Identifying the Resource Adequacy Value of Energy Efficiency

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ABSTRACT

This paper evaluates the time and weather-dependent value of energy efficiency (EE) in resource adequacy (RA) modeling frameworks. While EE is widely recognized as a cost-effective resource, it is typically represented in RA models as an average reduction in load based on Typical Meteorological Year (TMY) data, which does not capture the extreme conditions that drive reliability risk. As a result, the contribution of EE to reducing Loss of Load Expectation (LOLE) and Expected Unserved Energy (EUE) may be incorrect. To address this gap, this study explored integrating customized building energy simulations from ResStock into the Strategic Energy and Risk Valuation Model (SERVM), aligning EE savings with the same historical weather years used in RA analyses. A North Carolina (NC) case study was used to assess residential efficiency measures, including standard air-source heat pumps (ASHPs), cold-climate heat pumps (CCHPs), and envelope improvements, under a cold winter year (2018). Results show that while EE measures reduce overall electricity demand, their impact on RA outcomes depends on the timing and magnitude of savings during high-risk periods. Conventional ASHPs provide limited reliability benefits due to increased reliance on electric resistance backup heating during extreme cold, resulting in minimal load reductions during peak risk hours. In contrast, cold-climate heat pumps and envelope improvements deliver more substantial demand reductions under these conditions. These findings demonstrate that EE can be evaluated as a time and weather-dependent resource to accurately capture its contribution to system reliability and inform resource planning decisions.

Introduction

Climate-related hazards pose a growing threat to the reliability and resilience of electric power systems (Panteli et al. 2016). Severe weather events, including flooding, hurricanes, heat waves, and winter storms, are increasingly affecting power system operations and increasing the likelihood of service interruptions (Espinoza et al. 2016). These risks are further compounded by rapid load growth, including the addition of large new loads to the grid (NERC 2025), which can increase system stress during periods of extreme weather and high demand. When power systems operate near their limits, such conditions can trigger cascading failures and widespread outages.

A recent example is Winter Storm Elliott. During the event, 1,702 generating units in the Eastern Interconnection experienced 3,565 unplanned outages, deratings, or start failures. At the most critical moment of the event, approximately 90,500 MW of generation capacity was simultaneously unavailable. When including generation that was already offline prior to the storm, the total unavailable capacity exceeded 127,000 MW, approximately 18% of the expected resources in the U.S. portion of the Eastern Interconnection (FERC, NERC, and Regional Entity Staff 2023).

Given these challenges, strategies that reduce electricity demand during periods of high system stress are increasingly important for maintaining grid reliability. Energy efficiency (EE) can play a key role by lowering peak demand and mitigating risks during extreme weather events. Modeling of the Texas/ERCOT residential building stock, for example, found that large-scale deployment of EE and other demand-side resources could reduce seasonal peak demand by thousands of megawatts (Rhodes et al. 2022). However, EE is rarely evaluated explicitly in resource adequacy (RA) models (Frick et al. 2021) and is typically represented as an average reduction in load forecasts based on Typical Meteorological Year (TMY) weather data, which does not capture extreme conditions. As a result, the potential reliability benefits of EE during severe weather events remain underexplored.

This study begins to address this gap by evaluating the time and weather-dependent value of EE in RA modeling using customized residential energy simulations integrated into a resource adequacy framework to assess impacts on metrics such as Loss of Load Expectation (LOLE) and Expected Unserved Energy (EUE).[1]

Why Time and Weather Matter for Energy Efficiency in Resource Adequacy Modeling

Resource adequacy (RA) is defined by the North American Electric Reliability Corporation (NERC) as "the ability of the electricity system to supply the aggregate electrical demand and energy requirement of the end-use customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system elements" (NREL 2024). RA models are designed to evaluate how well different portfolios of electric generation resources enable a power system to meet customer demand while accounting for factors such as generator outages and extreme weather events. RA frameworks evaluate system reliability using metrics such as LOLE and EUE, which focus on the hours when system demand exceeds available supply. As a result, RA outcomes are often driven by extreme conditions rather than average system performance over the course of a year. This distinction has important implications for how demand-side resources, such as energy efficiency, should be evaluated within RA frameworks.

EE measures are typically evaluated based on their average annual energy savings. As a result, EE analyses conducted for purposes such as Technical Reference Manuals (TRMs) often rely on TMY weather data. This approach is appropriate for utility program planning and long-term savings estimation, but it does not capture the performance of EE measures during extreme weather events or the limited set of hours that drive RA outcomes. To fully incorporate EE into RA modeling, it is therefore important to account for the time- and weather-dependent nature of EE savings. The timing of EE savings relative to peak system demand is particularly important when evaluating EE in RA analyses. EE measures that reduce load during periods when the power system is operating well below capacity have little effect on reliability metrics. In contrast, measures that reduce demand during peak demand periods, often associated with extreme weather events, can significantly alleviate capacity constraints. Accurately capturing these benefits requires modeling approaches that reflect the hourly coincidence between EE savings and the periods when LOLE or EUE risks are highest.

The performance of many EE measures also varies significantly with outdoor temperature. As a result, their system value can change depending on the weather conditions

[1] The Electric Power Research Institute (EPRI) defines LOLE as "the expected count of event-periods per study horizon, with an 'event-period' defined as a period of time during which system resources are insufficient to meet demand." EPRI defines EUE as "The total expected amount of unserved energy in MWh in a given study horizon."

associated with extreme events. For example, insulation upgrades and improved air sealing typically deliver the greatest benefits during periods when the temperature differential between indoor and outdoor environments is large. Their impact is smaller when this temperature difference is minimal. Space heating technologies provide another example. Heat pumps can substantially reduce energy use compared with electric resistance heating, but their efficiency declines as outdoor temperatures fall. Even cold-climate heat pumps experience some performance degradation at very low temperatures, which can affect their contribution to peak load reduction during winter events.

These dynamics highlight a conceptual misalignment between traditional EE savings assessments and the needs of RA modeling. Conventional EE analyses may show that different measures deliver similar annual energy savings, but those measures can have very different impacts on system reliability during extreme weather events and peak demand periods. Addressing this mismatch requires new approaches to integrating EE into RA analyses. From the EE perspective, measures should ideally be evaluated under the same historical weather years and weather events considered in RA modeling. From the RA perspective, modeling frameworks may require updated parameters or methodological adjustments to better capture the time- and weather-dependent value of EE.

demand

Using ResStock to Develop Resource-Adequacy-Relevant Energy Efficiency Profiles

Overview Of ResStock and ComStock Modeling Capabilities

ResStock is the U.S. residential building stock energy model developed and maintained by the National Laboratory of the Rockies (NLR) for the U.S. Department of Energy. It is a highly granular, bottom-up modeling platform designed to represent the diversity of homes across the United States. The model integrates multiple public and private datasets, statistical sampling methods, and detailed building energy simulations to generate representative building prototypes that reflect variations in climate, construction characteristics, equipment, and household demographics. Through these simulations, ResStock addresses two fundamental questions: how energy is currently used across the U.S. housing stock and how energy use would change if specific energy efficiency or electrification technologies were adopted at scale (NLR 2026). As a result, the platform is widely used to evaluate energy-saving strategies and estimate potential impacts on energy demand, emissions, and peak demand.

In this study, ResStock was used to analyze residential building energy use in North Carolina and to evaluate how energy efficiency and electrification measures affect electricity demand profiles relevant to RA planning. Because ResStock can generate simulation outputs at temporal resolutions as fine as 15 minutes, it supports detailed analysis of load patterns during critical peak hours and estimation of how efficiency measures influence demand under different weather conditions. Simulations were conducted across 42 weather years (1980–2022), with 2018 selected as the case study discussed in the “Energy Efficiency Performance During Winter Event: Case Study – 2018 North Carolina Weather Year” section. Although the present analysis addresses only the residential sector, a companion tool, ComStock, serves the commercial building sector; both are part of NLR's broader BuildStock framework and share a common methodology for simulating building energy performance. Together, these models provide a comprehensive platform for evaluating building-sector impacts on electricity demand.

The simulation and analysis workflow begins by defining the key parameters in ResStock: a representative North Carolina residence, electricity as the primary heating fuel, the analysis year, and the upgrade scenario to be evaluated. Three upgrade scenarios were considered, which are explained in more detail in the section “Accounting for Measure Type, Building Characteristics, and Adoption Rates”. Simulations were then run for both the baseline case and the upgrade scenarios to generate hourly electricity demand profiles. Because of computational constraints, just one scenario was simulated across the full 42-year weather dataset, while the remaining two were evaluated only for the representative year 2018. The outputs were then processed to calculate comparative metrics, including hourly demand reductions and annual energy savings for the selected year. Finally, the resulting load profiles were analyzed in SERVM to compare the resource adequacy impacts of the baseline case and the first upgrade scenario, enabling an assessment of the reliability value of energy efficiency improvements.

Customizing Weather Inputs

To ensure that building energy simulations reflect the weather conditions assumed in the RA analysis, customized weather inputs were developed and integrated into the ResStock modeling framework. Simulations were executed locally using BuildStock Batch in an Amazon workspace, a toolset that enables the management and execution of large-scale batch simulations for the ResStock and ComStock platforms (BuildStock Batch 2026). BuildStock Batch supports multiple computing environments, including local workstations, NRL high-performance computing systems, and cloud platforms such as Amazon Web Services. In this study, simulations were executed in an Amazon Workspace environment to ensure reproducibility and flexibility in configuring model parameters.

Figure 1 shows the workflow for developing custom weather files and configuring ResStock simulations for weather demand analysis. The left branch illustrates the custom weather pipeline, in which historical meteorological data obtained from Visual Crossing (Visual Crossing Corporation 2025) were subjected to quality-control checks for completeness and consistency, cleaned, and converted from CSV to EnergyPlus Weather (EPW) format. The right branch shows the simulation configuration process, in which a YAML configuration file defined key parameters including the weather files path, building sampling criteria, and the residential HPXML workflow. The sampling criteria constrained the building population to single-family homes in North Carolina using electric heating. Both branches converge as inputs to the ResStock simulations used for weather demand analysis.

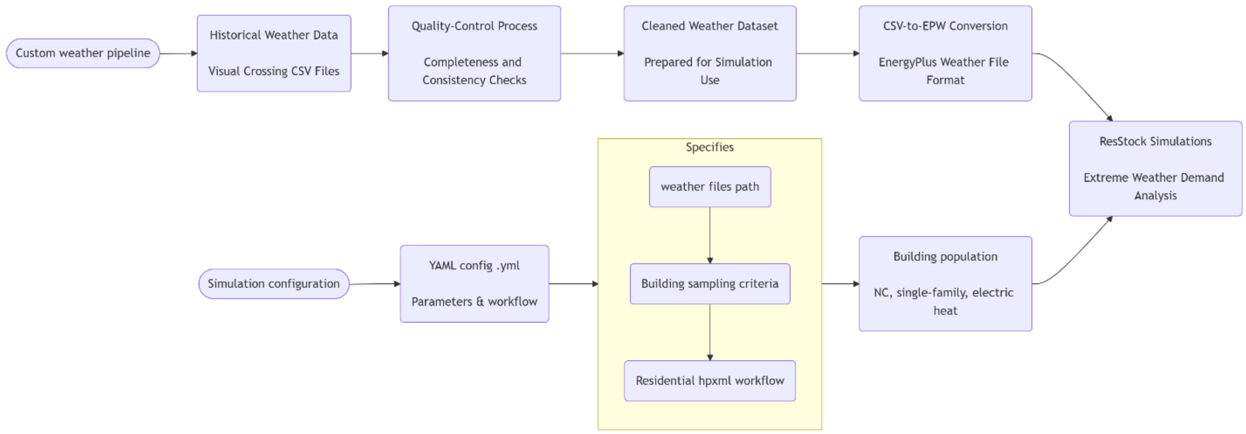

Figure 1. Custom weather file development workflow for ResStock simulations.

Generating Hourly Energy Efficiency Savings Profiles Under Weather Events

Using customized weather inputs and ResStock configurations, simulations were performed to generate detailed time-series electricity demand outputs for the modeled building population. The model produces results at sub-hourly time intervals, enabling the aggregation of results into hourly demand profiles suitable for resource adequacy analysis. Hourly energy efficiency savings profiles were derived by comparing electricity demand in the baseline scenario with demand under scenarios that include energy efficiency and electrification upgrades. Running simulations under extreme weather conditions, consistent with the resulting load profiles used in the RA modeling process, captures how efficiency measures affect electricity demand during periods of peak system stress. This approach enables the estimation of both energy savings and peak demand impacts associated with different upgrade scenarios.

Accounting for Measure Type, Building Characteristics, and Adoption Rates

The ResStock modeling framework allows the analysis to explicitly account for differences in efficiency measure types and building characteristics. Within the YAML configuration file, the upgrades block defines the efficiency technologies applied to the baseline building stock. In this analysis, three upgrade scenarios were simulated:

- ENERGY STAR heat pump with electric backup ("ASHP").
- High-efficiency cold-climate air-to-air heat pump with electric backup ("CCHP").
- ENERGY STAR heat pump with electric backup combined with Light Touch Envelope improvements ("ASHP+Envelope").

The first scenario represents a standard high-efficiency electrification pathway in which existing heating systems are replaced with ENERGY STAR–rated heat pumps, this scenario was simulated across the full 42-year weather dataset. The second scenario reflects the adoption of advanced cold-climate air-source heat pumps designed to maintain higher efficiency and capacity under low-temperature conditions. The third scenario combines efficient heat pump technology with moderate envelope improvements ("Light Touch Envelope"), which may include measures such as improved air sealing and insulation upgrades that reduce heating and cooling loads. Each of these upgrade packages were specified as part of the ResStock 2024.2 release and associated technical documentation (NREL 2024).

ResStock simulations incorporate detailed information about building characteristics, including construction year, floor area, insulation levels, equipment types, and occupant behavior patterns. These characteristics influence baseline energy demand and determine how buildings respond to efficiency upgrades and extreme weather conditions.

Finally, adoption rates were not modeled within the ResStock simulation runs. The ResStock analysis assumes the entire specified population installs the upgrade measure modeled in each simulation. As a result, technology adoption was incorporated during the post-processing stage of the analysis. After generating baseline and upgrade-specific energy demand profiles from the ResStock simulations, hourly savings profiles were calculated for each upgrade scenario by comparing baseline and upgraded building performance.

These savings profiles were then scaled according to assumed adoption rates representing the share of eligible buildings that would implement efficiency measures through utility programs or market adoption. Applying adoption rates during post-processing allows flexibility in evaluating multiple program participation scenarios without requiring additional building energy simulations. This approach also ensures that the underlying building physics and hourly performance characteristics derived from ResStock remain unchanged while enabling the analysis to represent different levels of deployment across the residential building stock.

Energy Efficiency Performance During Winter Event: Case Study - 2018 North Carolina Weather Year

Snow Event in the 2018 Weather Year

The year 2018 was selected as the test weather year to evaluate system performance under cold conditions, which can place significant stress on electricity systems and increase the likelihood of reliability events such as EUE. The first week of 2018 was one of the coldest periods on record across much of eastern North and South Carolina. Temperatures fell into the single digits and teens, reaching levels not seen since the freeze events of the 1980s and mid-1990s. (NOAA 2018).

Figure 2 highlights the temperature comparison between the 2018 weather year and the Typical Meteorological Year (TMY) in North Carolina.[2] The figure illustrates that 2018 experienced significantly lower temperatures during winter periods, with extended cold spells that are not captured in the smoother and more moderate TMY profile. These deeper and more persistent temperature drops increase heating loads and therefore provide a useful scenario for evaluating how the system performs under extreme conditions. By using 2018 as the weather input for the simulations, the analysis captures a plausible weather stress case.

[2] TMY data was taken from the NLR National Solar Radiation Database (NSRDB). TMY data derived from NSRDB is based on satellite-derived Physical Solar Model (PSM) datasets (PSM v4).

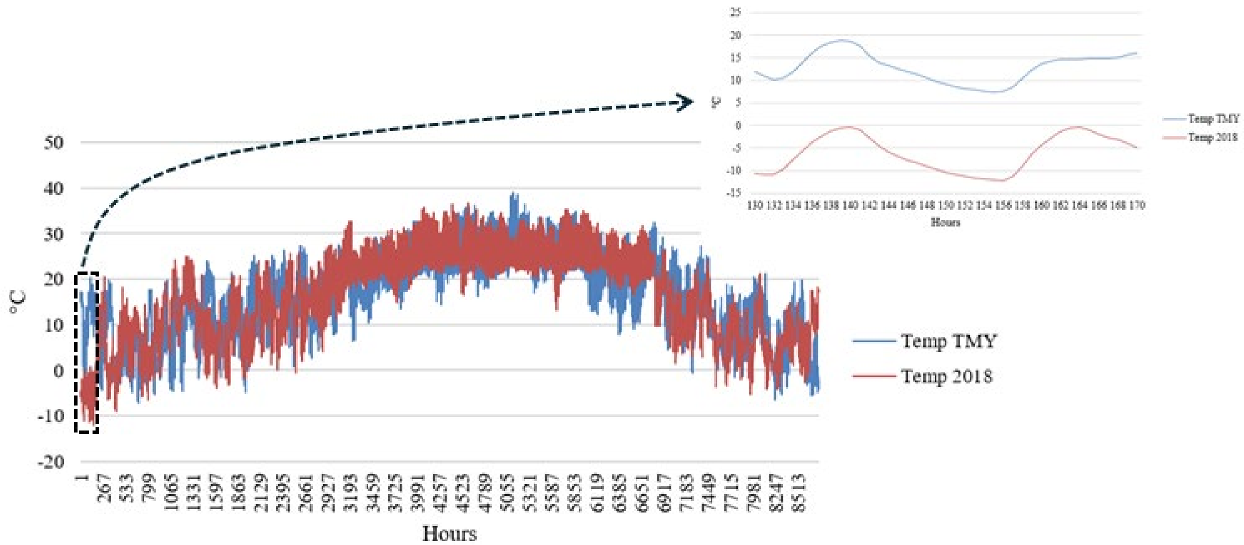

Figure 2. Temperature comparison: 2018 vs TMY in North Carolina.

Energy Efficiency Measure Analysis

Building on the preceding discussion, this section examines how residential energy efficiency measures perform under winter conditions, using 2018 as the representative weather year. The analysis focuses on single-family homes with electric heating, examining average hourly electricity demand during the cold weather event of January 2–7, 2018, in North Carolina. Figure 3 presents hourly demand profiles for the baseline case and the three upgrade scenarios over this period. The baseline scenario consistently shows the highest demand—roughly 3 to 11 kW per household—peaking during the coldest morning hours (6:00–9:00), when outdoor temperatures fall below about −10°C.

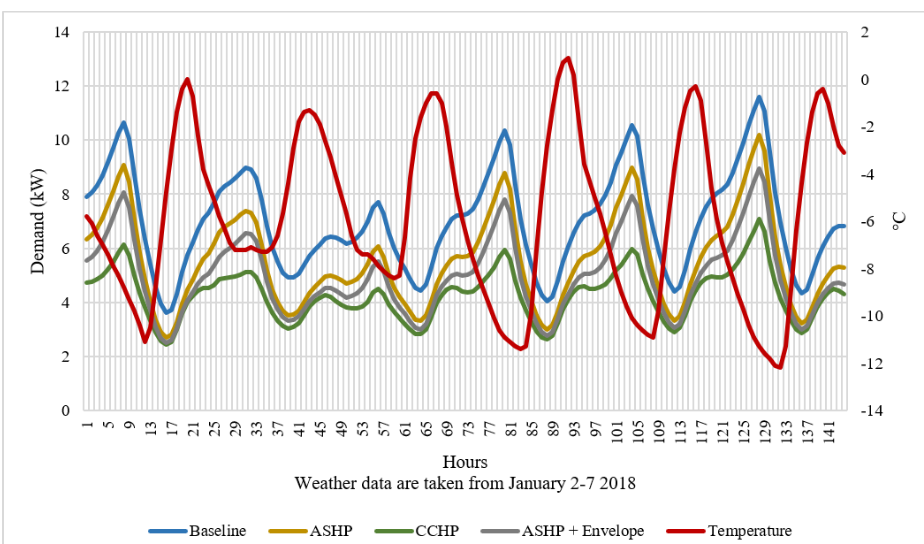

Figure 3. Average Hourly Energy Demand of Single-Family Homes in North Carolina Analysis

Figure 4 presents the hourly demand savings for each upgrade scenario, derived directly from the profiles in Figure 3 by subtracting each scenario's hourly demand from the baseline. All upgrade scenarios reduce electricity demand across the daily profile, demonstrating the ability of EE measures to moderate demand during winter conditions. However, the magnitude of these reductions varies substantially by technology. The ENERGY STAR ASHP provides consistent but more modest savings, generally reducing hourly demand by approximately 1.1–1.7 kW per hour relative to the baseline. In contrast, the CCHP delivers the largest reductions, with savings commonly ranging from about 1.5 to 4.6 kW per hour and reaching its highest values during the coldest morning hours. The ASHP combined with envelope improvements also produces meaningful demand reductions, typically between about 1.3 and 2.6 kW per hour. These results indicate that envelope improvements enhance the performance of conventional heat pump upgrades, while cold-climate heat pumps provide the greatest reliability value during periods of cold weather.

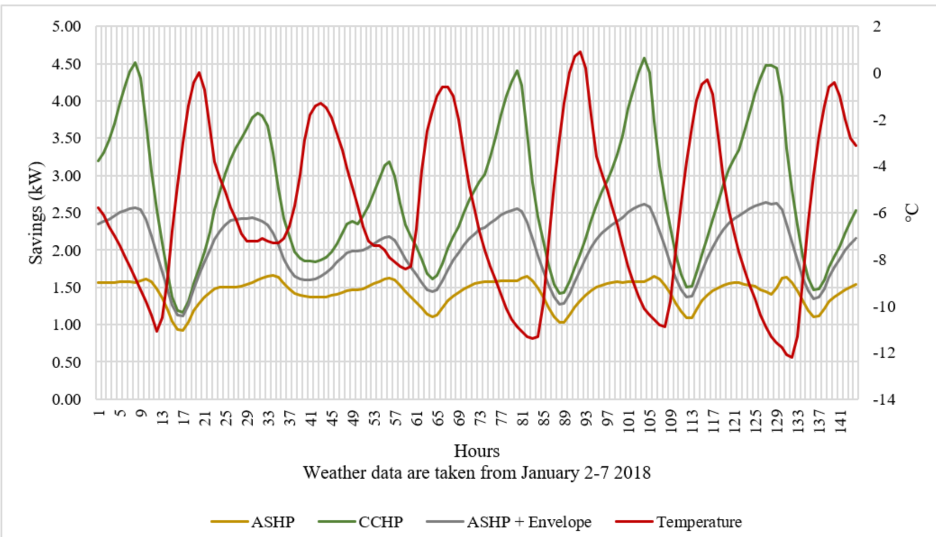

Figure 4. Energy Savings from EE Upgrades in North Carolina Analysis

A key finding is that the baseline and ENERGY STAR ASHP load profiles remain relatively similar during the coldest hours of the event. This behavior reflects the operational limitations of conventional air-source heat pumps, which typically rely on electric resistance backup heating when outdoor temperatures fall below their efficient operating range. During cold conditions, this transition can occur well before the lowest temperatures are reached, resulting in system performance that more closely resembles direct electric resistance heating. As a result, the ability of conventional ASHPs to reduce load during the hours that drive RA risk is limited.

In contrast, cold-climate heat pumps are specifically designed to maintain higher efficiency and heating capacity at lower outdoor temperatures, allowing them to continue operating without relying as heavily on resistance backup. This enables CCHPs to deliver substantially greater energy savings during the coldest hours of the event, precisely when system demand and reliability risk are highest. These results demonstrate that not all EE measures provide equivalent reliability value. In this case study a commonly deployed EE measure (e.g., standard ASHPs) appears unlikely to deliver meaningful reliability benefits due to performance degradation during cold conditions. Technologies that maintain performance during cold conditions, such as cold-climate heat pumps, are significantly more effective at reducing system risk than measures whose performance degrades during peak events. From an RA perspective, the effectiveness of EE measures is therefore closely tied not only to their average performance, but to their ability to sustain savings during cold weather events that drive system risk. Only EE measures that reduce load during the specific hours contributing to LOLE or EUE will materially affect RA outcomes.

Integrating EE into SERVM: Methods and Challenges

The Strategic Energy and Risk Valuation Model (SERVM) is a platform used by utilities, regional transmission operators (RTOs), and other entities to conduct resource adequacy (RA) studies (PowerGEM 2026). RA studies can be used to determine system planning reserve margins and generator accreditation values or just to measure the overall "adequacy" of a particular portfolio of resources. RA studies characterize risk primarily through testing variables that are weather driven including renewable energy profiles, demand, and even correlated generator forced outages. Whereas an integrated resource planning model tends to be conducted with smoothed and "typical" assumptions, the point of RA modeling is to understand how extremes can influence the ability to serve load.

Oftentimes, SERVM users will populate their model with data from historical "weather years". For example, weather data from 2019 can be used to simulate both load response to temperature and renewable generation profiles under those same conditions. In practice, RA models typically apply this approach across 30 or more historical weather years to capture variability in both demand and supply.

Generally, demand-side measures are not represented explicitly in RA models. One challenge associated with doing so is characterizing how those measures might perform differently under different temperature assumptions. Using ResStock's customizable functionality, weather data for all weather years can be run for the combination of measures and households of interest so that those measures can be included directly in SERVM.

Some of the challenges of doing so include the time and effort needed to run custom ResStock simulations, the potential mismatch between hours of risk identified by SERVM and the savings from the EE measures of interest, and the need for savings of sufficient magnitude to reduce risk in the RA model.

SERVM is typically run to measure the ability to meet a loss of load expectation (LOLE) reliability standard of 0.1 day/year, it means that, on average, the system is expected to experience resource shortages once every 10 years. LOLE measures the expected frequency of periods when available resources are insufficient to meet electricity demand.. Since SERVM simulations are conducted on a single study year, this is how the 1 day in 10 years loss of load event standard that is typically used in the electric industry is transferred into the SERVM context. For a system that fails to meet that standard, i.e., t has a LOLE that exceeds 0.1, the ability of any resource to reduce risk is dependent on its ability to eliminate expected unserved energy in the SERVM simulations. Therefore, demand-side savings must correlate with the hours and the magnitude of risk identified in SERVM.

North Carolina RA Results

For the NC simulations, we evaluated upgrading existing electric heating systems to ENERGY STAR–qualified conventional air-source heat pumps (ASHPs) with electric resistance backup. This measure was assessed across 42 weather years to align with SERVM modeling assumptions. Ultimately, this upgrade did not produce savings that aligned well with the hours of risk identified in SERVM, nor were the savings of sufficient magnitude to materially reduce risk.

These results are illustrated in the heat maps below (Figure 5). The left frame of Figure 5 shows system average risk prior to the inclusion of EE savings, while the right frame of Figure 5 second shows the impact of the ASHP upgrade. The heat maps highlight that system risk remains concentrated in the same extreme periods, with a modest reduction in the magnitude of EUE during those hours. Instead, the conventional ASHP has only a modest effect during shoulder periods and in the summer.

The results reflect population-level impacts, including assumed adoption rates under a robust utility incentive program. Even under these conditions, the measure provides limited reduction in RA risk hours. This outcome is primarily driven by the performance characteristics of conventional ASHPs, which rely on electric resistance backup during extreme cold conditions. As a result, load reductions during the highest-risk hours are minimal. This contrasts with the building-level results presented earlier, which show that technologies capable of maintaining performance during extreme cold, such as cold-climate heat pumps, can deliver substantially greater load reductions during these same periods.

In hindsight, alternative measures such as cold-climate ASHPs or ASHPs combined with envelope improvements, both discussed in the previous section, would likely have produced more meaningful reductions in RA risk compared to conventional ASHPs. These findings highlight a key takeaway: the impact of EE on RA outcomes depends on multiple factors, including measure performance under cold conditions, adoption rates, and the temporal alignment of savings with system risk. Identifying effective EE strategies for RA applications may therefore require iterative modeling and targeted measure selection.

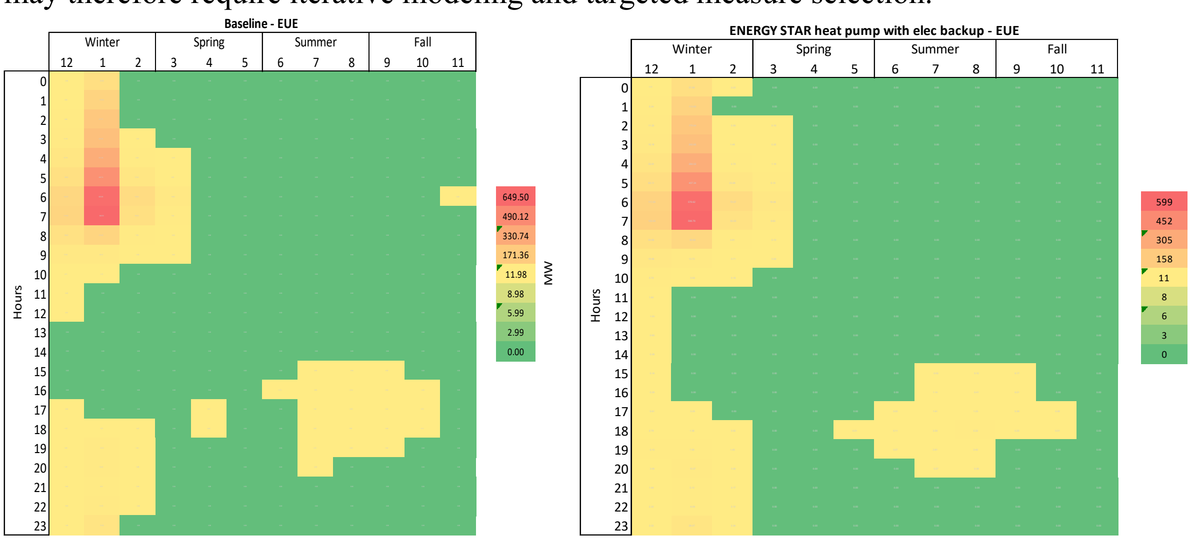

Figure 5. System EUE Under Baseline (left frame) and Heat Pump Upgrade (right frame) Conditions

As noted above, only the conventional ENERGY STAR ASHP was simulated across the full 42-weather-year period in SERVM. As a result, this analysis does not estimate how the conventional ASHP with envelope upgrade or the cold-climate heat pump would affect EUE-based reliability outcomes. The 2018 ResStock simulations for the high-efficiency, cold-climate air-to-air heat pump with electric backup nonetheless offer useful insight into the timing of savings (Figure 6). Although 2018 was not among the most extreme cold-weather years, the hourly savings profiles align closely with the baseline EUE risk hours identified across the 42-weather-year analysis. In other words, savings tend to occur during the periods of greatest reliability risk: for example, EUE is concentrated in the morning hours of January (left frame of Figure 5), and the CCHP savings cluster in that same period (Figure 6). This suggests that the modeled efficiency measures are likely to reduce load during the hours most relevant to resource adequacy risk. The magnitude of any reliability benefit, however, also depends on the size of the adopting population: load reductions translate into measurable EUE improvements only when applied across a population large enough to meaningfully influence system load during extreme peak conditions.

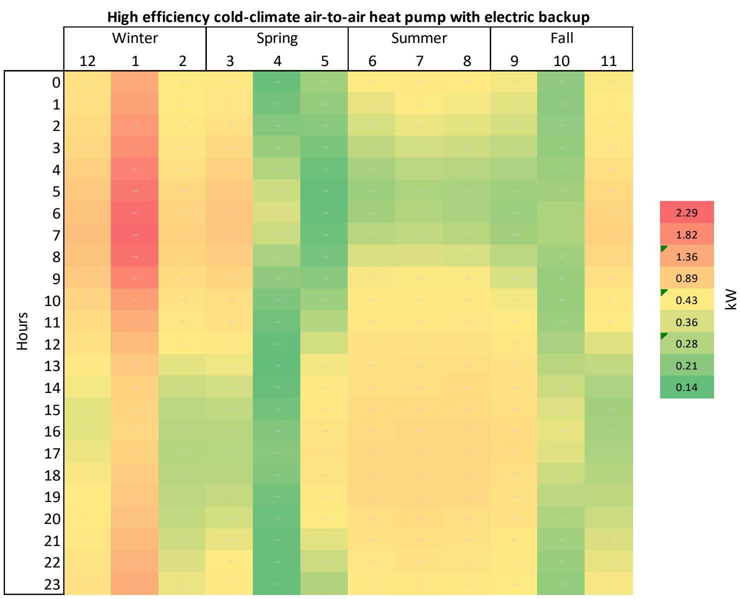

Figure 6. Energy Savings with CCHP

One way to help narrow the identification of measures worth running in ResStock is to first run SERVM to identify the weather years and time periods with risk and then, using those same weather years that show risk (because not all will), run custom simulations of the measures of potential interest in ResStock. This would allow the modeler to more quickly identify which measures could reduce risk in the system of interest and allow valuable computational time to be spent on only measures with a likelihood of producing savings in the hours of need.

Lessons Learned and Best Practices

For Energy Efficiency Analysts

This study revealed several lessons regarding how EE measures can be modeled for integration into RA frameworks. First, this analysis modeled EE measures across 42 different weather years to align with the weather inputs used in SERVM. While this approach ensured consistency between the EE and RA modeling environments, it proved to be computationally intensive. One potential way to reduce computational burden is to first identify the weather years and periods associated with reliability risk within the RA model and then run EE simulations only for those years. This targeted approach could allow analysts to focus on the weather conditions most relevant to LOLE or EUE outcomes while avoiding unnecessary simulation time.

A second lesson is the importance of ensuring that the modeled population is large enough to meaningfully influence system load during extreme peak conditions. In this study, the ResStock analysis was limited to single-family electrically heated homes in North Carolina. This restriction was based on the assumption that this population would be the most straightforward and cost-effective to upgrade to air-source heat pumps or replace with higher-efficiency systems. However, the resulting load reductions were not large enough to meaningfully reduce LOLE or EUE in the RA model. Expanding the population of eligible buildings, such as including additional housing types or considering fuel-switching opportunities, could produce different results. In this instance, the measure selection, not the population, was likely the limiting factor in terms of LOLE and EUE impacts. However, the analysis highlighted the fact that broad populations would need to impacted for efficiency measures to meaningfully reduce LOLE or EUE.

A third lesson is that measure selection and adoption assumptions are critical for generating system-level impacts large enough to influence RA outcomes. In the case of North Carolina, the study team initially excluded cold climate heat pumps based on the assumption that these technologies would have limited relevance in a southern region. However, these systems may be particularly valuable during extreme winter events that drive RA risk. This process revealed that analysts may need to consider a wider range of measures than those typically prioritized in EE programs when evaluating EE within RA frameworks. Measures that appear unconventional in a program planning context may nonetheless provide significant reliability value during extreme conditions.

Overall, these findings highlight the importance of aligning EE modeling assumptions with the conditions that drive reliability risk. Traditional EE analyses often prioritize annual energy saving and cost-effectiveness, while RA models identify a relatively small number of high-risk hours. The value of traditional EE remains, but it could be supplemented with considering additional EE opportunities through the lens of system reliability. Identifying EE measures that specifically reduce demand during those hours is more important from an RA perspective than maximizing annual energy savings.

All of these considerations raise important questions about the role of EE in resource planning. For example, utilities and regulators may need to consider whether investments in measures that specifically address system reliability risks, such as cold climate heat pumps in regions with only occasional extreme winter events, are justified when compared with alternatives such as new generation or other capacity resources. Addressing this question involves assessing the cost-effectiveness of these measures—weighing their costs against their benefits—in the context of system reliability. This would require understanding the economics associated with potential outages and generation, and comparing those against the costs of supporting these demand-side management (DSM) measures.

For RA Analysts

Our initial focus on heat pump upgrades for single-family residences was intended as a proof-of-concept for explicitly representing energy efficiency (EE) within an RA modeling framework. However, this narrow scope limited the magnitude of achievable load reductions, resulting in minimal observable impacts on reliability metrics such as LOLE and EUE. This outcome highlights an important consideration for RA modelers: the ability of EE to influence system reliability is highly dependent on both the scale of deployment and the alignment of savings with system risk conditions.

A key lesson is the importance of identifying system risk drivers within the RA model before conducting detailed EE simulations. Because only a subset of weather years and hours contribute meaningfully to reliability risk, first identifying the specific years, periods, and conditions associated with elevated LOLE or EUE lets modelers target EE analysis toward the highest-risk scenarios. Focusing initially on this smaller set of high-risk years enables more efficient screening of which measures most effectively reduce demand during critical periods, improving both computational efficiency and analytical relevance.

EE should also be evaluated across a sufficiently broad set of measures and building types, since limiting the analysis to a narrow subset of technologies or customer segments may underestimate its potential reliability contribution. From an RA perspective, the goal is not only to identify measures that are cost-effective under typical conditions but to understand which combinations meaningfully reduce demand during extreme events—often requiring consideration of less common technologies beyond traditional program boundaries. More broadly, integrating EE into RA frameworks requires closer coordination between the two approaches through iterative workflows in which RA outputs inform EE inputs and EE results are fed back to assess reliability impacts.

Conclusion

This paper presents methods for integrating energy efficiency (EE) into resource adequacy (RA) modeling frameworks. Aligning EE savings with the weather assumptions used in RA models provides a more accurate representation of EE impacts than traditional approaches based on average conditions. Tools such as ResStock and ComStock, combined with BuildStock Batch, enable EE simulations using custom weather inputs that are consistent with RA modeling assumptions.

The North Carolina case study highlights the importance of optimizing EE upgrade strategies and provides practical lessons for modelers applying this methodology. Simulating EE measures across 30 or more weather years is computationally intensive. Targeting initial EE modeling efforts toward weather years associated with high reliability risk can improve efficiency and help identify the measures most likely to reduce LOLE and EUE.

Demand for new power generation is increasing rapidly, and EE remains one of the most cost-effective resources available to meet this need. EE can often be deployed more quickly than supply-side resources and, when properly targeted, can reduce demand during critical peak periods. The approaches presented in this paper provide a pathway for more accurately incorporating EE into RA frameworks and better capturing its contribution to system reliability. More broadly, these methods highlight the need to treat EE as a time- and weather-dependent reliability resource, rather than as a static reduction in load.

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Disclosure

AI-assisted tools used: ChatGPT and Claude
Used for: Editing and references
Extent: Light editing, creation of reference list based on sources
Human review: The authors reviewed and verified all content, calculations, and citations.