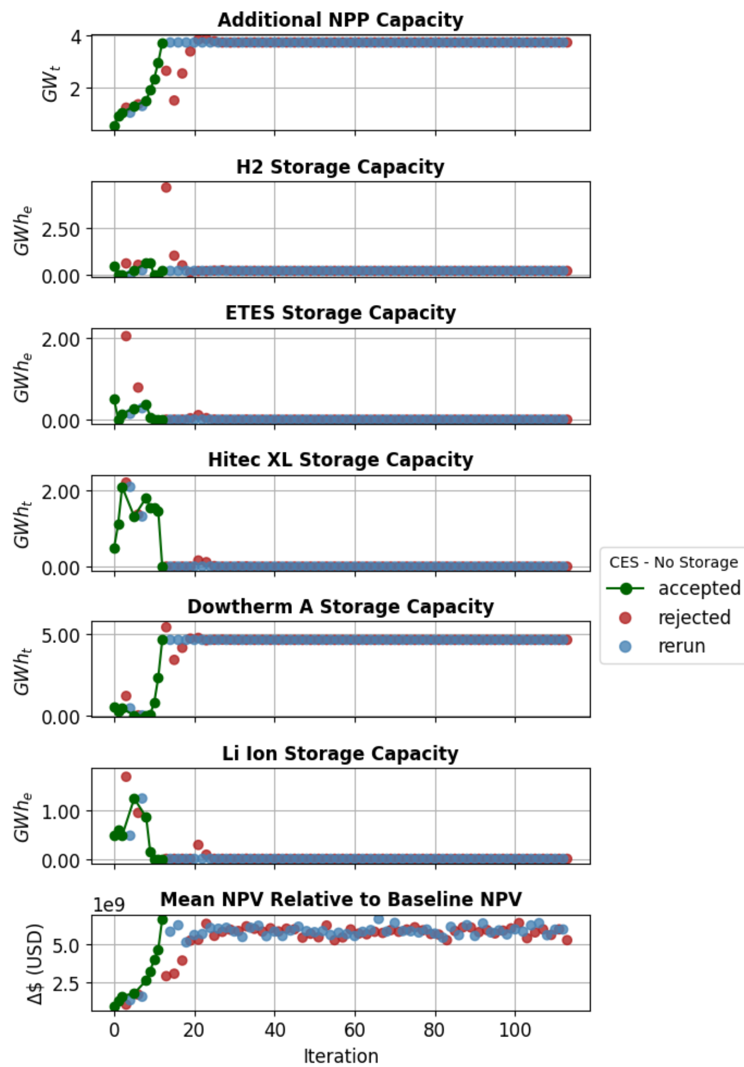


Figure 18. Optimization results of CES – EPRI-No-Storage scenario.

### 6.2.4 CES – EPRI-Storage

The CES – Storage scenario employs the same assumptions as the previous case with the addition of Li-ion storage in the baseline case. The optimizer struggled to converge this case but found profitability in installing some additional nuclear capacity and some TES capacity as well. While this result is not as well-converged as the CES No-Storage scenario, we observe significant variance in the Mean NPV with respect to very small changes in the TES parameters. This suggests additional synthetic scenarios would be required in this case to resolve useful gradients in the optimization process; the noise to signal ratio is simply too high for effective optimization in this scenario.

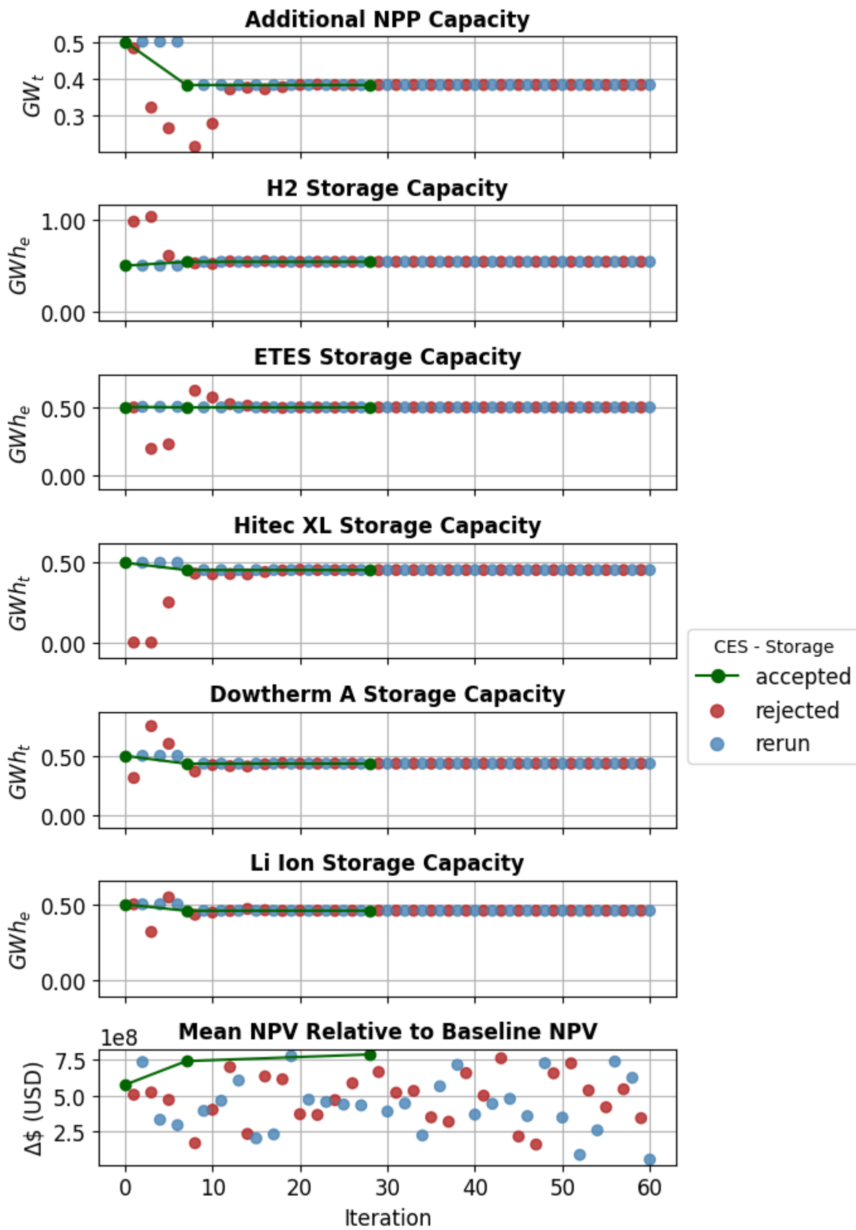


Figure 19. Optimization results of CES – EPRI-Storage scenario.

# 7. CONCLUSIONS

## 7.1 TES Analysis with HERON

This analysis demonstrates the effectiveness of HERON's workflow in examining the potential increase in NPP economic competitiveness through flexible plant operations. Using a variety of TES technologies, this work performs stochastic dispatch optimization to highlight the potential benefits of coupling energy storage to NPP competitiveness in the NYISO market.

For TES to be economically viable as a solution for flexible plant operation, the added benefits of flexible plant operation must outweigh the cost of construction. In our analysis, benefits are only realized if the NPP with TES can take advantage of energy arbitrage – storing energy in times of low electricity costs and regenerating power to sell to the grid in times of high electricity costs. Therefore, profitability of TES is determined by both a high mean electricity price as well as large variance. The benefit of a TES in this consideration is a direct competition between the TES CAPEX and the mean and variance of the electricity prices.

Based on our simulation analysis and the scenarios evaluated, our results show that participating in energy arbitrage with TES provides economic benefit to NPP revenue in the NYISO market under certain policy and cost assumptions. Under a nationwide CES, the clearing price of electricity is high without the option to import low-cost fossil-fired generation from neighboring regions. With a high clearing price for electricity, HERON chooses to build TES as it leads to a profitably optimal solution for flexible plant operation. Additionally, due to the lower cost nuclear assumption in the CES scenarios, HERON chooses to build significantly more nuclear in combination with TES to maximize potential profitability. This suggests that if new installation of nuclear becomes sufficiently inexpensive, new NPP coupled to TES may be an economically promising counterpart to VRE generation.

In our Reference scenarios, without a nationwide CES and with higher cost nuclear, TES is not cost-effective and therefore HERON chooses to minimize storage capacity. In these cases, high capital costs of TES or too low of electricity prices, or a combination of the two, prevent TES from being economically viable. Our results show that only under the policy and cost assumptions in the CES scenarios do the added benefits of flexible plant operation with TES outweigh the cost of construction. In the scenarios without these assumptions, current TES capital costs and low clearing prices produce a barrier for TES viability for NPP operators.

We observe the profitability of NPP coupling with TES to be a competition between capital cost and electricity prices. Most of the TES technologies considered are of high TRL, with low uncertainty in CAPEX costs. However, low TRL TES have more uncertain CAPEX costs, presenting an opportunity for future improvement. Through targeted design, reducing low-TRL TES capital costs may yield additional economically viable options for direct coupling with NPP.

## 7.2 Future Work

While the framework to demonstrate storage as an optimizing component has been implemented in HERON, there is still research to be done regarding optimization heuristics and low TRL storage technologies. Additionally, this work only considers TES with nuclear in a power-storage-power scenario. Future work may consider additional applications of storage to other markets, both electricity and otherwise, to investigate a potential increase in NPP revenue. This may provide TES additional avenues to add economic benefit to a NPP if stored heat can used to generate a secondary revenue source.

Regarding optimization, HERON's current optimizer can traverse the parameter space but struggles with the pathological "valley problem" common to gradient descent algorithms, where locally dominant gradients in some dimensions greatly increase the challenge of optimizing non-dominant dimensions. For example, the dominant gradient in many of the scenarios considered in this work was the amount of storage to build; the NPV was much less sensitive to the choice of individual storage options than it was sensitive to the total available storage. Currently, the optimizer lacks the heuristics to recognize a valley and adaptively increase or decrease its step size and direction to navigate this phenomenon. Improving this capability would lead to more robust results in less computational time. It would also be beneficial to implement a feature in HERON that can visualize low-dimensional optimization surfaces so that users can see how the optimization algorithm traversed the response surface.

Also, while this analysis focuses significantly on many high TRL storage technologies, the sensitivity to capital costs may lead to an increased industry interest in analyzing emergent technologies. There is the possibility that these newer technologies have lower costs than currently projected. If so, there might be an opportunity for these newer technologies to become profitable given the current market dynamics in addition to high-electricity-cost scenarios.

Noted in the text, this study does not include the option of burning hydrogen in an existing natural gas turbine, nor in a peaking plant for hydrogen. It also does not consider reversible solid-oxide electrolysis. These are scenarios for future work. The lower capital costs and improved round-trip efficiencies of these technologies will provide for an informative analysis.

In conclusion, HERON today provides storage optimizing capabilities that will be instrumental in future economic analyses. From a computational and software perspective the work has been successful. HERON will continue to help industry make well-informed investment decisions and will be used as a planning tool in the near term.

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