INL/EXT-20-60968
Revision 0

Light Water Reactor Sustainability Program

Evaluation of Hybrid Flexible Plant Operation and Generation Applications in Regulated and Deregulated Markets Using HERON

December 2020

U.S. Department of Energy

Office of Nuclear Energy

INL/EXT-20-60968
Revision 0

Evaluation of Hybrid Flexible Plant Operation and Generation Applications in Regulated and Deregulated Markets Using HERON

Paul W. Talbot, Dylan McDowell, James Richards, Joshua Cogliati, Andrea Alfonsi, Cristian Rabiti, Richard D. Boardman (INL)

S. Bernhoft, F. de la Chesnaye, E. Ela, R. Hytowitz, C. Kerr, J. Taber, A. Tuohy, D. Ziebell (EPRI)

December 2020

Prepared for the
U.S. Department of Energy
Office of Nuclear Energy

EXECUTIVE SUMMARY

Recent changes in the U.S. energy market, such as low natural gas prices and increased electricity production for variable renewable energy (VRE) sources, have led to financial challenges for existing light-water reactor (LWR) nuclear power plants (NPPs). Many owners and operators of LWRs have elected to decommission these plants rather than continue using them as consistent sources of clean baseload power. This has led to the exploration of various possibilities for increasing the economic viability of these units, including market restructuring to monetize the benefits that LWRs already provide to the grid through ancillary markets, load following and economic dispatch, and possible integration of secondary systems directly with the NPP in order to generate additional products through technologies such as hydrogen electrolysis or water desalination. Previous studies have considered the technologies associated with these Integrated Energy Systems (IES) activities, as well as market analyses for these secondary products.

To analyze the economic viability of various system configurations such IES, particularly given the uncertainty surrounding load demand, electricity prices, and the availability of VRE resources, the stochastic technoeconomic analysis package Heuristic Energy Resource Optimization Network (HERON) was released earlier this year as an extension of the risk analysis framework Risk Analysis Virtual Environment (RAVEN). HERON mostly focuses on making complex tools for uncertainty quantification analysis approachable for energy systems analysts, while also providing general dispatch optimization algorithms for those workflows. HERON continues to be improved upon and tested as a significant part of the IES viability analyses performed in this work.

HERON, currently has no capacity expansion capabilities. To consider market and grid energy system development in a variety of scenarios, HERON is best used when coupled with modeling tools such as US-REGEN that sacrifice some of the uncertainty analysis and resolution of HERON's modeling for the ability to efficiently predict changes in the grid energy system's profile as the result of economic drivers over decades. HERON can then use this information to explore the economic viability of introducing changes to the predicted outcomes, such as the introduction of an IES. In this work, experts at the Energy Power Research Institute (EPRI) used US-REGEN to provide six projection scenarios for use in HERON stochastic technoeconomic analysis (STEA) to consider the options available for increasing LWR economic viability by introducing a hydrogen-centric IES featuring a high-temperature steam electrolysis plant (HTSE), hydrogen storage, and a constant-rate contracted hydrogen consumer. The results obtained are differential in nature; they do not report expected profits for any configuration, but rather the possible increase in the NPV of a configuration with respect to a baseline no-IES configuration. Due to the uncertainty captured in the variable net load of the systems, there is likewise uncertainty in the mean values reported. We consider this viability both in terms of a regulated market, in which the energy producers and IES are owned and operated by a single entity, as well as a deregulated market, in which the IES chooses its bid for electricity generation and is then dispatched by the grid system operator.

The main goal of this report is to test the capability of HERON to coherently model economic performances of flexible nuclear power utilization in both regulated and deregulated markets. Making actual and specific predictions of the market evolution is outside the scope of this report. Instead, the report focuses on testing the tool and proving its capability to perform such analysis. Given the market structure represented and the assumptions used, the HERON model results were explainable and coherent with expectations. Results indicate that, for deregulated markets, inclusion of the IES is often statistically beneficial. This is especially true in regard to policies unfavorable towards nuclear, as nuclear is less often dispatched and must deal with frequent idle capacity. In the nominal case as well as in the case of carbon tax policies, inclusion of the IES clearly benefited the economic performance of the NPP. In the regulated case, however, there was a trend towards minimizing the IES, likely due to US-REGEN's optimal sizing of the NPP within the system, as well as the lack of penalties for idle NPP capacity in the regulated

market analyses. While these conclusions are not general, they are coherent with the assumptions made and therefore substantiate the proper development of the HERON software.

CONTENTS

FIGURES

TABLES

ACRONYMS

ARMA	Auto-regressive moving-average
ACE	Area Control Error
CAPEX	Capital expenditures
CCS	Carbon capture and sequestration
DAM	Day-ahead electricity market
EPRI	Energy Power Research Institute
FPOG	Flexible Plant Operation and Generation
HERON	Holistic Energy Resource Optimization Network
HTSE	High-temperature steam electrolysis
IES	Integrated Energy Systems
INL	Idaho National Laboratory
ISO	Independent System Operators
LNHR	Low-nuclear, high-renewable
LMP	Locational marginal price
LWR	Light-water reactor
MACRS	Modified Accelerated Cost Recovery System
NGCC	Natural gas combined cycle
NGCT	Natural gas combustion turbine
NPP	Nuclear power plant
O&M	Operating and maintenance
PV	Photovoltaic
RAVEN	Risk Analysis Virtual Environment
RPS	Renewable portfolio standards
RTM	Real-time electricity market
RTO	Regional Transmission Organizations
SMR	Small modular reactor
SOEC	Solid oxide electrolysis cell
STEA	Stochastic Techno-Economic Assessment
US-REGEN	U.S. Regional Economy, Greenhouse Gas, and Energy Model
VRE	Variable renewable energy

ACKNOWLEDGEMENTS

This research made use of resources of the High Performance Computing Center at Idaho National Laboratory, which is supported by the Office of Nuclear Energy of the U.S. Department of Energy and the Nuclear Science User Facilities under Contract No. DE-AC07-05ID14517.

1. INTRODUCTION

For decades in electricity markets around the world, nuclear power generation has been a competitive resource for baseload power generation. In recent years, historically low costs for natural gas energy production have challenged economic energy generation from nuclear power. Furthermore, many areas of the U.S. are expanding their variable renewable energy (VRE) portfolios, such as through solar photovoltaic (PV) and wind generation. These VRE sources are not available on demand; rather, they align with uncertain, time-dependent weather phenomena such as global horizontal irradiance and local wind speeds. This stretches the net load duration curves, requiring less baseload generation and more on-demand peak-following generation. Such developments have put pressure on nuclear power plants (NPPs) to find more flexible approaches to energy generation in order to increase economic viability.

One potential solution is to operate NPPs flexibly, ramping up power production during times of low VRE production and ramping down at others. This method has been successful in some parts of the world [25] but has not been demonstrated to always offer significant benefits to NPP operators in the U.S. [3], due to operation strategies such as fixed refueling contracts and existing license limitations. However, it is possible for NPPs to participate in expanding ancillary markets, depending on their region and characteristics.

Another potential solution is to closely couple the NPPs to secondary systems such as hydrogen production or water desalination [26]. This would allow the NPP to produce a different product (e.g., hydrogen or water) for most of the time while being available to the electric grid in moment of high electricity demand. Introducing storage for the secondary product allows for some flexibility in NPP operations while also ensuring consistent product availability for secondary markets.

In this work, we perform Stochastic TechnoEconomic Analyses (STEA) of potential Integrated Energy Systems (IES) in existing energy markets, using state-of-the-art software tools to determine whether the economic viability of NPPs is likely to increase by being included in IES—both from an Independent System Operators (ISO) and Regional Transmission Organizations (RTO) perspective in a regulated market sense, as well as from an independent NPP operator perspective in a deregulated market sense. We do this by first establishing several baseline capacity expansion possibilities under a variety of possible assumptions and policies, without including IES. We then consider the impact of introducing IES into this system, comparing the change in economic outlook.

1.1 Simulation Tools Review and Design Overview

To perform this analysis, two distinct modeling steps are required. First, capacity expansion analysis without including IES provides a baseline representation of the expected energy system evolution over a multi-decade project life. This requires a macro-level model capable of comprehending the potential driving policies and assumptions that could lead to capacity expansion phenomena in an energy market For this analysis, capacity expansion modeling was performed by experts at the Energy Power Research Institute (EPRI), using the U.S. Regional Economy, Greenhouse Gas, and Energy Model (US-REGEN). With the capability to enable and adjust a wide variety of energy policies and economic development outlooks, US-REGEN is a powerful resource for considering many possible outcomes stemming from a particular germination scenario.

In the second modeling step, the baseline scenarios produced by the macro model are used as boundary conditions for a set of STEA that includes IES. The optimal sizing of the components in the IES is explored for a wide variety of potential scenarios based on uncertainties in load and weather data. These uncertainties require a more detailed analysis than deterministic problems since there is an intrinsic uncertainty associated with stochastic input data. The STEA in this work is performed using the Risk Analysis Virtual Environment (RAVEN) framework plugin Holistic Energy Resource Optimization Network (HERON). HERON leverages RAVEN's synthetic history production algorithms to train models for producing unique synthetic scenarios, each sharing statistical similarity but having numerical

uniqueness. This allows uncertainty to be introduced in the economic metrics for any given energy mix and propagated through the optimization of IES capacities.

1.2 Report Purpose and Organization

The objective of this report is to demonstrate real-market application of the STEA using HERON software in conjunction with the EPRI capacity expansion analysis software US-REGEN for performing an economic assessment of Flexible Plant Operations and Generation (FPOG) dispatch in regulated and deregulated markets. We demonstrate this by considering the potential economic benefits of introducing IES into an existing energy market to enable flexible operation of NPPs in the system. Notably, we do this in the presence of electricity market feedback; that is, we do not make the simplifying assumption that IES power usage is negligible relative to the electricity market. Without this assumption, IES are not free to dispatch based only on electricity and hydrogen prices [2] and instead must interact with the ISO/RTO through production bids in the deregulated market cases.

The remainder of this report is organized as follows. In Section 2, we discuss the capacity expansion modeling projections performed by EPRI using US-REGEN, including the various policy options and the outlooks produced. In Section 3, we discuss the markets worthy of consideration for NPPs in the U.S., including both electricity and ancillary markets in the electricity sector. In Section 4, we consider the possible hydrogen market for IES that include NPPs as well as loosely coupled hydrogen production via high-temperature steam electrolysis (HTSE). In Section 5, we discuss capacity and dispatch optimizations performed by HERON, along with improvements to that software as a result of this work. In Section 6, we discuss the specific analysis cases targeted by this work, including the technologies, geographical location, system compositions, and system definitions. In Sections 7 and 8, we discuss the results of both the capacity optimization and dispatch optimization for the regulated and deregulated markets, respectively. Finally, in Section 9, we summarize the conclusions drawn from this work and speculate on future opportunities presented as a result.

2. CAPACITY EXPANSION MODELING IN US-REGEN

US-REGEN is a deterministic capacity expansion model that allows users to adjust cost, policy, and technology inputs to explore their effects on capacity, generation, and system cost throughout the modeling time horizon. For this analysis, scenarios were developed to cover a wide range of potential decarbonization schemes. Marginal cost dispatch order, also referred to as a "dispatch stack," and generator capacity outputs from US-REGEN were used as inputs for the main HERON IES dispatch analysis. The EPRI team developed scenarios and performed US-REGEN runs.

The US-REGEN model is a capacity expansion model representing the U.S. electric sector in national-level to state-level detail. The model finds the economically optimal electricity portfolio for meeting electricity system constraints such as serving load, reliability, and policy measures. US-REGEN makes decisions about building, upgrading, or retiring electricity generation units. The Integrated Electric & End-Use model also adjusts load in response to possible investments in electrification in several sectors of the US economy, including light duty vehicles and HVAC. US-REGEN model characteristics are given in Table 1.

Table 1. General characteristics of the US-REGEN dynamic model [9].

	Integrated Electric & End-Use
Optimization Horizon	Multi-decadal (35 years)
Temporal Granularity	~100 segments per year
Capacity Mix	Model driven (Endogenous)
Existing Unit Aggregation	100+ capacity blocks per region (dispatched together)
Geographical Detail	User-specified regions, up to state-level
Dispatch Constraints	Load balancing
Optimization Type	Linear program
Sectors	Electric
Energy Demand	Model driven (Endogenous), detailed end-use model

Fuel Prices	User defined (Exogenous), may use supply curves for some inputs

During capacity expansion runs, US-REGEN gives optimal capacity portfolios each year for of the specified time horizon. Each year is represented by ~100 segmented time slices. These time slices represent different representative periods in the year, such as several hours in shoulder seasons or peak demand in the summer. Running with time slices—as opposed to an hourly or sub-hourly time set—significantly improves the run time. These time periods are chosen to explore the full range of variability in load in renewable availability.

The US-REGEN model is split into 16 regions, with options for using states as regions in order to achieve further spatial resolution. Each region's load is balanced by the optimizer. US-REGEN does account for inter-regional transmission, but regions are constrained by the net transfer capacities set in the model. Figure 1 shows the standard US-REGEN regions.

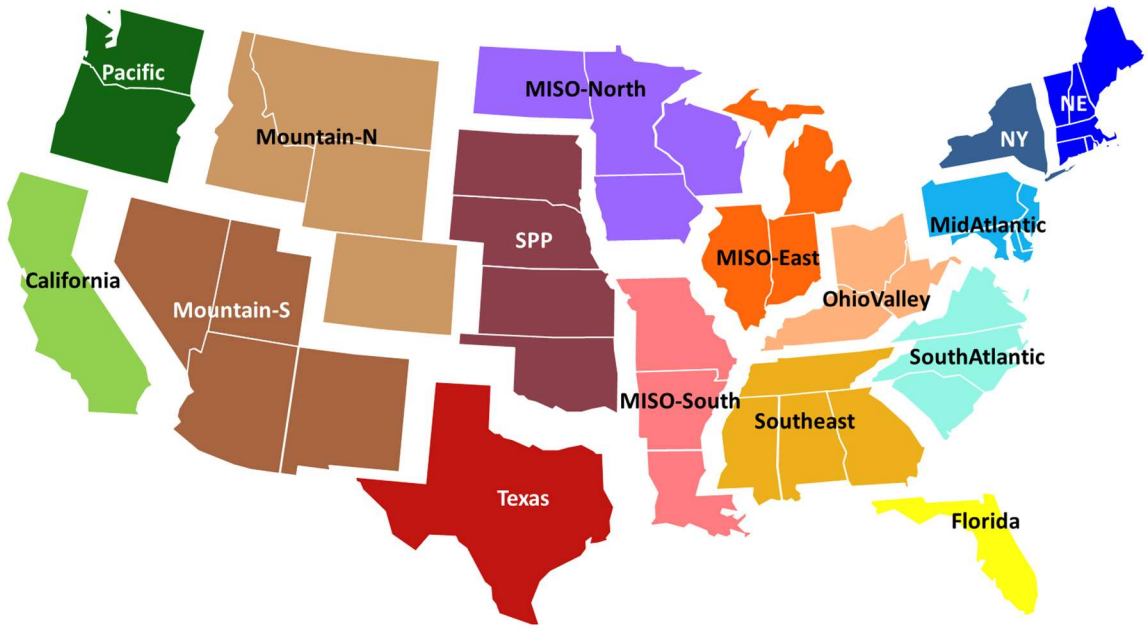


Figure 1. US-REGEN regions for capacity expansion problems [9].

This modeling work uses the US-REGEN optimized capacity and marginal dispatch stack from Illinois. More details about standard, specific US-REGEN inputs and assumptions can be found in [9].

2.1 Scenarios and Assumptions

The goal of this suite of scenarios was to cover several decarbonization possibilities. This included changes in nuclear cost, the inclusion of renewable portfolio standards (RPS), and the addition of a carbon tax. It is important to note that these scenarios are forecasts, meaning they represent future electric system possibilities for these inputs, not firm projections of what will happen in the future.

Each scenario has a nuclear cost, renewable cost, and policy assumption. Table 2 shows the matrix of the US-REGEN model runs. In total, six individual scenarios were run. Sections 2.1.1 and 2.1.2 detail the assumptions made in each of these scenarios.

Table 2. US-REGEN scenario descriptions.

Name	Short Name	Nuclear Costs	Renewable Costs	Policy
Default	Default	Reference	Reference	Current
Low Nuclear (LN) + High Renewable (HR) Costs	Default.LNHR	Lower	Higher	Current
100% Renewable Portfolio Standard (RPS)	RPS	Reference	Reference	100% RPS by 2050 (Allowing Nuclear)
100% RPS + HN & LR	RPS.LNHR	Lower	Higher	100% RPS by 2050
Carbon Tax	CTax.	Reference	Reference	Carbon Tax ($50 in 2025)
Carbon Tax + HN & LR	Ctax.LNHR	Lower	Higher	Carbon Tax ($50 in 2025)

2.1.1 Policy Assumptions

The nominal policy case uses the current policies implemented in US-REGEN. This includes individual state RPS that have been implemented, but not a national policy. The nominal policy also includes current tax incentives for specific generators, such as the investment tax credit and production tax credit for solar and wind, respectively, as well as renewable energy credits from various regions.

The renewable portfolio standard cases implement national RPS requiring 100% of load be served with power from qualifying sources by 2050. The RPS start at 30% in 2030 and increase by 17.5% per year until 2050. These cases allow nuclear in the RPS, in addition to standard renewable resources such as solar, wind, and hydro. The RPS is treated as a binding constraint, meaning that the model requires the RPS target to be met.

A carbon tax was also implemented for certain scenarios in order to investigate the difference between requiring low carbon generation and letting electricity markets drive decisions. The carbon tax starts at $50/metric ton CO_2 in 2025 and increases by 4% each year. Table 3 shows the price per metric ton of CO_2

emissions throughout the modeling horizon. Fifty dollars per ton represents a modest carbon tax that falls in the middle of the range of currently levied carbon taxes worldwide ($2–120 per ton).

Table 3. US-REGEN Assumed Carbon price by year.

Year	Carbon Price ($/metric ton CO_2)
2025	$50
2030	$60.83
2035	$74.01
2040	$90.05
2045	$109.56
2050	$133.29

Only one of each of these three policy options was used in each model run. This meant that US-REGEN runs used either the nominal, RPS, or carbon tax policy, and did not run any combination thereof.

2.1.2 Nuclear and Renewable Cost Assumptions

The model economic assumptions focused on nuclear and renewable costs. By adjusting the costs, the scenarios could represent more extreme cases favorable to nuclear. This became important in the HERON IES runs because it allowed for different IES and grid dynamics to create a more complete forecasting picture.

The average default cost cases use the US-REGEN default capital costs for nuclear and renewables. These costs are detailed in Table 4. US-REGEN assumes some degree of learning and thus reduces the capital costs in later years. Only the generators (nuclear and renewable) whose costs are manipulated are listed here. US-REGEN uses detailed geographic information including land and labor costs to establish different costs in each state or region across the US. The costs shown below represent the average costs across the US.

Table 4. US-REGEN average default capital costs.

Generator	2025 ($/kW)	2035 ($/kW)	2050+ ($/kW)
Nuclear (Greenfield)	5640	5480	5160
Wind – Onshore	1290	1090	1090
Wind – Offshore	3790	3210	3210
Solar PV – Fixed	1270	860	620
Solar PV – Single Axis	1370	920	670
Solar PV – Dual Axis	1470	980	720

There are two cost options: the nominal and the LNHR. When combined with the three policy options, we are left with six US-REGEN scenarios in total. In the low-nuclear, high-renewable (LNHR) cases, the capital cost of nuclear is reduced by 25%, and all renewable costs are increased by 50%. These are applied consistently throughout every modeled year.

2.2 Capacity Expansion Results

2.2.1 Capacity Evolution

In this section, we consider the capacity evolution of the tracked technologies over the 26-year project, as divided into 5-year intervals. These outputs are from the US-REGEN runs for each of the six scenarios. Figure 2–Figure 7 show the resulting capacities for each model scenario in 5-year increments for the state of Illinois. As seen in Figure 2, the majority of Illinois' capacity at the beginning of the modeling period is in the form of thermal (fossil and nuclear) generators. The carbon tax cases do have more renewables and zero coal capacity in the beginning, due to the huge penalties incurred by coal for its greenhouse gas emissions. A table of legend acronyms used in Figure 2–Figure 9 is given in Table 5.

Table 5. Generator acronyms for Figures 2-Figure 9.

Legend Name	Generator Name
Storage	Battery, pumped hydro, and other
Solar	Solar PV and solar thermal
Wind	Onshore and offshore wind
H_2	Hydrogen used for electricity production
NGCCS	Natural gas with carbon capture and sequestration
NGCT	Natural gas combustion turbine
BECCS	Biomass with carbon capture and sequestration
Other	Oil, diesel, and minor generation methods that don't fit other categories
Coal CCS	Coal carbon capture and sequestration
Coal	All types of coal that do not have CCS
Hydro	All hydroelectric
Nuclear	All nuclear facilities

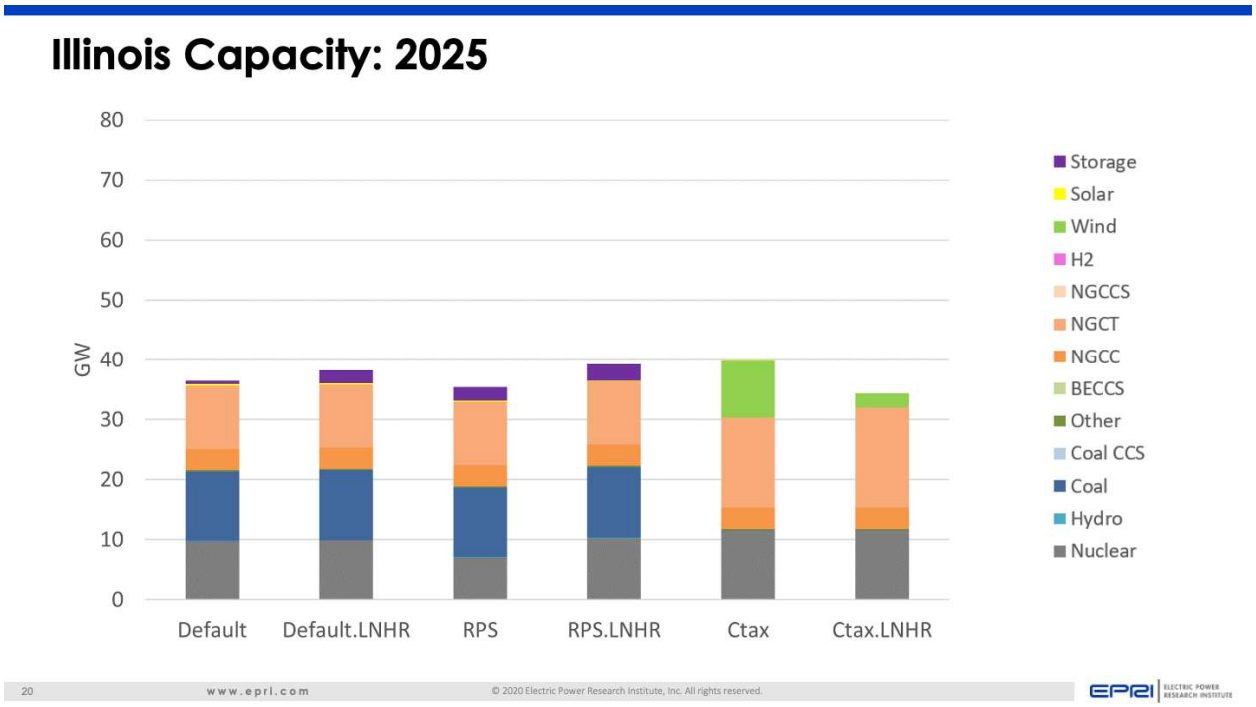


Figure 2. Capacity, 2025.

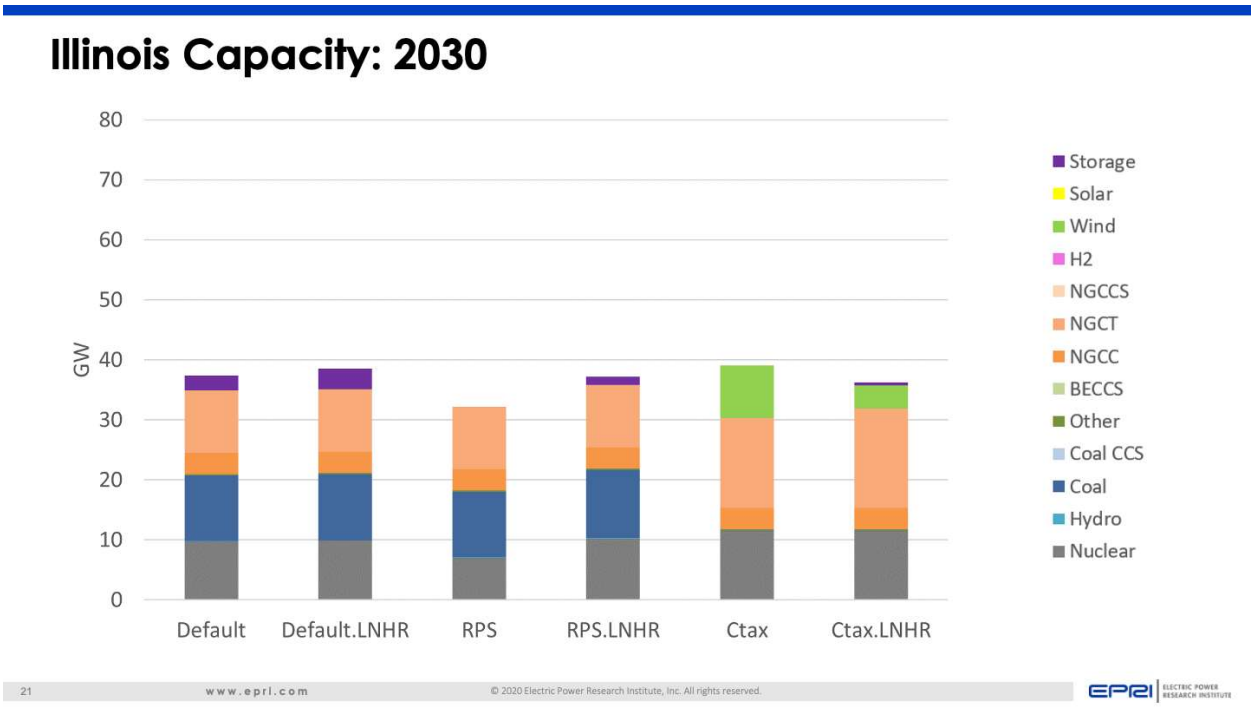


Figure 3. Capacity, 2030.

Model year 2030 still has relatively small deviations between scenarios. Modest retirements in thermal generators occur, and not much new capacity is built. By 2035, the effects of the policy and economic assumptions begin to manifest. The carbon tax and RPS scenarios start to see renewables build out in 2035. The LNHR cases suppressed new renewables and kept existing nuclear online for longer. The

default case and the default LNHR case continued along a similar track because no nuclear or renewables needed to be built, thus dampening the differences between the varying economics.

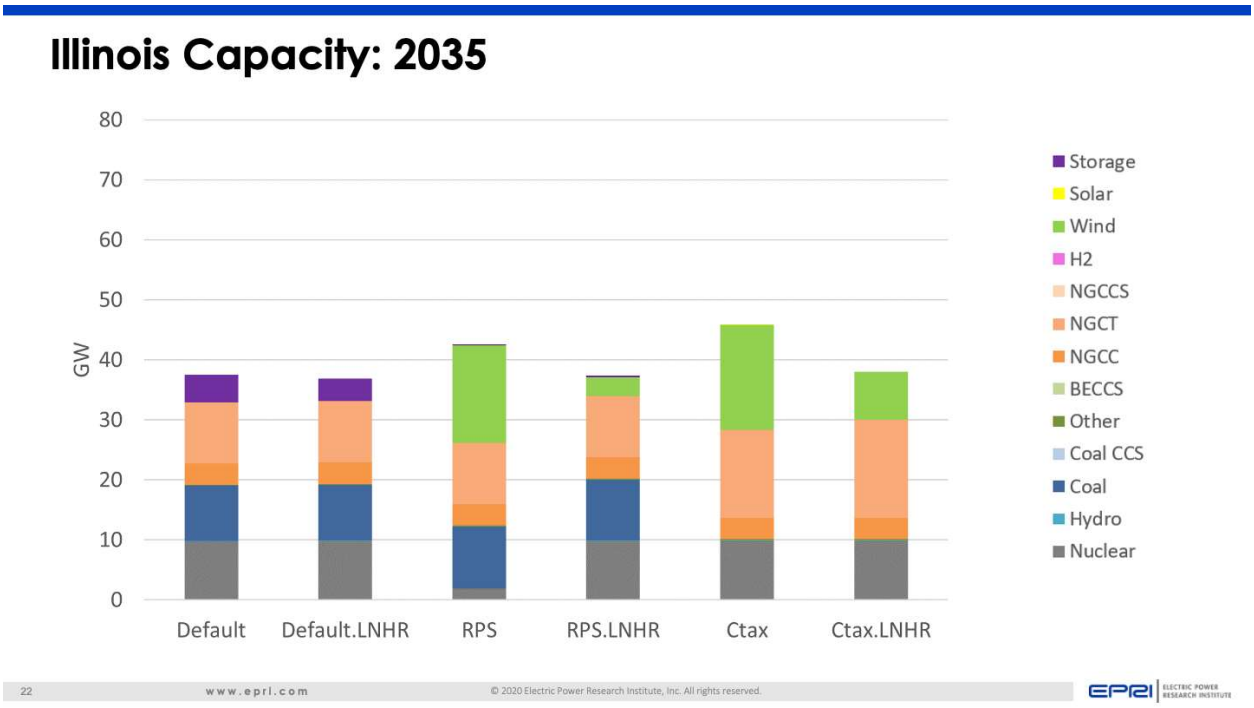


Figure 4. Capacity, 2035.

In the 2040 output, as shown in Figure 5, the negative effect of RPS on nuclear is made clear. All nuclear is retired in the RPS case, while most nuclear is retired in the RPS LNHR case. The small amount left on the grid in the RPS LNHR case is due to it still being cheaper to run the existing nuclear than build new high-cost renewables. All the other scenarios essentially maintain the existing nuclear fleet. From the standpoint of fossil fuel reduction, the carbon tax case was the most effective up to this point, since it got rid of the coal fleet. The RPS scenario retires nuclear and replaces it with wind. With no economic disincentive for fossil fuels, US-REGEN took the nuclear offline before cheaper fossil generators. The default case did not change substantially from its initial capacity mix.

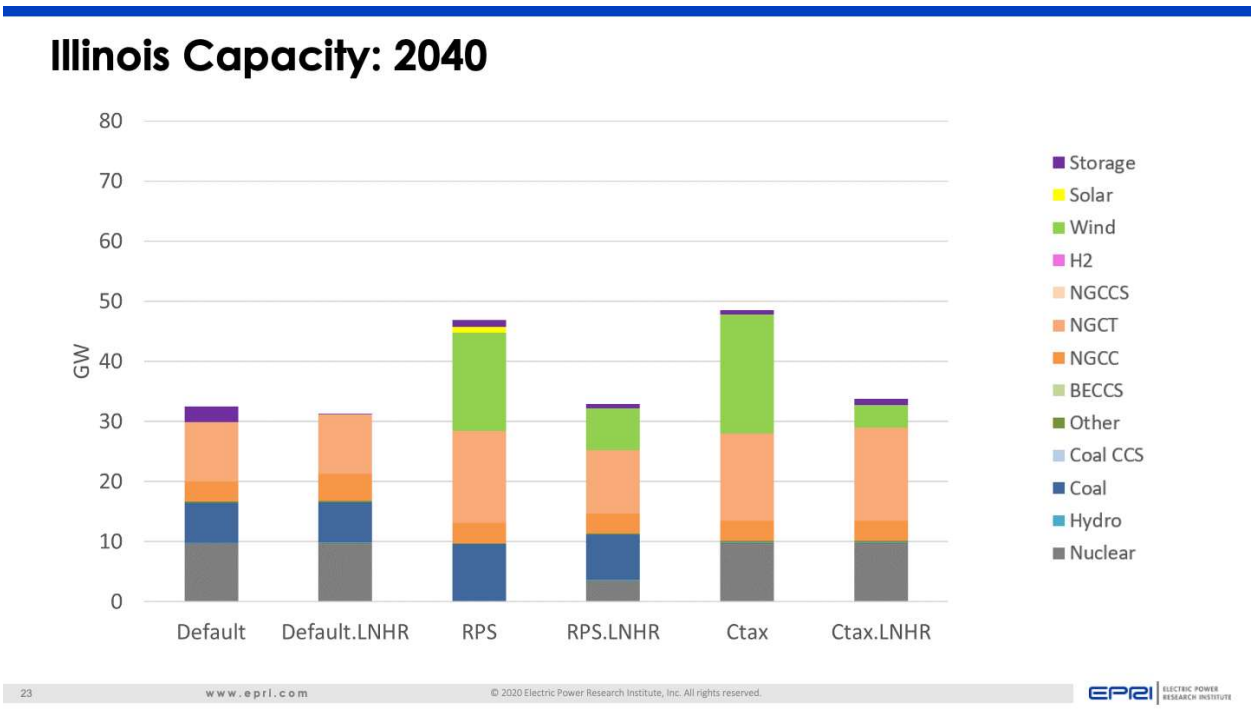


Figure 5. Capacity, 2040.

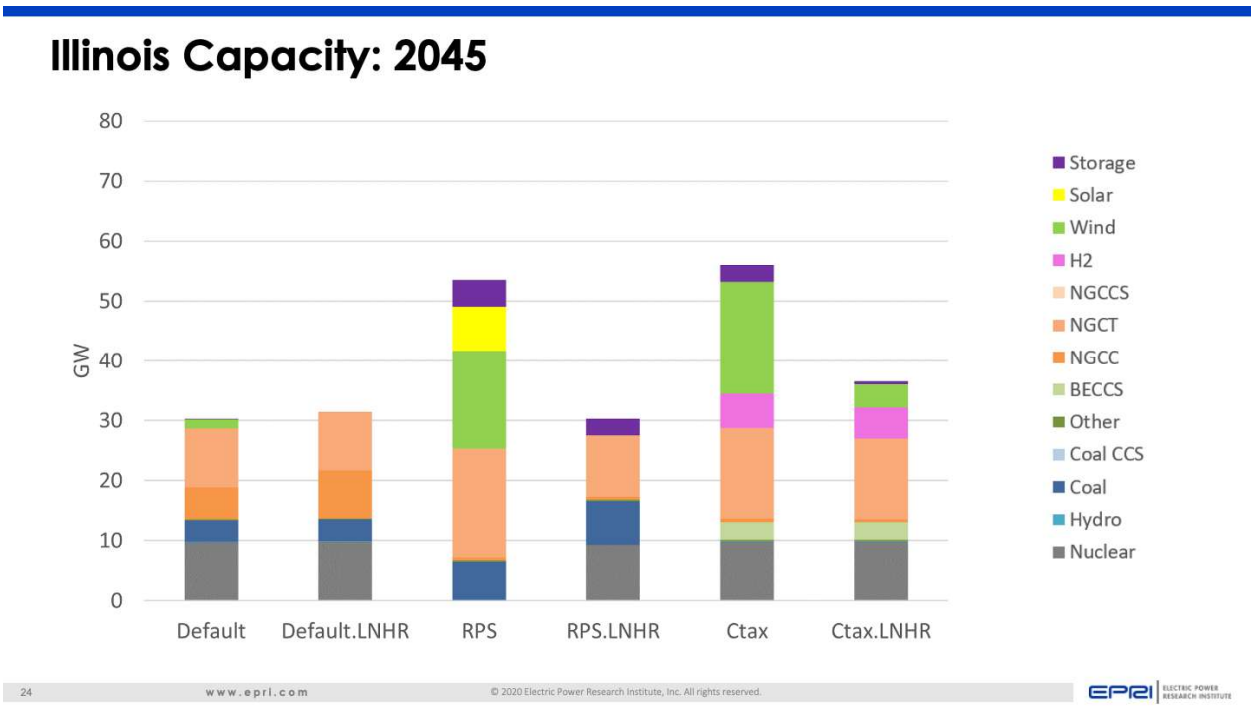


Figure 6. Capacity, 2045.

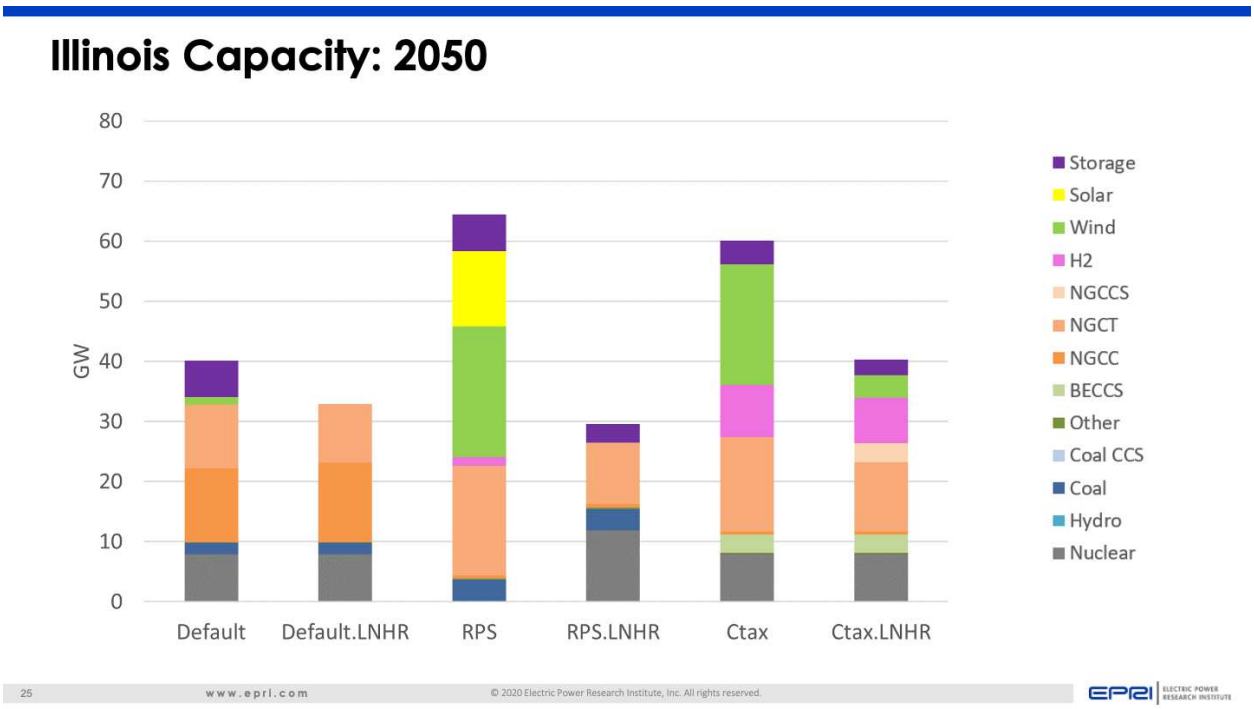
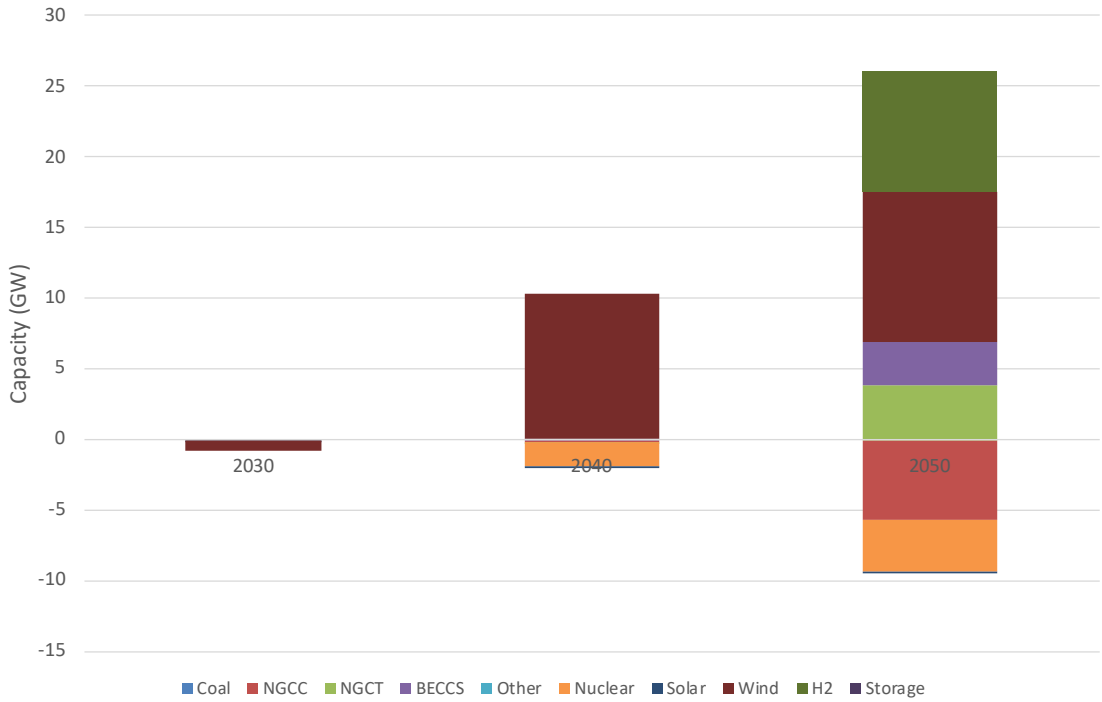


Figure 7. Capacity, 2050.

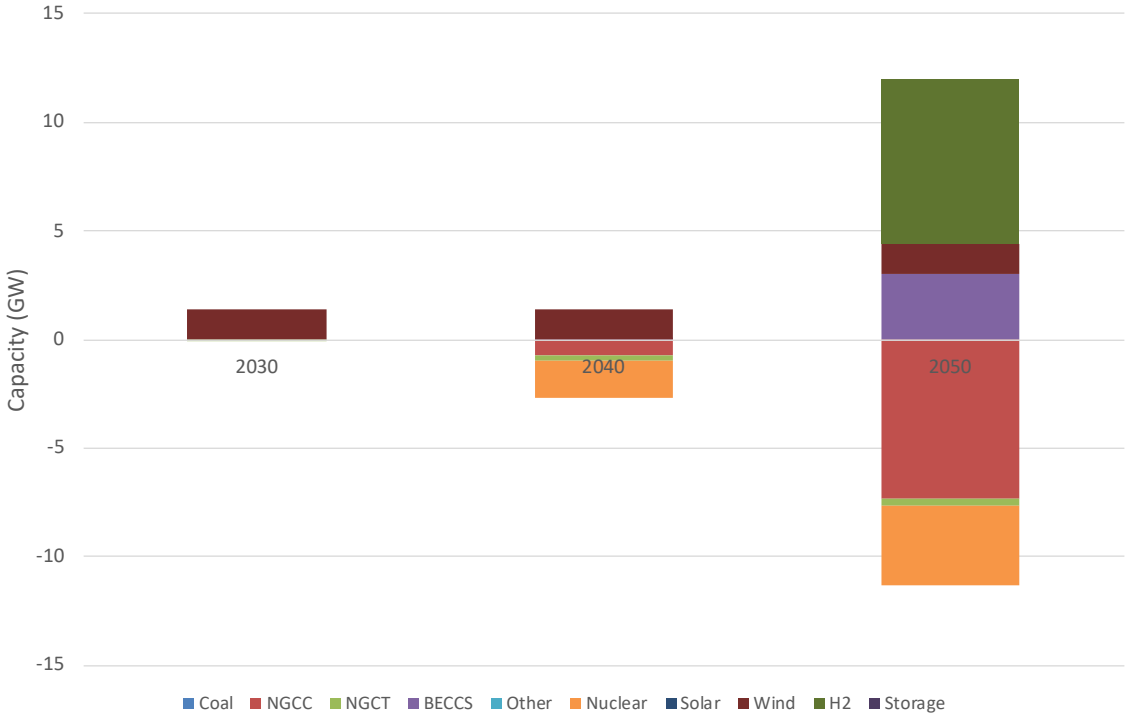
The final two model years, 2045 and 2050, show dramatic differences between the scenarios. The RPS case starts to retire coal in 2045 and gets rid of most of it by 2050. The coal is mostly replaced by solar and wind. The RPS case is the only scenario with an appreciable amount of solar. The RPS LNHR case builds new nuclear to replace the retiring coal and natural gas generation. US-REGEN builds small modular reactor (SMR) nuclear plants in the RPS LNHR case to make up for the reduction in coal and natural gas. The higher capacity factor nuclear means that the total system capacity of the RPS LNHR case is less than half that of the RPS case. The carbon tax cases see a similar trend: the carbon tax case adds wind capacity, but the carbon tax LNHR case prefers to add other resources such as natural gas combined cycle (NGCC) or biomass. Both carbon tax cases also build ~5 GW of hydrogen capacity.

From the standpoint of carbon reduction, the carbon tax scenarios reduced fossil fuel usage the quickest, and the RPS LNHR scenario ended up with the fewest fossil fuels. The carbon tax scenarios immediately retired the coal, such that there was no capacity in 2025. By 2050, both carbon tax scenarios had retired all their NGCC, and the carbon tax LNHR case retrofit carbon capture and sequestration (CCS) to some existing natural gas combustion turbine (NGCT). Beyond that, the carbon tax cases only reduced NGCT a few GW from the 2025 levels. The RPS retired coal at a slower rate, without seeing any significant reductions in coal until 2040. By 2050, the RPS case had retired most of its coal and all its NGCC. There was still a significant portion of NGCT in the RPS case, whereas the RPS LNHR case required less backup and, therefore, less natural gas altogether.

The capacity evolution of the carbon tax scenarios is plotted in Figure 8. The plot shows the difference in capacity, according to each given year, based on the initial model year. Both the carbon tax case and carbon tax LNHR case retired nuclear and NGCC plants at the same rate. The carbon tax scenario built wind, ending with an additional 10 GW than in 2025. Because of the large capacity of VRE, the carbon tax case also built 4 GW of new NGCT capacity despite the carbon price. The LNHR case did not require this, due to the higher ratio of firm to variable resources.



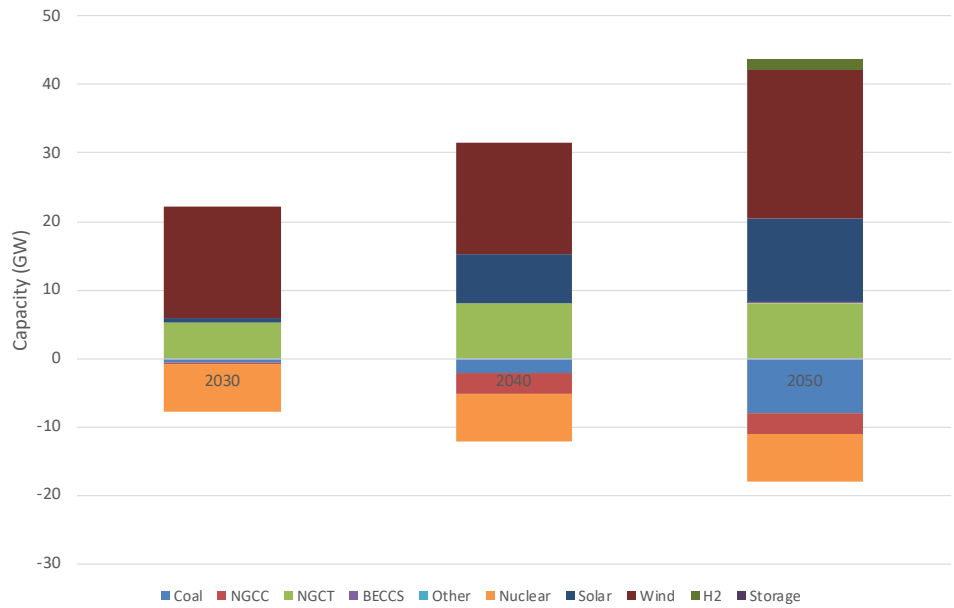
(a)



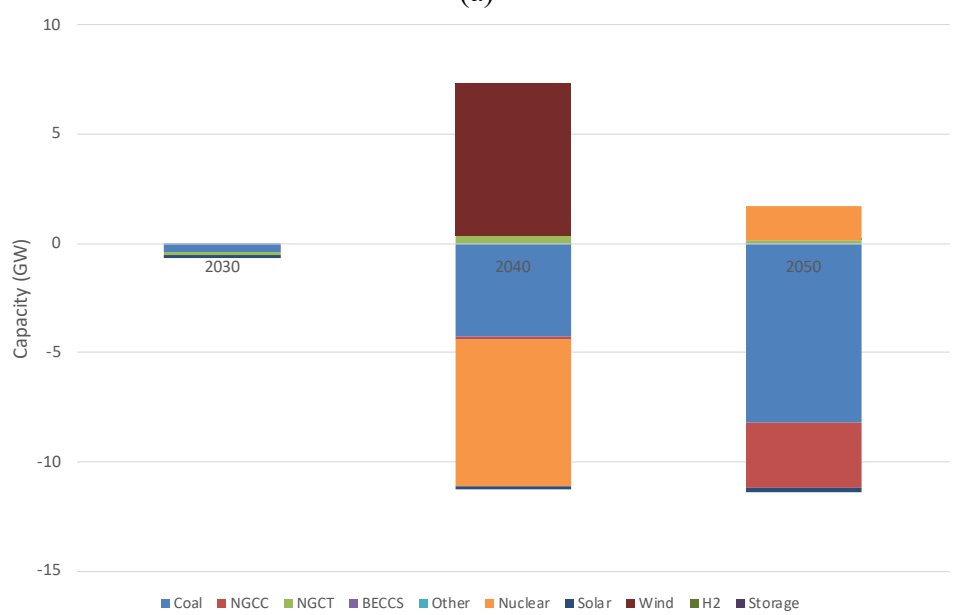
(b)

Figure 8. Capacity differences between 2025 and the given year for the (a) carbon tax and (b) carbon tax LNHR scenarios.

The RPS cases, as shown in Figure 9, are of interest because they trade renewables in the RPS run for nuclear in the RPS LNHR run. The RPS case builds out renewables, including both wind and solar. As with the carbon tax case, the model builds greater NGCT capacity to back up the additional VRE. In the RPS LNHR case, the old nuclear is retired and then replaced by new nuclear built between 2040 and 2050. This case built only a few MW of NGCT.



(a)



(b)

Figure 9. Capacity differences between 2025 and the given year for (a) RPS and (b) RPS LNHR scenarios.

The total capacities for each year, as plotted in Figure 10, were the highest in those scenarios friendlier to renewables. The LNHR economic assumption usually depressed the total system capacity because the model chose resources with higher utilization rates (such as nuclear) rather than VRE with a natural gas combustion turbine backup. This phenomenon even occurs in the default case, as wind is added in 2050 in the default, but not in the default LNHR.

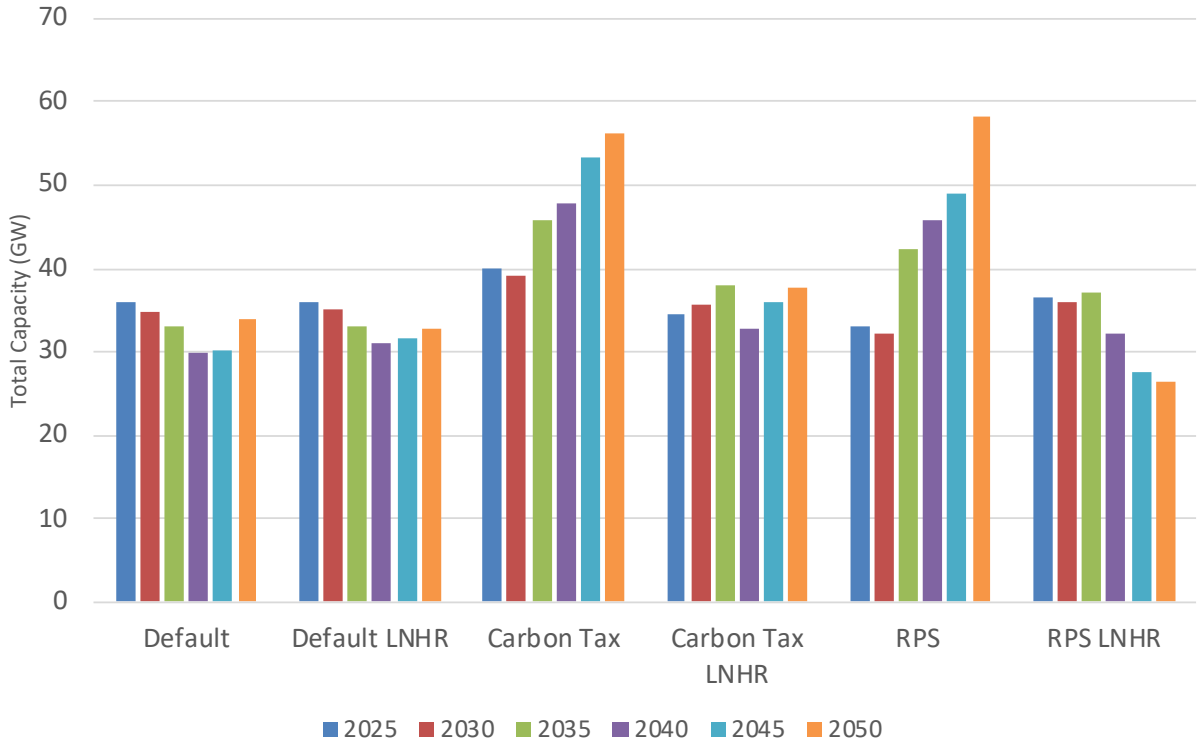


Figure 10. Total capacities for each scenario by year.

2.2.2 Average LMP Evolution

As capacity evolves, the average locational marginal price (LMP) changes over time. It is useful to recall that LMPs reflect the marginal costs of electricity production not the total costs. A system might have a low LMP despite requiring large capital expenditures. This means that scenarios exist in which it is less cost effective to have a capital-intensive unit that can operate at lower LMP as opposed to a unit with a higher marginal cost but lower capital expenditure.

US-REGEN's forecasted LMPs for Illinois are displayed in Figure 11. The general LMP evolution trends over the entire US-REGEN time horizon showed that the carbon tax scenarios led to the most expensive LMP and the RPS scenarios led to the cheapest. The LNHR cases were generally higher than the default economics case, though there was some switching between the default LNHR case and the default case.

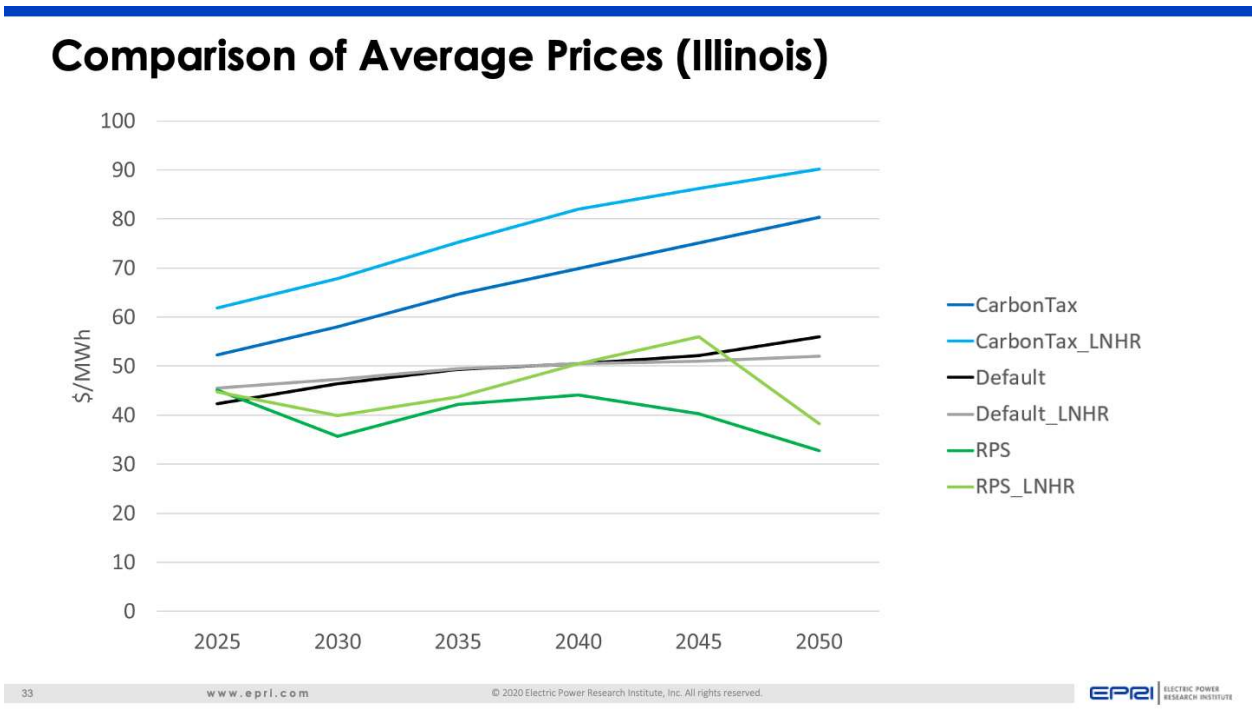


Figure 11. Illinois LMP forecast results from US-REGEN.

The carbon tax LMPs are the highest, increasing steadily over the 35-year horizon. Despite the carbon penalty, a significant amount of natural gas remains in the system, driving up the LMPs relative to other cases. The carbon tax LNHR case still sees a large buildout of renewables despite their cost increase, contributing to the higher system cost relative to the default carbon tax case. In comparing the default and LNHR carbon tax cases, nuclear remains fairly consistent without any new builds, meaning that the low nuclear cost does not cause any difference between the default and LNHR cases.

The default policy cases represented a middle ground for LMP. The LNHR LMP is higher in the early years but cheaper in the later ones. This could be because US-REGEN starts to build storage in the later years of the default case, but the LNHR case is almost exclusively served by nuclear, coal, and natural gas.

The lowest prices are generally seen in the RPS scenarios. The price in both the default and LNHR scenarios drops over the short term, as some excess generation is retired, but then increases between 2030 and 2040 when large amounts of VRE are built. Once the main VRE buildout is complete, the LMP drops back down to near the minimum level. LNHR is more expensive relative to the default RPS case, because the system still builds renewables to meet the RPS but does not build new nuclear.

3. LIGHT-WATER REACTOR MARKETS

As discussed, the changing energy scene is causing a reevaluation of NPPs' role as energy suppliers in the energy markets. The quality and reliability of service often taken for granted from NPPs as baseload energy suppliers may not be guaranteed from all energy suppliers in those energy markets in which VRE plays a significant role. This provides an opportunity to distinguish the various services of an energy supplier as being distinct assets (e.g., frequency regulation, on-hand capacity, etc.) beyond simply providing energy to the grid. In this section, we discuss some of these existing or potential markets and the impact they might have on existing LWRs in the U.S. This activity identifies driving economic factors leading to circumstances in which an NPP owner/operator might consider flexible operations, including through IES.

3.1 Electricity Market

3.1.1 U.S. Electricity Market Structure

The U.S. energy grid is generally organized into wholesale electricity markets operated by ISOs and RTOs. ISOs and RTOs are independent, non-profit organizations tasked with operating the energy transmission system reliably and in a just, reasonable manner. The goal of energy markets is to facilitate the lowest-cost solution to electricity customers in order to meet energy needs, both short term (months to years) and long term (decades). This includes operating the system reliably, with minimal chance of failing to meet the required demand, real-time energy balancing, generator and transmission scheduling, and assured long-term reliability of the system. The duties of ISOs and RTOs also include coordinating and facilitating long-term planning for generation and transmission, as well as operating and administering energy markets; however, in general, there is a hands-off policy when it comes to retail transactions such as services and electricity rates. Actors within energy markets include ISOs and RTOs, vertically integrated utilities, transmission owners, merchant generators and independent power producers, load serving entities, municipalities, cooperatives, public power agencies, and privately run power trading companies.

Figure 12 gives a high-level overview of ISOs and RTOs in North America. This demonstrates the wide variety in not only capacity and peak load, but also in composition and transmission when it comes to the different organizations. Figure 13 shows the fuel mix (by percentage) generated by the North American ISOs and RTOs, particularly highlighting the contribution from nuclear power, which ranges from 61% in the Ontario IESO to non-existent in the AESO.

	2018 Peak Load (MW)	Historical Peak Load (MW)	Total Generation Capacity (GW)	Generating Units	Annual Energy (TWh)	Transmission (Miles)
AESO	11,697	11,697 (01-11-18)	16.1	284	85.3	26,000
CAISO	46,427	50,270 (7-24-06)	80.3	1,080	223.7	26,000
ERCOT	73,473	73,473 (07-19-18)	78	650	376	46,500
IESO	23,240	27,005 (08-01-06)	37	171	137.4	18,600
ISO-NE	25,559	28,038 (08-02-06)	31	350	123.3	9,000
MISO	121,600	127,125 (07-20-11)	174	1,400	600-680	65,800
NYISO	31,861	33,956 (07-19-13)	39.3	760	160.9	11,173
PJM	147,042	165,492 (Summer '06)	186	1,379	806.5	84,000
SPP	49,926	51,181 (07-20-17)	89.1	795	259.6	66,497

Figure 12. High-level overview of select ISOs and RTOs in North America.

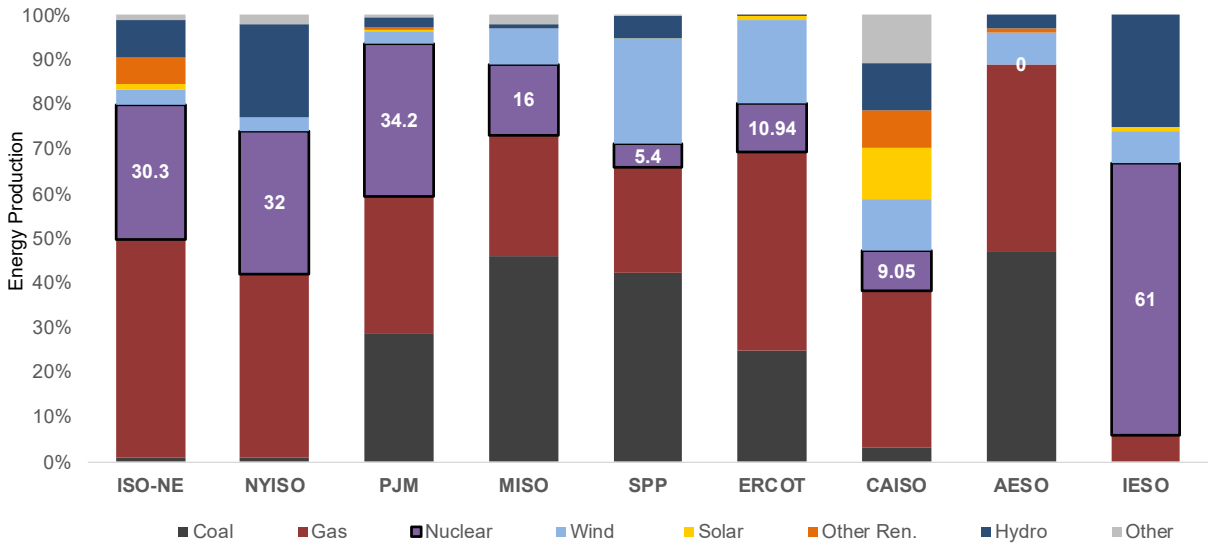


Figure 13. Fuel mix of North American ISOs and RTOs in 2018.

The energy markets in North American RTOs and ISOs can be divided into two market strategies: regulated and deregulated. In the 1990s, some vertically integrated utilities separated into generation, transmission, and distribution companies to increase incentives for efficiency and innovation. Furthermore, some states have restructured retail markets, allowing customers to select their energy provider. These "deregulated" markets are still regulated by the Federal Energy Regulatory Commission and so may be considered organized, restructured, or liberalized markets. Some such markets, particularly MISO and SPP, consist nearly entirely of vertically integrated utilities. In the U.S., all ISOs and RTOs operate both a day-ahead and real-time auction for electricity and some ancillary service products. Most also run a longer-term auction for capacity or have a resource adequacy procurement mechanism. The remainder operate under bilateral markets composed of vertically integrated utilities that balance their own supply resource with customer demand.

All U.S. ISOs and RTOs operate both an hourly day-ahead market and a shorter time frame market (15, or 5, or 1 minute-markets, with the 5-minute being the most common). Individual producers bid into the hourly day-ahead hourly market. These bids consist of three parts: incremental generation cost, no-load minimum operating costs, and startup costs. Incremental generation, sometimes referred to as "marginal cost," is the cost per kilowatt to produce electricity using the particular unit, including fuel, operations and maintenance (O&M), and similar variable costs. No-load minimum operating costs represent fixed costs for the unit, including capital and fixed O&M costs. Startup costs reflect any costs required to bring the unit online and begin producing electricity on the grid. These resource generators provide generator characteristics to the ISO or RTO, including the minimum economic operating level, minimum up/down time, ramp rates, hot/warm/cold start time, and maximum weekly starts. The hourly day-ahead market typically closes mid-morning. Some markets have offer requirements tied to capacity or resource adequacy requirements. Furthermore, ISOs and RTOs run a reliability unit commitment model to ensure that sufficient generation is online; this model can commit additional generators. The bidding and commitment schedules are summarized in Figure 14.

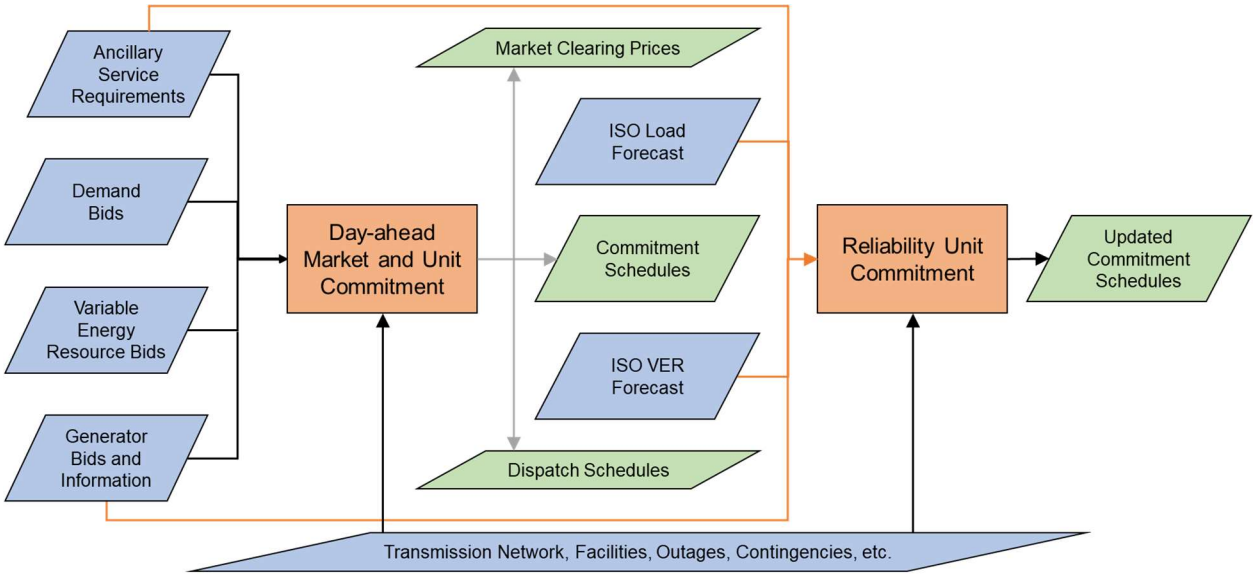


Figure 14. Hourly day-ahead bidding and commitment.

Because the hourly day-ahead commitment is predictive in nature, the real-time 5-minute market serves to make up the difference between predicted and actual load demand. Some ISOs and RTOs use multiple intervals between the hourly and 5-minute resolutions, and some perform look-ahead for several hours; for example, California operates a 15-minute market. These correction markets close 30–75 minutes ahead of time. Not all ancillary service products are offered on both the day-ahead and real-time markets, and availability depends on the ISO/RTO.

The interaction between the ISO/RTO and generators for economic dispatch involves a series of signals to resource offerings into the market. Day-ahead and real-time markets optimize supply offers and demand bids, then send dispatch signals to market participants. These dispatch signals are the economic dispatch. Suppliers then follow the load by following the dispatch signal sent by the ISO/RTO. Similarly, ancillary services (discussed below) are signals directing resources to respond in ways that support system reliability. The key factors impacting the economic dispatch of a supplier are the cost offer, including incremental and short-term commitment costs; generator characteristics such as ramp rates, minimum economic operating level, and minimum on/off times; and system needs and constraints, such as transmission congestion, losses, and demand forecast.

By way of example, consider the hourly day-ahead and 5-minute real-time market daily averages for PJM, as shown in Figure 15. While real-time variations are often small compared to the day-ahead pricing, there are notable exceptions. Participation in real-time markets may provide an opportunity for NPPs in flexible operation to leverage both of these markets.

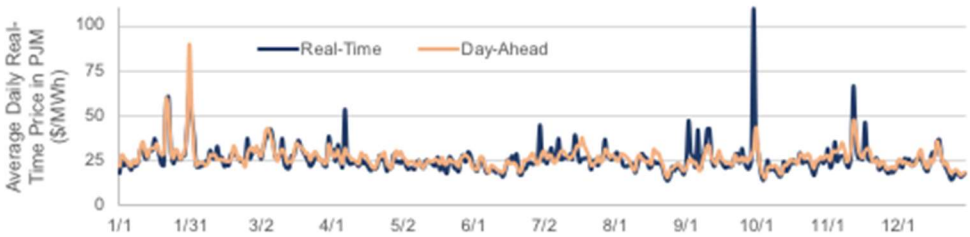


Figure 15. Average daily price of day-ahead and real-time energy in PJM in 2019.

3.1.2 Regulated and Deregulated Markets

ISOs and RTOs in the U.S. operate within two major market categories: regulated and deregulated. Both are regulated by the Federal Energy Regulatory Commission.

Regulated markets are those in which the energy generation and transmission utilities are owned by the ISO or RTO. As such, meeting energy demand at any time involves strategically dispatching the least expensive generation units until the demand is met. This cost-minimization strategy results in a cost to consumers that covers the generation costs. Optimization of dispatch for regulated markets involves a cost-minimization optimization formulation in which the cost is minimized for the ISO or RTO to meet demand.

Deregulated markets are those in which units bid production costs (dollars per megawatt) and available capacity a priori—for example, in hourly day-ahead markets. During each production cycle, the ISO/RTO then dispatches the units required to meet the load, from least to most expensive. The bidding price of the most expensive generation unit dispatched is then the "clearing price" paid per megawatt dispatched to each generation unit during the cycle. Optimization within a deregulated market is usually done with a particular generator or technology as the center of focus, the intent being to maximize profit for that focus rather than for the ISO/RTO as a whole.

3.2 Alternative Markets

Ancillary services are used in electric power systems to ensure the operational reliability of the bulk power system. While a relatively small component of overall electric power costs, these services are a critical need, and in some regions the types and needs of these services are changing.

Four major products in U.S. wholesale markets were identified as part of this work: energy, ancillary services, capacity, and financial transmission rights. While the policies and nomenclatures surrounding each of these market products differ among each ISO and RTO, we can consider them in these loose groupings.

Financial transmission rights are markets used to hedge congestion charges and are purely financial in nature. They are sometimes referred to as transmission congestion contracts, transmission congestion rights, or congestion revenue rights, and it is not expected that NPPs can play on these markets. Energy markets were discussed in Section 3.1. We discuss the other two major market products in turn below. The approximate financial volumes of these markets by ISO/RTO are shown in Table 6.

Table 6. Market financial volume by ISO/RTO.

	Total Market Volume ($B)	Energy ($B)	Ancillary Services Markets ($M)	Capacity Market ($M)	All-in-Price ($/MWh)
AESO (CAD$)	6.6	4.3	240	N/A	50.35
CAISO	10.8	10.6	189	N/A	49.50
ERCOT	15.1	13.4	603.5	N/A	35.63
IESO (CAD$)	17	3.3	73.85	N/A	24.3
ISO-NE	12.1	6.0	130.9	3,600	98
MISO	29.9	21	70.5	431	32.57
NYISO	7.5	6.38	491	1,800	49
PJM	49.79	29.61	654	11,000	62.3
SPP	20.5	7.5	76	N/A	27.65

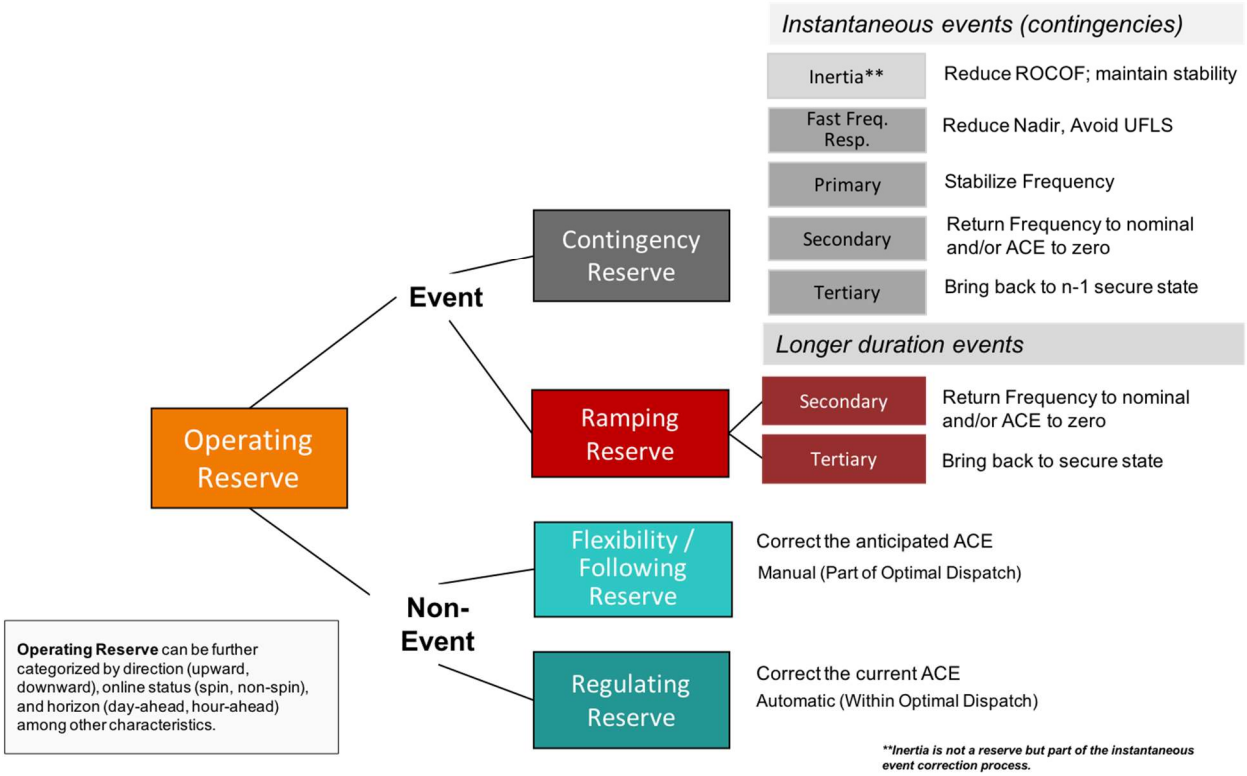
Additional information in EPRI Report IDs 3002009273, 3002016226

3.2.1 Ancillary Services Market

There are many names for the various services captured by the ancillary services market, and the availability of these service markets differs from ISO to ISO and RTO to RTO. Ancillary services are defined as "necessary to support the transmission of capacity and energy from resources to loads while maintaining reliable operation of the Transmission Service Provider's transmission system in accordance with good utility practice" [10].

An example breakdown of services is shown in

Figure 16. A wide variety of system benefits is shown under Operating Reserve services, including frequency regulation, regulation, and flexibility. The operating reserve that is required by an ISO or RTO can be broken into two sub-categories; reserve used for grid event response and reserve used for non-events. Contingency and ramping reserve generally exist as units that can be brought online quickly to respond to an event such loss of generator or an unexpectedly high load day. The non-event reserve, such as flexible following reserve and regulation reserve are used to smooth the smaller fluctuations that occur on a given electric grid. These can be used to automatically maintain frequency or remedy an area control error (ACE), which is an imbalance between balancing area's original anticipated electricity needs and the actual.



Adapted from Ela et al., *An Enhanced Dynamic Reserve Method for Balancing Areas,* EPRI, Palo Alto, CA: 2017. 3002010941.

Figure 16. Example ancillary services breakdown.

ISOs/RTOs have ancillary service requirements that differ from organization to organization. For example, in ISO-NE, the contingency requirement is a 10-minute reserve greater than or equal to the largest first contingency loss times the contingency reserve adjustment factor (a number between 1 and 2, representing the previous quarter's DCS score [with 1 being the perfect score]). In NYISO, the requirement is a total 10-minute operating reserve greater than or equal to the largest single contingency. In PJM, the requirement is a total contingency reserve greater than or equal to 150% of the largest single contingency. The nature of these requirements is critical in understanding the availability and depth of the markets for those ancillary services. Further, there appears to be no direct correlation between the size of the requirement and the size of the region, requiring local definition for each geographical region's requirements.

To bid into ancillary service markets, requirements are outlined for each ISO/RTO governing the participation of suppliers. If a supplier fails to follow signals, they may be temporarily disqualified from supplying a particular resource. Generally, a more flexible asset has more opportunities to participate in these markets and, thus, more opportunities for economically viable operation. Based on the requirements of many ISOs and RTOs, the minimum set of generator characteristics for participating in ancillary service markets should be practical for NPPs in flexible operation.

3.2.2 Capacity Market

All U.S. markets except for ERCOT operate a capacity market or ensure long-term resource adequacy. ERCOT operates an "energy only" market. These capacity markets have a variety of names, such as Reliability Pricing Model in PJM or Installed Capacity Market in NYISO. Most markets operate both a day-ahead market (DAM) and a real-time market (RTM). Maximum prices in each ISO or RTO are set to some proportion of the cost of new entry (CONE). The characteristics of these markets also differ

from market to market, as shown in Table 7. Most ISOs/RTOs use a loss-of-load-expectation model to determine the resource adequacy requirement. Payments from capacity auctions support initial investment costs and fixed going-forward costs. Many capacity markets have developed updated designs in consideration of state-sponsored resource participation.

Table 7. Capacity markets in several ISOs and RTOs.

Capacity Markets	PJM	ISO-NE	NYISO	MISO
Name	Reliability Pricing Model (RPM)	Forward Capacity Market (FCM)	Installed Capacity Market (ICAP)	Planning Resource Auction (PRA)
Sloped demand curve	yes	Yes	yes	no
Max. price	150% Net CONE	160% Net CONE	200% Net CONE	Net CONE
Minimum offer price rule	yes	yes	yes	no
Number of locations	9 zones	3 zones	4 zones	10 zones
Must-offer requirement	DAM energy	DAM energy and RTM energy	DAM energy	DAM energy
Forward Period	3 years ahead	3 years ahead	1 month prior	2 months prior
Commitment Period	1 year	1 year	6 months	1 year

An NPP in flexible operation, especially one with tight coupling as part of an IES, may find opportunities to increase revenue through participation in capacity markets, depending on the ISO or RSO they participate in.

4. HYDROGEN PROCESSES AND MARKETS

4.1 IES introduction

As electricity markets have changed with increases in variable renewable energy within the last few decades, NPPs have been investigating ways to increase profitability, flexibility, and efficiency. Companies and research entities have looked beyond the sale of electricity to production of other commodities such as heat, potable water, hydrogen, or chemical products. These co-generation systems, or IES, include a nuclear reactor, electricity generation turbomachinery, and an industrial process for the production and/or storage of a secondary commodity. The secondary-commodity production process can be coupled to the nuclear reactor via heat, electricity, or a combination of the two. These IES have also been proposed for currently operating NPPs and next-generation reactors [2, 11].

One IES configuration uses an NPP to generate heat and electricity for hydrogen production. Much of the discussion about nuclear-hydrogen IES is driven by their ability to produce carbon-free H_2. Producing hydrogen via the sulfur-iodine (SI) cycle, copper-chlorine cycle, and steam electrolysis have all been discussed in the literature.

The SI cycle uses a chemical process that converts water into hydrogen and oxygen via a Bunsen reaction and then into hydrogen iodide (HI) via heat. Because the SI cycle requires higher temperatures (upwards of 850°C) than the U.S. LWR fleet can provide, research in the U.S. has moved away from SI. The Japan Atomic Energy Agency, which operates a high-temperature test reactor, has been extensively researching the SI cycle with the goal of commercializing the technology and coupling it with a 300-MW high-temperature reactor. It is estimated that the SI and a high temperature gas reactor system can achieve 50% thermal efficiency in this configuration [11].

Figure 17 shows the design schematic for the SI cycle. Heat, as well as electrical topping heat, is input from the coupled NPP to maintain correct conditions in the chemical reactors and separation units. Water is input, and hydrogen iodine and sulfuric acid are produced. The HI is then split into H_2 and I_2. The H_2 product is separated and the I_2 recycled. An oxygen byproduct is also produced via the decomposition of sulfuric acid [12].

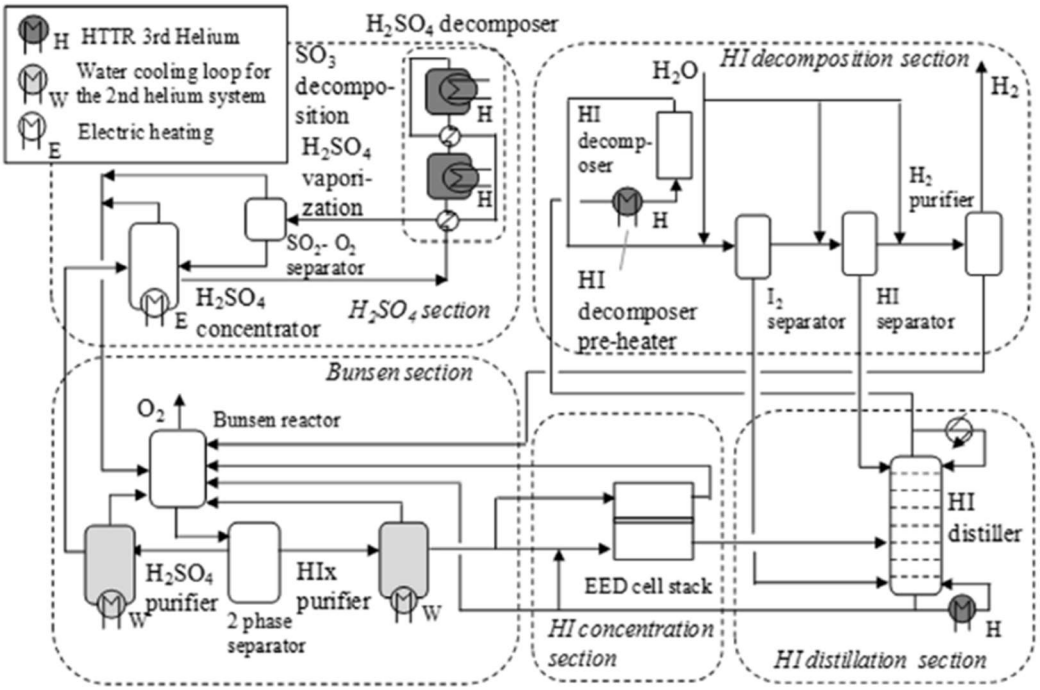


Figure 17. Sulfur-iodine cycle process flow diagram [12].

The copper-chlorine cycle is similar to the SI cycle in its use of chemical reactions to split water into hydrogen and oxygen. With the large bulk of research coming from Canada, the Cu-Cl cycle was designed to be coupled with a Generation-IV supercritical water reactor [13]. The Cu-Cl cycle requires temperatures of around 500°C, making it is also promising for Generation IV reactors but a poor candidate for direct heat coupling with existing LWRs.

Water is input to the Cu-Cl cycle and converted to HCl via a chemical reaction with CuCl. The HCl and CuCl then undergo an electrochemical reaction to create $CuCl_2$ and H_2 [14]. As with the SI cycle, a separate O_2 stream is produced as a usable byproduct. Figure 18 shows a process flow diagram of the Cu-Cl cycle. A nuclear reactor would provide heat directly to the O_2 chemical reactor, and electricity to the electrolyzer and other system components.

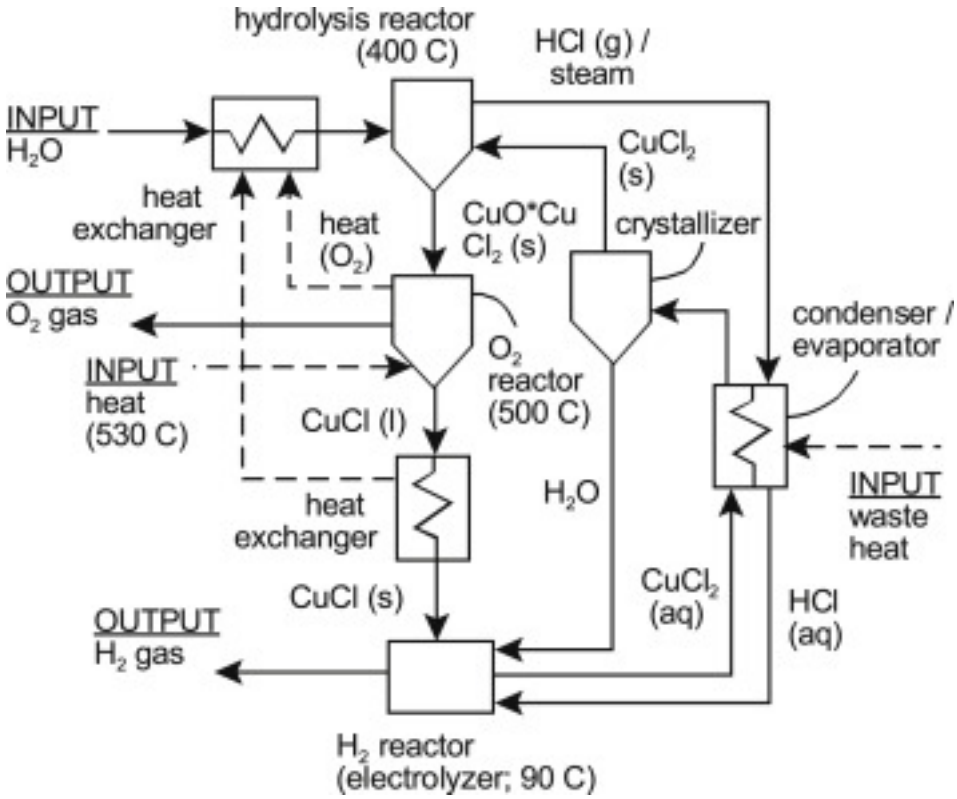


Figure 18. Copper-chlorine cycle process flow diagram [14].

Steam electrolysis, both high- (HTSE) and low-temperature (LTE), has been proposed for coupling hydrogen with nuclear facilities. An LTE utilizes nuclear heat and some electricity in an electrolysis cell to split water into oxygen and hydrogen at an anode and a cathode. The HTSEs split water in a similar manner but operate at a higher temperature and require more heat initially, though potentially less electricity in the electrolysis cell. NPPs and electrolysis systems can be coupled by using nuclear process heat as a preheat, along with electricity from the nuclear reactor, to assist in heating and run electricity through the electrolysis cell. Because of this flexibility, electrolysis is a potential candidate for current LWRs. The steam electrolysis cells also reduce the system's chemical complexity when compared to SI or copper-chlorine cycles. HTSEs are generally more efficient than LTEs. Of all the reviewed hydrogen production methods, HTSE systems are the closest to commercialization within current LWRs.

In contrast to the Cu-Cl and SI hydrogen production methods, HTSEs do not have complicated chemical processes to contend with. Water is passed through various heating and compression stages until it reaches optimal pressures and temperatures. The water is then run through a solid oxide electrolysis cell (SOEC). An SOEC stack schematic is shown in Figure 19. An electrical current is sent through as water passes through the stack. A nickel cermet cathode and a perovskite anode collect hydrogen and oxygen, respectively [2].

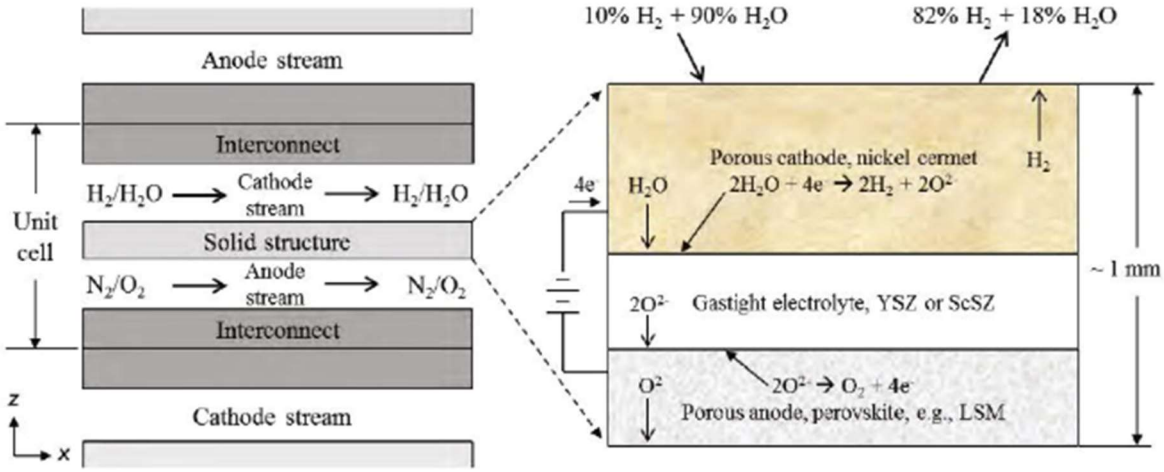


Figure 19. Cross-section of SOEC stack [15].

The IES HTSE generally uses 3–10% of its energy input as heat, 5–20% as electrical topping heat, and the balance electricity is run through the SOEC for the electrolysis reaction. This equates to approximately 43 kWh consumed per kg H_2 produced [2]. A schematic of how the HTSE process would be coupled to a nuclear reactor is shown in Figure 20. Heat is input to the HTSE by diverting steam from the turbine to the HTSE unit. Electricity is provided to the HTSE via the turbine.

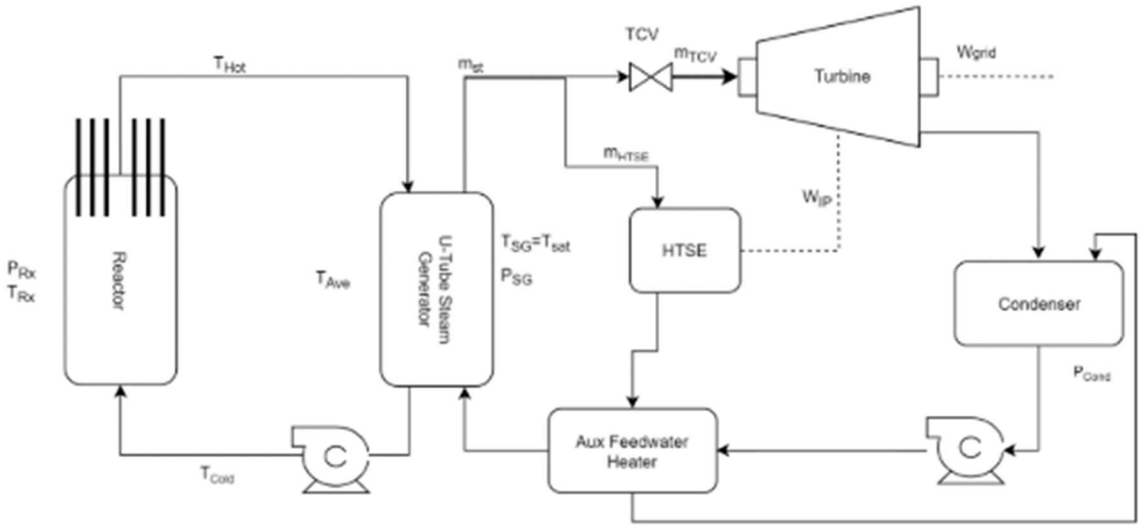


Figure 20. HTSE IES process flow diagram [2].

HTSE costs for this research were pulled from Frick et al. [2]. Their estimates used the Aspen Process Economic Analyzer in tandem with Aspen HYSYS process models to estimate the capital cost of the entire IES HTSE system. The capital expenditures (CAPEX) for a 7.4 kg/s HTSE unit coupled to an NPP is $545,263,737. This number was normalized to $73,684,288/kg/s, and an economy of scale factor of 0.955 was used for plants larger or smaller than 7.4 kg/s. Table 8 breaks down all the HTSE economic parameters used in this analysis. Note that the O&M accounts for replacing the SOEC every 3–5 years and is applied entirely as fixed O&M. Depreciation occurs on a Modified Accelerated Cost Recovery System (MACRS) 15-year schedule. Costs are in 2019 dollars.

Table 8. HTSE economic parameters [2].

	Cost
CAPEX (per year, normalized by H_2 production capacity)	$73,684,288/ kg/s
O&M (per year, normalized by H_2 production capacity)	$9,561,176/ kg/s
Economy of Scale Factor	0.955
Storage CAPEX	$500-600/ kg
Depreciation Scheme	MACRS 15
Lifetime	30

4.2 Hydrogen Market Simulation

The U.S. hydrogen market is a relatively small but quickly changing sector. Development of new production techniques, the promise of using hydrogen in industry or transport, and the depression of natural gas prices have all played a role in increasing H_2 demand and generating projections for increased consumption in the future.

4.2.1 Hydrogen Production and Consumption

Hydrogen is generally produced in one of three ways: merchant, captive, or by-product hydrogen. Merchant hydrogen is produced at a dedicated hydrogen production facility and made available for transport and sale to a customer. Captive hydrogen is produced and used in the same facility, such as in the case of refining processes that produce H_2 via methane reforming and use it to reduce sulfur content in diesel fuel. Approximately 10 million metric tonnes (MMT) of merchant and captive hydrogen, sometimes termed “on-purpose” hydrogen, are produced and sold in the U.S. [16]. Additional hydrogen is produced as a byproduct of other chemical processes and sold to reduce the overall process costs. Table 9 gives three different estimates for U.S. hydrogen production, based on three different sources. Because different sources estimate production in different ways, there is a range of production from 8.04 to 15.37 MMT H_2.

Table 9. U.S. hydrogen production estimates.

Source	Markets & Markets [19]	Brown Procedure [18]	IHS Market Capacity [17]
Merchant (MMT)	3.78	3.83	4.30
Captive (MMT)	5.27	5.86	4.08
By-product (MMT)	-	5.68	0.43
Total (MMT)	**9.04**	**15.37**	**8.04**

Hydrogen in the industrial sector is mainly consumed in the production of chemicals and metals, electronics, and food processing. Petroleum refining and ammonia production are the largest consumers of hydrogen, both in the U.S. and worldwide. Other processes such as metal production, food processing, and electronics production use only a small amount of hydrogen [20]. Figure 21 shows global hydrogen consumption and its growth over time. This plot only encompasses merchant or "pure" hydrogen.

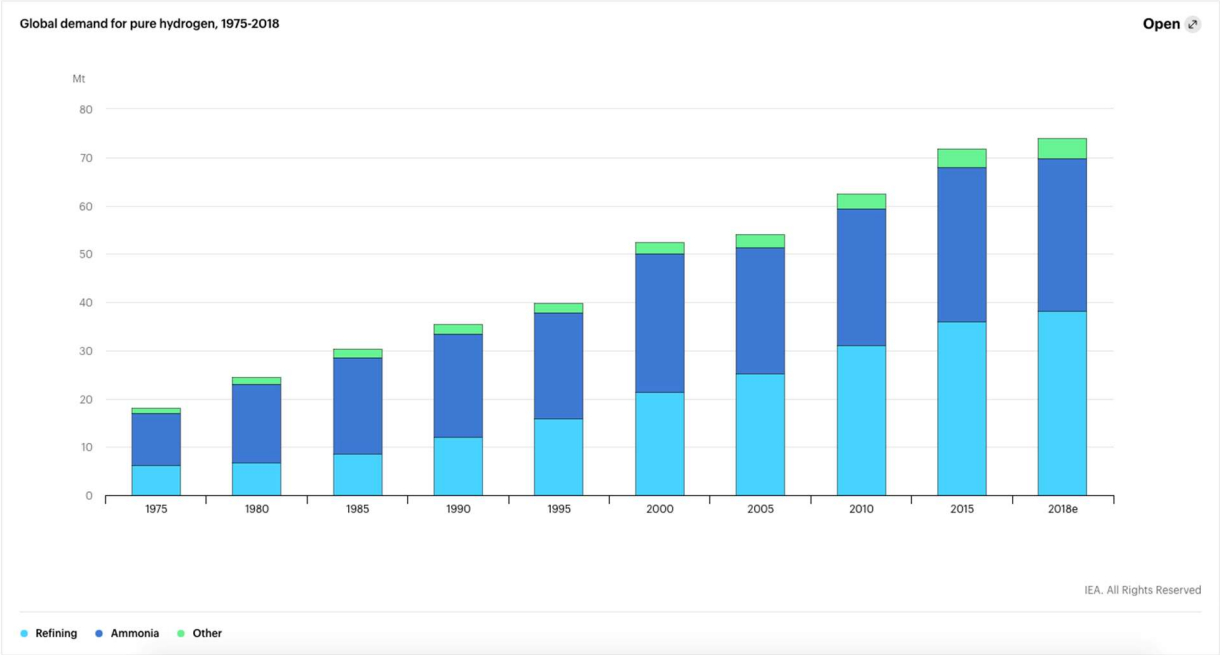


Figure 21. Global demand for pure hydrogen [20].

Transportation hydrogen, while only accounting for a small amount of the current demand, is expected to grow over the next several decades. In Figure 21, the "other" designation includes the transportation sector's hydrogen use, making it a very small percentage of overall hydrogen use, both globally and in the U.S. While this number is currently small, it is expected to grow rapidly as countries continue to increase their decarbonization efforts, generating higher demand for merchant-produced hydrogen.

The growth in hydrogen demand has caused governments and utilities to reevaluate how hydrogen is produced. The cheapest method of hydrogen production, steam methane reforming, uses natural gas and produces CO_2 as a byproduct. Meeting hydrogen demand in a low- or zero-carbon emission scenario

requires hydrogen produced from sources other than methane reforming. The IES configurations discussed in Section 4.1 provide this low-carbon hydrogen. This research effort assesses the economic fitness of IES hydrogen production when compared to steam methane reforming.

4.2.2 Hydrogen Market Modeling

A well-quantified hydrogen market is important for assessing IES economics. A demand curve is needed to relate the price of hydrogen to the size of the hydrogen market. In other words, the price of hydrogen should correlate to the amount of hydrogen produced by the IES. The actual supply curve for existing hydrogen markets can be difficult to quantify, since hydrogen is produced in so many ways, with varying purities and uses.

One method for developing a hydrogen supply curve would be to compare the IES to the cost of hydrogen production via the cheapest producer: steam methane reforming. If IES can produce hydrogen equally or less expensively than steam methane reforming, the IES hydrogen will be competitive in the market. In this sense, using steam methane reforming to approximate the market is a conservative approach. If the IES hydrogen is cheaper than the methane reforming hydrogen, the IES hydrogen will always be the cheapest option.

The H2A production model was used to develop hydrogen market curves. H2A, developed at the National Renewable Energy Laboratory, estimates the selling price of hydrogen, based on technology assumptions [21]. H2A outputs for this research are based on steam methane reforming default cost assumptions. Based on natural gas prices, the selling price of hydrogen for different-sized reforming processes is the output. The plot of H_2 prices for each natural gas price of note is shown in Figure 22. Each natural gas price corresponds to the 2020 EIA annual energy outlook price for 2025–2050, in five-year increments [22]. Each of these years shown corresponds to a HERON model run. In this way, the model accounts for the projected price evolution over the forecasted years.

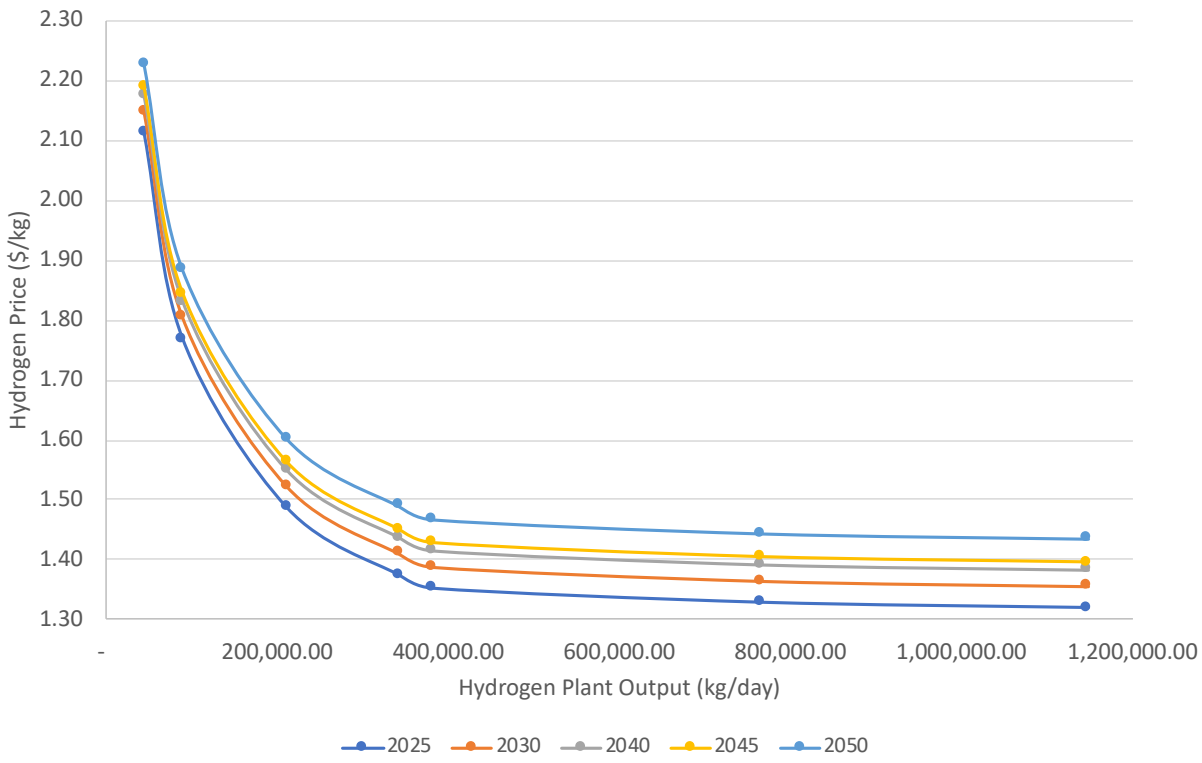


Figure 22. Hydrogen supply curve by year.

The hydrogen market function for each solve year is used in the corresponding HERON economic optimization. As the inner loop performs the dispatch, the associated IES HTSE capacity is input into the market function, and the H_2 price is output. This H_2 price is then used to determine if electricity or hydrogen should be produced, as discussed in Section 5. This dispatch informs the outer loop optimization of the HTSE capacity.

5. HERON FOR STOCHASTIC TECHNO-ECONOMIC ANALYSIS

5.1 Introduction

HERON [4] is a software plugin for the uncertainty framework RAVEN [5]. HERON provides a set of tools specifically for using RAVEN to perform STEA for systems of components connected through mutual resource production and consumption in the presence of economic drivers. More specifically, it was designed to perform uncertainty-centric analysis of generation units (or *components*) with multiple potential *resource* markets (energy, hydrogen, water, etc.). HERON has previously demonstrated performance for regulated markets [3, 24] and deregulated markets [1, 2].

HERON has specific strengths regarding stochastic analysis of small or large systems, where large numbers of components with similar technologies can be grouped effectively into a small group of homogeneous producers. HERON leverages the synthetic history generation tools in RAVEN [23] to analyze the distribution of performances for capacity profiles of a grid energy system. This makes it well-suited for exploratory analysis of the viability of different technologies in both regulated and deregulated markets.

HERON (github.com/idaholab/HERON) is an open-source software available via the RAVEN plugin system (github.com/idaholab/raven). HERON is software quality-controlled [4], utilizes continuous integration, and maintains a user list as well as issue tracking through its software repository.

5.2 Simulation Workflow

Performing STEA with HERON involves a two-layer optimization approach, as shown in Figure 23. In the outer layer, macro variables such as component capacity, market sizes, and tuning variables are analyzed. In the inner layer, the macro variables are taken as constant, while generations of synthetic multiyear scenarios are produced to assess the economic viability of the selected component mix. Each inner-layer analysis results in a statistical representation of economic metrics such as the NPV, given optimized component dispatch for the generated scenarios. The outer layer is then informed by the economic metric distribution to determine how, and if possible, to further improve financial performance of the system. The manner of dispatch optimization depends on the nature of the system under analysis. Below, we discuss this separately for regulated and deregulated markets.

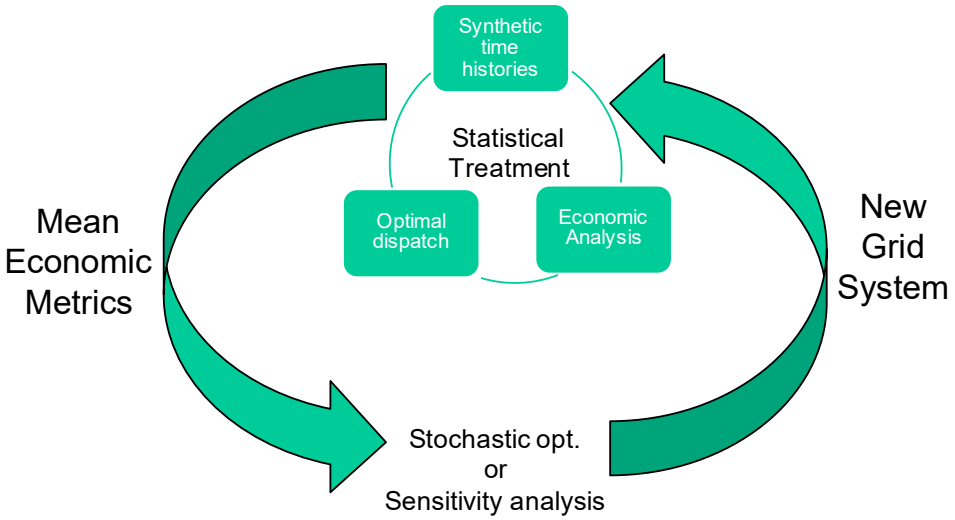


Figure 23. HERON workflow.

5.2.1 Projection: US-REGEN

HERON itself is not yet capable of long-term projection modeling of interconnected grid systems to determine the supplier portfolio evolution. To provide this feature in this study, we utilized the EPRI economic modeling tool US-REGEN [9], a capacity expansion economic model for policy and regulation analysis up to the year 2050. It provides regional details and takes a representative hourly approach to the yearly modeling of wind, solar, and load variability. US-REGEN accepts a large number of input choices in order to build a guiding direction for projection analysis, including policy decisions and expected technical and economic development directions. The results are periodic (e.g., every 5 years) data regarding the installed capacity and operating costs of units or technologies within the simulation, in addition to load profiles.

5.2.2 Synthetic History Scenarios

Each synthetic history generation represents a multiyear scenario with the same statistical characteristics as the data on which it is trained, but with distinct signals [23]. This enables a set of components with fixed capacities to be tested under a variety of realistic circumstances and determine the system's statistical economic viability. The synthetic histories represent a series of years as long as the desired project life, often 20–60 years.

For each year in the synthetic histories, the synthetic history generator was trained, on hourly (8760) resolution from real-world data. This training is then treated with machine-learning algorithms to characterize and cluster the behavior, reducing the required analysis in each year. This reduction factor can often be as large as 10–20 without losing meaningful data, and highly depends on the system and histories used in the analysis. Furthermore, RAVEN provides mechanics to interpolate the characteristics of the signal between years, producing signals that are not direct interpolations between time histories but rather statistical interpolations between the histories. This allows the synthetic history algorithm to acquire data from long-term projection tools, or higher fidelity grid representation, such as ReEDS [7], PLEXOS [8], or US-REGEN [9] and generate statistically interesting yearly samples that are still computationally feasible to analyze under uncertainty (see Section 6.1.3).

5.2.3 Regulated Market Analysis Workflow

The regulated market is somewhat simpler to formulate as an optimization problem than the deregulated market. The regulated market desires cost minimization to meet load demands; as in the deregulated market, the transmission and generation is owned by the ISO/RTO. This results in a straightforward mixed linear optimization problem, with the dispatch of individual components as the optimization variables and the system cost as the optimization objective function. In a system with no inertial terms (e.g., storage or ramp rates) and a single resource (e.g., electricity), this is as simple as using the marginal cost stack to find the minimum cost to cover the load and it does not differentiate with respect the deregulated market. However, in the presence of inertial terms and/or multiple resource markets, this becomes a more complex optimization problem.

In HERON, this regulated market optimization is performed using rolling windows in Pyomo [6]. Each window encompasses a 24-hour day-ahead projection and optimizes the dispatch of each component to minimize system cost over that 24 hours. For slowly ramping components, this may involve beginning a ramp early or deciding not to ramp during a sharp peak. For storage units, this may involve stockpiling resources during periods of low demand for use during periods of high demand.

5.2.4 Deregulated Market Analysis Workflow

A deregulated analysis seeks to maximize the profit for a subset of components, not to minimize the cost of electricity production generally. This results in modeling ISO/RTO behavior separate from the

analysis target component(s), as the ISO/RTO minimization of cost has different economic drivers than the subset of components (though they often have many drivers in common).

To accommodate the interplay between the ISO/RTO and the focus subset of components, deregulated dispatch optimization consists of three steps. First, the subset of components prepares their bid for hourly electricity production during a 24-hour window. This bid includes both a price for production and the capacity they will make available at that price, and may potentially involve multiple bids for different capacities, especially where multiple opportunity costs are at play for the units generating electricity. Of particular note is that the subset of components determines their bid without access to knowledge of other components in the system and without knowledge of the expected or real load in the bidding period.

Once the bid is submitted, the focus turns to the ISO/RTO, who collects all the bids and builds the electricity stack based on production cost, available capacity, and any other constraints they may have in dispatch selection. The ISO/RTO then uses this stack to meet the demand at minimum cost. These dispatch instructions are passed back to the subset of components, which can then decide what to do with any unused capacity during each hour.

5.3 Recent Improvements

HERON's open-source release [1] has lowered the barrier for acquiring HERON as a plugin of RAVEN, resulting in increased user activity. Requests for improvements in code features and interface usability, as well as the needs of this STEA activity, resulted in many code developments. We discuss a few notable new features here.

5.3.1 Features

The following are features added to HERON since the open-source release.

- ***Custom Dispatch API***

One of the most common accelerations of the inner-loop optimization dispatch is to write a specific algorithm for dispatch decisions based on problem parameters. For example, in previous analyses [2, 3, 24], custom dispatching was based on single drivers such as the price of electricity vs. the price of hydrogen, priority dispatch, or integral load over a 24-hour period. This feature is required in this work for representing the deregulated market as an interaction between the IES and ISO/RTO. As such, a custom API for including arbitrary dispatch algorithms written in Python was added to HERON. These dispatchers have access to information about the energy mix and the synthetic history scenario and are expected to return the applicable dispatch of components in the system for the given signals. Otherwise, the implementation of individual dispatch algorithms is completely flexible to user input.

- ***Validators***

Funded by the Integrated Energy Systems Program, and in collaboration with Argonne National Laboratory, a validation system was added to HERON [27]. This validation system enables development of custom validation algorithms to check the proposed dispatch setpoints during the HERON inner-loop optimization. This allows HERON dispatchers to use simplified process models while being tested against more rigorous mechanics. In their initial demonstration, the researchers showed how reduced-order models could be used to project HERON's dispatch space (e.g., electricity production) into process model state space (e.g., temperature and pressure) for more resilient model validation of the dispatch setpoint practicality.

- ***Storage Simulation***

As needed for the regulated-market analysis in this work, storage representation was added to the Pyomo dispatch optimization algorithm. The storage is somewhat different than the other component

archetypes in the system, in that its activity is recorded as levels stored rather than production or absorption rates. The dispatch optimization algorithm uses the initial value along with activity during the optimization window to use the storage in the most economically viable manner, often to flatten peaks and fill valleys in noisy load signals. Proper treatment of storage, especially with respect to the length of the rolling windows and its impact on grid capacity needs are still to be fully developed and its treatment in this analysis while acceptable could be further improved. The development of better treatments for the simulation of storage will be an area of future research.

5.3.2 User Interface Improvements

In addition to basic code features, several interface improvements were made to enhance the accessibility of HERON for STEA.

- ***Executable***

An executable for HERON was added that behaves in a fashion similar to the RAVEN executable. This bash executable handles the loading of the appropriate Python libraries before building the RAVEN XML inputs based on the user's input. This reduces the number of steps required between the user opening a terminal and running HERON.

- ***Automatic switching between sweep and opt modes***

Also, a highly requested user feature, it is now possible to switch between optimizing in the outer loop and a parametric study in the outer loop. Both perturb the macro variables (often component capacities). The optimization option seeks the ideal set of macro variable values to maximize profit or minimize cost, while the parametric option samples the full optimization space in a grid pattern to determine the overall behavior of the economic metrics with respect to the macro variable values.

- ***Case Labels***

It is common for HERON users (including for this work) to perform multiple STEA with very similar input files. To this end, we implemented case labels, which are carried throughout the code at all levels and can be inquired in functions and dispatchers, as well as observed in output files. This allows for tracking of specific runs through custom labels such as geographic region, policy assumptions, etc.

- ***Custom Time, Year Names***

Previously, it was necessary to train synthetic history generators in RAVEN using the name "time" for the micro time parameter and "year" for the macro time parameter. This restriction has been lifted, allowing the user to specify arbitrary macro and micro time parameters, alleviating an inconvenience in data manipulation prior to training synthetic history generators.

- ***Minimum Production Levels***

The Pyomo dispatch optimization algorithm in HERON was initially designed to assume a minimum production of zero for all components. This feature has been extended, and users can now specify minimum production levels for components through the HERON input file. These are then respected in the Pyomo dispatch optimization.

6. HERON DISPATCH ANALYSIS DESCRIPTION

The objective of this study is to determine how the introduction of IES for hydrogen production coupled to the nuclear generation components could impact the economic viability of the system (regulated market) or nuclear power components (deregulated market). We selected the state of Illinois in the U.S. from 2025 through 2050 as a baseline case, due to its markets and existing nuclear generation. US-REGEN provides long-term load and capacity projections based on a variety of scenarios, yielding snapshot data every 5 years for both hourly load and projected component capacity.

6.1 System Description

6.1.1 Components

US-REGEN tracks 40 homogenized technologies in the market region, with retirements and new builds optimized over the 26-year project life. These technologies include VREs such as solar and wind, natural gas and coal generators, hydro, nuclear, storage assets, etc. Every 5 years, the US-REGEN model provides the load for a full year, as well as capacities for each technology and marginal costs for producing each technology. US-REGEN provides these for each of the six scenarios described below.

Once US-REGEN provides its projection scenario results, we consider these scenarios in HERON—along with the addition of IES—to determine the potential economic viability of such a coupling. The IES we use is the high-temperature steam electrolysis (HTSE) hydrogen production plant, which couples directly to the NPP for electricity. As with the market for hydrogen described in Section 4, we consider a supply contract in which a fixed price of hydrogen is paid to the IES for a constant stream of hydrogen throughout the year. To provide flexibility in the volatile energy market, we also include a hydrogen storage unit as part of the IES, and this unit can supply hydrogen to the consumer when the NPP is unable to provide electricity to the HTSE because it is fully dispatched to the grid.

The size of the NPP is fixed within each year and comes from the US-REGEN projection. The size of the hydrogen consumer contract, HTSE, and hydrogen storage are all macro-optimization variables in the outer optimization loop of HERON.

6.1.2 Scenarios

For this analysis, six projection scenarios were selected for US-REGEN [9], involving a combination of policies (nominal, carbon tax, and renewable energy policy [RPS]) and pricing structures (nominal, LNHR]). We discuss each of these scenarios briefly in this section. These scenarios were analyzed in the states of Illinois and Ohio, and the Illinois results are discussed in detail in Section 2.1. Table 10 summarizes the scenarios.

- Carbon Tax – indicates that a tax is levied on generation components that produce carbon as a byproduct of energy generation—in this case $50/metric ton by 2025.
- RPS – indicates an incentivized strategy to meet 100% renewable penetration by 2050.
- LNHR – indicates nuclear costs reduced by 25% and renewable costs increased by 50%.

Table 10. STEA analysis scenarios.

Name	Short Name	Nuclear Costs	Renewable Costs	Policy
Default	Default	Reference	Reference	Current
Low Nuclear + High Renewable Costs	Default.LNHR	Lower	Higher	Current
100% RPS	RPS	Reference	Reference	100% RPS by 2050 (Allowing Nuclear)
100% RPS + HN & LR	RPS.LNHR	Lower	Higher	100% RPS by 2050
Carbon Tax	CTax	Reference	Reference	Carbon Tax ($50 in 2025)
Carbon Tax + HN & LR	CTax.LNHR	Lower	Higher	Carbon Tax ($50 in 2025)

6.1.3 Synthetic Scenario Training and Validation

A series of synthetic histories were generated for each scenario discussed in Section 6.1.2. These histories represent grid demand for electricity under each scenario's policies and regulations. By taking the snapshots provided by US-REGEN, a continuous history was interpolated and fit as an auto-regressive moving-average (ARMA) process. This process generally fits the projections provided by US-REGEN but adds elements of uncertainty and randomness that would be expected in the fluctuation of energy market demands. The mathematic description of an ARMA process is given as:

$$x_t = \sum_{i=1}^{p} \phi_i \, x_{t-i} + \alpha_t + \sum_{j=1}^{q} \theta_j \, \alpha_{t-j},$$

where x is a vector of dimension n, and ϕ_i and θ_j are both n by n matrices. When $q = 0$, the process is strictly autoregressive; when $p = 0$, the process is strictly moving average (MA).

Since the initial representation of grid demand is often non-stationary, a detrending step in the training process was required to extract seasonality from the time-series data. The ARMA process leveraged detrending via a Fourier series before the actual training began and will be referred to as a Fourier-ARMA. The Fourier trend can be described as:

$$x_t = y_t - \sum_{m} \{a_m \, sin(2\pi f_m t) + b_m \, cos(2\pi f_m t)\}$$

where $\frac{1}{f_m}$ are the defined bases that can be modified to enhance the fit during the training process. More information on this model can be found in Talbot et. Al [23].

In total, six different synthetic histories were generated using data collected from US-REGEN. Each history was modeled under a different pricing structure scenario described in Table 10. The synthetic histories were generated with an hourly resolution making up the grid-demand for each year from 2025 to 2050. US-REGEN provided the original market demand signal for years 2025, 2030, 2035, 2040, 2045, and 2050. For every year not provided by US-REGEN, the synthetic history was generated through an interpolation step in the training process. Therefore, model validation was performed by comparing the years provided by US-REGEN with its respective synthetic year. As all scenarios produced similar results, this section will detail findings using the Carbon Tax LNHR scenario. The training results for each case can be found in APPENDIX E: All ARMA Results.

To determine an optimal set of bases for the Fourier detrending step, a Fast-Fourier-Transform (FFT) was performed on the market data for each respective snapshot from US-REGEN. This analysis provided a set of periods with an associated amplitude indicating periods of strong cyclical behavior. It was discovered that many of the periods identified by the analysis were natural boundary points that occur throughout the year. These periods range from trends occurring on a mid-day, daily, weekly, and quarterly basis to a mid-year and yearly basis. Table 11 details the non-normalized amplitudes for each significant period discovered through the FFT analysis.

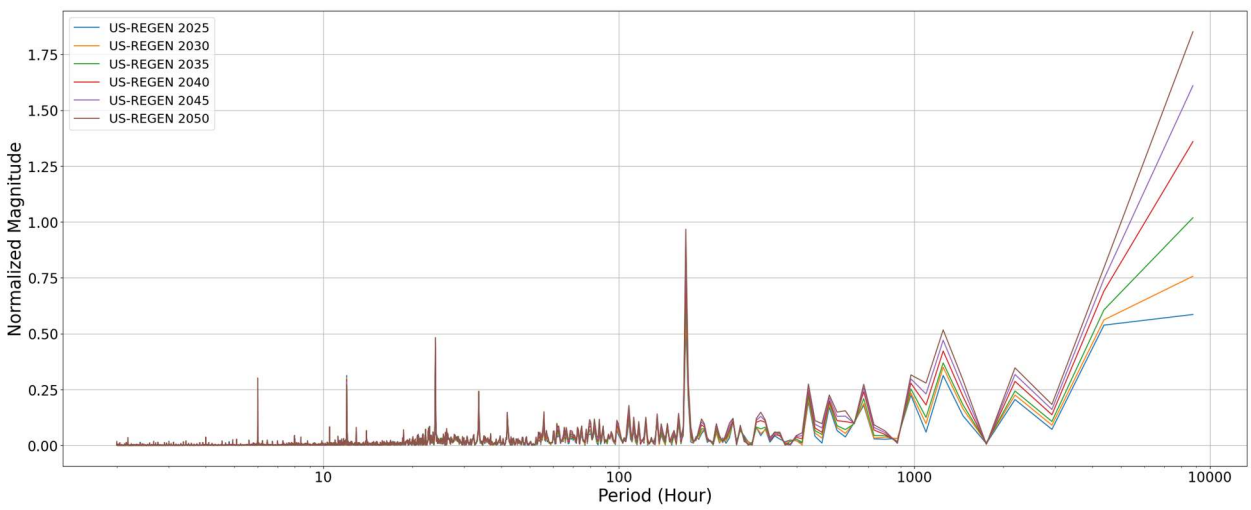


Figure 24. Carbon Tax LNHR, FFT amplitude results.

Establishing a set of bases leads to a nominally strong initial fit for market demand. The initial detrending step can be thought of as the process of describing the deterministic nature of demand; thus, leaving the residuals to be modeled as the random process that influences market demand over time. Figure 25 displays an example of the initial fit generated by the final chosen bases for all ARMA processes. It was determined that the Fourier series required a wide range of basis points to encapsulate the cyclical nature of market demand. Changes to base selection greatly affected the initial fit of the time-series data. Figure 26 shows an initial fit with a limited selection of bases.

Table 11. Carbon Tax LNHR, FFT significant periods with amplitudes of greater than 0.10.

Year	Period													
	6	12	24	33	168	172	438	673	973	1251	1460	2190	4380	8760
2025	819.22	2738.33	3368.05	1473.20	4786.88	1766.52	1712.73	1574.40	1965.83	2738.65	1161.72	1798.67	4715.05	5132.14
2030	1058.85	2646.29	3465.44	1497.23	5245.68	1888.25	1821.47	1640.99	2057.85	3065.33	1435.14	1975.39	4919.79	6632.44
2035	1376.64	2602.23	3598.09	1623.86	5872.33	1946.55	1952.69	1835.51	2211.08	3231.69	1591.97	2131.30	5313.38	8924.66
2040	1793.80	2577.29	3827.11	1824.64	6757.92	2139.50	2121.80	2103.93	2438.49	3699.36	1920.38	2509.07	6052.70	11911.40
2045	2214.22	2494.02	4030.54	x	7719.64	2345.09	2268.81	2257.33	2606.36	4121.71	2246.70	2779.83	6525.42	14104.55
2050	2644.79	x	4224.85	x	8475.90	2518.11	x	x	2762.68	4527.77	2561.92	3038.89	6968.94	16218.87

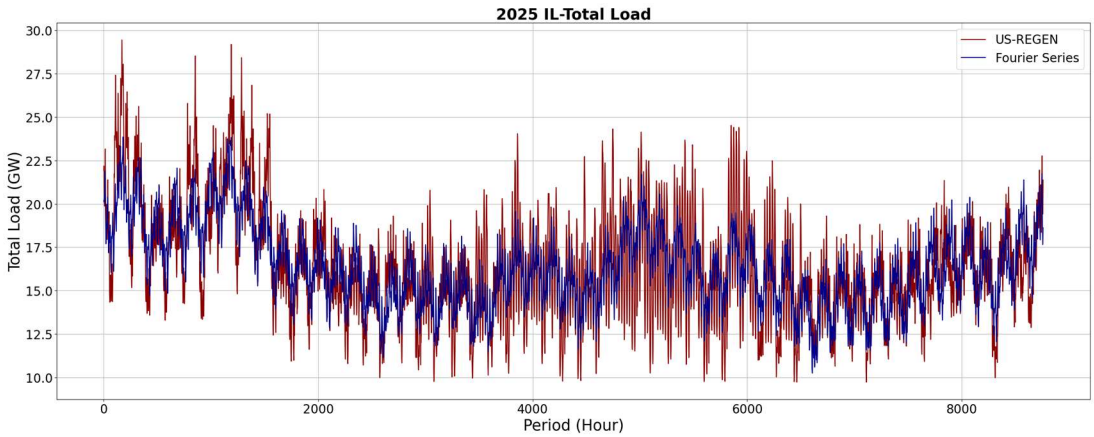


Figure 25. Carbon Tax LNHR, Fourier series with bases of 8760, 4380, 2190, 1251, 973, 515, 438, 172, 168, 33, 24, 12, 8, and 6.

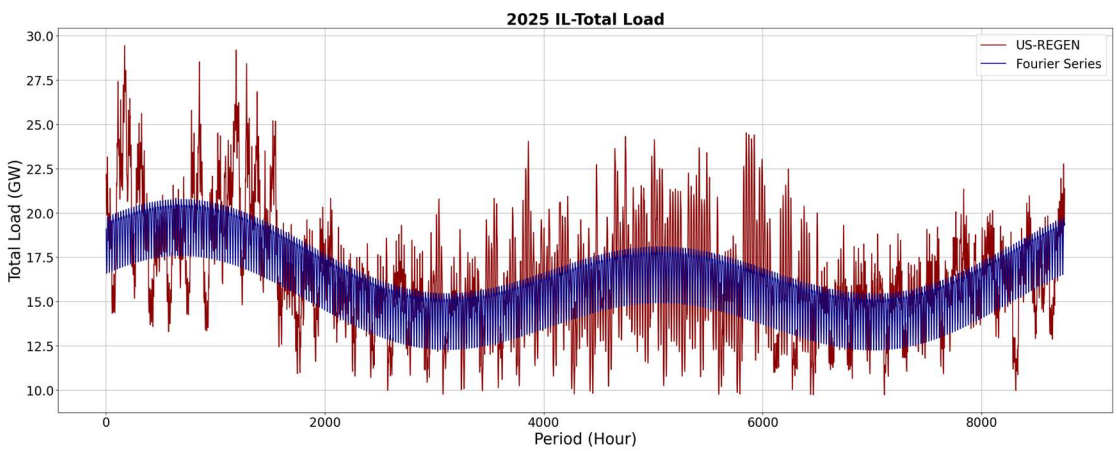


Figure 26. Carbon Tax LNHR, Fourier series with bases of 8760, 4380, 24, and 12.

Choosing the model order (e.g., p and q) is another factor of model selection that can heavily influence model fit. The US-REGEN data displays highly autocorrelated behavior that suppresses the available selection for the p and q terms for training. Given the autocorrelation present in the data, a model of order AR(1) was selected for all ARMA processes. The autocorrelation is visualized in Figure 27.

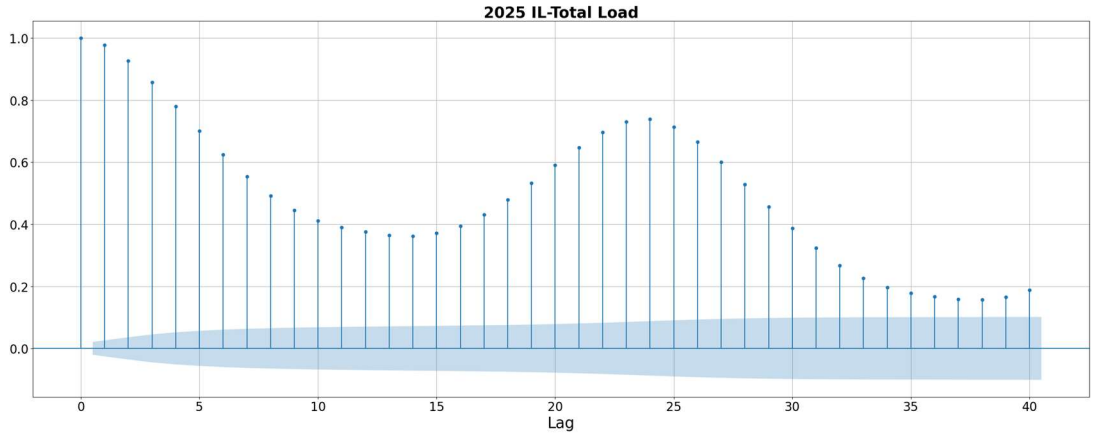


Figure 27. Carbon Tax LNHR autocorrelation function plot.

The hourly residual data was then segmented into 365 portions containing 24 chronological observations each. Following a series of normalization steps, an ARMA process was trained on each segment, representing a day of the year. After gathering all 365 ARMAs, a KMeans clustering algorithm was applied in order to group similar days of the year. The clustering algorithm was trained with a target of 30 representative clusters. This allows the entire year generated by the synthetic history to be represented by 30 unique processes. A sample year and its associated clusters is shown in Figure 28.

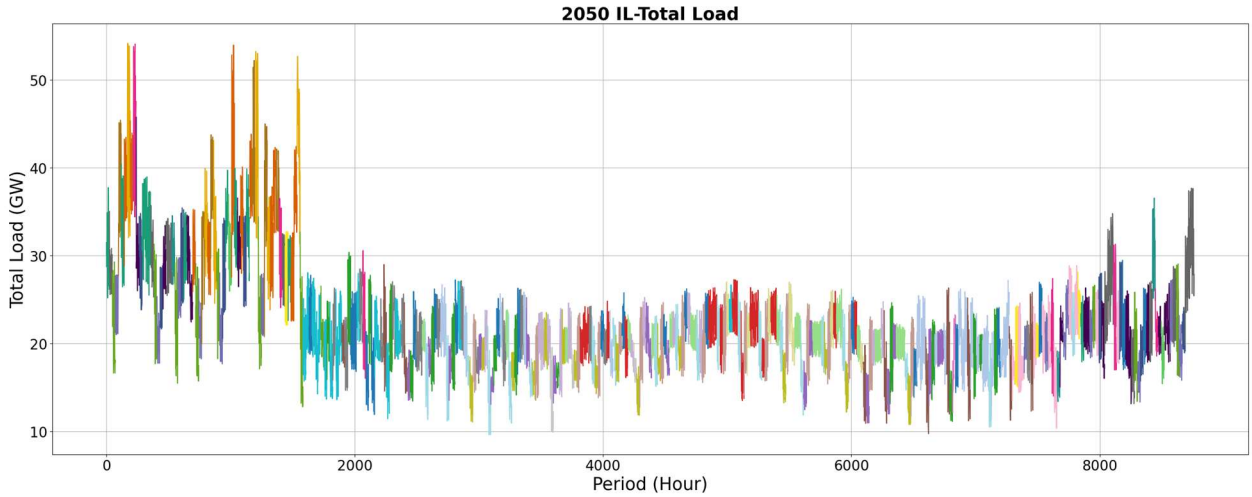


Figure 28. Carbon Tax LNHR, time-series clustering results.

Figure 29 displays a heatmap of the clustering results, showing which days were identified as similar throughout the year. Several patterns can be observed in this data—primarily that, during the summer months projected, grid demand stayed relatively consistent in Illinois.

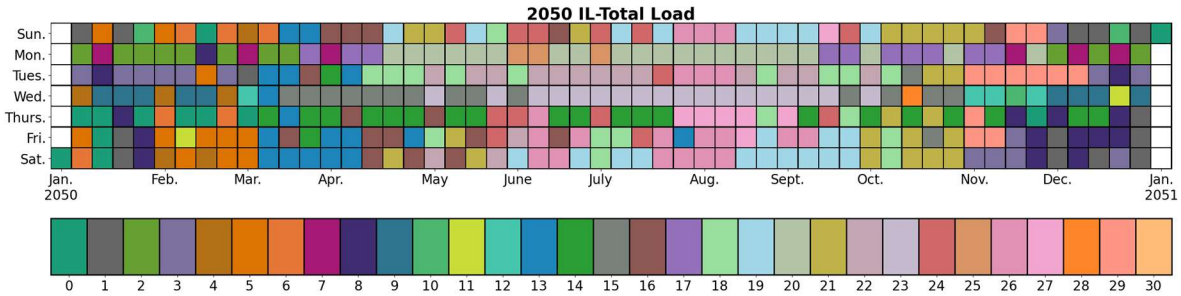


Figure 29. Carbon Tax LNHR clustering results heatmap.

After the clustering step is complete, the synthetic histories are generated for each year in each scenario. The final histories were then compared with the original market signals, and load duration curves were created to display a nominally well-fit history. Figure 30 depicts a histogram comparing the original and sampled histories. These distributions match well in descriptive statistics, including skewness and kurtosis. The tails of these distributions have the strongest economic implications and are observed to match sufficiently.

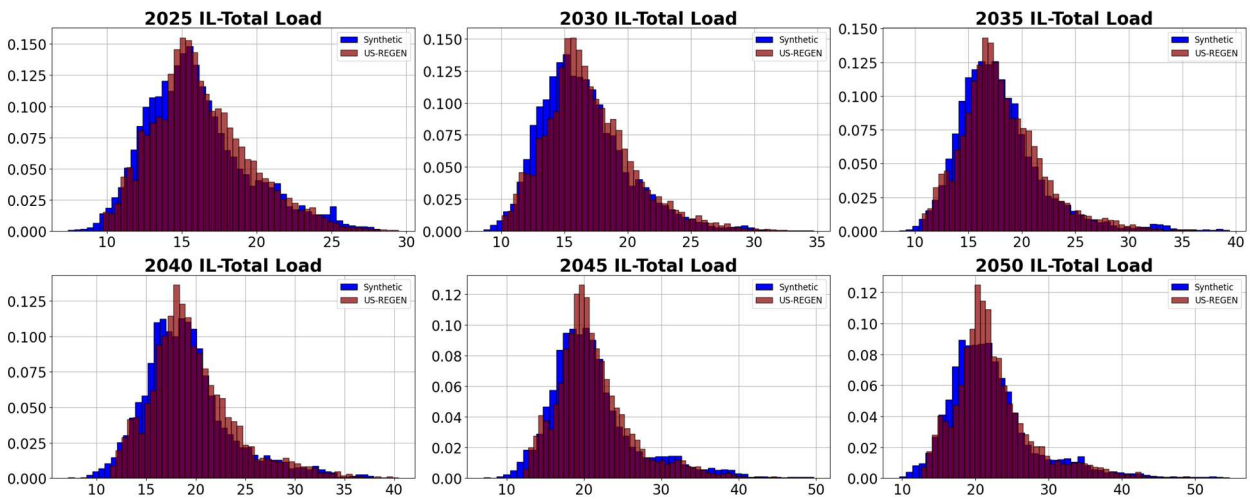


Figure 30. Carbon Tax, LNHR comparative histogram results.

Figure 31 displays the sampled synthetic histories plotted beneath the original signal. This is the final result of the training process. There are few periods that do not match, as is to be expected. Further development in RAVEN will seek to add tools to diagnose model fit and performance. Currently, a few parameters accept only global inputs; by adding the ability to tune the model on a local basis, it would naturally follow that generated fits would have a tighter bound around the signal.

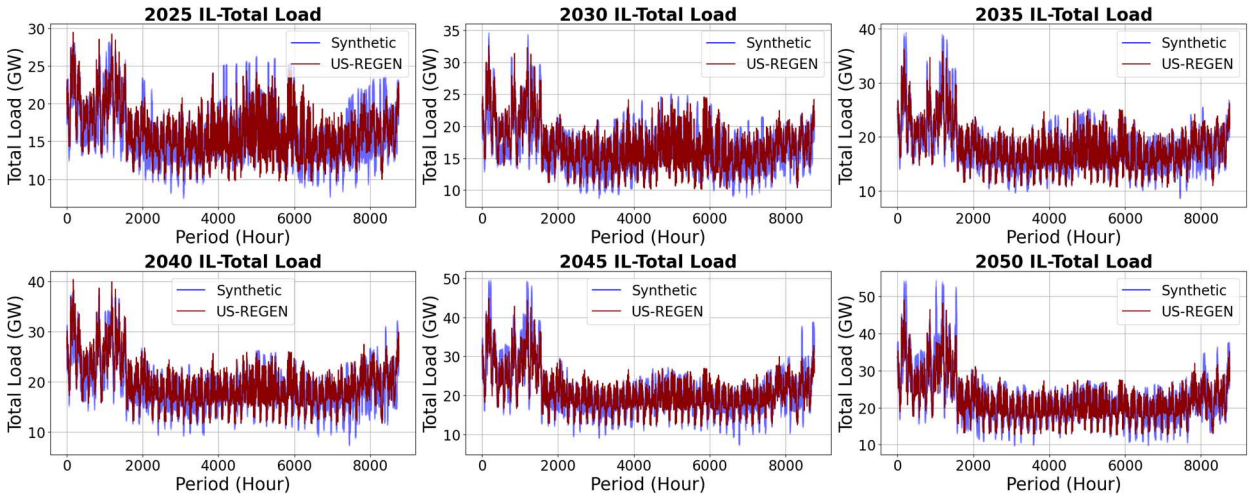


Figure 31. Carbon Tax, LNHR time series comparative results.

Finally, a plot of the load-duration curves can be seen in Figure 32. These plots depict the cumulative probability of producing a certain amount of energy for the year. As mentioned previously, the tail probabilities have the largest influence over driving economic factors, so it is critical for the ARMAs to match these with some degree of accuracy. Overall, the generated load-duration curves match with their counterparts, indicating a well-fit synthetic history. These histories will later be used in the dispatching and optimization steps.

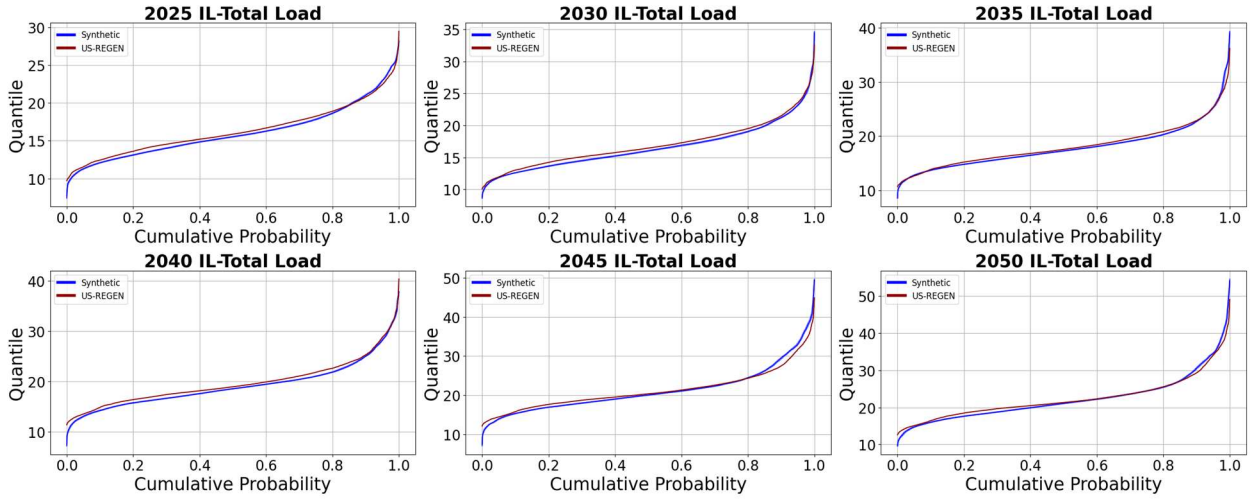


Figure 32. Carbon Tax, LNHR, load-duration curve results.

6.1.4 Dispatch Optimization

As mentioned in Section 5.2.3, optimizing the dispatch of the regulated market case is straightforward. For this particular regulated case, the NPP, HTSE, hydrogen storage, hydrogen consumer, and grid demand define the system of components. The grid and hydrogen consumer are both required demands; that is, both must be completely satisfied during each simulation hour. The grid demand is given by the synthetic history, while the hydrogen consumer is a constant flat demand whose quantity is determined in the outer optimization and remains constant in the inner. The production of the NPP is a constant level of electricity that can either be used to meet the grid demand or produce hydrogen

at the HTSE. This makes the hydrogen storage the critical degree of freedom in the dispatch optimization problem. The optimization solve determines the best utilization of the storage in order to ensure that as much hydrogen is made as possible when the NPP does not need to be dispatched; therefore, when the NPP is dispatched, there is sufficient hydrogen to supply to the consumer.

In the deregulated case, the focus subset of components is the NPP, HTSE, and hydrogen storage. Together, these comprise the IES and are assumed to be the financial interests of a single entity. The interplay between the IES and the ISO/RTO is as described in Section 5.2.4. The IES determines its electricity bid price by considering the marginal cost of producing electricity at the NPP, the opportunity cost of producing hydrogen, and an optimization tuning variable called the "bid adjustor." The opportunity cost for producing hydrogen is the value of hydrogen to the consumer, minus the cost of producing the hydrogen (marginal costs at the NPP, HTSE, and hydrogen storage). The bid adjustor is a constant additive to the IES bid price that represents its ability to balance use at the grid with use as a hydrogen producer, and is a variable optimized in the outer macro-optimization.

As described previously, in the deregulated case, the IES submits a bid for each hour in the 24-hour cycle, and the ISO/RTO builds the dispatch stack and dispatches according to marginal cost. The required dispatch is then provided to the IES, who is required to provide electricity at the designated times and at the designated level. However, it is possible that the required dispatch will disrupt the production of hydrogen for the consumer (for example, during many consecutive high-load hours, depleting the hydrogen storage)—something obviously unacceptable. In this case, we allow the IES to purchase electricity from the imbalance market during the hours in question to provide the HTSE with sufficient electricity to meet the hydrogen demand. Rather than directly simulating the imbalance market, we add the electricity to the load for the hour in question, find the new "effective clearing price" from the stack, and charge a 10% fee as a driver to disincentivize leveraging the imbalance market Furthermore, it is possible that, if the NPP is not fully dispatched for many consecutive hours, the hydrogen storage may fill up, and the generated electricity may not have a destination. In this case, we charge the NPP a rate of 17 $/MWh, which is a simplification of the IES bidding at a loss in order to bid sufficiently below the VREs. This again serves to disincentivize an inefficient choice of HTSE, storage, and hydrogen consumer (market) size.

6.1.5 Capacity Optimization

Optimization of the capacity space can cause unexpected complications, depending on how it is formulated for the RAVEN optimization algorithms. The optimization variable space for the deregulated market analysis has four nominal variables (sizes for HTSE, hydrogen market, hydrogen storage, as well as the nuclear bid adjustment scalar), while the regulated market analysis has four (omitting the nuclear bid adjustment). These optimization variables have upper and lower bounds. Furthermore, a constraint needs to be applied to ensure that the HTSE is always at least the same size as the hydrogen market; otherwise, it is quite likely that some hours will result in insufficient hydrogen available to supply to the market This leads to an optimization variable space, as shown in Figure 33.

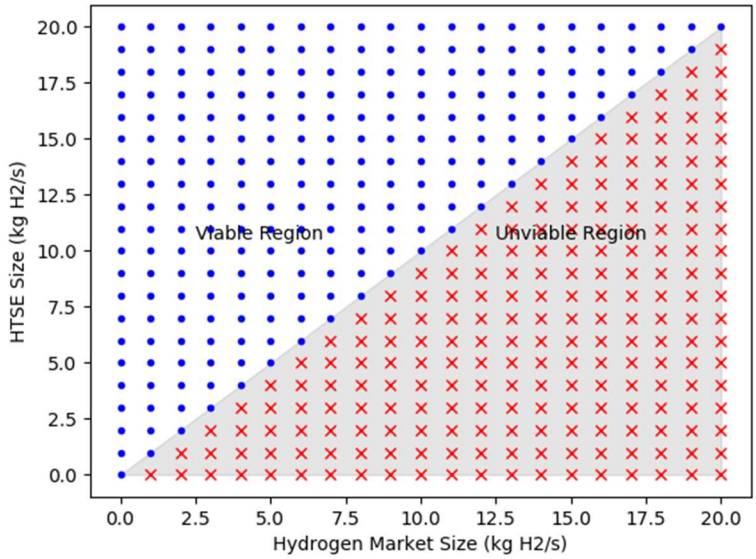


Figure 33. Original optimization space, HTSE vs. Hydrogen Market.

Due to the small optimization variable space for both market types, we employ a stochastic gradient descent algorithm in RAVEN for searching the optimization space, with the settings shown in the HERON-generated RAVEN input in Appendix C. However, some complications arise from the constraint, requiring the HTSE size to at least match the hydrogen market size. If, during the course of the optimization search, the algorithm elects to consider a 0-sized IES (meaning a capacity of 0 kg/s for both the HTSE and hydrogen market), there are no suitable orthogonal points to use for accurately evaluating the gradient. Further, experimenting with the viability of different component configurations suggests that over- or underbuilding the IES system has a large impact on the mean NPV, whereas the difference between the size of the HTSE and the hydrogen market has a distinct impact. Additionally, the size of the hydrogen storage depends less on the absolute size of the HTSE than on the difference in size between the HTSE and the hydrogen market.

We can leverage these characteristics and provide a less valley-like optimization objective response space by pursuing a change of coordinates. Rather than optimize for the HTSE size and the hydrogen market size separately, we can instead optimize the hydrogen market size, along with the difference between the size of the HTSE and that of the hydrogen market (Δ). This transformation of coordinates orthogonalizes the viable region (as captured in Figure 34), preventing complications with the optimization algorithm and increasing the efficiency of optimization variable space exploration.

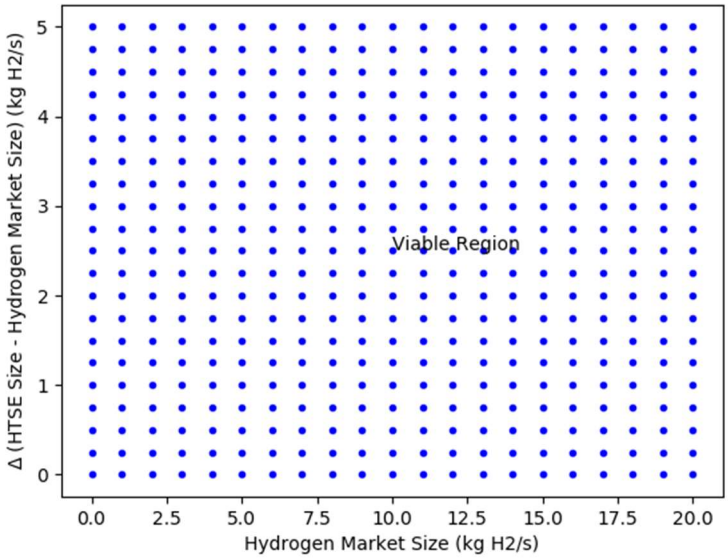


Figure 34. Projected optimization space, HTSE vs. hydrogen market.

After making this projection, it is then trivial to retrieve the HTSE size as the hydrogen market size plus Δ (the difference between the two).

The RAVEN optimization algorithm for stochastic models uses an adaptive step sizing strategy based on the optimization performance and changes in gradient as the simulation progresses. The process begins at a starting point, the choice of which is up to the user. For this case, we initialized component sizes to roughly 5% of the total possible size, as we expect a modest-sized IES to be preferable to a very large one, based on exploratory simulations. From the starting point, the algorithm samples nearby orthogonal points to estimate the magnitude and direction of the local gradient. Based on the initial step size, the algorithm then guesses a new optimal point in the direction of the local gradient (climbing towards an expected higher mean NPV). The algorithm then samples the mean NPV at that new potential optimal point and confirms or rejects the point, based on the amount of improvement relative to the previous step.

If the new potential optimal point is confirmed, the local gradient direction around the new point is estimated. The new step size then adapts based on the scalar product of the two most recent gradient directions. If they are aligned (the scalar product is near 1), the step size grows, seeking to follow a long gradient trend towards any maxima. If the recent gradients are anti-aligned (the scalar product is near -1), the step size is cut, as this indicates there should be a maximum between the two most recent samples. This process continues until the convergence criteria (gradience magnitude, minimum step size) are achieved.

If a new potential opt point is rejected due to having a sufficiently less desirable value than the previous point, the algorithm returns to the previous optimal point. The algorithm assumes that one of two phenomena occurred: either the step size was too large, and the maxima was missed; or, due to the stochastic nature of the model, the gradient direction was insufficiently resolved and gave a misleading direction. Thus, the local gradient around the previously accepted optimal point (including the optimal point itself) is re-evaluated, the step size is cut relative to the step size to get to the rejected point, and the new, re-evaluated gradient direction is used. Hence, in reporting iterative results, three types of optimizer samples are observed: accepted points, rejected points, and rerun points. A rerun point follows each rejection point.

When reporting the objective variable, we report a change in mean NPV. This is because the analysis is differential; we are not considering the absolute mean NPV, but the change in NPV due to introducing an IES. As a result, each scenario was run with a single outer sample setting the IES components to 0 in order to establish an NPV baseline and standard deviation for each. These baselines are shown in Table 12.

Table 12. Baseline NPV values.

Market Type	Policy	Pricing	Mean NPV	Std. NPV	Std/Mean
Regulated	Carbon Tax	Default	-2.67E+09	1.57E+07	-0.93%
Regulated	Carbon Tax	LNHR	-1.74E+10	9.13E+07	-0.53%
Regulated	Nominal	Default	-1.74E+10	6.18E+07	-0.35%
Regulated	Nominal	LNHR	-1.73E+10	6.04E+07	-0.35%
Regulated	RPS	Default	-9.24E-09	2.74E+07	-0.30%
Regulated	RPS	LNHR	-1.50E+10	6.23E+07	-0.43%
Deregulated	Carbon Tax	Default	4.56E+09	6.36E+07	1.39%
Deregulated	Carbon Tax	LNHR	3.28E+10	1.72E+09	5.27%
Deregulated	Nominal	Default	3.39E+09	1.35E+09	39.71%
Deregulated	Nominal	LNHR	8.32E+09	1.58E+09	18.95%
Deregulated	RPS	Default	4.39E+03	4.39E+03	-0.01%
Deregulated	RPS	LNHR	3.16E+10	2.10E+09	6.64%

Since the only source of differential cashflows for the Regulated Market cases is the construction, maintenance, and sale of hydrogen and hydrogen producers, the base case represents only the marginal costs to produce enough electricity to cover demand. Deregulated cases, however, involve the NPPs being dispatched at times (revenue) or carry a penalty for overproduction (cost), leading to a variety of values for the base cases.

Interestingly, the Deregulated Carbon Tax Default and Deregulated RPS Default cases show far lower NPV than the other deregulated cases. In both these circumstances, substantially more VRE and natural gas are constructed, suggesting that the existing nuclear is in the process of being phased out over the scenario and gets dispatched infrequently. This results in paying significant penalties due to overproduction, reflected in the low mean NPV values.

Also of interest: the standard deviation of the NPV for the Deregulated RPS Default case is quite a bit smaller than that of the other cases. The RPS Default case is one for which nuclear is quickly phased out in the interests of VRE and natural gas, likely leading to a reduced source of stochastic uncertainty in the NPV values.

Note that none of these values should be taken as the expected absolute NPV of the NPP; many cashflows have been omitted because they fall out in the differential analysis. These simply provide baseline values for each of the scenarios. As pointed out the cash flow between regulated and deregulated market and have a very different in meaning. For the deregulated case the cash flow is the relevant cash flow of the NPP (revenue), while for the regulated case it is the cost of covering demand by all the sources employed. Moreover, penalties for not dispatching VRE (in the form of Tax Production Credit) are applied only to deregulated market.

7. REGULATED MARKET SIMULATION RESULTS

Performing analysis with HERON involves a two-level optimization algorithm, as discussed in Section 6. In the outer level, optimization is performed to seek the ideal economic metrics by changing the built capacity of various components in the simulated system. Each evaluation in the outer-level involves performing many inner-level simulations. Each inner-level simulation involves sampling from the stochastic history set synthesizers, then optimally dispatching the components in the system to find the ideal economic metrics for that system, given the stochastic scenario.

Given HERON's two-level optimization structure, in this section we report on both the capacity optimization results as well as the representative dispatch optimization results. The capacity optimization results show the evolution of the variables representing component capacities over successive iterations of the gradient-based optimization process in RAVEN, while the dispatch optimization results show the hourly dispatch of components in the IES system over time, as well as some related signals. Of particular note is that each capacity optimization step requires thousands of hourly dispatch results, so the dispatch results shown are indicative of performance without being a complete set

7.1 Dispatching

In this section, we show and briefly discuss one example of a 24-hour dispatch optimization. Since each dispatch optimization is part of the solution to one year within one sample, within a single outer optimization cycle, the example in Figure 35 is only demonstrative of the dispatch optimization mechanics, rather than demonstrative of entire the dispatch dynamics. Note difference in scales between the plots.

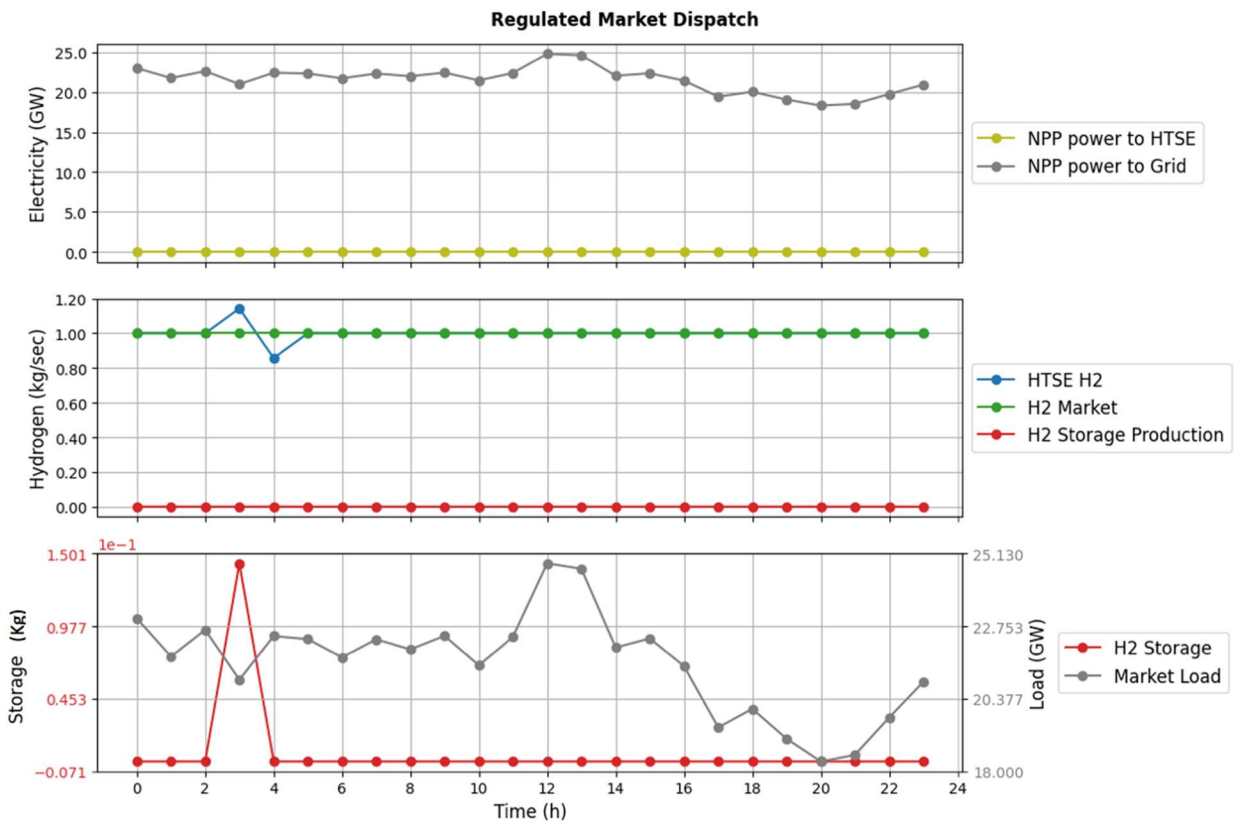


Figure 35. Regulated, example dispatch optimization.

This figure shows the behavior of the system in three parts. In the top plot, we see the routing of electricity from the NPP either to the HTSE or the grid; in this particular case, the electricity from the NPP to the HTSE was almost always just sufficient to keep the steady stream of hydrogen available to the hydrogen customer, while the remainder was used at the grid. Note that this means some of the NPP's capacity may not have been dispatched, as per the ISO/RTO's discretion. In the second plot, we see the behavior of the hydrogen components in the system. In the optimal dispatch found, the storage was hardly used, since the NPP was never fully dispatched and always able to run the HTSE to meet the hydrogen contract. In an NPV-neutral action, during hour 2, the storage first absorbed and then released a small amount of electricity; however, it appears this is economically equivalent to not using the storage at all, as no cash flows were impacted by the decision.

The final plot shows the load throughout the 24-hour cycle along with the storage hydrogen levels, overlaid on the same axis.

7.2 Optimization Results

For regulated markets, the entire system, including the IES and all electricity generating units, are considered owned by a single entity, ostensibly the ISO/RTO. The goal of this owning entity is to minimize the cost of providing the demanded electricity. The IES does not represent a new source of electricity; however, it does represent a new revenue flow through sales of hydrogen to a secondary market. The question posed to regulated markets is as follows: can the sales of hydrogen to a secondary market overcome the capital cost of constructing/maintaining the HTSE and hydrogen storage unit, as well as the extra electricity required to produce the hydrogen? The extra electricity results in an increase of the highest cost-per-gigawatt technology already dispatched, possibly requiring a new, more expensive technology to be brought online.

It appears that, for the cases considered in this work the electricity market model, and with the assumptions made about the potential hydrogen market and the capital costs of IES components, none of the scenarios results in profitable IES usage. In reality to fully capture the benefit of hydrogen production it would be necessary to consider the impact of the nuclear power plant and the HSE becoming a flexible source of power. This alteration of the use profile of the nuclear power plant would lead to a change in the optimal electricity supply portfolio. This could lead to a decrease of the overall system cost when the capacity requirements and cost are also accounted. Future work is planned to include those effects as part of the analysis. HERON is already capable, unlike from software such as PLEXOS, to perform long term financial analysis, but currently does not optimize the system capacity. In fact, the system capacity was actually generated by US-REGEN.

We consider each of these scenarios in the following sections. A summary of the results is shown in Table 13. The capacities of the three optimization targets are shown, along with the optimized mean NPV discovered and the change in NPV with reference to the baseline case. We emphasize that the optimal mean NPV and baseline mean NPV are calculated statistically, so there is a standard deviation associated with both these values. For reference, standard deviations for the baseline cases are given in Table 12. Note that in all cases apart from the Nominal Default case, the system drove the IES size to 0, and the resulting change in NPV is well within one standard deviation of the mean baseline case. For these cases, including an IES did not prove economically justifiable. Given that the NPPs' total capacities were sized to be ideal for each scenario in US-REGEN without considering the possible addition of hydrogen production, this is not an unexpected result, since the goal function by US-REGEN and HERON will coincide.

For the Nominal Default case, however, the optimization algorithm yielded a buildout of 0.034 kg/s (approx. 3000 kg/d) capacity for both the HTSE and hydrogen market contract, with no storage included. This suggests that the hydrogen serves less as a flexibility tool for the ISO/RTO and more as a profitable secondary resource. This seems a natural conclusion, as the ISO/RTO was not modeled with a penalty for not dispatching the NPP, so it could elect to either generate hydrogen with excess electricity or curtail

capacity during low demand hours. As seen in the next chapter, this is different from the deregulated case results.

Table 13. Regulated, final accepted iteration step results.

Case	HTSE (kg/s)	H2 Storage (kg)	H2 Market Capacity	Opt. Mean NPV	Δ NPV
Carbon Tax Default	1.00E-10	0.00E+00	-1.00E-10	-2.67E+09	-2.00E-01
Carbon Tax LNHR	1.00E-10	0.00E+00	-1.00E-10	-1.74E+10	1.35E+06
Nominal Default	3.41e-02	0.00E+00	-3.41E-02	-1.74E+10	1.54E+07
Nominal LNHR	1.00E-10	0.00E+00	-1.00E-10	-1.73E+10	-1.60E+06
RPS Default	1.00E-10	0.00E+00	-1.00E-10	-9.24E+09	-2.97E+06
RPS LNHR	1.00E-10	0.00E+00	-1.00E-10	-1.50E+10	3.94E+07

7.2.1 Carbon Tax Default

The Regulated Carbon Tax Default case represents a scenario in which a carbon tax is levied on components that release carbon as part of their electricity production. "Default" refers to the current trend of technology pricing for both nuclear and VRE. In this case, we see the optimizer quickly drive capacity to zero and converge on the no-IES baseline mean NPV value. Since NPPs are not carbon producers, this favors nuclear as a dispatchable technology, so the IES does not see opportunity to be of benefit.

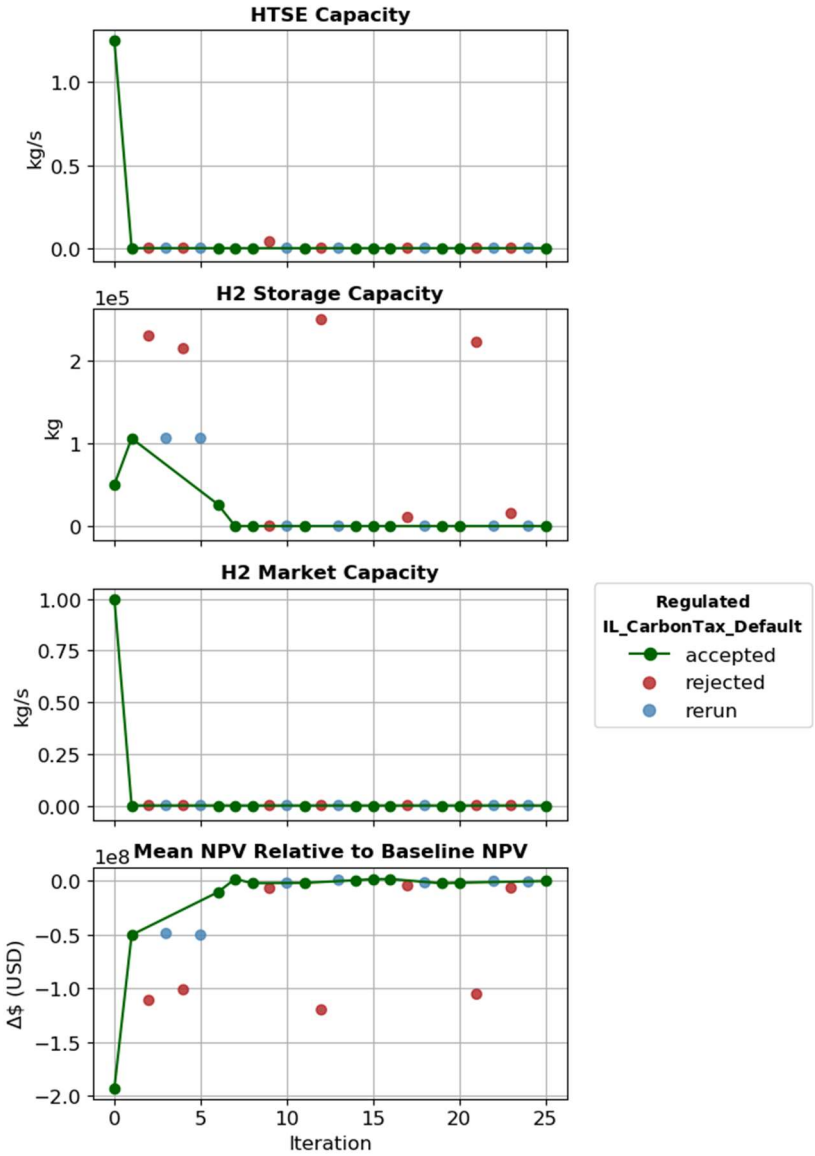


Figure 36. Regulated Carbon Tax Default scenario results.

7.2.2 Carbon Tax LNHR

The Regulated Carbon Tax LNHR case also imposes carbon taxes on energy produced by units that release carbon as part of their electricity generation, but also includes a trend towards lower nuclear costs and higher VRE costs. This case likewise approaches the no-IES case quickly. The low-nuclear, high-VRE pricing serves to further push the ISO/RTO to dispatch nuclear, and so leaves little room for the IES to be leveraged.

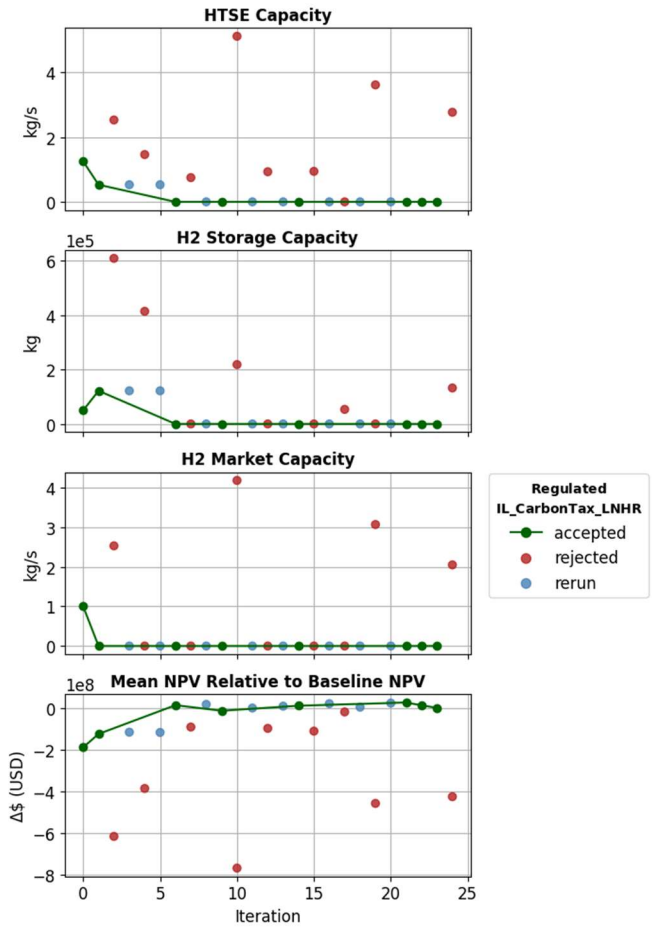


Figure 37. Regulated Carbon Tax LNHR scenario results.

7.2.3 Nominal Default

The Regulated Nominal Default case supposes no carbon tax and no renewable penetration strategy and uses prices for nuclear and VRE based on their current trajectories. While this case also optimized to a minimal IES, it did settle on a nonzero-sized IES, as shown in Table 13. However, the small value of the IES suggests that, in a regulated market sense, the IES shows limited benefit for the NPP size optimized in the scenario by US-REGEN.

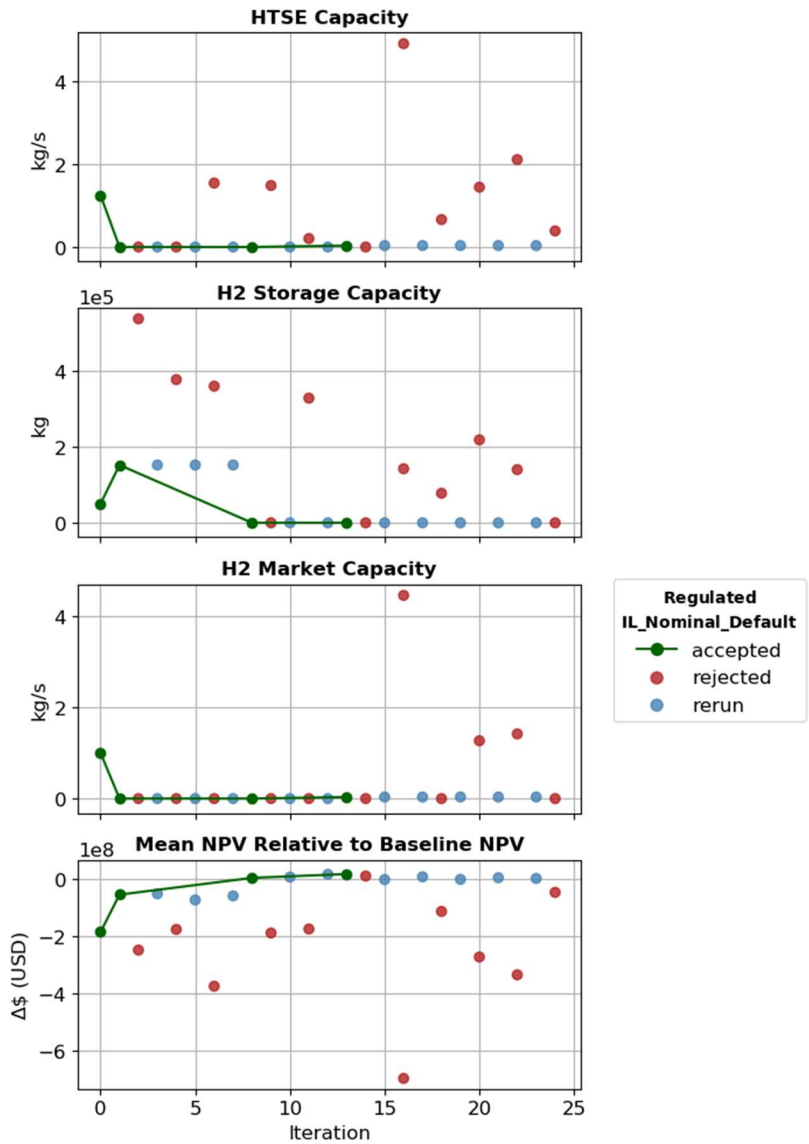


Figure 38. Regulated Nominal Default scenario results.

7.2.4 Nominal LNHR

The Regulated Nominal LNHR case also does not impose a carbon tax or renewable penetration strategy but does predict a trend of increasing VRE costs and reducing NPP costs. As expected, since this trend favors the dispatch of nuclear, the IES is once again minimized in the optimization.

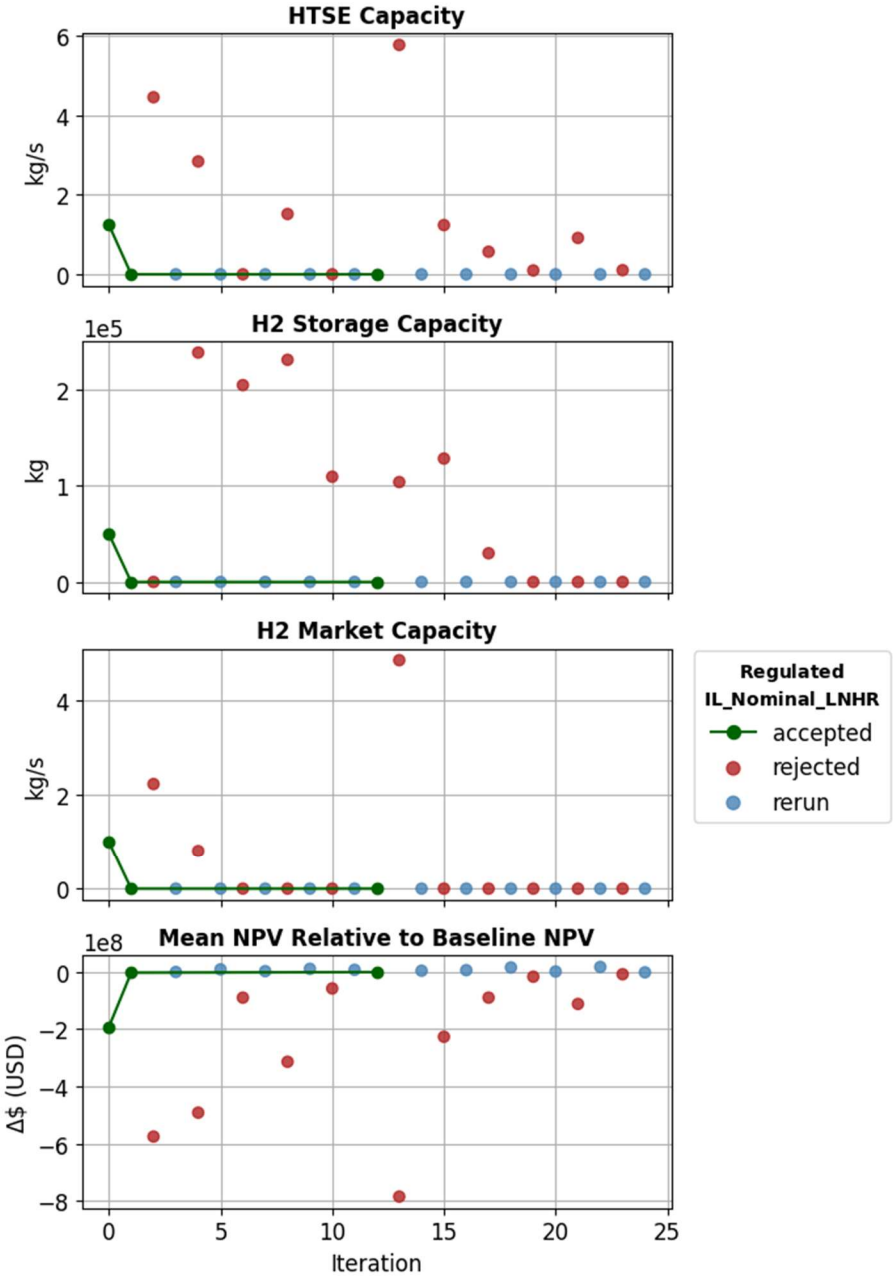


Figure 39. Regulated Nominal LNHR scenario results.

7.2.5 RPS Default

The Regulated RPS Default case imposes a 100% renewable portfolio strategy by 2050, while still allowing nuclear. With the reduction in production from technologies such as natural gas, nuclear power becomes a more favorable unit to dispatch, so there is minimal beneficial economic impact from adding an IES.

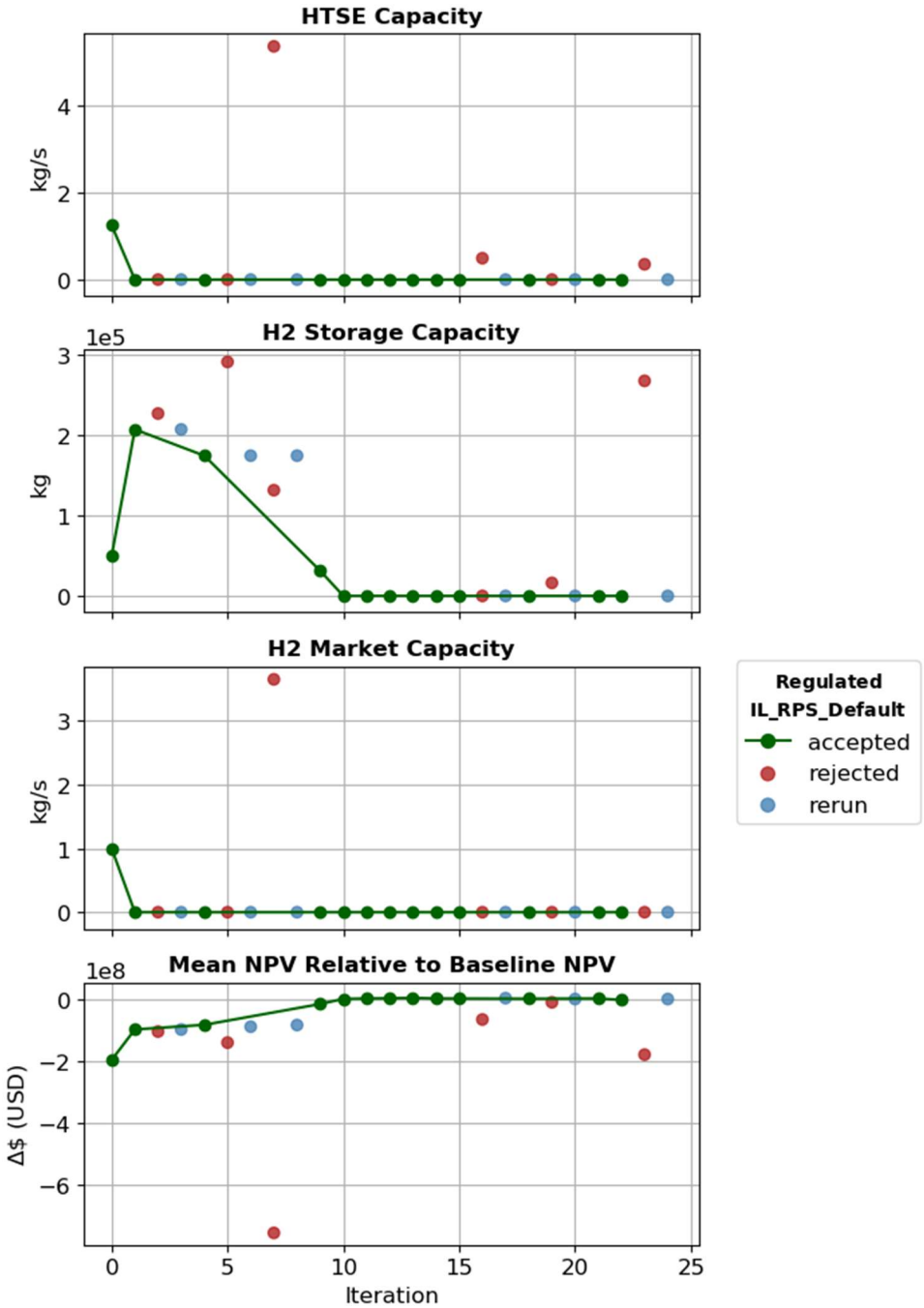


Figure 40. Regulated RPS Default scenario results.

7.2.6 RPS LNHR

Even more so than in the previous case, the Regulated RPS LNHR case benefits nuclear over other technologies, causing it to be preferentially dispatched and minimizing the potential benefit of introducing an IES.

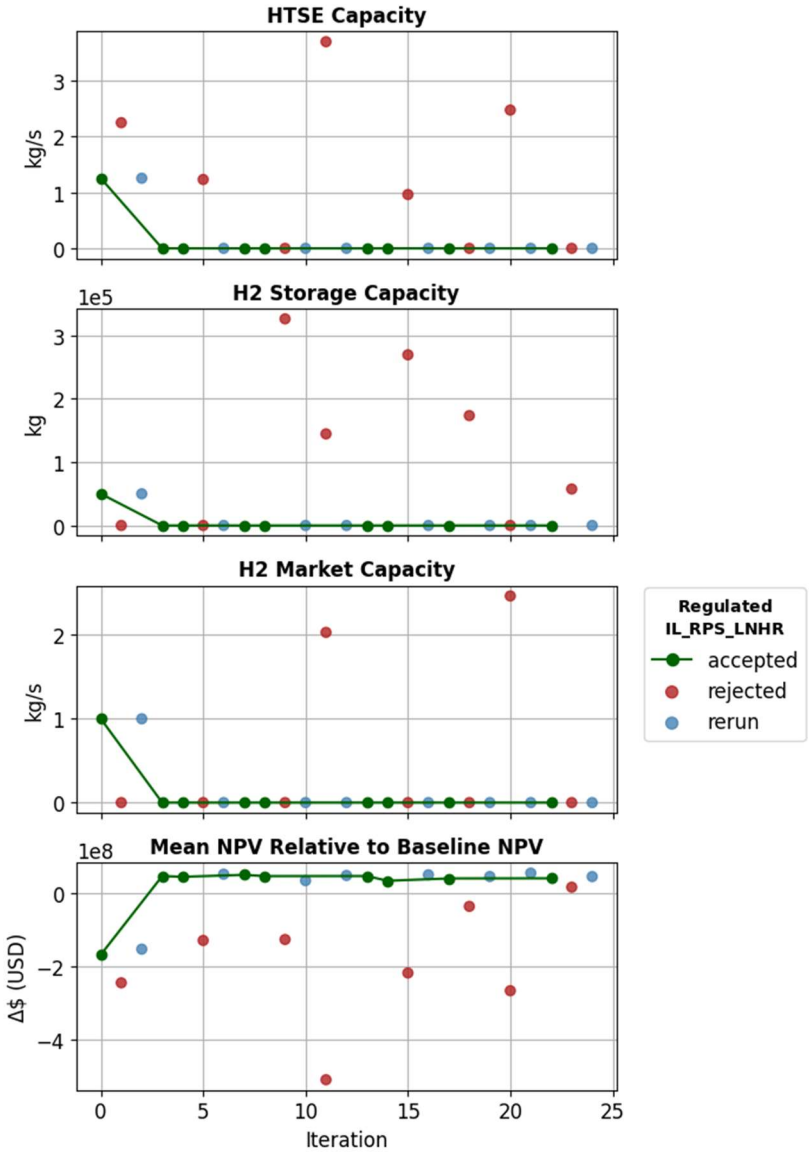


Figure 41. Regulated RPS LNHR scenario results.

8. DEREGULATED MARKET SIMULATION RESULTS

8.1 Dispatching

In this section, we show and briefly discuss one example of 24-hour dispatch optimization. Since each dispatch optimization is part of the solution to one year within one sample, within a single outer optimization cycle, the example in Figure 42 is only demonstrative of the dispatch optimization mechanics.

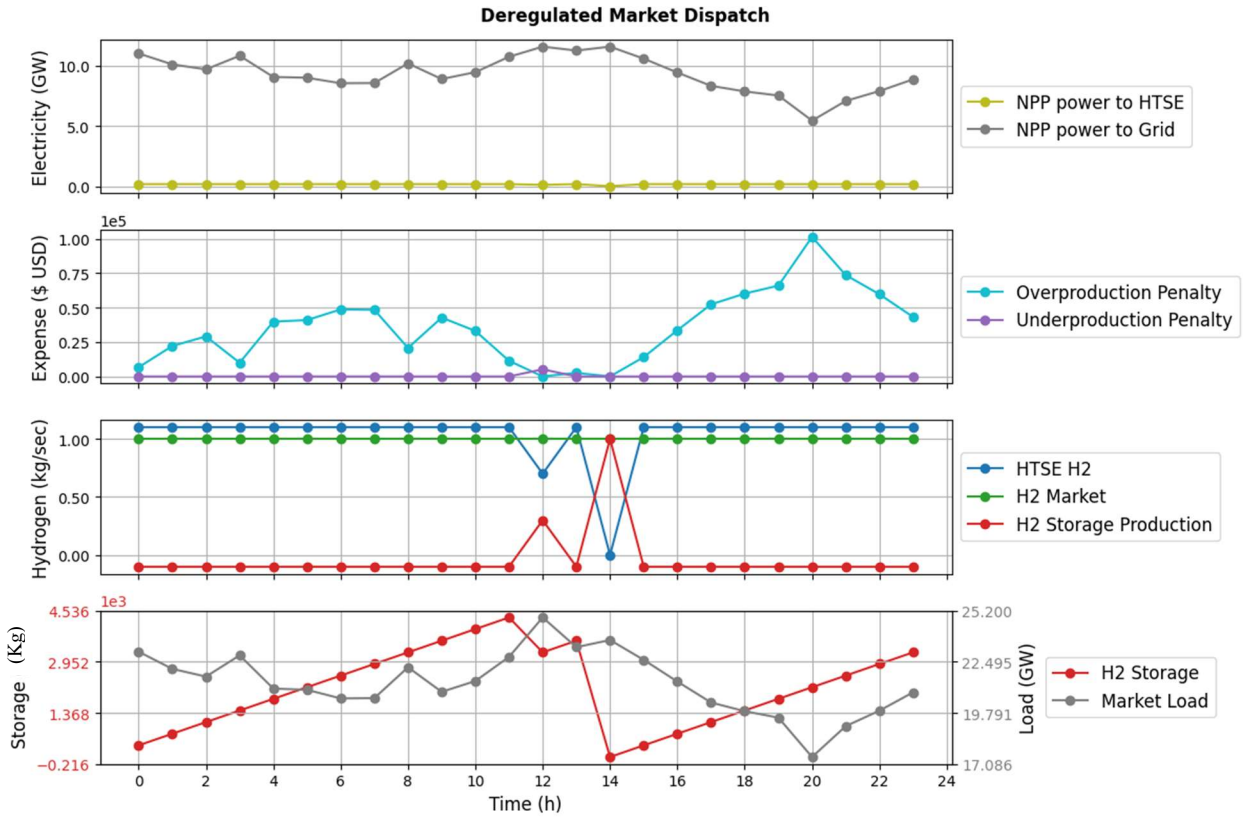


Figure 42. Deregulated, example dispatch optimization.

In Figure 42, from top to bottom, we show the electricity usage, over/under production penalties, hydrogen usage, and storage level overlaid with the load.

Electricity production has two possible sources: generation at the NPP, which is a constant full-capacity generation; and the secondary market, which shows up in the second plot as an Underproduction Penalty, simulates purchasing electricity on a short-term imbalance market, and is only used when insufficient hydrogen is available to meet the hydrogen customer demand. There are three possible destinations for the electricity: use at the HTSE to produce hydrogen, sale to the grid so the ISO/RTO can meet the load demand, or the Overproduction Penalty, which centers on the VRE production tax credit and loosely simulates the cost to sufficiently underbid to use the electricity at the grid.

The primary hydrogen source is the HTSE but can also be the hydrogen storage. The storage can also act as a sink, with the primary sink being the hydrogen market. The production rates of each of these components are shown in the third plot.

For this case, the NPP is frequently not used sufficiently at the grid, and the HTSE is modest in size. As a result, over many hours, the NPP overproduces and pays an overproduction penalty. We expect that, in the greater optimization, this would result in a larger IES (HTSE and hydrogen market) in the next iteration to reduce this penalty. In hour 12, however, the optimized solution pays an underproduction

penalty to acquire energy from a secondary market in order to operate the HTSE enough to keep the hydrogen stream constant to the hydrogen market.

On the hydrogen side, there is a consistent buildup of storage until the peak load demands are seen, which corresponds to the highest clearing prices and the ISO/RTO fully dispatching the NPP. During these hours, the stored hydrogen is used as much as possible, then additional production at the HTSE is taking electricity from the secondary electricity market.

8.2 Optimization Results

For deregulated markets, we consider the IES and ISO/RTO as independent entities. Unlike in the regulated case, the ISO/RTO pays the same price for electricity to all electricity units dispatched in an hour, i.e., the *clearing price*. The clearing price is determined by the costliest per-megawatt electricity generator dispatched during the hour. Thus, each component bids their price for production and available capacity, and each hour the ISO/RTO dispatches units from cheapest to most expensive to cover the demand. Meanwhile, the IES (including the NPP) has an alternative revenue stream in the form of hydrogen production, allowing the IES to increase its electricity production bid to ensure more favorable electricity prices but still generate useful production when the NPP is not fully dispatched in order to cover the demand. The driving question for the NPP owner is, can increasing the electricity bid and selling hydrogen result in sufficient profits to overcome the capital costs of constructing and maintaining an IES?

It appears that it is not generally economical for the NPP entity to construct an IES. The cases generally show a trend towards reducing the IES size to increase NPP revenue, with many converging on a 0-size IES. Gradients near 0-size IES continue to persistently point towards minimizing the IES size. Especially for the deregulated case the LPM could be the main reason for this behavior. Referring to Figure 11 we can notice that the prices of LMP are quite high and therefore the opportunity cost of electricity production versus hydrogen production places the hydrogen generation out of the market in order to compete with the electricity. Once more, interaction with industry is providing a different projection for the long term LMP, which is notably lower. It is probably worth stressing again that at this point we are seeking the proper response from the software rather than zooming in a specific case. So, the fact that hydrogen production generally is not built given the high opportunity cost of not supplying electricity is a point of coherence of the results that we take as a success. Moreover, the fact that in the case "Carbon Tax policy with a LNHR" there is construction of hydrogen production, as discussed below, is again a testimony of the proper implementation of the market dynamics. In fact, the scenario has plenty of nuclear but an issue with covering the volatility in net demand with the high cost of carbon, preferring then using the hydrogen production to absorb the cost of volatility.

The one exception is the Carbon Tax policy with a LNHR construction cost outlook. This case tends to retain more nuclear to cover the load due to the increased bid prices of the carbon-producing units; when not dispatched, this nuclear capacity can be used for producing hydrogen at a net profit for the NPP owner. Though the RPS LNHR case has similar characteristics, the average nuclear present over the years is lower by nearly 10%, thus affording less opportunity to make use of the IES.

We discuss each of these scenarios specifically in the following sections. A summary of the results is shown in Table 14. In contrast to the Regulated Market cases, a wide variety of outcomes were seen for the Deregulated Market cases, ranging from no inclusion of the IES (the RPS Default case) to very significant gains from including the IES (the Carbon Tax Default and Nominal Default cases). Because the perspective is shifted from the ISO/RTO to the benefit to the NPP itself, driving forces such as over- or under-production of energy become economically dominating, driving the NPP to find alternative options to make use of its capacity. This greatly increases the potential benefit of including the IES.

Table 14. Deregulated, final accepted iteration step results.

Case	HTSE Capacity	H2 Storage Capacity	H2 Market Capacity	NPP Bid Adjust	Mean NPV	ΔNPV
Carbon Tax Default	3.04E+00	3.69E+04	-2.88E+00	0.00E+00	-1.59E+09	2.97E+09
Carbon Tax LNHR	1.68E-01	2.14E+05	-9.04E-03	7.68E+03	3.28E+10	8.86E+07
Nominal Default	5.04E+00	1.69E+04	-4.70E+00	0.00E+00	7.24E+09	3.85E+09
Nominal LNHR	9.41E-02	4.74E+05	0.00E+00	9.67E+04	8.62E+09	3.01E+08
RPS Default	0.00E+00	0.00E+00	0.00E+00	4.39E+03	0.00E+00	0.00E+00
RPS LNHR	1.51E-01	2.62E+04	-1.15E-01	2.70E+04	3.19E+10	2.65E+08

8.2.1 Carbon Tax Default

This scenario represents the behavior of the IES as a deregulated entity with a policy enacting carbon taxes on components that release carbon as part of electricity generation, and with currently expected renewable and nuclear construction cost trends. Broadly speaking, this case resulted in significant installation of wind and natural gas technologies, along with some nuclear power production. The results of the capacity optimization are shown in Figure 43.

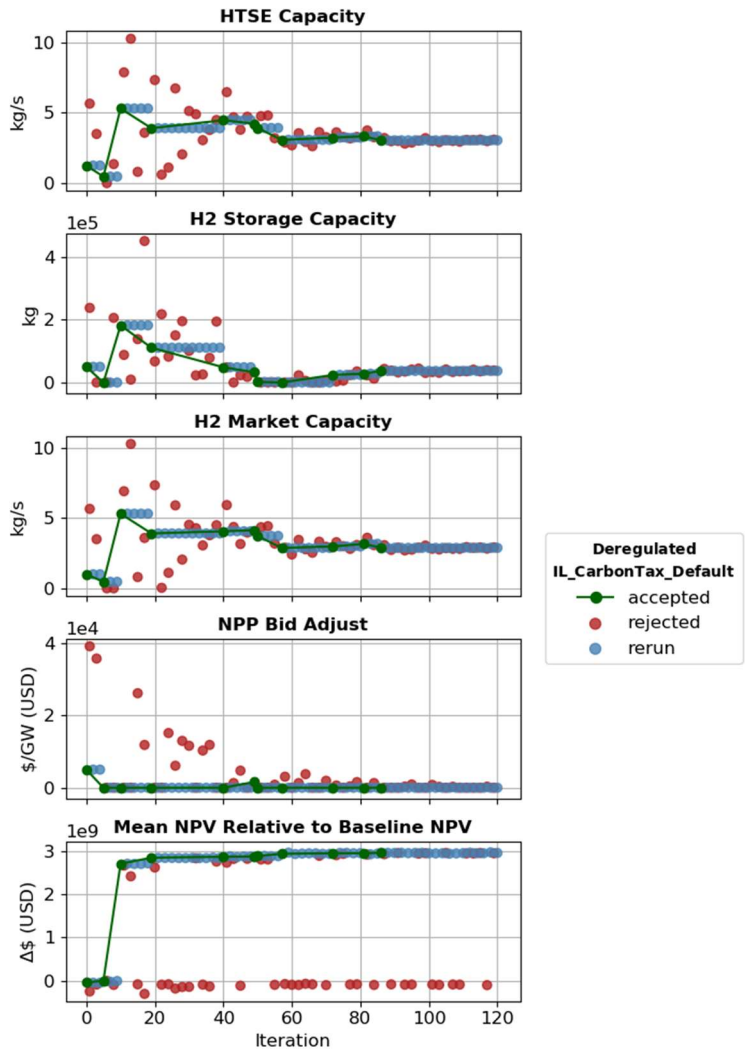


Figure 43. Deregulated Carbon Tax Default scenario results.

In this optimization, we see the algorithm explore a large part of the variable input space, eventually landing on a modestly sized IES system with an HTSE sized at 3 kg/s (roughly 260,000 kg/d, or 470 MW), a contract to deliver 2.88 kg/s to the hydrogen market, and a storage unit with sufficient capacity to store 3.37 hours of contracted hydrogen delivery. The improvement in NPV is far larger than the standard deviation of the baseline, suggesting a clear benefit in including the IES in this system.

8.2.2 Carbon Tax LNHR

The Deregulated Carbon Tax LNHR case includes the carbon tax for carbon-releasing technologies as well as a trend in lower nuclear costs and higher VRE costs. This trend benefits the use of nuclear technology over the Carbon Tax Default case, so we expect—and observe—a reduced optimal IES size with respect to the non-LNHR case.

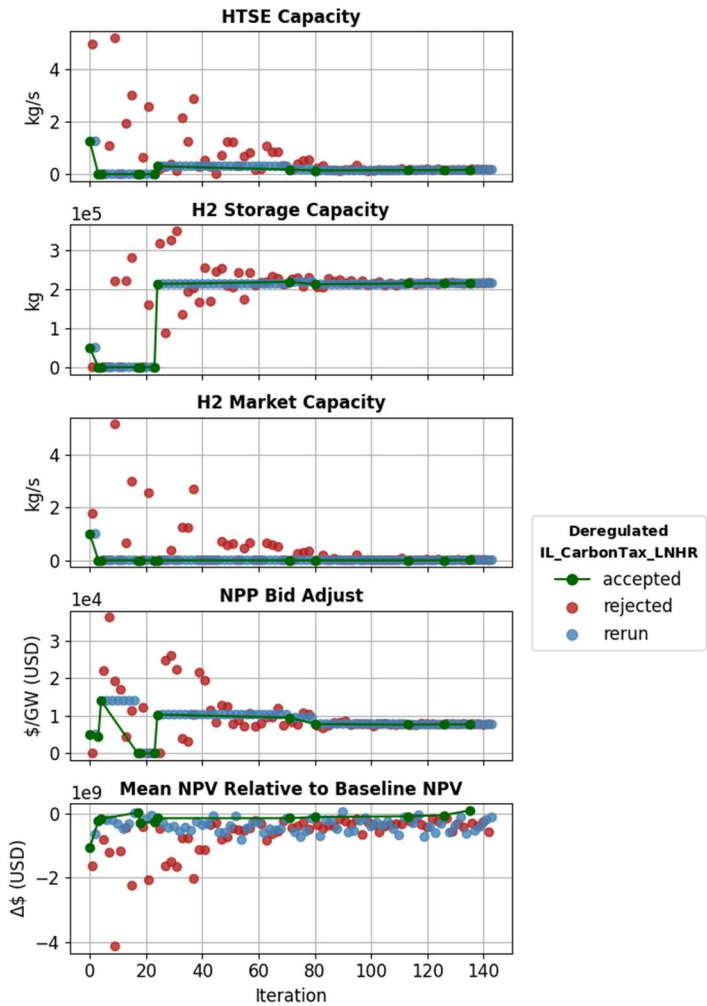


Figure 44. Deregulated Carbon Tax LNHR scenario results.

The optimal point for this case includes an HTSE sized at 0.17 kg/s (14,000 kg/d, or 26 MW) and a nearly non-existent market, with surprisingly large storage. This is possibly because the other optimization variables (likely HTSE and hydrogen market size) dominated the optimization, leaving little opportunity to fine-tune less dominant optimization variables such as storage size. When comparing the change in NPV due to the inclusion of the IES, we see a small improvement that is two orders of magnitude smaller than the baseline NPV standard deviation; this suggests that the IES may have some impact on this system, though this cannot be confirmed without greater resolution of the uncertainty.

8.2.3 Nominal Default

The Deregulated Nominal Default case is one in which no carbon tax or renewable policy is applied, and technology costs continue on their current trajectory. This case is arguably the least favored toward utilizing nuclear for meeting demand. As such, we see the greatest impact of including the IES to provide both a flexible generation tool and a secondary market when the NPP is under-dispatched.

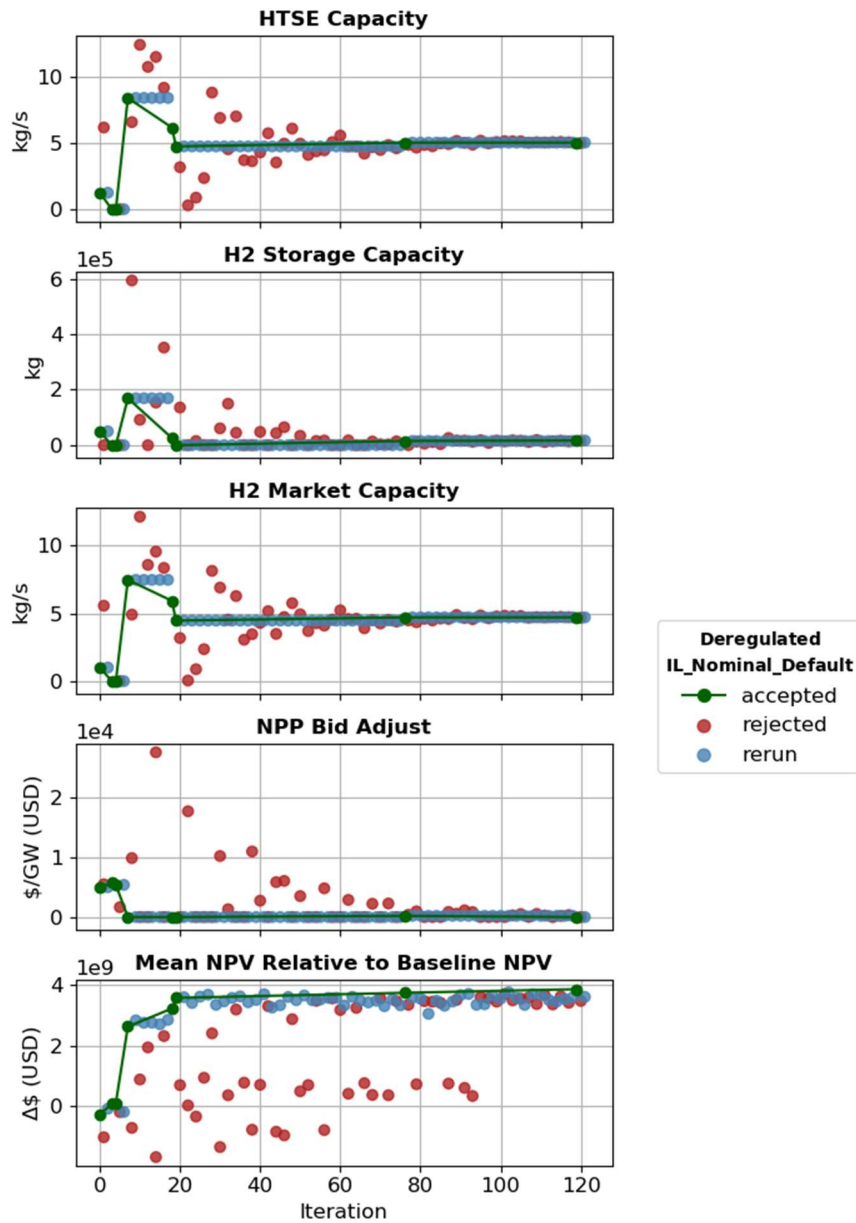


Figure 45. Deregulated Nominal Default scenario results.

The optimal results show an HTSE sized at 5.04 kg/s (435,000 kg/d, 780 MW) with a market contract just below that at 4.7 kg/s, and approximately one hour's worth of market hydrogen in storage. This results in an NPV increase of nearly three standard deviations of the baseline NPV above the baseline, suggesting a very likely benefit for IES inclusion in the system.

8.2.4 Nominal LNHR

The Deregulated Nominal LNHR case adjusts the Nominal Default case by assuming a trajectory of decreasing nuclear and increasing VRE costs, driving down the potential for leveraging an IES. As shown in the figure, the optimizer explores a wide range of possibilities around the no-IES system, without finding improvements.

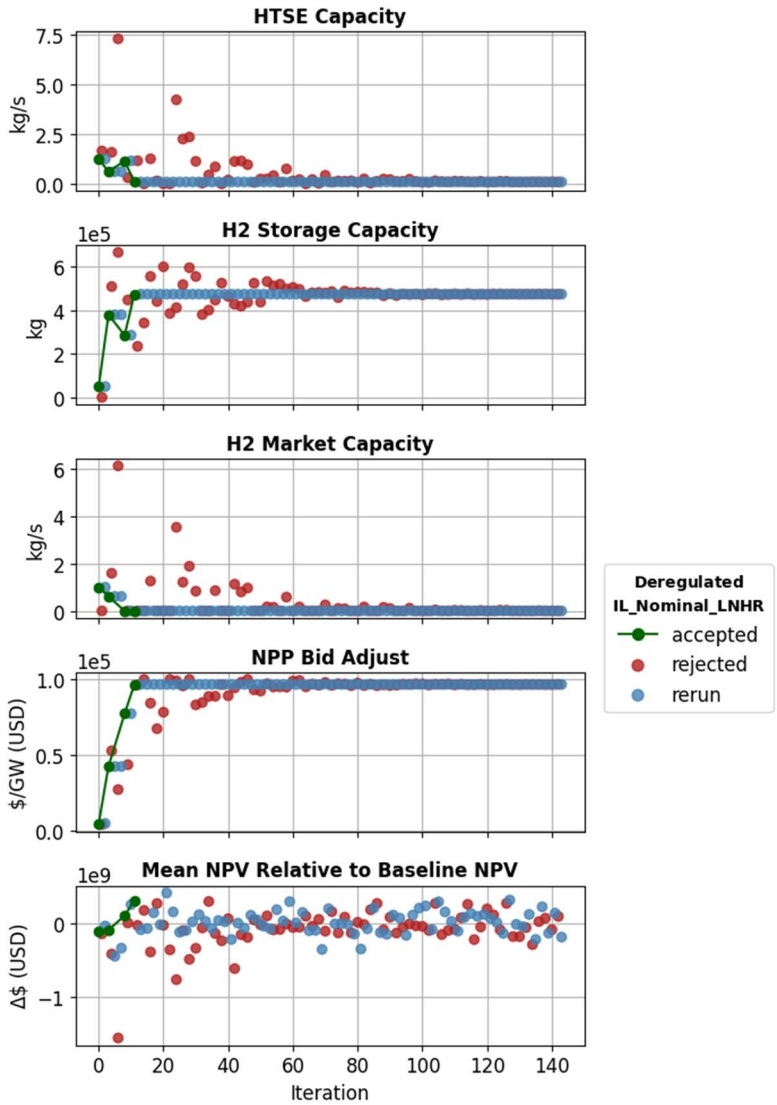


Figure 46. Deregulated Nominal LNHR scenario results.

The optimization results for this case lead to a very small HTSE and a non-existent market, with arbitrarily sized storage and NPP bid. This solution is well within the noise of the baseline NPV and suggests minimal benefit from IES inclusion.

8.2.5 RPS Default

The Deregulated RPS Default case includes a policy of 100% renewables by 2050, which allows for nuclear. This scenario resulted in phasing out nuclear power early on in the scenario, making IES inclusion impractical. In agreement with this expectation, the optimization algorithm immediately reduced the size of the IES to zero and consistently agreed with that conclusion until persistence was reached.

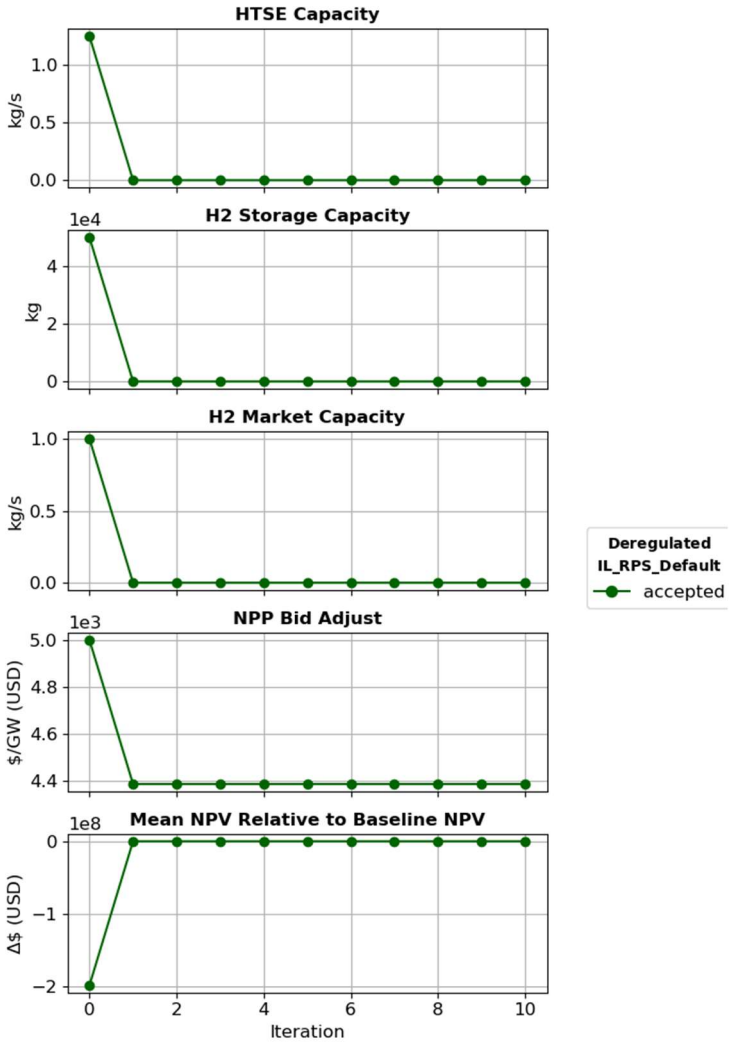


Figure 47. Deregulated RPS Default scenario results.

8.2.6 RPS LNHR

As with the case above, the Deregulated RPS LNHR scenario is one in which a policy of 100% renewables by 2050 is applied, but with a trend toward increasing VRE costs and decreasing NPP costs. This scenario retained, and even constructed, some new nuclear in later years; as a result, there is still some room for leveraging an IES in the system, though the desired dispatch of the NPP limits the practical IES size.

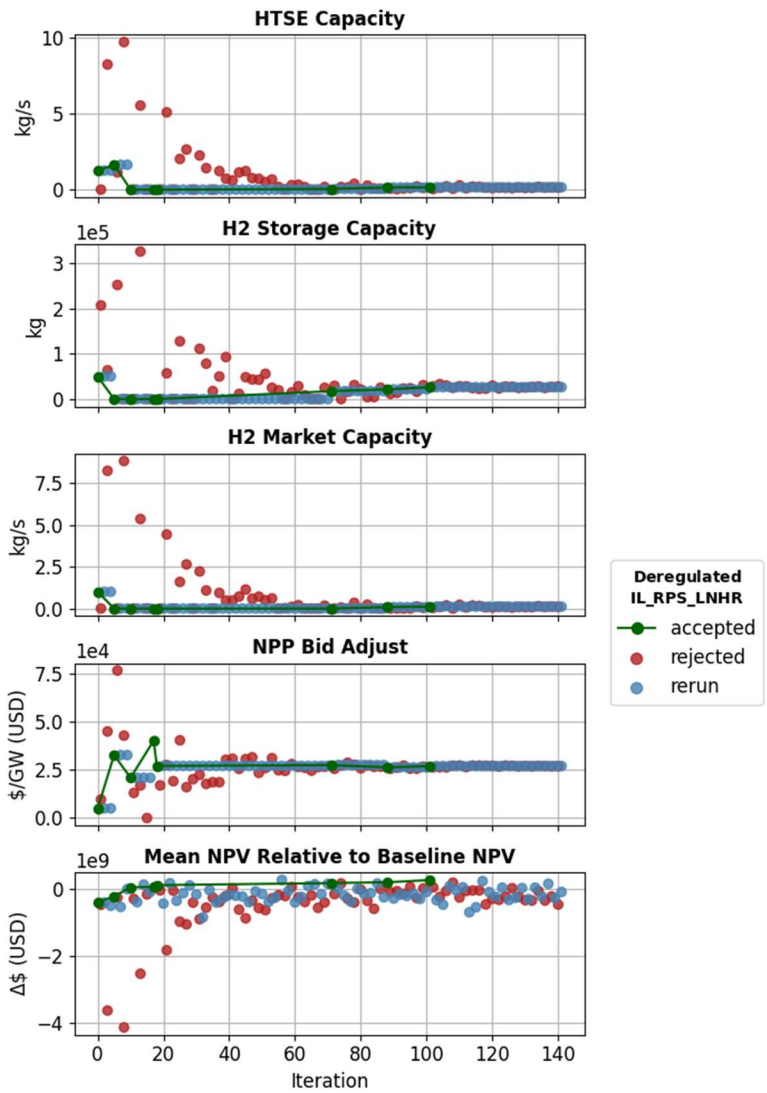


Figure 48. Deregulated RPS LNHR scenario results.

The optimal result for this case includes a small HTSE sized at 0.15 kg/s (13,000 kg/d, 23.4 MW) and a market of 0.12 kg/s, with sufficient storage to provide 63 hours to the market This solution's increase in NPV is well within one standard deviation of the baseline NPV and is insufficiently resolved to clearly indicate the benefit of an IES within this system.

9. CONCLUSIONS

In this work, we demonstrated, from both a deregulated and regulated perspective, the use of HERON as a tool for STEA by considering the viability of introducing an IES into an existing grid energy system. We considered the impact over six different projection scenarios developed using US-REGEN and expertise at EPRI, showing one potential coupling between long-term capacity expansion modeling and long-term STEA. This work builds significantly on previous work with HERON by introducing direct electricity market feedback based on the activities of the IES in both regulated and deregulated systems. The IES is considered in a way that might allow existing NPPs to perform under flexible operation without curtailing generation. In the following sections, we discuss the impact of the results obtained in this work. Once more, the focus of this work is to assess the viability of the software rather than focusing on the results of the analysis. To properly achieve conclusion on the economic viability of hydrogen production one should focus on a specific scenario, be sure to represent correctly each possible revenue stream from multiple markets, which would require a better treatment of the storage aspects and its implication in terms of reduction of necessary capacity.

Another aspect in this effort that deserves highlighting is the computational achievements of these simulations. Thankfully due to recent improvement in the RAVEN infrastructure it was possible to run these simulations using ~500 processors in parallel. 96 realization of the NPV were executed in parallel to ensure a good statistical sample of each of the 5 points used for the calculation of the gradient to drive the optimization. Accounting also for the reduction of computational time due to the use of clustering in the selection of representative days, it has been demonstrated that, without loss of accuracy, a combination of parallel implementation and AI led to an increase in computational speed by a factor of 5000. Without these computational choices, these analyses would not have been feasible, since each run, fully accelerated, each took more than few hours.

9.1 HERON for STEA in Regulated and Deregulated Markets

When considered along with recent demonstrations of HERON for regulated and deregulated market analysis [1-4], this work demonstrates the viability of using HERON in a variety of STEA scenarios, including regulated and deregulated markets, systems in which the IES is either small or large compared to the existing grid energy system, multiple forecasting scenarios, and coupled with a long-term capacity expansion model. Through the use of synthetic history generation in RAVEN, HERON can comprehend critical stochastic behavior in load, weather, and price data in order to more effectively capture the economic viability of various grid profiles, especially when including an IES that delivers secondary products with their own market structure.

Specific to this work, introducing electricity market feedback for IES operation significantly increased the ability to capture the real behavior of deregulated market systems, especially given the day-ahead dispatch requirements of the electricity producing NPP within the IES. Whereas in previous HERON demonstrations it was possible to assume the shift of electricity production was negligible for the NPP and therefore caused no notable impact in electricity prices, in the majority of cases considered in this work, NPPs made up a significant part of the grid energy profile. This necessitated capturing the impact of IES operation on the dispatching activities of the ISO/RTO, leading to greater flexibility in capturing markets with a strong nuclear presence that may also wish to participate in secondary markets via IES.

During the analyses in this work, the capacities for all electricity-generating components was taken from the capacity expansion scenarios in US-REGEN, without the inclusion of the IES. This allowed each scenario to have a baseline performance and enabled us to determine the relative economic viability of introducing an IES into the scenario. However, this does not answer the question of whether building more nuclear capacity could result in an even more profitable opportunity for IES inclusion. The nuclear

capacities have been optimized by the capacity expansion model specifically for a grid-energy system with no IES in place, and the STEA is trying to see if there is room to insert an IES posteriori. An interesting follow up to this set of studies would be to introduce a variable allowing the nuclear capacity to increase by some degree and seeing if more nuclear would be built in the interest of building a larger IES.

In the future, this work could be extended to answer questions about building new plants with IES built at the beginning. Tighter coupling between the capacity expansion and IES dispatch would allow the capacity expansion models to make investment decisions based on IES availability. This could, in turn, show the system's propensity to build larger plants with IES, or whether smaller increments of plants (such as small modular or microreactors) would be more useful in building out the nuclear fleet.

9.2 Future Work

While the capability of HERON to optimize dispatch and capacity of co-product production has been proven, some of the possible benefits of co-generation are still to be included in the analysis.

In particular, it is currently possible to add capacity payments in HERON in deregulated markets, but this would not be captured as reduction of capacity expansion costs so it would not be seen in regulated market. From current ongoing analysis in cooperation with the industry we learned that this could reveal itself being a large contribution to establishing the benefits of having flexible power output from NPPs. In the current FY it is a goal to improve the treatment of storage in HERON. A large part of properly capturing the benefits of storage is to accurately assess its impact on the reduction of the installed capacity requirements.

HERON can be used today to perform revenue forecasts for flexible power operations with a level of accuracy above what was available before and while areas of improvement remain, we look forward to using the software to perform real case applications.

During the development of this large set of user case example a few minor desired improvements were identified, like the capability to run the simulation directly for the differential NPV instead of post processing the results. In addition, a graphical user interface dedicated to the visualization of the data flow would be very helpful.

In conclusion, HERON today provides capabilities that were needed and not available before for the financial analysis of flexible power operations. From a computational and software standpoint the work has been very successful. The availability of this tool will help the industry to make more informed investment decisions in the near term.

References

1. Talbot, Paul W, Abhinav Gairola, et al., 2019. "HERON as a Tool for LWR Market Interaction in a Deregulated Market", Idaho National Laboratory, Report INL/EXT-19-56933.
2. Frick, Connor L., Paul W. Talbot, Daniel S. Wendt, et al., 2019. "Evaluation of Hydrogen Production feasibility for a Light Water Reactor in the Midwest," Idaho National Laboratory, Report INL/EXT-19-55395.
3. Talbot, Paul W., Pralhad H. Burli, James D. Richards, et al., 2019. "Analysis of Differential Financial Impacts of LWR Load-Following Operations," Idaho National Laboratory, Report INL/EXT-19-55614.
4. Talbot, Paul W., Cristian Rabiti, et al., "HERON," Idaho National Repository, Computer Software, https://www.osti.gov//servlets/purl/1668297, USDOE Office of Nuclear Energy (NE).
5. Rabiti, Cristian, Andrea Alfonsi, Joshua J. Cogliati, et al., 2015. "RAVEN User Manual", Idaho National Laboratory, Report INL/EXT-15-34123.
6. Hart, W.E., Watson, J.P., Woodruff, D.L., et al., 2017. "Pyomo-optimization modeling in python", Berlin: Springer.
7. Short, Sullivan, et al., 2011. "Regional Energy Deployment System (ReEDS)", National Renewable Energy Laboratory, Report NREL/TP-6A20-46534.
8. Papadopoulos, C., Johnson, R. et al., 2014. "PLEXOS Integrated Energy Modelling around the Globe", Energy Exemplar, 10. Retrieved from https://old.energyexemplar.com/wp-content/uploads/publications
9. PRISM, EPRI, 2020. "US-REGEN Model Documentation", Electric Power Research Institute, Report 3002016601.
10. FERC. "FERC ELECTRIC TARIFF Volume No. 5", Union Electric Company.
11. Kasahara, S., Imai, Y., Suzuki, K., Iwatsuki, J., Terada, A., & Yan, X. L., April 2017 "Conceptual design of the iodine–sulfur process flowsheet with more than 50% thermal efficiency for hydrogen production." Nuclear Engineering and Design.
12. Yan, X. L., Sato, H., Sumita, J., Nomoto, Y., Horii, S., Imai, Y., Suyama, K., 2017. Design of HTTR GT/H2 test plant. Nuclear Engineering and Design.
13. Rosen, M.A., Naterer, G.F., Chukwu, C.C., Sadhankar, R. and Suppiah, S., 2012. "Nuclear-based hydrogen production with a thermochemical copper–chlorine cycle and supercritical water reactor: equipment scale-up and process simulation." International Journal of Energy Research.
14. Naterer, G. F., Suppiah, S., Stolberg, L., Lewis, M., Wang, Z., Rosen, M. A., Papangelakis, V., 2015. "Progress in thermochemical hydrogen production with the copper-chlorine cycle." International Journal of Hydrogen Energy.
15. Kim J.S., McKellar M, Bragg-Sitton S.M., Boardman R.D., 2016 Oct. "Status on the Component Models Developed in the Modelica Framework: High-Temperature Steam Electrolysis Plant & Gas Turbine Power Plant." Idaho Falls (ID): Idaho National Laboratory, Nuclear Science and Technology Division; Report No. INL/EXT-16-40305. Contract No. DE-AC07-05ID14517. Sponsored by the U.S. Department of Energy.
16. Connelly, E., Elgowainy, A., 2019. "DOE Hydrogen and Fuel Cells Program Record 19002: Current Hydrogen Market Size: Domestic and Global."

17. Suresh, B., et al., 2018. “Hydrogen.” IHS Markit, Chemical Economics Handbook.
18. Brown, D., 2016. “US and World Hydrogen Production – 2014.” Pacific Northwest National Laboratory.
19. Markets and Markets, 2016. “Hydrogen Generation Market – Global Tends and Forecasts to 2019.”
20. IEA, Paris, 2017. “The Future of Hydrogen,” https://www.iea.org/reports/the-future-of-hydrogen.
21. Penev, M., Saur, G., Hunter, C., & Zuboy, J., 2018. “H2A Production Model H2A Hydrogen Production Model: Version 3. 2018 User Guide.” Retrieved from www.hydrogen.energy.gov/h2a_production.html.
22. U.S. Energy Information Administration (EIA), 2020. “The Annual Energy Outlook explores long-term energy trends in the United States.” Retrieved from www.eia.gov/aeo.
23. Talbot, Paul W., Cristian Rabiti, Andrea Alfonsi, et al., 2020. “Correlated synthetic time series generation for energy system simulations using Fourier and ARMA signal processing,” International Journal of Energy Research.
24. Epiney, Aaron S., Cristian Rabiti, Paul W. Talbot, et al., 2020. “Economic analysis of a nuclear hybrid energy system in a stochastic environment including wind turbines in an electricity grid,” Applied Energy, 260, 114227.
25. Morilhat, Patrick, Stéphane Feutry, Christelle Le Maitre, et al., 2019. “Nuclear Power Plant flexibility at EDF,” <hal-01977209>.
26. Bragg-Sitton, Shannon M., Cristian Rabiti, James E. O’Brien, et al., 2020. “Integrated Energy Systems: 2020 Roadmap,” Idaho National Laboratory, Report INL/EXT-20-57708.
27. Wang, Haoyu, Roberto Ponciroli, Richard B. Vilim, Andrea Alfonsi, 2020. “Development of Control System Functional Capabilities within the IES Plug-and-Play Simulation Environment,” Argonne National Laboratory, Report ANL/NSE-20/35.

APPENDIX A: Example Deregulated HERON Input

This is an example of the HERON input XML file for the Deregulated Carbon Tax Default case. This HERON input results in compilation of component characteristics, as well as the generation of RAVEN outer and inner input files.

```
<HERON>
 <Case name="D_CarbonTax_Default">
  <mode>opt</mode>
  <label name="state">IL</label>
  <label name="strategy">CarbonTax</label>
  <label name="price_struct">Default</label>
  <label name="regulated">No</label>
  <label name="rotated">Yes</label>
  <num_arma_samples>96</num_arma_samples>
  <time_discretization>
   <year_variable>YEAR</year_variable>
   <time_variable>HOUR</time_variable>
   <end_time>23</end_time>
   <num_steps>24</num_steps>
  </time_discretization>
  <economics>
   <ProjectTime>26</ProjectTime>
   <DiscountRate>0.08</DiscountRate>
   <tax>0.25</tax>
   <inflation>0.025</inflation>
   <verbosity>50</verbosity>
  </economics>
  <dispatcher>
   <custom>
    <location>../../dispatchers/dereg.py</location>
   </custom>
  </dispatcher>
 </Case>

 <Components>
  <Component name="NPP">
   <produces dispatch="fixed" resource="electricity">
    <capacity resource="electricity">
     <Function method="NPP_cap">functions</Function>
    </capacity>
   </produces>
   <economics>
    <lifetime>30</lifetime>
   </economics>
  </Component>
  <Component name="HTSE">
   <produces dispatch="dependent" resource="H2">
    <capacity resource="H2">
     <Function method="get_HTSE_cap_from_delta">functions</Function>
    </capacity>
    <consumes>electricity</consumes>
    <transfer>
     <linear>
      <rate resource="electricity">-0.043</rate>
      <rate resource="H2">1</rate>
     </linear>
    </transfer>
   </produces>
```

```
  <economics>
    <lifetime>30</lifetime>
    <CashFlow inflation="none" mult_target="False" name="capex" taxable="True" type="one-time">
      <driver>
        <Function method="get_HTSE_cap_from_delta_driver">functions</Function>
      </driver>
      <reference_price>
        <fixed_value>-545263737</fixed_value>
      </reference_price>
      <reference_driver>
        <fixed_value>7.4</fixed_value>
      </reference_driver>
      <scaling_factor_x>
        <fixed_value>0.955</fixed_value>
      </scaling_factor_x>
      <depreciate>15</depreciate>
    </CashFlow>
    <CashFlow inflation="none" mult_target="False" name="fixed_OM" period="year" taxable="True" type="repeating">
      <driver>
        <Function method="get_HTSE_cap_from_delta_driver">functions</Function>
      </driver>
      <reference_price>
        <fixed_value>-70752705</fixed_value>
      </reference_price>
      <reference_driver>
        <fixed_value>7.4</fixed_value>
      </reference_driver>
      <scaling_factor_x>
        <fixed_value>0.955</fixed_value>
      </scaling_factor_x>
    </CashFlow>
  </economics>
</Component>
<Component name="H2_storage">
  <stores dispatch="independent" resource="H2">
    <capacity resource="H2">
      <opt_bounds>0, 1e6</opt_bounds>
    </capacity>
    <initial_stored>
      <fixed_value>0</fixed_value>
    </initial_stored>
  </stores>
  <economics>
    <lifetime>30</lifetime>
    <CashFlow inflation="none" mult_target="False" name="capex" taxable="True" type="one-time">
      <driver>
        <variable>H2_storage_capacity</variable>
      </driver>
      <reference_price>
        <fixed_value>-550</fixed_value>
      </reference_price>
      <depreciate>15</depreciate>
    </CashFlow>
  </economics>
</Component>
<Component name="grid">
  <demands dispatch="dependent" resource="electricity">
    <capacity>
      <Function method="get_load">functions</Function>
    </capacity>
```

```
  </demands>
  <economics>
    <lifetime>1</lifetime>
    <CashFlow inflation="none" mult_target="False" name="grid_sales" taxable="True" type="repeating">
      <driver>
        <Function method="e_consume">functions</Function>
      </driver>
      <reference_price>
        <Function method="grid_price">functions</Function>
      </reference_price>
    </CashFlow>
  </economics>
</Component>
<Component name="H2_market">
  <demands dispatch="dependent" resource="H2">
    <capacity>
      <opt_bounds>0, -20</opt_bounds>
    </capacity>
  </demands>
  <economics>
    <lifetime>1</lifetime>
    <CashFlow inflation="none" mult_target="False" name="H2_sales" taxable="True" type="repeating">
      <driver>
        <Function method="H2_activity">functions</Function>
      </driver>
      <reference_price>
        <Function method="H2_price">functions</Function>
      </reference_price>
    </CashFlow>
  </economics>
</Component>
<Component name="Secondary">
  <produces dispatch="dependent" resource="electricity">
    <capacity resource="electricity">
      <fixed_value>1e4</fixed_value>
    </capacity>
  </produces>
  <economics>
    <lifetime>1</lifetime>
    <CashFlow inflation="none" mult_target="False" name="secondary_e_fixup" taxable="True" type="repeating">
      <driver>
        <Function method="secondary_activity">functions</Function>
      </driver>
      <reference_price>
        <fixed_value>1</fixed_value>
      </reference_price>
    </CashFlow>
  </economics>
</Component>
<Component name="E_Penalty">
  <demands dispatch="dependent" resource="electricity">
    <capacity resource="electricity">
      <fixed_value>-1e4</fixed_value>
    </capacity>
  </demands>
  <economics>
    <lifetime>1</lifetime>
    <CashFlow inflation="none" mult_target="False" name="penalty_e_fixup" taxable="True" type="repeating">
      <driver>
        <Function method="penalty_activity">functions</Function>
```

```
        </driver>
        <reference_price>
          <fixed_value>1</fixed_value>
        </reference_price>
      </CashFlow>
    </economics>
  </Component>
</Components>

<DataGenerators>
  <ARMA evalMode="clustered" name="Load" variable="TOTALLOAD">../../../train/carbontax/IL/arma.pk</ARMA>
  <Function name="functions">../../functions.py</Function>
</DataGenerators>
</HERON>
```

APPENDIX B: Example Regulated HERON Input

This is an example of the HERON input XML file for the Regulated RPS LNHR case. This HERON input results in compilation of component characteristics as well as the generation of RAVEN outer and inner input files.


```
<HERON>
 <Case name="R_RPS_LNHR">
  <mode>opt</mode>
  <label name="state">IL</label>
  <label name="strategy">RPS</label>
  <label name="price_struct">LNHR</label>
  <label name="regulated">Yes</label>
  <label name="rotated">Yes</label>
  <num_arma_samples>96</num_arma_samples>
  <time_discretization>
   <year_variable>YEAR</year_variable>
   <time_variable>HOUR</time_variable>
   <end_time>23</end_time>
   <num_steps>24</num_steps>
  </time_discretization>
  <economics>
   <ProjectTime>26</ProjectTime>
   <DiscountRate>0.08</DiscountRate>
   <tax>0.25</tax>
   <inflation>0.025</inflation>
   <verbosity>50</verbosity>
  </economics>
  <dispatcher>
   <pyomo />
  </dispatcher>
 </Case>

 <Components>
  <Component name="Coal">
   <produces dispatch="dependent" resource="electricity">
    <capacity resource="electricity">
     <Function method="get_coal_cap">functions</Function>
    </capacity>
   </produces>
   <economics>
    <lifetime>30</lifetime>
    <CashFlow inflation="none" mult_target="False" name="VOM" taxable="True" type="repeating">
     <driver>
      <Function method="get_e_activity">functions</Function>
     </driver>
     <reference_price>
      <Function method="get_coal_mgc">functions</Function>
     </reference_price>
    </CashFlow>
   </economics>
  </Component>
  <Component name="Gas">
   <produces dispatch="dependent" resource="electricity">
    <capacity resource="electricity">
     <Function method="get_gas_cap">functions</Function>
    </capacity>
   </produces>
   <economics>
```

```
    <lifetime>30</lifetime>
    <CashFlow inflation="none" mult_target="False" name="VOM" taxable="True" type="repeating">
      <driver>
        <Function method="get_e_activity">functions</Function>
      </driver>
      <reference_price>
        <Function method="get_gas_mgc">functions</Function>
      </reference_price>
    </CashFlow>
  </economics>
</Component>
<Component name="Petrol">
  <produces dispatch="dependent" resource="electricity">
    <capacity resource="electricity">
      <Function method="get_petrol_cap">functions</Function>
    </capacity>
  </produces>
  <economics>
    <lifetime>30</lifetime>
    <CashFlow inflation="none" mult_target="False" name="VOM" taxable="True" type="repeating">
      <driver>
        <Function method="get_e_activity">functions</Function>
      </driver>
      <reference_price>
        <Function method="get_petrol_mgc">functions</Function>
      </reference_price>
    </CashFlow>
  </economics>
</Component>
<Component name="Other">
  <produces dispatch="dependent" resource="electricity">
    <capacity resource="electricity">
      <Function method="get_other_cap">functions</Function>
    </capacity>
  </produces>
  <economics>
    <lifetime>30</lifetime>
    <CashFlow inflation="none" mult_target="False" name="VOM" taxable="True" type="repeating">
      <driver>
        <Function method="get_e_activity">functions</Function>
      </driver>
      <reference_price>
        <Function method="get_other_mgc">functions</Function>
      </reference_price>
    </CashFlow>
  </economics>
</Component>
<Component name="H2gen">
  <produces dispatch="dependent" resource="electricity">
    <capacity resource="electricity">
      <Function method="get_h2gen_cap">functions</Function>
    </capacity>
  </produces>
  <economics>
    <lifetime>30</lifetime>
    <CashFlow inflation="none" mult_target="False" name="VOM" taxable="True" type="repeating">
      <driver>
        <Function method="get_e_activity">functions</Function>
      </driver>
      <reference_price>
```

```
      <Function method="get_h2gen_mgc">functions</Function>
    </reference_price>
   </CashFlow>
  </economics>
</Component>
<Component name="Nuclear">
  <produces dispatch="dependent" resource="electricity">
   <capacity resource="electricity">
    <Function method="get_nuclear_cap">functions</Function>
   </capacity>
  </produces>
  <economics>
   <lifetime>30</lifetime>
   <CashFlow inflation="none" mult_target="False" name="VOM" taxable="True" type="repeating">
    <driver>
      <Function method="get_e_activity">functions</Function>
    </driver>
    <reference_price>
      <Function method="get_nuclear_mgc">functions</Function>
    </reference_price>
   </CashFlow>
  </economics>
</Component>
<Component name="VRE">
  <produces dispatch="dependent" resource="electricity">
   <capacity resource="electricity">
    <Function method="get_VRE_cap">functions</Function>
   </capacity>
  </produces>
  <economics>
   <lifetime>30</lifetime>
   <CashFlow inflation="none" mult_target="False" name="VOM" taxable="True" type="repeating">
    <driver>
      <Function method="get_e_activity">functions</Function>
    </driver>
    <reference_price>
      <Function method="get_VRE_mgc">functions</Function>
    </reference_price>
   </CashFlow>
  </economics>
</Component>
<Component name="HTSE">
  <produces dispatch="dependent" resource="H2">
   <capacity resource="H2">
    <Function method="get_HTSE_cap_from_delta">functions</Function>
   </capacity>
   <consumes>electricity</consumes>
   <transfer>
    <linear>
      <rate resource="electricity">-43e-6</rate>
      <rate resource="H2">1</rate>
    </linear>
   </transfer>
  </produces>
  <economics>
   <lifetime>30</lifetime>
   <CashFlow inflation="none" mult_target="False" name="capex" taxable="True" type="one-time">
    <driver>
      <Function method="get_HTSE_cap_from_delta_driver">functions</Function>
    </driver>
```

```
      <reference_price>
        <fixed_value>-545263737</fixed_value>
      </reference_price>
      <reference_driver>
        <fixed_value>7.4</fixed_value>
      </reference_driver>
      <scaling_factor_x>
        <fixed_value>0.955</fixed_value>
      </scaling_factor_x>
      <depreciate>15</depreciate>
    </CashFlow>
    <CashFlow inflation="none" mult_target="False" name="fixed_OM" period="year" taxable="True" type="repeating">
      <driver>
        <Function method="get_HTSE_cap_from_delta_driver">functions</Function>
      </driver>
      <reference_price>
        <fixed_value>-70752705</fixed_value>
      </reference_price>
      <reference_driver>
        <fixed_value>7.4</fixed_value>
      </reference_driver>
      <scaling_factor_x>
        <fixed_value>0.955</fixed_value>
      </scaling_factor_x>
    </CashFlow>
  </economics>
</Component>
<Component name="H2_storage">
  <stores dispatch="independent" resource="H2">
    <capacity resource="H2">
      <opt_bounds>0, 1e6</opt_bounds>
    </capacity>
    <initial_stored>
      <fixed_value>0</fixed_value>
    </initial_stored>
  </stores>
  <economics>
    <lifetime>30</lifetime>
    <CashFlow inflation="none" mult_target="False" name="capex" taxable="True" type="one-time">
      <driver>
        <variable>H2_storage_capacity</variable>
      </driver>
      <reference_price>
        <fixed_value>-550</fixed_value>
      </reference_price>
      <depreciate>15</depreciate>
    </CashFlow>
  </economics>
</Component>
<Component name="grid">
  <demands dispatch="fixed" resource="electricity">
    <capacity>
      <Function method="get_load">functions</Function>
      <multiplier>-1</multiplier>
    </capacity>
  </demands>
  <economics>
    <lifetime>1</lifetime>
  </economics>
</Component>
```

```
    <Component name="H2_market">
      <demands dispatch="fixed" resource="H2">
        <capacity>
          <opt_bounds>-1e-10, -20</opt_bounds>
        </capacity>
      </demands>
      <economics>
        <lifetime>1</lifetime>
        <CashFlow inflation="none" mult_target="False" name="H2_sales" taxable="True" type="repeating">
          <driver>
            <Function method="H2_activity">functions</Function>
          </driver>
          <reference_price>
            <Function method="H2_price">functions</Function>
          </reference_price>
        </CashFlow>
      </economics>
    </Component>
  </Components>

  <DataGenerators>
    <ARMA evalMode="clustered" name="Load" variable="TOTALLOAD">../../../train/rps_lnhr/IL/arma.pk</ARMA>
    <Function name="functions">../../functions.py</Function>
  </DataGenerators>
</HERON>
```

APPENDIX C: Example RAVEN Outer Input

The following is an example of one of the HERON-generated RAVEN outer optimization inputs, in this instance for the Deregulated Carbon Tax Default case. This input is used to optimize the capacity space by running the RAVEN inner optimization input.

```
<Simulation verbosity="debug">
 <RunInfo>
  <JobName>D_CarbonTax_Default_o</JobName>
  <WorkingDir>D_CarbonTax_Default_o</WorkingDir>
  <Sequence>optimize</Sequence>
  <batchSize>5</batchSize>
  <RemoteRunCommand>raven_sawtooth_qsub.sh</RemoteRunCommand>
  <NumMPI>96</NumMPI>
  <mode>mpi
   <runQSUB />
   <memory>10gb</memory>
  </mode>
  <expectedTime>20:0:0</expectedTime>
  <clusterParameters>-P lwrs</clusterParameters>
  <internalParallel>True</internalParallel>
  <PYTHONPATH>/home/talbpaul/projects/HERON/src</PYTHONPATH>
 </RunInfo>

 <Steps>
  <MultiRun name="optimize">
   <Input class="Files" type="raven">inner_workflow</Input>
   <Input class="Files" type="">heron_lib</Input>
   <Input class="Files" type="">transfers</Input>
   <Model class="Models" type="Code">raven</Model>
   <Optimizer class="Optimizers" type="FiniteDifference">cap_opt</Optimizer>
   <Output class="DataObjects" type="PointSet">opt_eval</Output>
   <SolutionExport class="DataObjects" type="PointSet">opt_soln</SolutionExport>
   <Output class="OutStreams" type="Print">opt_soln</Output>
  </MultiRun>
 </Steps>

 <VariableGroups>
  <Group name="GRO_capacities">H2_storage_capacity, H2_market_capacity, Secondary_capacity, E_Penalty_capacity,
IES_delta_cap, NPP_bid_adjust</Group>
  <Group name="GRO_outer_results">
   mean_NPV, std_NPV, med_NPV, max_NPV, min_NPV,
   perc_5_NPV, perc_95_NPV, samp_NPV, var_NPV
  </Group>
  <Group name="GRO_case_labels">state_label, strategy_label, price_struct_label, regulated_label, rotated_label</Group>
 </VariableGroups>

 <DataObjects>
  <PointSet name="opt_eval">
   <Input>GRO_capacities</Input>
   <Output>mean_NPV</Output>
  </PointSet>
  <PointSet name="opt_soln">
   <Input>trajID</Input>
   <Output>iteration, accepted, GRO_capacities, mean_NPV</Output>
  </PointSet>
 </DataObjects>

 <Models>
  <Code name="raven" subType="RAVEN">
```

```
    <executable>/Users/talbpw/projects/raven/raven_framework</executable>
    <outputExportOutStreams>disp_results</outputExportOutStreams>
    <conversion>
      <input source="../write_inner.py" />
    </conversion>
    <alias type="input" variable="denoises">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:denoises</alias>
    <alias type="input"
variable="NPP_capacity">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:NPP_capacity</alias>
    <alias type="input"
variable="HTSE_capacity">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:HTSE_capacity</alias>
    <alias type="input"
variable="H2_storage_capacity">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:H2_storage_capacity</alias>
    <alias type="input"
variable="grid_capacity">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:grid_capacity</alias>
    <alias type="input"
variable="H2_market_capacity">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:H2_market_capacity</alias>
    <alias type="input"
variable="Secondary_capacity">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:Secondary_capacity</alias>
    <alias type="input"
variable="E_Penalty_capacity">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:E_Penalty_capacity</alias>
    <alias type="input" variable="state_label">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:state_label</alias>
    <alias type="input"
variable="strategy_label">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:strategy_label</alias>
    <alias type="input"
variable="price_struct_label">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:price_struct_label</alias>
    <alias type="input"
variable="regulated_label">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:regulated_label</alias>
    <alias type="input"
variable="rotated_label">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:rotated_label</alias>
    <alias type="input"
variable="IES_delta_cap">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:IES_delta_cap</alias>
    <alias type="input"
variable="NPP_bid_adjust">Samplers|MonteCarlo@name:mc_arma_dispatch|constant@name:NPP_bid_adjust</alias>
  </Code>
 </Models>

 <Distributions>
  <Uniform name="H2_storage_capacity_dist">
    <lowerBound>0.0</lowerBound>
    <upperBound>1000000.0</upperBound>
  </Uniform>
  <Uniform name="H2_market_capacity_dist">
    <lowerBound>-20.0</lowerBound>
    <upperBound>0.0</upperBound>
  </Uniform>
  <Uniform name="IES_delta_cap_capacity_dist">
    <lowerBound>0</lowerBound>
    <upperBound>5</upperBound>
  </Uniform>
  <Uniform name="NPP_bid_adjust_capacity_dist">
    <lowerBound>0</lowerBound>
    <upperBound>100000.0</upperBound>
  </Uniform>
 </Distributions>

 <Optimizers>
  <GradientDescent name="cap_opt">
    <objective>mean_NPV</objective>
    <!-- <variable> nodes filled by HERON -->
    <constant name="denoises">96</constant>
```

```
    <TargetEvaluation class="DataObjects" type="PointSet">opt_eval</TargetEvaluation>
    <samplerInit>
      <limit>800</limit>
      <writeSteps>every</writeSteps>
      <type>max</type>
    </samplerInit>
    <gradient>
      <FiniteDifference>
        <gradDistanceScalar>0.005</gradDistanceScalar>
      </FiniteDifference>
    </gradient>
    <stepSize>
      <GradientHistory>
        <growthFactor>1.25</growthFactor>
        <shrinkFactor>1.1</shrinkFactor>
        <initialStepScale>0.3</initialStepScale>
      </GradientHistory>
    </stepSize>
    <acceptance>
      <Strict />
    </acceptance>
    <convergence>
      <gradient>1e-8</gradient>
      <objective>1e-8</objective>
      <stepSize>0.01</stepSize>
    </convergence>
    <constant name="state_label">IL</constant>
    <constant name="strategy_label">CarbonTax</constant>
    <constant name="price_struct_label">Default</constant>
    <constant name="regulated_label">No</constant>
    <constant name="rotated_label">Yes</constant>
    <variable name="H2_storage_capacity">
      <distribution>H2_storage_capacity_dist</distribution>
      <initial>50000.0</initial>
    </variable>
    <variable name="H2_market_capacity">
      <distribution>H2_market_capacity_dist</distribution>
      <initial>-1.0</initial>
    </variable>
    <constant name="Secondary_capacity">10000.0</constant>
    <constant name="E_Penalty_capacity">-10000.0</constant>
    <Constraint class="Functions" type="External">h2_sizing</Constraint>
    <variable name="IES_delta_cap">
      <distribution>IES_delta_cap_capacity_dist</distribution>
      <initial>0.25</initial>
    </variable>
    <variable name="NPP_bid_adjust">
      <distribution>NPP_bid_adjust_capacity_dist</distribution>
      <initial>5000.0</initial>
    </variable>
  </GradientDescent>
</Optimizers>

<Files>
  <Input name="inner_workflow" type="raven">../inner.xml</Input>
  <Input name="heron_lib">../heron.lib</Input>
  <Input name="transfers">../../../functions.py</Input>
</Files>

<OutStreams>
```

```
    <Print name="opt_soln">
      <type>csv</type>
      <source>opt_soln</source>
      <clusterLabel>trajID</clusterLabel>
    </Print>
  </OutStreams>

  <Functions>
    <External file="../../functions" name="h2_sizing">
      <variables>IES_delta_cap, H2_market_capacity</variables>
    </External>
  </Functions>
</Simulation>
```

APPENDIX D: Example RAVEN Inner Input

This is an example of a generated RAVEN inner input file for synthetic signal sampling and dispatch optimization. The blueprint for this file is generated by HERON and subsequently filled in by RAVEN outer optimization for each point in the outer optimization space.

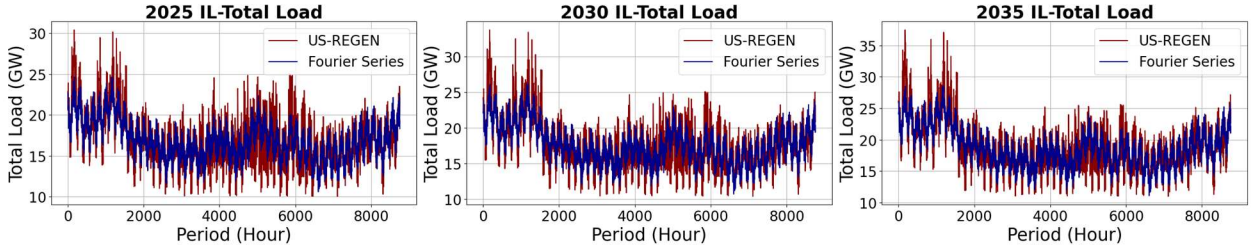
```
<Simulation verbosity="debug">
        <RunInfo>
          <JobName>D_CarbonTax_Default_i</JobName>
          <WorkingDir>D_CarbonTax_Default_i</WorkingDir>
          <Sequence>arma_sampling, summarize</Sequence>
          <internalParallel>True</internalParallel>
          <batchSize>96</batchSize>
        </RunInfo>

        <Steps>
          <MultiRun name="arma_sampling">
                <Input class="DataObjects" type="PointSet">dispatch_placeholder</Input>
                <Model class="Models" type="EnsembleModel">sample_and_dispatch</Model>
                <Sampler class="Samplers" type="MonteCarlo">mc_arma_dispatch</Sampler>
                <Output class="DataObjects" type="DataSet">arma_metrics</Output>
          </MultiRun>
          <PostProcess name="summarize">
                <Input class="DataObjects" type="PointSet">arma_metrics</Input>
                <Model class="Models" type="PostProcessor">average</Model>
                <Output class="DataObjects" type="PointSet">metrics_avg</Output>
                <Output class="OutStreams" type="Print">disp_results</Output>
          </PostProcess>
        </Steps>

        <VariableGroups>
          <Group name="GRO_dispatch">GRO_dispatch_in, GRO_dispatch_out, _ROM_Cluster, HOUR, YEAR</Group>
          <Group name="GRO_dispatch_in">GRO_dispatch_in_scalar, GRO_dispatch_in_Time</Group>
          <Group name="GRO_dispatch_out">NPV</Group>
          <Group name="GRO_dispatch_in_scalar">GRO_capacities, scaling, GRO_case_labels</Group>
          <Group name="GRO_dispatch_in_Time">TOTALLOAD</Group>
          <Group name="GRO_armasamples">GRO_armasamples_in, GRO_armasamples_out</Group>
          <Group name="GRO_armasamples_in">GRO_armasamples_in_scalar</Group>
          <Group name="GRO_armasamples_out">GRO_armasamples_out_scalar</Group>
          <Group name="GRO_armasamples_in_scalar">scaling, time_delta, GRO_capacities, GRO_case_labels</Group>
          <Group name="GRO_armasamples_out_scalar">NPV</Group>
          <Group name="GRO_final_return">
    mean_NPV, std_NPV, med_NPV, max_NPV, min_NPV,
    perc_5_NPV, perc_95_NPV, samp_NPV, var_NPV
   </Group>
          <Group name="GRO_means">Dispatch__NPP__electricity, Dispatch__HTSE__electricity, Dispatch__HTSE__H2,
Dispatch__H2_storage__H2, Dispatch__H2_storage__H2, Dispatch__grid__electricity, Dispatch__H2_market__H2,
Dispatch__Secondary__electricity, Dispatch__E_Penalty__electricity</Group>
          <Group name="GRO_interp">stepwise</Group>
          <Group name="GRO_capacities">HTSE_capacity, H2_storage_capacity, H2_market_capacity, Secondary_capacity,
E_Penalty_capacity, NPP_bid_adjust</Group>
          <Group name="GRO_init_disp">Dispatch__NPP__electricity, Dispatch__HTSE__electricity, Dispatch__HTSE__H2,
Dispatch__H2_storage__H2, Dispatch__H2_storage__H2, Dispatch__grid__electricity, Dispatch__H2_market__H2,
Dispatch__Secondary__electricity, Dispatch__E_Penalty__electricity</Group>
          <Group name="GRO_case_labels">state_label, strategy_label, price_struct_label</Group>
        </VariableGroups>

        <DataObjects>
          <DataSet name="arma_samples">
                <Input>GRO_armasamples_in</Input>
                <Output>GRO_armasamples_out</Output>
```

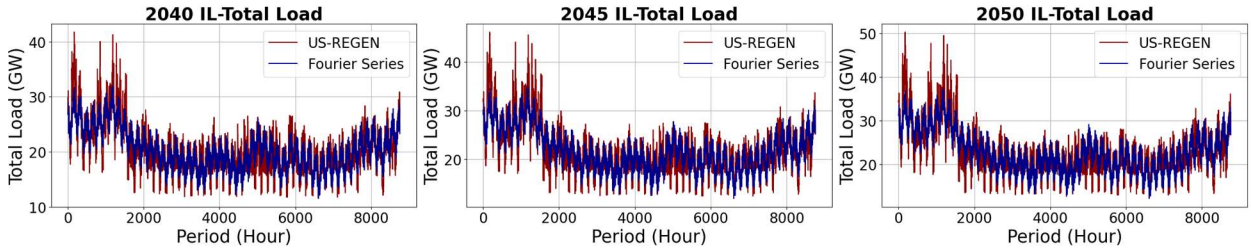
```
        </DataSet>
        <PointSet name="arma_metrics">
            <Output>NPV</Output>
        </PointSet>
        <PointSet name="metrics_avg">
            <Output>GRO_final_return</Output>
        </PointSet>
        <DataSet name="disp_avg">
            <Output>GRO_means</Output>
            <Index var="HOUR">GRO_means</Index>
            <Index var="YEAR">GRO_means</Index>
        </DataSet>
        <DataSet name="dispatch_eval">
            <Input>GRO_dispatch_in</Input>
            <Index var="HOUR">GRO_dispatch_in_Time</Index>
            <Index var="YEAR">GRO_dispatch_in_Time</Index>
            <Index var="_ROM_Cluster">GRO_dispatch_in_Time</Index>
        </DataSet>
        <PointSet name="dispatch_placeholder">
            <Input>GRO_dispatch_in_scalar</Input>
        </PointSet>
        <DataSet name="Load_meta"/>
        <PointSet name="Load_placeholder">
            <Input>scaling</Input>
        </PointSet>
        <DataSet name="Load_samples">
            <Input>scaling</Input>
            <Output>TOTALLOAD</Output>
            <Index var="HOUR">TOTALLOAD</Index>
            <Index var="YEAR">TOTALLOAD</Index>
            <Index var="_ROM_Cluster">TOTALLOAD</Index>
        </DataSet>
    </DataObjects>

    <Models>
        <ExternalModel ModuleToLoad="/Users/talbpw/projects/HERON/src/DispatchManager.py" name="dispatch" subType="">
            <variables>GRO_dispatch, GRO_armasamples</variables>
        </ExternalModel>
        <ExternalModel ModuleToLoad="/Users/talbpw/projects/HERON/src/DispatchBypass.py" name="dispatch_bypass"
subType="">
            <variables>GRO_dispatch, GRO_armasamples</variables>
        </ExternalModel>
        <ExternalModel ModuleToLoad="/Users/talbpw/projects/HERON/src/ArmaBypass.py" name="arma_bypass" subType="">
            <variables>TOTALLOAD, YEAR, _ROM_Cluster, HOUR, scaling</variables>
        </ExternalModel>
        <EnsembleModel name="sample_and_dispatch" subType="">
            <Model class="Models" type="ExternalModel">
                dispatch_bypass
                <Input class="DataObjects" type="PointSet">dispatch_placeholder</Input>
                <TargetEvaluation class="DataObjects" type="DataSet">dispatch_eval</TargetEvaluation>
            </Model>
            <Model class="Models" type="ExternalModel">
                arma_bypass
                <Input class="DataObjects" type="PointSet">Load_placeholder</Input>
                <TargetEvaluation class="DataObjects" type="DataSet">Load_samples</TargetEvaluation>
            </Model>
        </EnsembleModel>
        <PostProcessor name="average" subType="BasicStatistics">
            <expectedValue prefix="mean">NPV</expectedValue>
            <sigma prefix="std">NPV</sigma>
```

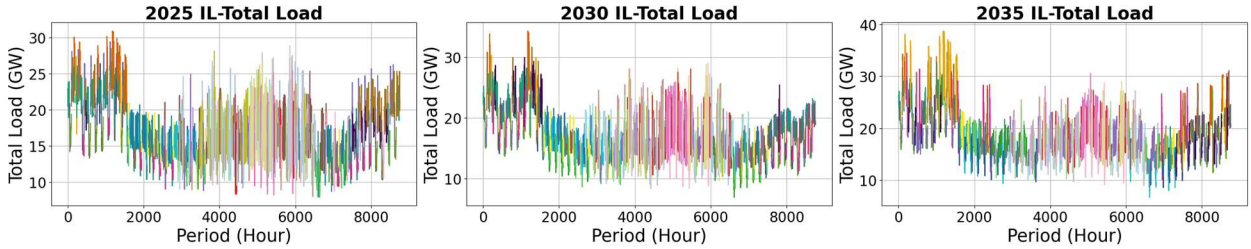
```
            <median prefix="med">NPV</median>
            <maximum prefix="max">NPV</maximum>
            <minimum prefix="min">NPV</minimum>
            <percentile prefix="perc">NPV</percentile>
            <samples prefix="samp">NPV</samples>
            <variance prefix="var">NPV</variance>
        </PostProcessor>
        <ROM name="Load" subType="pickledROM">
            <clusterEvalMode>clustered</clusterEvalMode>
        </ROM>
    </Models>

    <Files>
        <Input name="libs">heron.lib</Input>
    </Files>

    <Samplers>
        <MonteCarlo name="mc_arma_dispatch">
            <samplerInit>
                <initialSeed>42</initialSeed>
                <limit>96</limit>
            </samplerInit>
            <constant name="scaling">1.0</constant>
            <constant name="HTSE_capacity">10.0</constant>
            <constant name="H2_storage_capacity">500000.0</constant>
            <constant name="H2_market_capacity">-10.0</constant>
            <constant name="Secondary_capacity">10000.0</constant>
            <constant name="E_Penalty_capacity">-10000.0</constant>
            <constant name="state_label">IL</constant>
            <constant name="strategy_label">CarbonTax</constant>
            <constant name="price_struct_label">Default</constant>
            <constant name="denoises">3</constant>
            <constant name="NPP_bid_adjust">50000.0</constant>
        </MonteCarlo>
    </Samplers>

    <OutStreams>
        <Print name="disp_debug">
            <type>csv</type>
            <source>arma_samples</source>
        </Print>
        <Print name="disp_results">
            <type>csv</type>
            <source>metrics_avg</source>
        </Print>
        <Print name="Load_meta">
            <type>csv</type>
            <source>Load_meta</source>
        </Print>
    </OutStreams>

</Simulation>
```

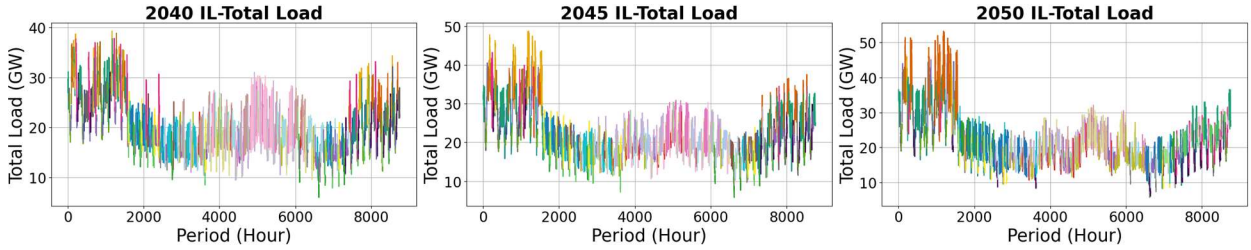
APPENDIX E: All ARMA Results

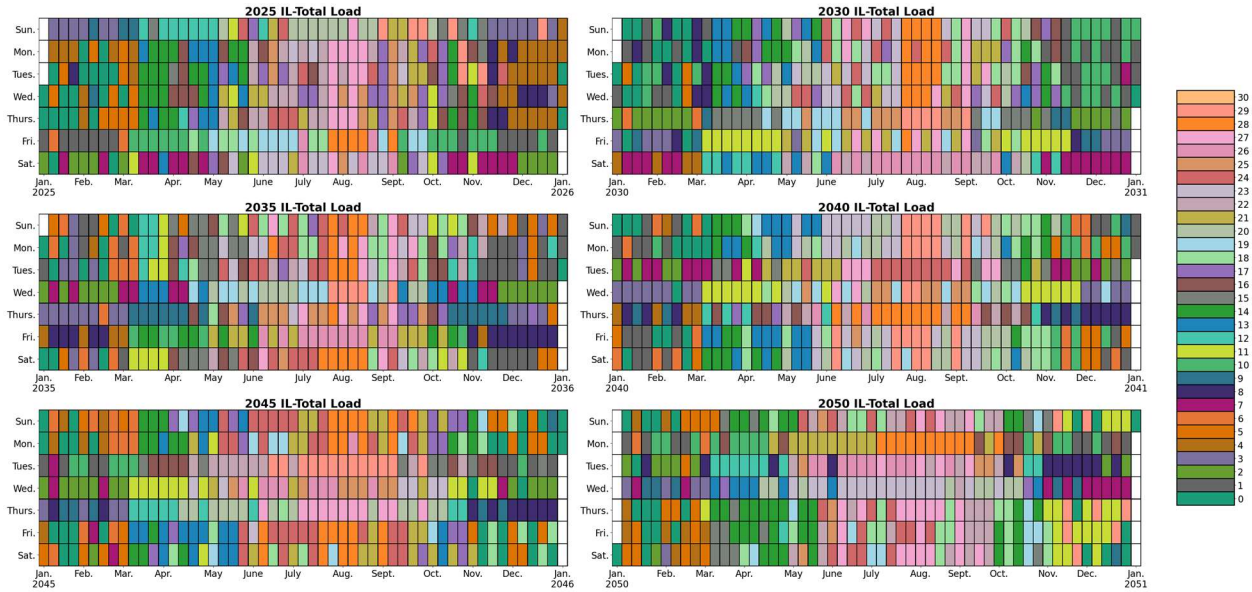
APPENDIX E.1 Carbon Tax Default

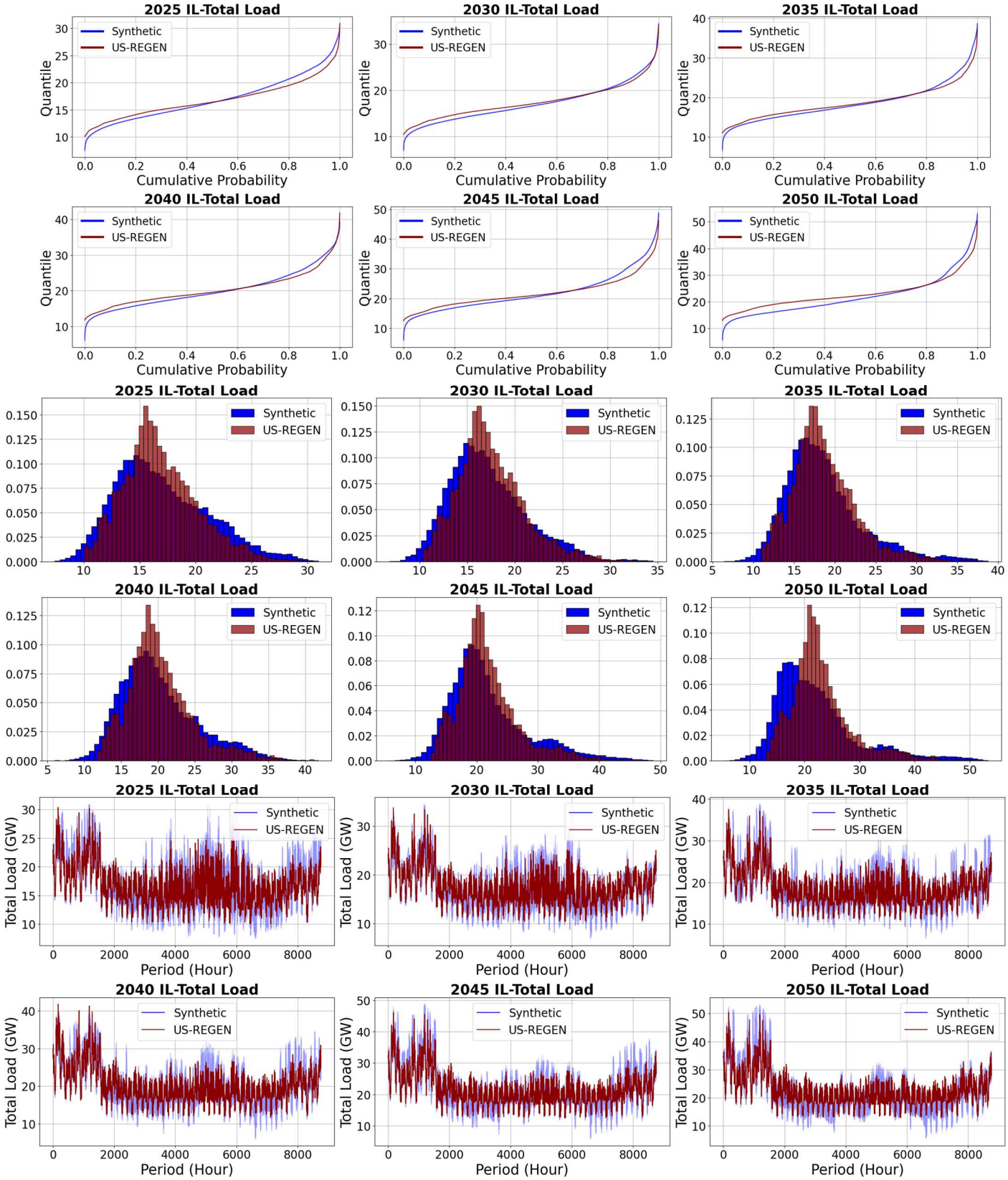




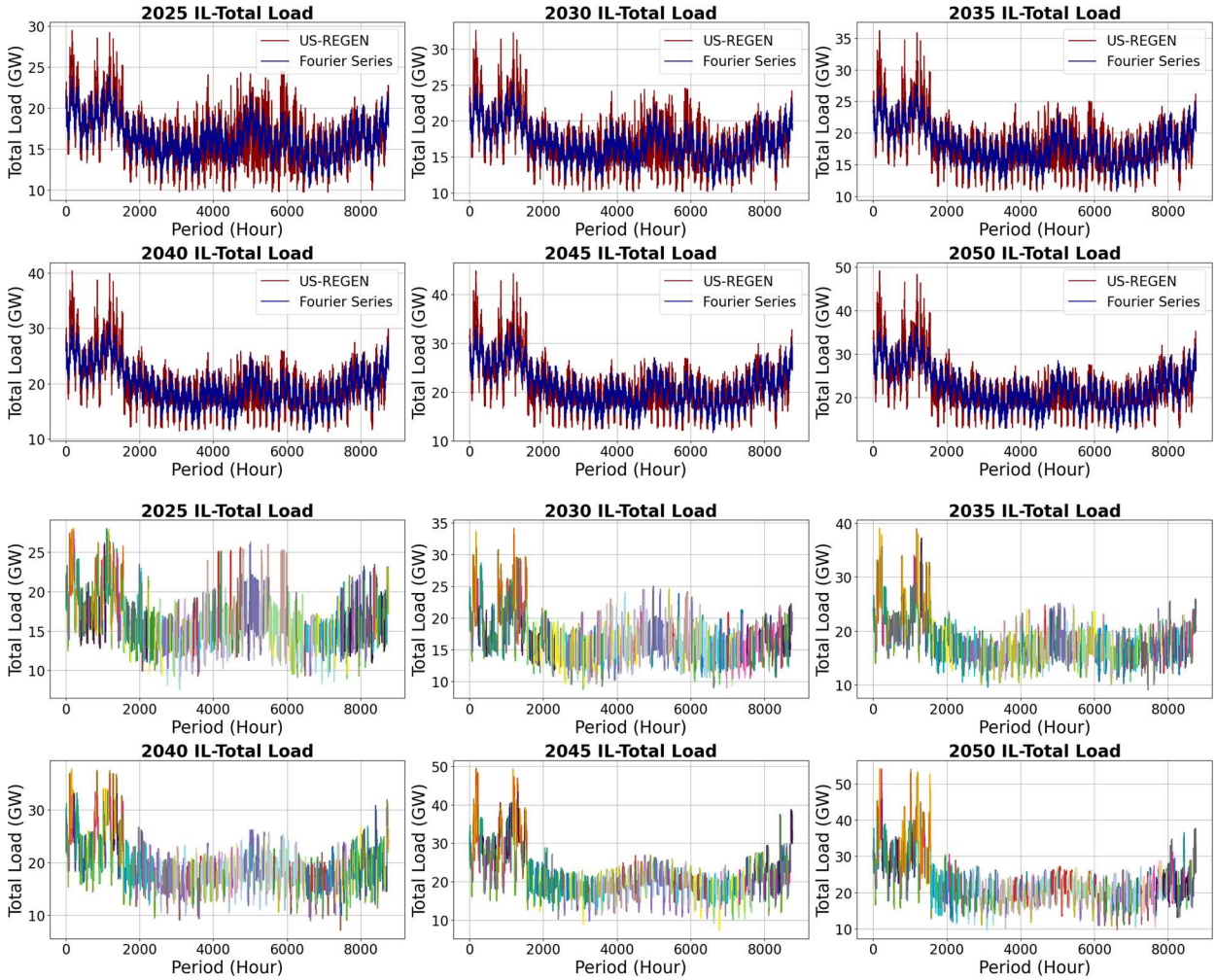


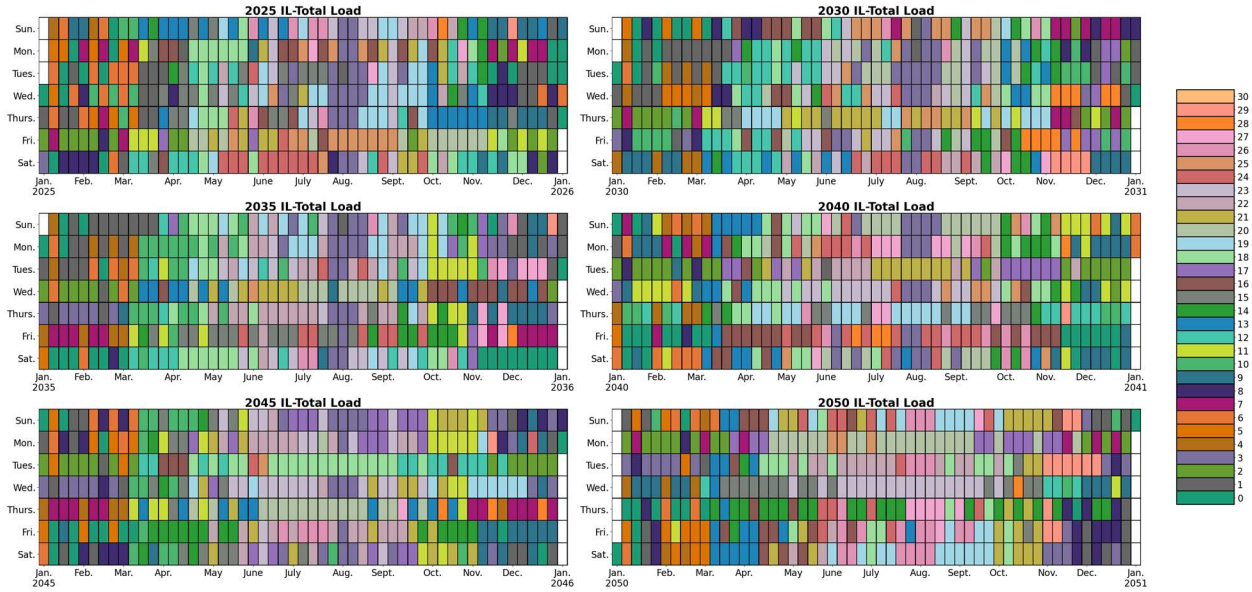


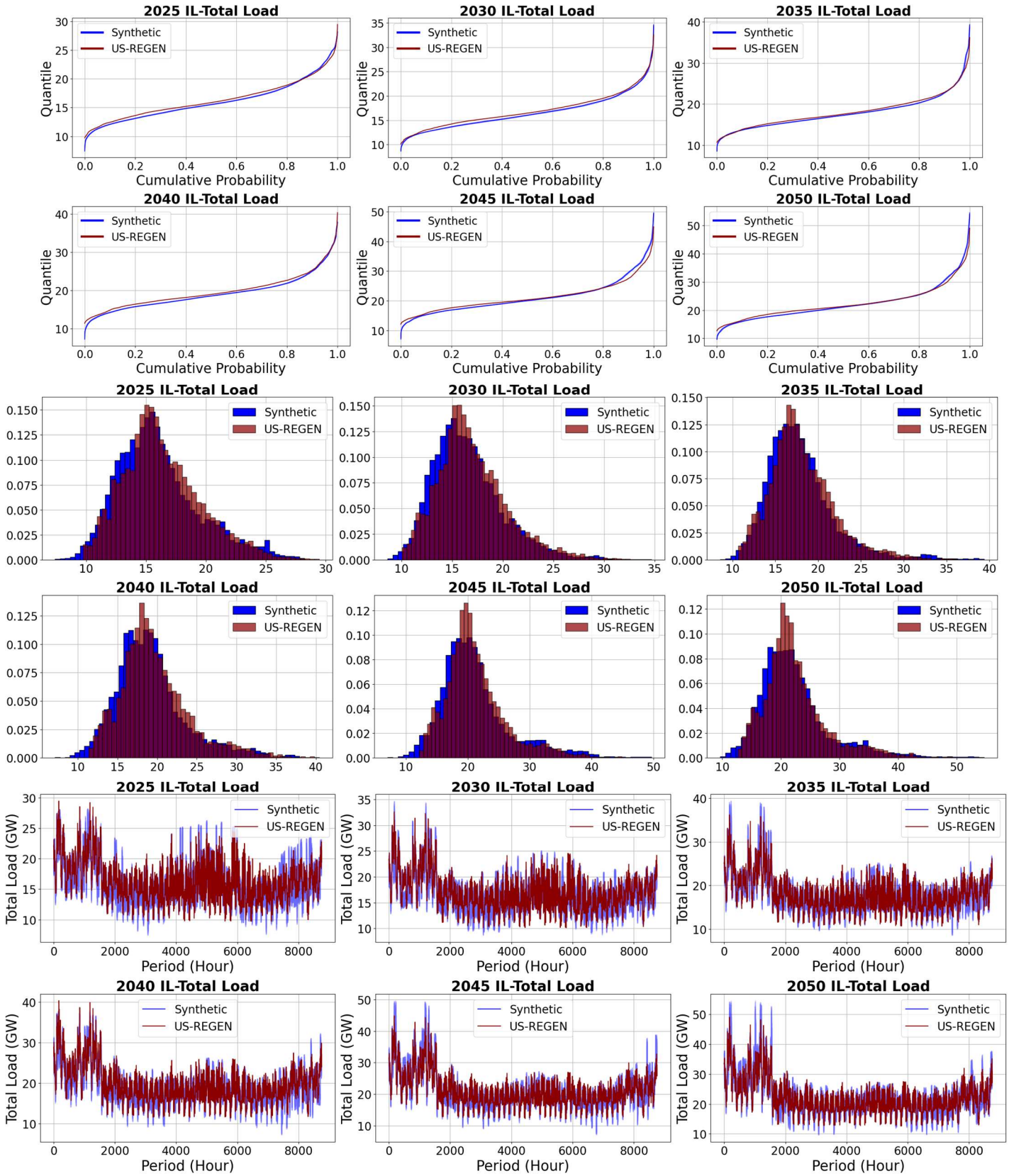



2025 IL-Total Load
2030 IL-Total Load
2035 IL-Total Load
2040 IL-Total Load
2045 IL-Total Load
2050 IL-Total Load
Synthetic
US-REGEN
Quantile
Cumulative Probability
Total Load (GW)
Period (Hour)

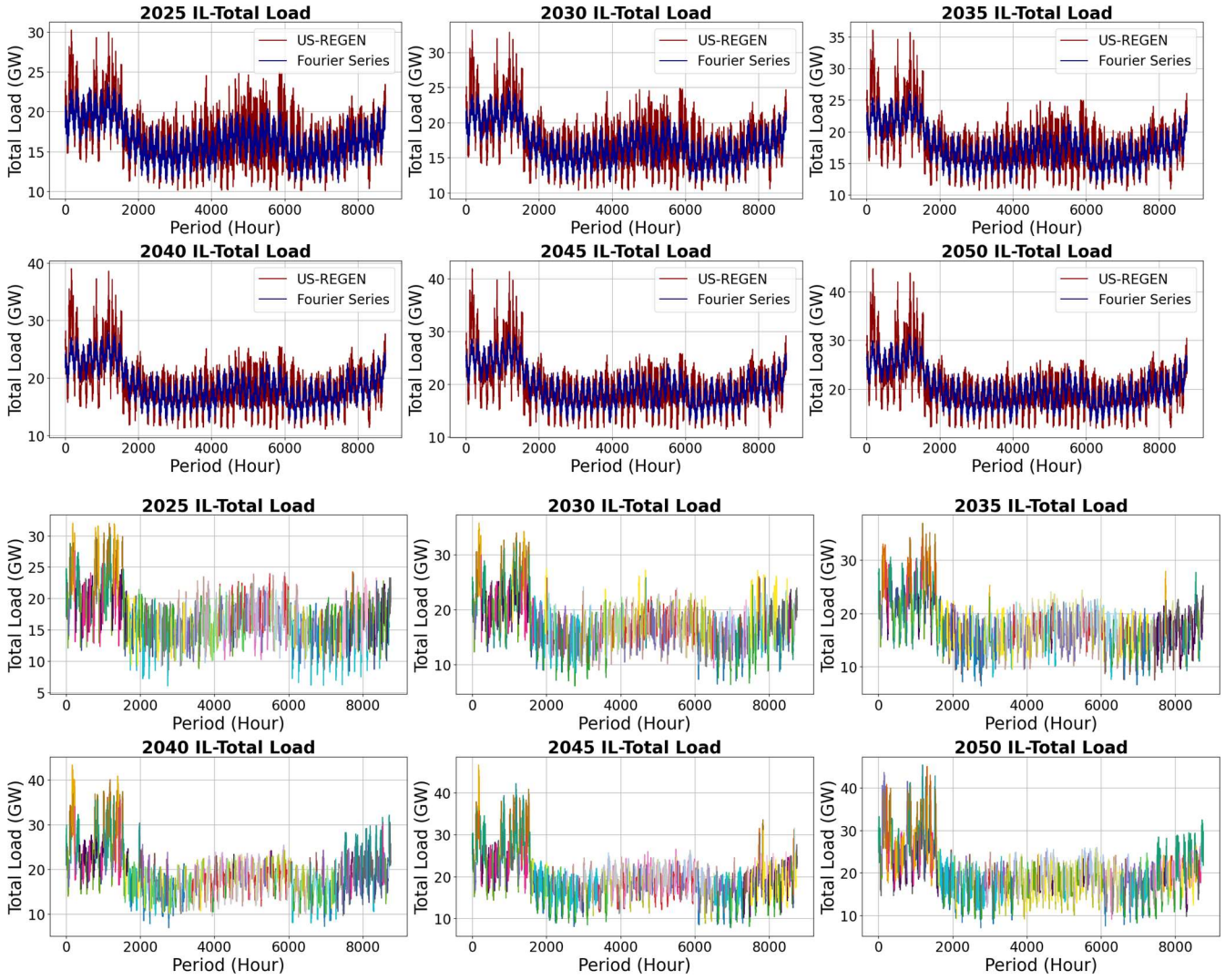
APPENDIX E.2: Carbon Tax LNHR

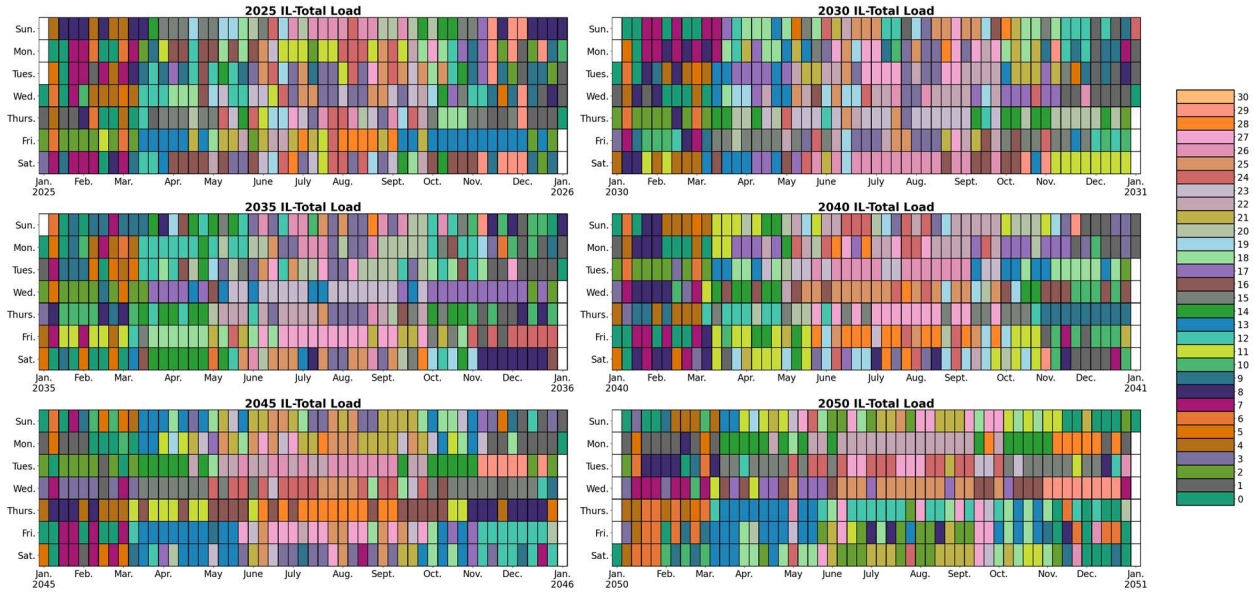


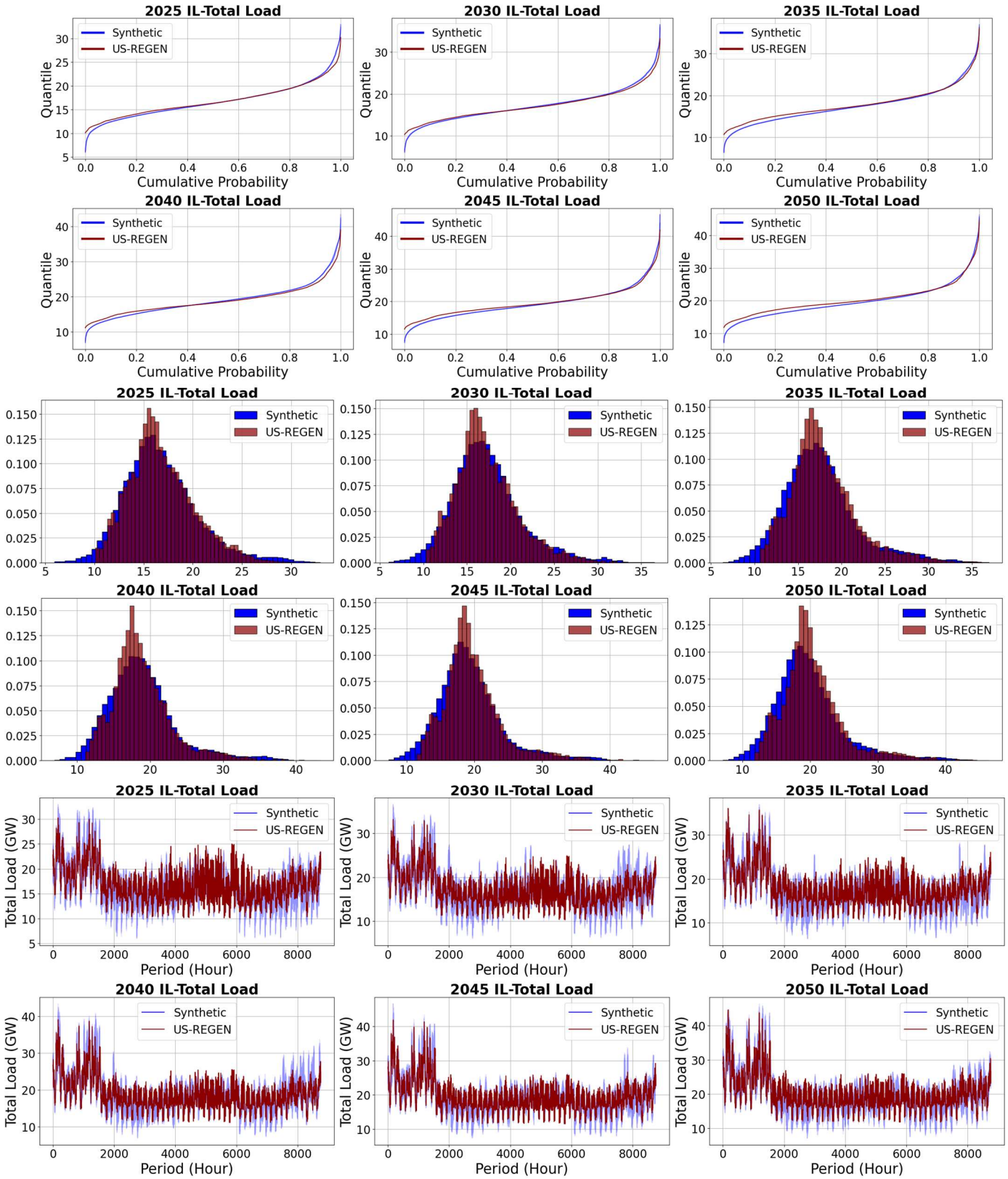



2025 IL-Total Load
2030 IL-Total Load
2035 IL-Total Load
2040 IL-Total Load
2045 IL-Total Load
2050 IL-Total Load
Synthetic
US-REGEN
Quantile
Cumulative Probability
Total Load (GW)
Period (Hour)

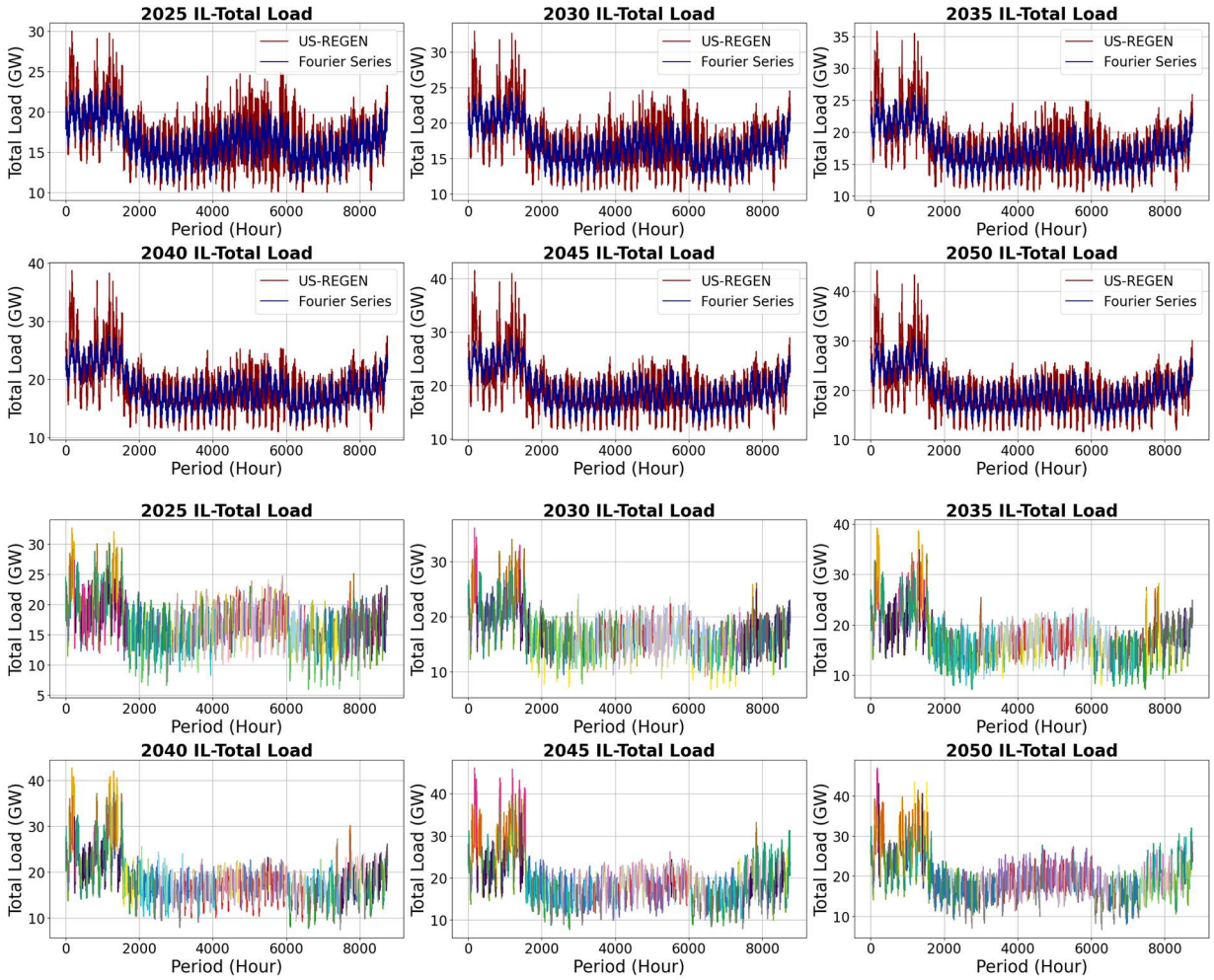
APPENDIX E.3: Nominal Default

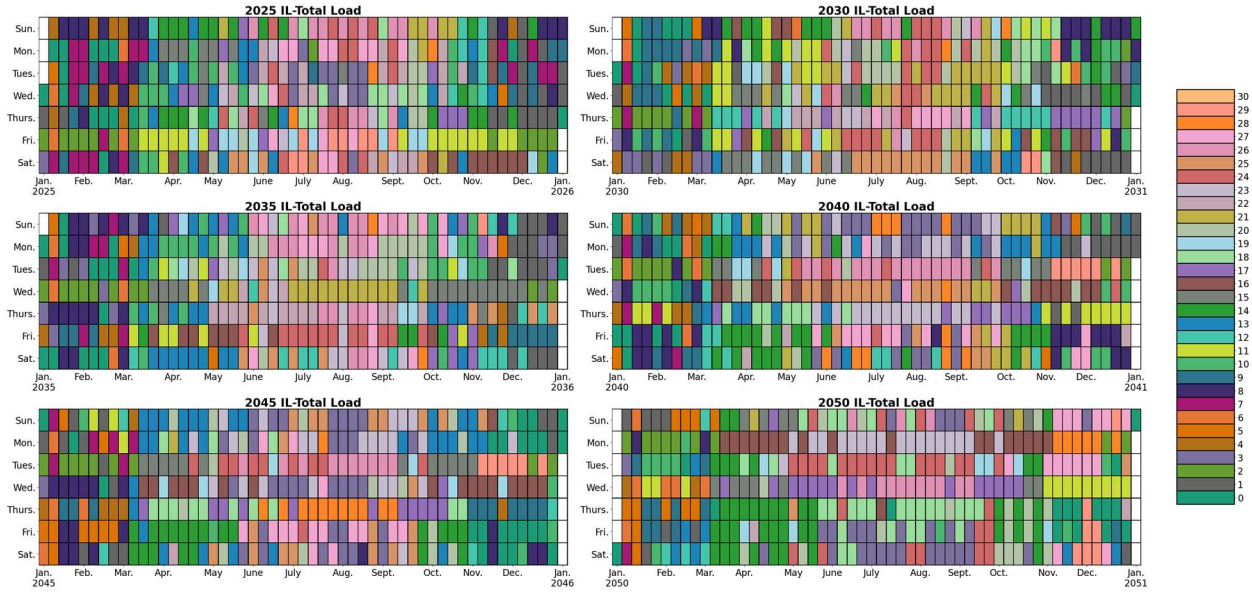


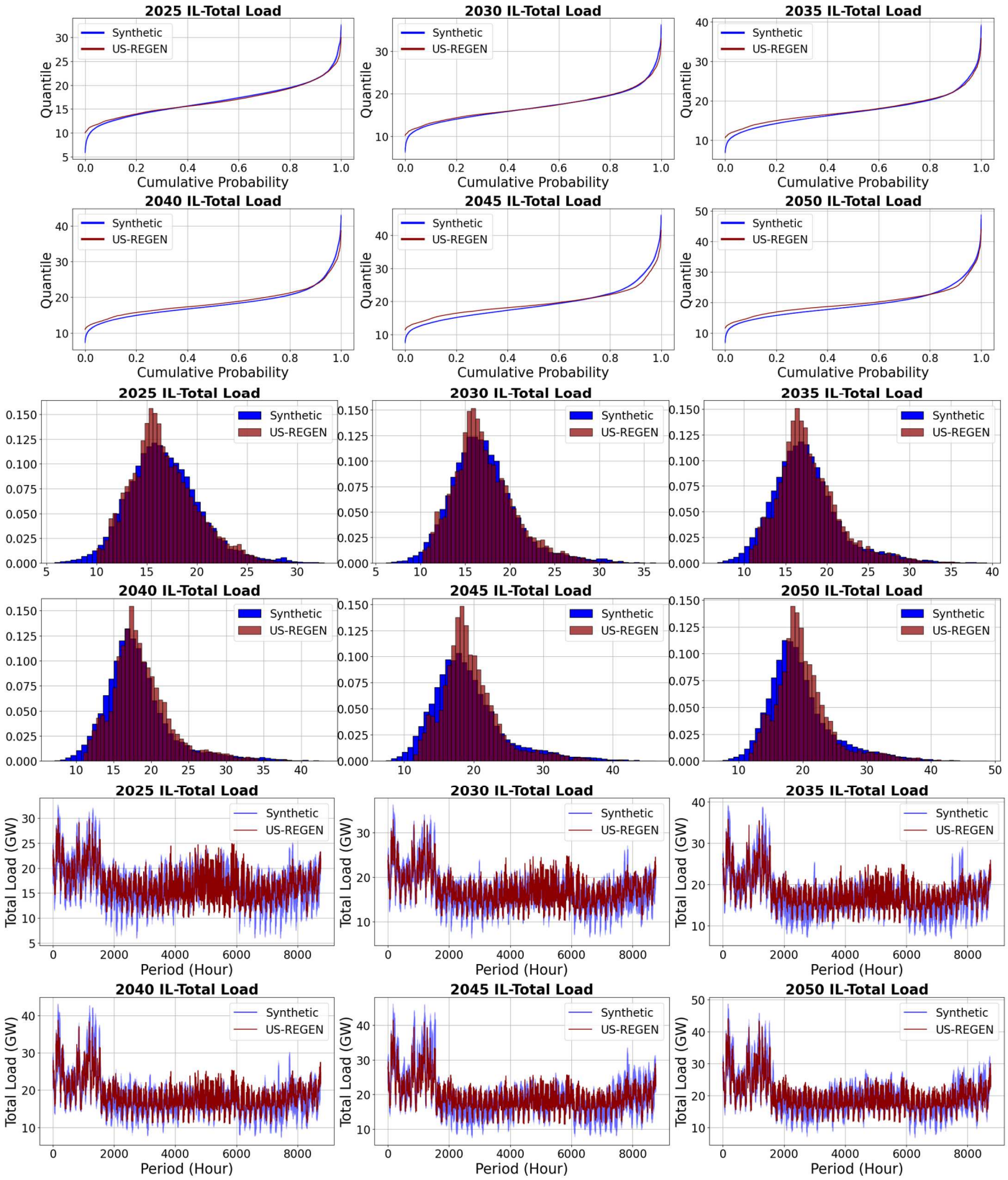



2025 IL-Total Load
2030 IL-Total Load
2035 IL-Total Load
2040 IL-Total Load
2045 IL-Total Load
2050 IL-Total Load
Synthetic
US-REGEN
Quantile
Cumulative Probability
Total Load (GW)
Period (Hour)

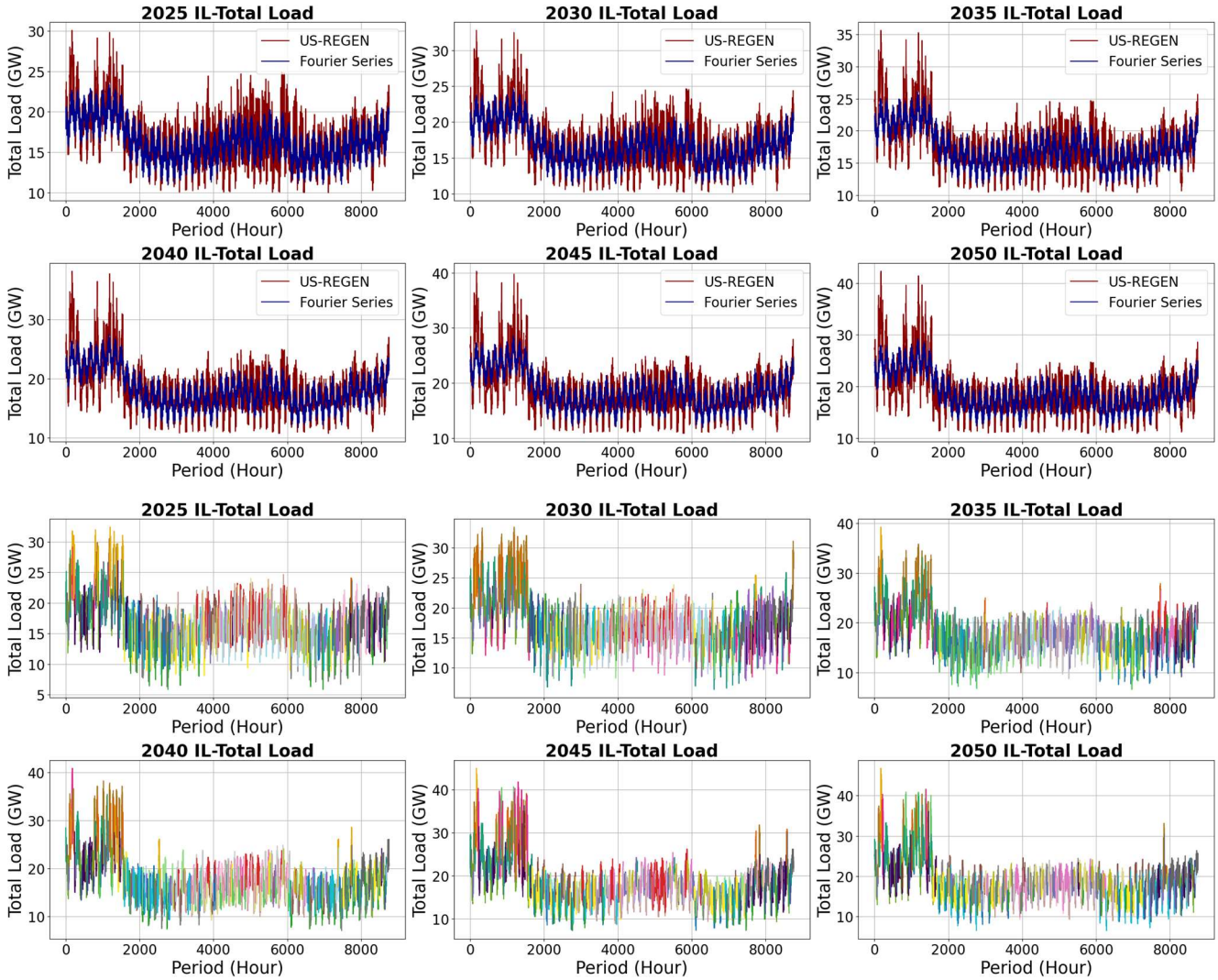
APPENDIX E.4: Nominal LNHR

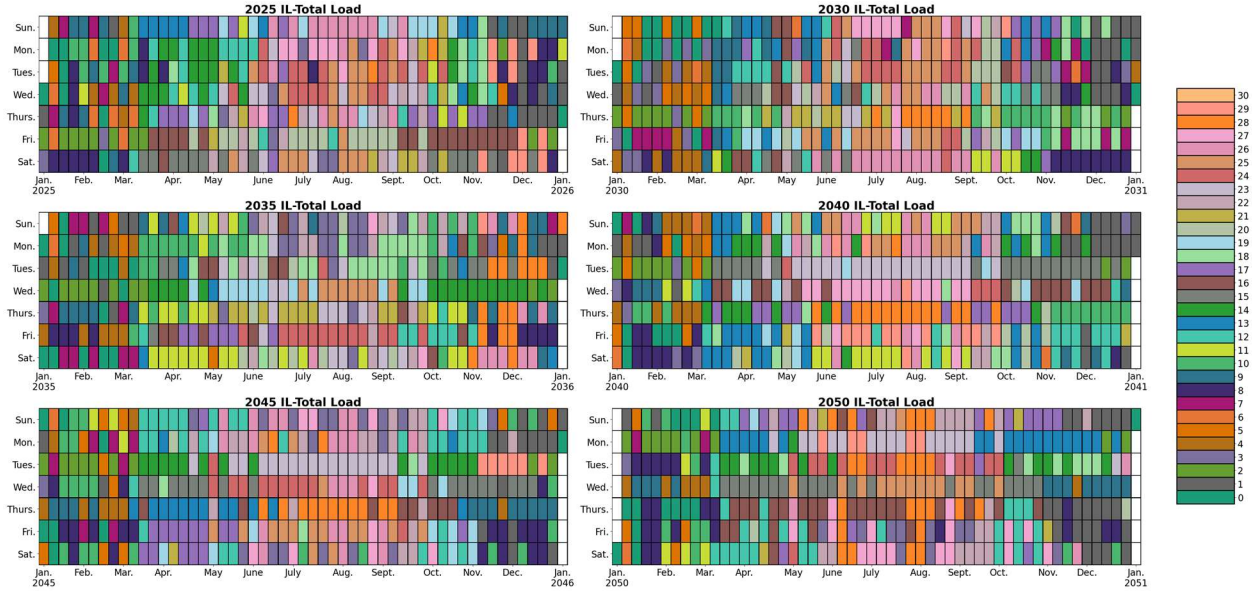


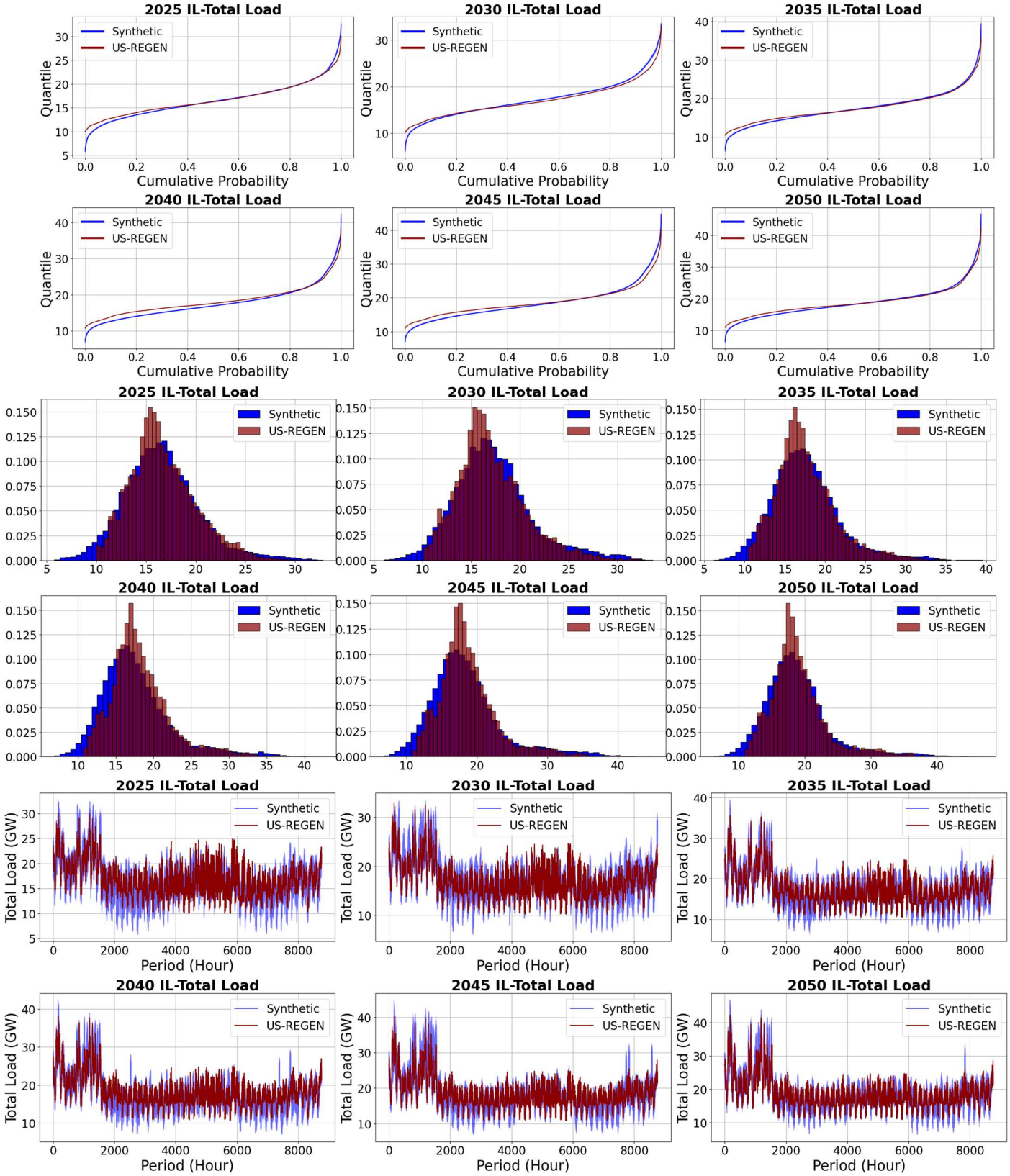



2025 IL-Total Load
2030 IL-Total Load
2035 IL-Total Load
2040 IL-Total Load
2045 IL-Total Load
2050 IL-Total Load
Synthetic
US-REGEN
Quantile
Cumulative Probability
Total Load (GW)
Period (Hour)

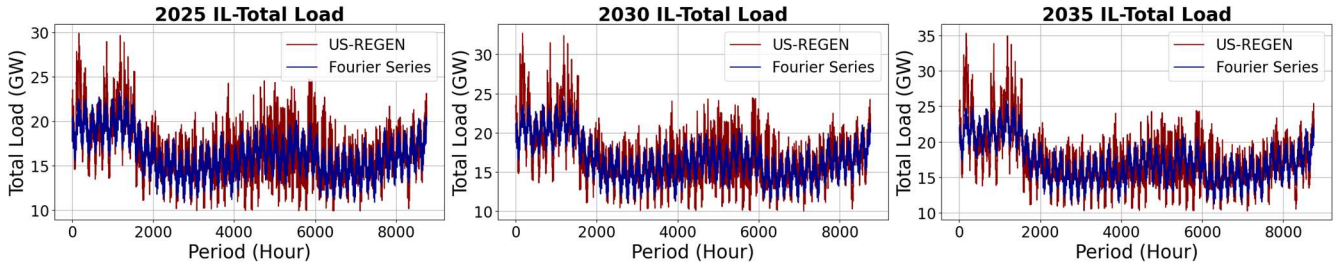
APPENDIX E.5: RPS

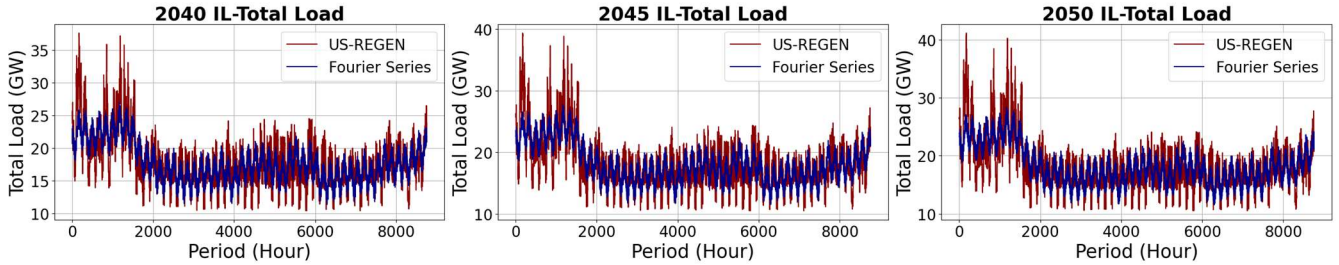


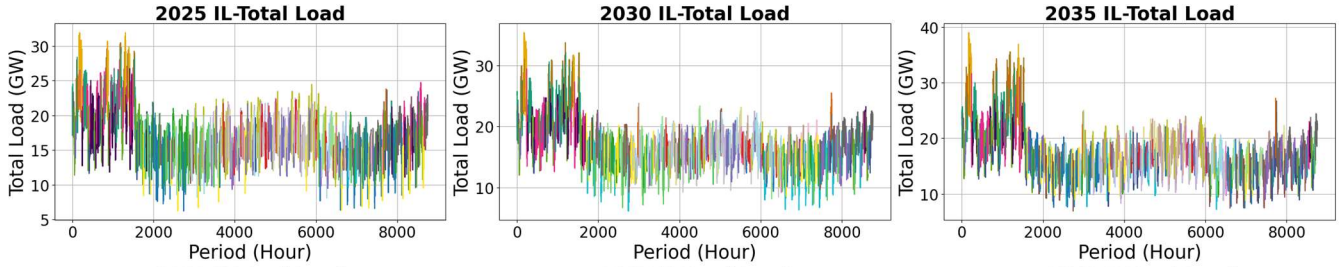


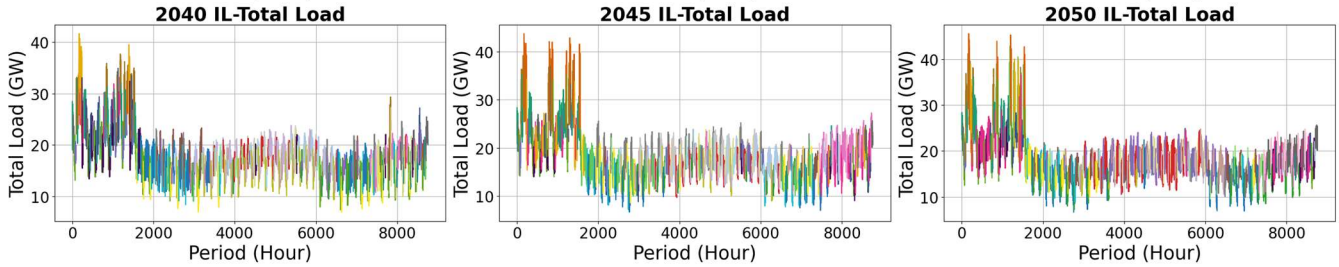

2025 IL-Total Load
2030 IL-Total Load
2035 IL-Total Load
2040 IL-Total Load
2045 IL-Total Load
2050 IL-Total Load
Synthetic
US-REGEN
Quantile
Cumulative Probability
Total Load (GW)
Period (Hour)

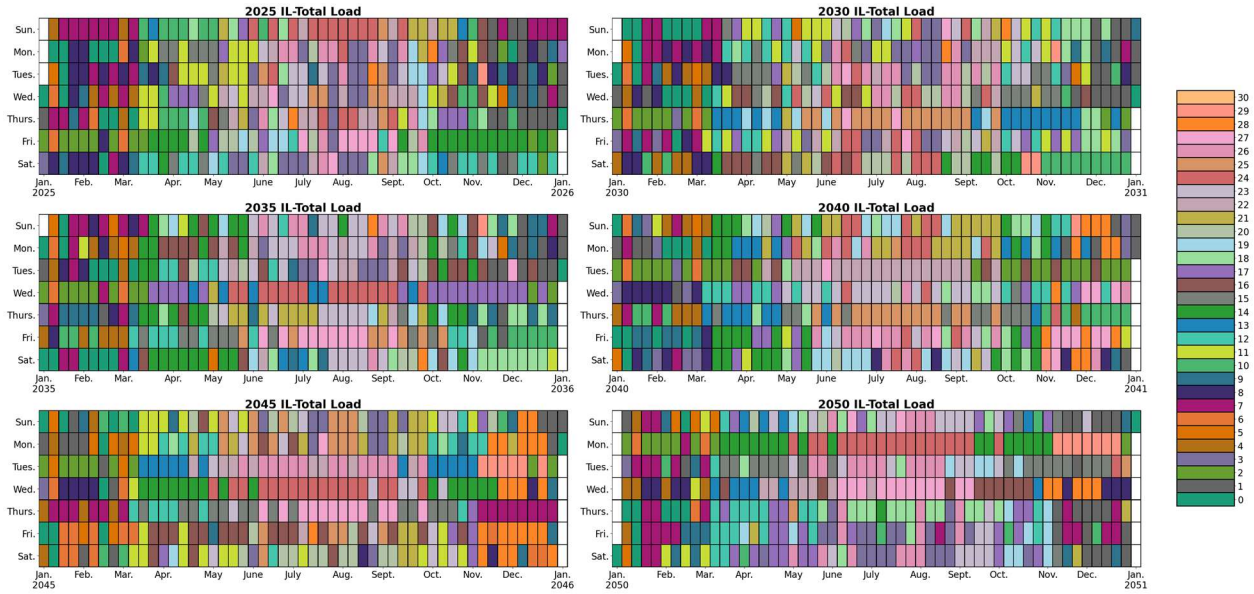
APPENDIX E.6: RPS LNHR

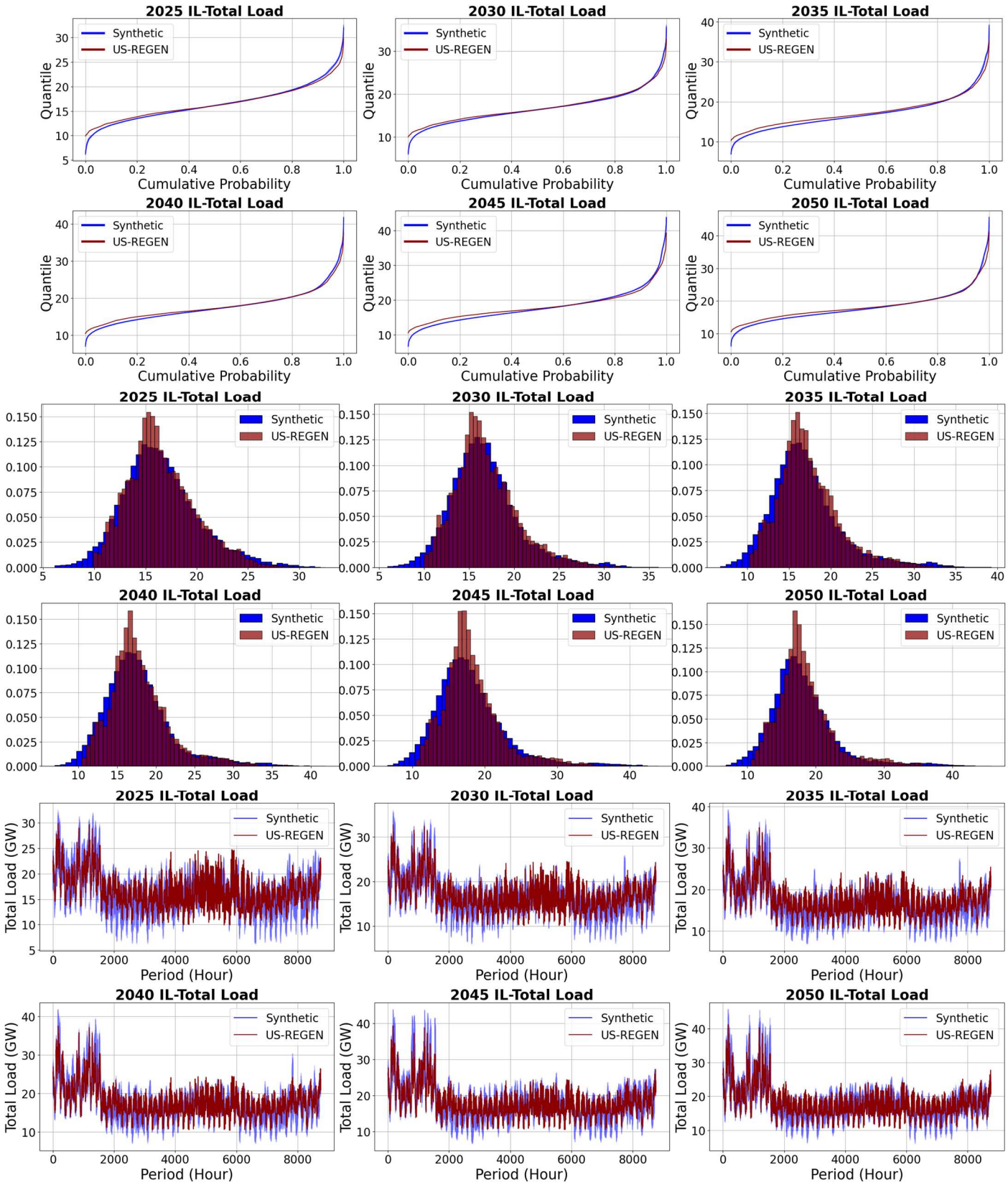











2025 IL-Total Load
2030 IL-Total Load
2035 IL-Total Load
2040 IL-Total Load
2045 IL-Total Load
2050 IL-Total Load
Synthetic
US-REGEN
Quantile
Cumulative Probability
Total Load (GW)
Period (Hour)