ABSTRACT

SODANO, DANIEL JOSEPH. A Sensitivity Analysis of Utility-Scale Solar Photovoltaic and Energy Storage Capacity Values. (Under the Direction of Drs. Joseph DeCarolis and Jeremiah Johnson).

Ensuring utility-scale solar and energy storage systems operate cost-optimally to provide maximum electric grid benefit is increasingly important as deployment of these resources continues to grow. Electricity supply must be sufficient to meet peak demand, a role traditionally undertaken by inefficient natural gas peaking plants. The capacity value, used to evaluate a generator's ability to meet peak demand, is high for most thermal generators because these generators are dispatchable and are typically unavailable only during periodic shutdowns. Since solar photovoltaic (PV) systems depend on variable solar irradiance, utilities and capacity markets often assign low capacity values to solar projects. Further, solar PV systems can alter the load profile of a grid system, potentially shifting peak net load to hours with little or no solar generation. Energy storage can mitigate some of the challenges associated with solar generation variability, but is limited by system capacity and discharge duration. In this thesis, I develop a model using loss of load probability (LOLP) and effective load carrying capability (ELCC) methods to calculate the capacity value of solar PV and energy storage. Through a series of Monte Carlo simulations, I demonstrate the sensitivity of solar PV capacity credit to the share of solar installed capacity. Then, using Temoa, an open-source energy model developed at NC State, I determine the cost-optimal charge and discharge pattern for energy storage under several different design considerations. The calculated capacity credits for solar PV and batteries are contingent on their installed capacities as well as the underlying grid mix. I use Duke Energy's balancing territory in North and South Carolina as a case study because the high amount of installed solar PV but low amount of energy storage makes for a unique grid system, and could represent near future grid systems for other regions. This grid system is also interesting because

the growth in solar generation shifted the hours of peak net load in Duke's territory from predominately summer hours to a winter season peaking system, though the respective season peaks remain close. The proximity of winter and summer peak load magnitude makes this grid system a valuable test case for assessing solar and storage capacity values. My study determined that the first MW of solar PV within Duke's territory provided capacity value equal to 44% of its nameplate capacity, while 3.5 GW of solar PV, roughly the amount of solar installed in Duke's territory in 2018, held a capacity credit of 36%. These results are well above Duke's current assumed capacity credit values. There are strong correlations between solar penetration and capacity value as well as storage duration and resource reliability, as having additional generating capacity on the grid presents more opportunities to meet demand. I observed an increase in capacity credit for energy storage with higher penetrations of PV on the system; the capacity credit of a 2 GW, four-hour duration storage system steadily increased from 41% to 87% as 1 MW to 13 GW of solar PV were added to the grid. This increase was caused by the shortened durations of net load peaks, which could be more easily served by energy storage. However, larger storage systems held lower capacity values: when considering a grid with 3 GW of solar, an 80 MW storage system had a capacity credit 1.27 times higher than a 2 GW system. Such analysis is timely as utilities aiming to replace their aging peaking plants consider energy storage as part of a low carbon pathway.

A Sensitivity Analysis of Utility-Scale Solar Photovoltaic and Energy Storage Capacity Values.

by
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A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Master of Science

Environmental Engineering

Raleigh, North Carolina

2020

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BIOGRAPHY

Daniel Sodano was born on July 8th, 1996, in Garwood, New Jersey. Growing up, Daniel always expressed a fascination with mathematics, learning how to add and subtract numbers in the millions shortly after learning to speak. He lived in New Jersey until his family moved to North Carolina in 2005. Daniel attended Cuthbertson High School in Waxhaw, NC and received his high school diploma in 2014. During this time, Daniel remained enthralled with math but also became intrigued by environmental science and public policy. He attended North Carolina State University for his undergraduate tenure where he began as a student in the Exploratory Studies program and matriculated into the Department of Chemical and Biomolecular Engineering at the end of his freshman year. Daniel worked in three different research laboratories while pursuing his undergraduate degree. He assisted with electrochemical engineering research under Dr. Peter Fedkiw in the Chemical and Biomolecular Engineering department and co-authored the manuscript "Cobalt-Doped Iron Sulfide as an Electrocatalyst for Hydrogen Evolution", published in 2017. He also initiated independent research in air quality engineering and analytical chemistry under the supervision of Dr. Andrew Grieshop in the Department of Civil, Construction, and Environmental Engineering and tackled research for an original design project under Dr. Jay Cheng in the Department of Biological and Agricultural Engineering. This research as well as relevant coursework and a short-term study abroad, kindled Daniel's interest in climate change and energy systems. Daniel graduated in May 2018 with a Bachelor of Science in Chemical Engineering and a minor in Economics. He began conducting graduate-level research towards a Master of Science degree in Environmental Engineering at NC State less than two weeks later, focusing on energy systems analysis and mathematical modeling. The ten days off were appreciated. Under the advisement of Drs. Joe DeCarolis, Jeremiah Johnson, and

Anderson Rodrigo de Queiroz, Daniel contributed research towards the comprehensive study "Energy Storage Options for North Carolina" mandated by NC House Bill 589 as well as the "North Carolina Clean Energy Plan," required by NC Executive Order 80 and published by the NC Department of Environmental Quality. After two years of intense work, Daniel successfully defended his thesis and intends to work for the Department of Energy in the Solar Energy Technologies Office in Washington, DC after graduation.

ACKNOWLEDGEMENTS

First and foremost, I would like to sincerely thank my three advisors, Drs. Joe DeCarolis, Jeremiah Johnson, and Anderson Rodrigo de Querioz for their guidance, patience, and comradery during my graduate tenure at NC State. I could not imagine having better mentorship throughout the past two years. The incredible work-ethic they demonstrate has been an inspiration to me and motivated me to perform to the best of my ability, especially during my three engaging and applied research projects in my graduate tenure. Most graduate students do not have the opportunity to constantly engage with their advisors on a weekly or semiweekly basis, but Joe, Jeremiah, and Anderson were there every step of the way.

I can still remember being fascinated with Joe's work during my years as an undergraduate student and how his guest lectures in ES 300 sparked my interest in energy systems. At the end of my senior year, I was at a crossroads between continuing my studies in graduate school at the Colorado School of Mines or accepting a position as an associate-level chemical engineer. I applied to graduate school at NC State late in the process and had not seriously considered accepting an offer if I received one, but I felt an instant connection the first few times I talked to Joe and Jeremiah. I was in shock when I discovered that the research topic I had proposed to Joe was the exact topic of the House Bill 589 energy storage study, which I did not know was being conducted. In about one week I went from hardly considering graduate research at NC State to planning to accept an offer to pursue a Master of Science degree in environmental engineering.

Next, I would be remiss if I did not mention the NC State Club Cross Country & Track team for the incredible experiences I have had with them. Were it not for some of the amicable, caring, and hardworking members of the team, I would never have rediscovered my passion for distance running and its therapeutic qualities. I attribute my accomplishments as part of the team almost entirely to their coaching and encouragement.

I'd like to thank my good friends I have lived with in various semesters throughout grad school for their understanding and tolerance during some of the most stressful times of my life and the fun experiences I have had with them. I hope they all remain lifelong friends as I move on in my professional career. Shoutouts to Derek Armour, Craig Prince, Max Robbins, Colby Purvis, and Erica Lisowe.

I would like to thank my coworkers and friends at the North Carolina Clean Energy Technology Center, some of whom I worked with on the energy storage study, but many of whom I met and befriended during my part time internship at the Center. I would like to acknowledge my bosses Steve Kalland, Art Samberg, Kimberly Conley, and Isaac Panzarella, as well as the members and honorary members of the "Millennial Office", Ted Spencer, Simon Sandler, Nicole Wilson, Allison Carr, Grace Levin, Sara Thornton, and Megan Berry. I can only hope that I continue to experience work cultures as lively as the one at the Center in my future positions.

I want to thank the friends I made in graduate school that helped guide me through an otherwise stressful degree program in a multitude of ways. I especially would like to thank Simran Singh for being the most genuinely caring person I have ever met. I wish him the utmost success in life. I also must acknowledge some of my friends outside of graduate school who have supported me not just throughout graduate school, but some for years before I even committed to the graduate program. They are Josh Rees-Jones, Anthony Sgro, and Spencer Crane, three of the most talented and versatile people in my life.

I'd like to thank the friendly administrative staff in the Civil Engineering department for showing kindness to myself and the other graduate students. I have not had the opportunity until now to formally do so, but I'd also like to thank Lisa Bullard in the Chemical and Biomolecular Engineering department for her guidance and energy throughout my undergraduate tenure. I could not have gotten through such a difficult degree program without her.

Finally, I must thank my family who, no matter what, have always believed in me. On my worst days, I know that they are still proud of what I have done and that they will always support me. This thesis is dedicated to all of them – my parents, my siblings, my cousins, my grandparents, and my extended relatives. My late grandmother, who passed away at the end of my penultimate semester, was passionate about environmental conservation. I wish she could have seen me accept a position to work in Washington, DC at the Department of Energy and earn not only the first graduate degree in my extended family, but one that is centered around clean energy. Perhaps more than anyone else, I would like to dedicate this thesis to her.

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1. INTRODUCTION

Scientific consensus clearly reflects the importance of reducing anthropogenic carbon emissions to alleviate the adverse effects of climate change on humanity and the environment (IPCC, 2018; DOE, 2015). Global decarbonization of the electricity sector, coupled with increased electrification of energy services, is one viable pathway to deep decarbonization. As a result, scientists, engineers, politicians, and environmental groups, among others, have advocated for policies that would reduce carbon dioxide emissions and increase energy efficiency in the United States. Research and development, financial incentives, and state-wide goals and mandates have resulted in the rapid deployment of clean energy technologies such as solar and wind power, as well as the widespread implementation of more energy efficient devices (IEA, 2019). Low or zero carbon emission electricity generation technologies have primarily served to replace generation from aging, carbon-intensive energy infrastructure in the United States. As variable energy resources (VERs), carbon sequestration technologies, and electric vehicle fleets have emerged, it has become clear that in order to meet the ambitious climate and energy goals that states and countries are setting, solar photovoltaic (PV) technology in particular will likely play a large role.

1.1 Meeting Electricity Demand

Electricity supply must match electricity demand at all times to ensure the electric grid runs properly. This requires consistent, precise planning from grid system operators, as both electricity demand and available electricity supply are constantly changing. In addition, electricity storage is not widely available on the grid, adding a level of uncertainty to the planning process (Ott, 2003; DEC, 2018). U.S. electricity market rules were designed for large, centralized baseload power plants and flexible, dispatchable power plants. These plants dominated the electricity sector for decades and are relatively reliable, making short- and long-term power system planning somewhat simpler (DOE, 2017).

Grid operators must plan to ensure there is enough available generation capacity to meet peak electricity demand. In the United States, during times of peak demand, power plants that are not often utilized must come online. These "peaking plants" tend to have relatively low capital costs compared to other generation resources and are flexible enough to ramp up energy output in minutes. However, they tend to incur high operational costs ($/kWh) as a result of using older, less efficient technology, and run for less than 10% of the year on average (John, 2014). Furthermore, these are highly polluting plants on a grid system, using either natural gas in simple cycle combustion turbine technology or, in some cases, fuel oil (EIA, 2019a). To reduce the construction and operation of peaking plants, utility-scale solar and energy storage assets have been commissioned to provide this necessary peaking capacity instead (Spector, 2019).

1.2 Variable Energy Reliability

VERs such as solar and wind power provide several grid benefits, including near zero operational costs, decentralization of generation assets, and increasing grid mix diversity; all of these provide increased energy security and resiliency by reducing the reliance on certain fuels. They also provide health and environmental benefits attributable to lower life-cycle emissions compared to fossil fuel energy generation (Buonocore et al, 2016). However, all of these benefits come with new challenges presented in power system planning (DOE, 2017). Given that generation from VERs is driven by meteorological factors and are non-dispatchable, increasing penetration levels of VERs has resulted in short-term operating constraints. This amplifies power system planning uncertainty on nearly all time scales. Thus, research to understand and quantify the value of VERs on electric grids is both useful and urgent (Ryan, 2016).

Capacity expansion energy models are often used to determine the least cost mix of generating capacity over multi-decadal time periods, making them a common tool among utilities, system planners, and researchers. When choosing new assets in a capacity expansion framework, planners must consider the reliability and effectiveness of a generator in meeting peak demand. The capability of a generating unit to contribute to meeting peak electricity demand is quantified as that unit's "capacity value," and is typically reported as a share of the unit's nameplate capacity (%) or its effective power capacity (MW). The percentage value is sometimes referred to as the "capacity credit" allocated to that unit; in this study I will use the terms "capacity credit" and "capacity value" interchangeably.

No unit has a capacity value that is 100% of its nameplate capacity, since there is always a chance that the unit will fail during a critical time when it is needed. Most thermal generation resources are dispatchable and have infrequent outages, so the capacity value they provide is fairly high, as the probability that the unit will fail at a critical time is low (NERC, 2011). Incremental VER capacity value, however, varies greatly depending on grid mix, the penetration of the given technology, and the correspondence between the resource and the system demand (Jilin, 2017). In addition, there is no consensus on the best method to determine capacity value for VERs (Dent, 2016).

1.3 Net Load and Energy Storage

Solar photovoltaic (PV) systems, as well as other VERs, effectively change the shape of a grid's demand profile because they generate electricity according to the availability of their respective resource (e.g., solar irradiance, wind speed). Given the variable nature of solar and wind production, system operators typically treat these resources as negative load, subtracting them from demand to find the *net load profile* or *net load curve*, which in turn must be met with dispatchable generators. In the summer, solar insolation mostly aligns with high demand hours, and thus can participate in “peak shaving,” which reduces of the magnitude of peak demand on the grid. The California Independent System Operator (CAISO), which has over 3.6 GW of solar on its grid system (CAISO, 2020), has experienced a peak net load shift to summer evenings when solar insolation wanes, creating diminishing returns in terms of peak shaving value as more solar PV is deployed (CAISO, 2016). Conversely, winter peak demand occurs early in the morning in CAISO when solar insolation is considerably weaker. It would indeed be difficult to make a compelling case for standalone VERs to reliably meet peak demand during these times, as even in ideal conditions, peak net load will shift towards hours when solar generation is low.

Fortunately, the rapidly declining investment costs of battery energy storage systems (Schmidt, 2017; IRENA, 2017) have motivated an abundance of research focused on maximizing the operational value of using VERs and storage systems in tandem. Energy storage can alter the net load profile of a grid system and, to an extent, can be dispatched to meet peak demand. The concurrent shift in net load from solar and storage assets can make solar PV more valuable as a peak shaving technology. Lithium-ion battery chemistries in particular have experienced considerable declines in capital costs, with lower life cycle costs than mature energy storage systems such as lead acid batteries or flywheels, and without the geographic restrictions of compressed air energy storage or pumped storage hydro plants (Zakeri, 2015; Lazard, 2018). It is because of these favorable qualities that I chose to study lithium ion battery energy storage systems and how they interact with solar PV.

1.3 North Carolina as a Case Study

The grid system owned and operated by Duke Energy Carolinas (DEC) and Duke Energy Progress (DEP), which covers most of North and South Carolina, makes for a unique and interesting case study. North Carolina saw a huge influx of solar PV capacity in the 2010s, becoming the state with the second highest installed solar PV capacity in 2016 (SEIA, 2017). Solar has continued to see development through 2019, with 864 MW installed in North Carolina in 2019 (SEIA, 2020). Installed costs of solar generation systems have decreased dramatically throughout the decade (Bolinger, 2019) and have bolstered widespread national deployment of solar PV (EIA, 2019). Incentives and policies, such as an Investment Tax Credit and favorable terms under the Public Utility Regulatory Policies Act (PURPA), were the cornerstones of growth in North Carolina (Sukunta, 2016). PURPA is a federal law that allows third-party qualifying facilities (QF) to generate renewable energy that can be sold at the utility's avoided cost, i.e., the cost the utility would have incurred had it not purchased the electricity from a QF (FERC, 2019). Though enacted in 1978, this policy has played an important role in recent years as a financially attractive option for small power producers looking to utilize solar technology (UtilityDive, 2017). Sukunta (2016) illustrates the effect that policy had on North Carolina's solar investments: over 90% of projects (in terms of total installed capacity) were commissioned by QFs.

This policy-driven growth has created ambiguity related to the grid operational value of these residential- and utility-scale systems, as these systems were not brought online as the result of market or grid value alone. With the potential for continued solar growth, determining that value has become increasingly important, illustrated by the way DEC and DEP have adjusted their methodology for calculating capacity value for solar PV. In DEC's 2014 Integrated Resource Plan (IRP), solar PV's capacity value is a single number: 46% of nameplate capacity (DEC, 2014). In the 2016 and 2017 IRPs, DEC reports solar PV's capacity value as two numbers: 46% of nameplate capacity in the summer and 5% of nameplate capacity in the winter

(DEC, 2016; DEC, 2017). In their 2018 IRP, an entire chapter of the report is dedicated to the capacity value of solar, including 3 tables and 30 different values depending on the season and amount of solar on their grid system (DEC, 2018). In this IRP, they assign less than 3% annual capacity values to new solar added onto their system. All values from the two IRPs are shown in Figure A1 in the Appendix.

With every new IRP, the capacity value of solar PV decreased, and this can be primarily attributed to Duke's recategorization of their grid systems as winter peaking. Previously, the grids were considered summer peaking systems (DEC, 2014; DEP, 2014), then recategorized as dual-peaking systems (DEC, 2016; DEP, 2016), which meant the summer peak and the winter peak had a negligible difference in magnitude. This shift stems from increasing solar PV deployments that have lowered summer afternoon and early evening net load while doing little to shave winter morning peaks (EIA, 2019a). After this shift, the net demand annual peak hour is in January and February as opposed to July and August, according to DEP (2018). This shift is illustrated in Figure A2 in the Appendix. Given that the difference between winter and summer demand in Duke's territory is only 102 MW, there is potential for solar capacity value to increase if new energy storage capacity can sufficiently shave winter peaks.

1.4 Near Future Planning in North Carolina

DEP and DEC currently use peaking plants running on natural gas and fuel oil, but many of these plants are approaching their end of life and will need to be replaced within the next several years (EIA, 2019a). In their 2018 IRPs, both DEP and DEC plan to replace these inefficient plants with newer gas turbines with slightly higher efficiency. Duke cites as their rationale behind this decision the more favorable economics of natural gas technology compared to the alternatives. This current situation makes North Carolina an even more interesting grid system to evaluate, as the results could prove important for Duke's capacity expansion planning process. Given battery project lifetimes are typically 20 years (DeCarolis, 2018) and solar projects can have even longer lifetimes (EIA, 2019), and assuming current cost trajectories of both technologies, a standalone storage or solar plus storage facility installed in 2020 or later could be more economically favorable than a new gas turbine in the long term.

This thesis investigates the capacity value for solar PV and explores the sensitivity of this value in a suite of scenarios that vary existing solar penetration levels, lithium-ion energy storage system capacity, and dispatch duration of the storage systems. For each value, I calculate the capacity value of additional solar PV capacity using a Loss of Load Probability (LOLP) approach to determine the Effective Load Carrying Capability (ELCC), a reliability metric that determines the amount of additional load that can be served on a grid post hoc the addition of the solar capacity. Capacity value estimations - including the inherent uncertainty, whether it is solar PV or energy storage - is rarely seen in literature, as I will discuss in the next chapter. My analysis uses publicly available information and uses an open source energy system optimization model to evaluate the impact of introducing energy storage, making the entire analysis replicable. This methodology can be used for other systems as long as the demand data, generator capacity data, and data on the availability and renewable resource characteristics for that system are provided.

The remainder of this thesis is structured as follows: Chapter 2 reviews the existing literature pertaining to valuation methods for solar, energy storage, and solar plus energy storage systems and identifies gaps in current work. Chapter 3 describes my approach to estimating the LOLP of Duke Energy's grid, ELCC values for incremental amounts of solar PV, and incorporating battery energy storage into the analysis. Chapter 4 discusses the results of my analysis. Chapter 5 concludes the thesis with a summary of findings, some of the limitations in the approach, and a discussion of future work.

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2. LITERATURE REVIEW

2.1 Variation in Solar Valuation

Despite their variable output, solar PV systems can and do contribute to meeting peak power demand. Peak demand often occurs in the middle of the day or early evening, and with high solar PV capacity, high marginal cost plants can ramp down or completely shut off production for a few hours, as seen in California (Denholm et al, 2015). At the same time, the capacity value of standalone solar is difficult to quantify as a point estimate and has no uniform evaluation method among utilities or energy modelers (Sullivan et al, 2014; Dent, 2016). For example, the Switch energy model from UC Berkeley simply uses the capacity factor of the resource at the annual peak hour to determine capacity value (Fripp, 2012). The MIT GenX model does not allocate capacity value to solar PV at all (Jenkins & Sepulveda, 2017). Some models quantify capacity value as an opportunity cost, including the grid service "peak capacity deferral," which avoids the construction of new peaking plants (Sullivan et al, 2014). Using multiple years of historical meteorological data can provide a range of generation values for any given hour, somewhat bounding the hourly capacity factors of the resource (Gami et al, 2017).

Capacity value estimations and methods vary throughout literature, and while there is a large range of reported values, all studies exhibit similar trends. Gami et al (2017) calculates the ELCC values for solar from 10 different locations throughout the United States to be between 10 and 50% of solar PV nameplate capacity. Madaeni et al (2012) estimates that the first 100 MW of solar PV at 10 different locations in the western United States may have a capacity value ranging from 52% (Los Angeles, CA; Cheyenne, WY) to as much as 70% (Congress, AZ) of nameplate capacity. Using the IEEE Reliability Test System (IEEE-RTS) and solar radiation data from NREL South Table Mountain site in Golden, Colorado, Samadi & Singh (2014) observe decreasing solar capacity value as solar deployments increased; they calculate a capacity value of 35% of nameplate capacity for solar at a 5% solar penetration level and a capacity value of 28% of nameplate capacity at 20% solar penetration. Frew et al (2017) assigns an initial PV capacity credit of about 45%, but marginal capacity value decreases to nearly 0% on a grid with 40% of generation from solar. Richardson & Harvey (2015) uses the irradiance and demand data of Guelph in Ontario, Canada and show a lower initial value of 28% for the first MW of PV but a slower decline in value, maintaining a 9% capacity value at 50% PV.

2.2 Incorporation of Energy Storage

Energy storage is unique in that it offers dispatchability but is energy limited (i.e., cannot discharge for an arbitrarily long period of time). Peak demand may last longer than the discharge duration of the storage system, limiting the storage system's effectiveness at shaving peak. Despite this limitation, some studies have observed that peak capacity deferral is one of the most valuable benefits energy storage can provide to ratepayers (MDER, 2016). NARUC (2019) found that storage, especially paired with VERs, can provide grid reliability and peak shaving benefits that surpass those of either resource alone.

Recent studies have developed and/or reviewed methodologies to assess solar and energy storage capacity values relative to the penetration of other generation resources, particularly solar PV (Qiu et al, 2017; NYISO, 2018; Lai & McCulloch, 2017; Richardson & Harvey, 2015; Alvarez et al, 2017; Denholm & Margolis, 2018). Alvarez et al (2017) analyzes capacity credits as a function of storage capacity and duration in California, providing data for storage capacity as a percentage of annual peak demand. Both Alvarez et al (2017) and Denholm & Margolis (2018) calculate a 100% capacity credit for 3,000 MW of four-hour battery storage and zero PV penetration in California, though the value declines rapidly as additional storage capacity is added. Richardson & Harvey (2015) finds that incorporating energy storage increased solar PV capacity value at 50% solar penetration from 9% of nameplate capacity to 16%.

While most studies report that storage improves the capacity value of solar, some literature suggests that higher PV penetration does not necessarily improve the capacity value of storage. Denholm & Margolis (2018) analyze short duration energy storage for peak deferral as a technological imperative to California's rising PV penetration levels and subsequent trend towards an imbalanced net load curve. The study observes storage capacity value initially declining as PV penetration increased from 0-5%, but surpassing its initial value at zero solar after 11% solar penetration; the initial decrease is attributable to PV-lengthened peak loads, but eventually, PV generation narrowed load peaks, improving the capability of storage to shave the peaks. This study is important to highlight as it shows that storage and solar assets may need to be deployed strategically to maximize their capacity value.

Given the energy limited nature of energy storage, storage operators may choose to allocate capacity to other grid services such as frequency regulation or minimizing emissions in order to maximize total grid value of the asset. For example, Arbabzadeh (2019) evaluates the capability to reduce carbon dioxide emissions in Texas and California with energy storage in the presence of various carbon taxes. In Jentsch et al (2014), the environmental benefit of storage was assessed in the context of achieving clean energy deployment goals. Ryan et al (2018) introduces environmental impact sensitivity as a function of coal and natural gas fuel prices, grid mix, and battery degradation, among other variables. Hittinger & Azevedo (2015) assesses how perfect versus imperfect information about future demand can change the environmental and economic impact of storage. Sioshansi (2010) reviews how energy storage systems can enhance the economic value of variable generation sources, particularly at high renewable penetration levels, through energy arbitrage, peak capacity deferral, and curtailment reduction. Berrada et al (2016) calculates the benefit of storage performing several grid services, including the three studied in Sioshansi (2010), all at once. Richardson & Harvey (2015) assesses the change in ramp-up and ramp-down capacity in MW/hour at various solar penetration levels and found that a grid with 30% solar PV penetration increased the ramp up requirement by 1300 MW/hour and ramp down requirement by 1600 MW/hour compared to a grid with zero PV; the presence of four-hour duration storage at the same power capacity as the solar PV additions reduced both of these ramping values to zero. These results were not considered in their capacity value assessment, but Richardson & Harvey (2015) conclude that ramping services may be necessary to include for certain grid systems in order to improve the perceived value of energy storage.

Though some of the studies cited above do not directly tie in to the research presented in this thesis, they provide noteworthy context for the additional services energy storage can provide in addition to peak shaving, should peak shaving by itself remain cost-ineffective in the future. After all, storage system investments in the United States have historically been driven primarily by policy mandates (Kintner-Meyer, 2014) or for ancillary services such as spinning reserves and frequency regulation (Hittinger et al, 2012), rather than peak shaving. The net marginal value of storage (discharge revenue minus charging costs) increases with higher renewable penetration, which could lead peak shaving services to be primary drivers for storage deployment in the near future as renewables continue to be deployed (Bistline, 2017).

2.3 Utility Studies

Capacity value assessments are not exclusive to academia, as there are many examples of utilities and grid operators quantifying the value of energy storage as storage and solar investments continue apace. Studies such as Indianapolis Power & Light (2018), Hawaiian

Electric Company (2017), Tucson Electric Power (2016), Portland General Electric (2016), and many others show that utilities have begun to consider storage in their long-term capacity planning studies. These utilities have planned or investigated investments in storage as grid balancing resources, providing ancillary services, ramping support, voltage support, and frequency regulation. In their 2016 Integrated Resource Plan, Portland General Electric determined the operational value of energy storage on a test year simulation that considered unit commitment, ancillary services, and sub-hourly dispatch. The operational value of storage was considered to be the net change in operational costs for the system. Capacity value was determined using an ELCC approach and varied with storage discharge duration, though not PV capacity. The net revenue of energy storage was compared to the net revenue of a conventional combustion turbine peaking plant. The combustion turbine and energy storage capacities were adjusted to provide the same system capacity value. Because energy storage resulted in a higher net cost, it was not further evaluated in their long-term capacity planning. General Electric modeled energy storage capacity value in the New York Independent System Operator (NYISO) territory using their MARS energy model (NYISO, 2018), treating storage capacity value as a function of VER penetration and storage duration. Glendale Water & Power recently canceled a peaking plant project, opting instead to pursue a solar + energy storage system with a small backup reciprocating engine for meeting peak demand (GTM, 2019). The municipal utility cited shifting economics and the pursuit of clean energy goals as reasons for adjusting their investment plan. Since there is no universally accepted methodological approach and different institutions have different rationales for storage investments, it is difficult to compare the results of utility studies to one another.

2.4 NC Energy Storage Study

North Carolina House Bill 589 mandated a study on the economic feasibility of energy storage in North Carolina (DeCarolis et al., 2018), and this study had perhaps the biggest influence on the topic of this thesis. DeCarolis et al. (2018) provides a holistic approach to the environmental and economic benefits of energy storage weighed against its costs. In the subsection of their analysis focused on bulk energy time shifting, storage primarily charged using free utility-scale solar generation and when discharged, displaced coal and natural gas generation, thereby reducing fuel costs and emissions. Both storage and solar altered the net load curve of Duke Energy's grid system and shifted the hours of highest demand in the modeled year 2030. To estimate peak capacity deferral, the study used the capacity credit estimates for stand-alone energy storage at certain storage durations as calculated by Sioshansi et al (2014). The effective capacity of the storage system considering this estimated capacity credit was multiplied by the Cost of New Entry (CONE) of a natural gas combustion turbine, as described in Newell et al (2018). CONE represents the fixed and capital costs of a natural gas turbine used entirely for backup services, thus excluding variable costs. The key assumption is that a new combustion turbine would fill the role of providing peak electricity in the absence of a storage system, so in the context of this analysis, CONE essentially is the benefit of using storage instead of investing in new gas turbine capacity. As storage costs decline, the benefit-cost comparison becomes more favorable, and storage becomes a more cost-competitive option than natural gas for meeting peak demand sometime before 2030.

Two limitations of the HB 589 study include investigating neither the sensitivity of energy storage capacity value to solar PV penetration nor the capacity credit allocated to storage. Only one capacity value for solar was used, 5%, and storage capacity value was determined solely by duration, not dependent on the level of storage penetration. The study observed an influence from PV generation on storage discharge but the extent to which the two technologies impacted each other's value was beyond the scope of the time-constrained report. This limitation is the main reason why I chose this topic. Analysis was done with a very low capacity value given to solar PV, but peak net load is currently on a *knife edge* between winter and summer peaking, depending on PV penetration. Energy storage can alter the net load curve to change when net load peaks in a year. The research presented in DeCarolis et al (2018) is just one example study with no sensitivity analysis of capacity values, and what makes Duke Energy an interesting case study is the many other scenarios that could illustrate a wide range of results.

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3. METHODOLOGY

3.1 Methods Overview

To evaluate the capacity value of solar PV and storage systems in Duke's territory, I used a Loss of Load Expectation (LOLE) approach. I provide a short summary here and elaborate on the process in the next few subchapters. Power plants were assigned an Equivalent Forced Outage Rate - Demand (EFOR-d) value based on data from the North American Electric Reliability Corporation (NERC, 2019). EFOR-d values denote the probability of a given generator being unable to generate due to a forced outage or derating when there is otherwise demand for it to operate. Even if a generator is used once, it has an EFOR-d value, because at some point, it was needed to meet demand (NERC, 2018). Thus, I assigned an EFOR-d value to every generator. By conducting a Monte Carlo simulation with 600,000 realizations of generator availability, I calculated the probability distribution for the grid-wide aggregate available generating capacity. Coupling this result with system load, I then determined the Loss of Load Probability (LOLP) of Duke's grid and how it is affected by standalone solar PV additions. In addition, Tools for Energy Modeling Optimization and Analysis (Temoa), an open source energy system optimization model, was used to optimize hourly energy storage charge and discharge over the course of a year under a series of scenarios with discrete additions of solar PV capacity. The database used in this model is a modified version of the operational model developed in DeCarolis (2018). The resultant storage dispatch pattern was subtracted from net load and used within the Monte Carlo model to determine storage capacity value in the presence of the specific solar deployment levels.

3.2 Loss of Load Probability and Effective Load Carrying Capability

The reliability of a grid can be measured by the number of instances in which a loss of load event occurs over a given time period. This is defined in articles such as Da Silva et al (1988) as the loss of load expectation (LOLE) of a grid. In my analysis, I evaluate loss of load events at an hourly temporal resolution. The probability that a loss of load event will occur at any given hour in a certain time period is the loss of load probability (LOLP) (Da Silva et al, 1988). Another metric utilized was the Effective Load Carrying Capability (ELCC) of the solar (and later, storage) capacity addition. ELCC compares the nameplate capacity of a generator to the additional load that can be served while maintaining the same level of reliability. For example, a 300 MW thermal generator that has an EFOR-d value of 0.1 would be expected to have an ELCC of approximately 270 MW, or 90% of the nameplate capacity of the generator (though there may be seasonality to the forced outages that occur which may slightly change this value). An ELCC approach is common when evaluating the reliability value of non-dispatchable generators, and usually both ELCC and LOLE are calculated concurrently during reliability analysis.

A database was developed in this study that was used to evaluate the LOLP of Duke Energy’s territory including Duke Energy Carolinas (DEC) and Duke Energy Progress (DEP). The database includes the generators and their nameplate capacities in Duke territory based on EIA 860 data (EIA, 2019a). Hourly demand data in DEC and DEP for 2018 and 2019 are from combined EIA 923 data for the DEC, Duke Energy Progress East (CPLE), and Duke Energy Progress West (CPLW) balancing areas (EIA, 2019b). Solar generation data are from EIA 930 (EIA, 2019c), with hourly capacity factors derived by comparing generation to installed capacity for every month from August 1, 2018 to July 31, 2019.

EFOR-d values from NERC (2019) were assigned to the firm generators in DEC and DEP territories. The generator nameplate capacity g_i is multiplied by a binary variable e_i, which is introduced to indicate whether g_i is available or not. A random number generator was used to determine the value of e_i. If a random number, which ranges from zero to one, exceeded the value of $(1 - EFORd)$ for a generator, the binary variable e_i has a value of one, and the generator is available at full capacity. Otherwise, the value of e_i is zero and g_i is considered unavailable.

For all existing power plants in the set, generate a random number r_i between 0 and 1:

$$\begin{cases} \text{If } r_i > 1 - \text{EFOR-d}_i \text{, then } e_i = 1, \\ \text{otherwise } e_i = 0 \end{cases}$$

The subsequent summation across all generators, each with a unique random number and determinant of availability e_i, is the cumulative generation available to meet demand in time period t, G_t, as described in Equation 1, where I is the set of existent power generators indexed by i and T is the set of time periods in the analysis indexed by t. Non-dispatchable generators (i.e., solar and wind) were treated as negative load, and thus not included in the summation.

$$G_t = \sum_{i \in I} g_i e_i, \quad \forall t \in T \qquad (1)$$

The cumulative available generation value is compared to the net load values for every hour of the year, represented as L_t. The number of instances in which G_t is lower than L_t throughout the selected time period T divided by the total number of instances is the *LOLE* of the grid during T, with each individual loss of load event denoted by d_t.

For all existing time periods in analysis,

$$\begin{cases} \text{If } G_t < L_t \text{, then } d_t = 1, \\ \text{otherwise } d_t = 0 \end{cases}$$

Equations (2a) and (2b) shows the LOLE computation, where $p\{G_t < L_t\}$ represents the probability of the random variable G_t been less than the parameter L_t over the analysis period.

$$LOLE = \frac{\sum_{t=1}^{T} d_t}{T}, \quad or \tag{2a}$$

$$LOLE = \sum_{t=1}^{T} p\{G_t < L_t\} \tag{2b}$$

Since cumulative generation is based on probability, I added a Monte Carlo simulation component to test the sensitivity of the cumulative generation value. A Monte Carlo simulation consisting of 600,000 iterations was conducted, evaluated in 12 separate trials of 50,000 iterations at a time. A histogram showing the distribution of all 600,000 available generation values is provided in the Appendix as Figure A3. This iteration total ensures a sufficient number of loss of load events when calculating *LOLP*. An insufficient number of iterations may not produce a single loss of load event, and iterations beyond 50,000 are computationally intensive and offer diminishing returns. The 50,000 resultant cumulative available generation values were compared to load across all 8,760 hours between August 2018 and July 2019. *LOLE* was calculated for every iteration *j* of the 50,000 available generation values across all 8,760 hours of demand. Since a typical grid targets a standard LOLP of 0.1 days per year, or a loss of load once every 10 years (NERC, 2011), in order to maintain this NERC LOLP value, 16 loss of load events can occur for every 50,000 iterations. Sometimes multiple G_t values in a 50,000-iteration trial (n) were lower than a single hour in L_t. This counted as multiple separate loss of load events. *LOLP* for each trial *k* can be described using Equation 3, where n is the number of iterations:

$$LOLP_k = \frac{1}{n} \sum_{j=1}^{n} LOLE_{j,k} \tag{3}$$

The combined DEP and DEC grid currently has excess available capacity to meet demand, so the current LOLE was estimated to be zero. Overall, the lowest cumulative available generation value calculated was 34.3 GW while peak demand is about 33.5 GW. Thus, each trial had its own minimum cumulative generation value greater than or equal to 34.3 GW. For each of the 12 trials, an initial fixed load L_I was added to every hour to increase the LOLP until it achieved a 0.1 days/year reliability. This value L_I was different for each trial. Then, incremental amounts of solar capacity G_s were added to the grid, decreasing the LOLP. Finally, additional fixed load L_s was added to every hour to return the grid to the 0.1 day/year LOLP. To account for the initial fixed load and solar capacity, LOLP is calculated using Equation 4, which is Equation 3 expanded to include L_I, G_s, and L_s.

For all existing time periods in analysis and each trial,

$$\begin{cases} \text{If } G_{t,k} + G_s < L_t + L_{I,k} + L_s \text{ , then } d'_{t,k} = 1, \\ \text{otherwise } d'_{t,k} = 0 \end{cases}$$

$$LOLP_k = \frac{1}{n}\sum_{j=1}^{n} \frac{\sum_{t=1}^{T} d'_{t,k}}{T}, \quad or \qquad \textbf{(4a)}$$

$$LOLP_k = \frac{1}{n}\sum_{j=1}^{n}\sum_{t=1}^{T} p\{G_{t,k} + G_s < L_t + L_{I,k} + L_s\} \qquad \textbf{(4b)}$$

The ELCC associated with solar generation G_s is L_s, which represents the amount of load that can be added in tandem with G_s to maintain an LOLP of 16/50,000. This value is used in the final calculation to arrive at the capacity credit for a solar capacity addition. Dividing L_s by G_s, which are both in power capacity units, returns the capacity credit (CC) for G_s, as shown in Equation 5. Depending on the values of L_s and G_s, this equation can be used to find either the cumulative capacity credit or incremental capacity credit. For cumulative capacity credit, the total amount of load that can be served and the total solar capacity on the grid are used in the equation. For incremental capacity credit, only the L_s and G_s values associated with the next increment of solar capacity are used.

$$CC = L_s / G_s \times 100\% \tag{5}$$

3.3 Incorporation of Energy Storage

Tools for Energy Modeling Optimization and Analysis (Temoa) is used to perform hourly operational analysis of solar and energy storage systems within the DEP and DEC balancing territories. Temoa is a bottom-up energy system optimization model developed at NC State that performs linear optimization to identify the least-cost pathway for energy system development (Hunter et al., 2013). The model code is open-source and all input data is publicly available. The energy system representation within Temoa is structured as a network in which technologies are linked together by a flow of energy commodities. Each technology has a set of engineering-economic characteristics, such as capital cost, fixed and variable operations and maintenance costs, and conversion efficiencies. The model also includes a variety of constraints that ensure realistic energy system performance. Additional information on Temoa development and operation can be found in Thomas et al (2017), DeCarolis et al (2018), and Hunter et al (2013).

The model objective function is given in Equation 6. The objective function minimizes the system-wide present cost of energy supply over a user-specified time horizon (one year in this case) by optimizing the installation and utilization of electricity generation technologies *t* built in a certain vintage year *v* across the system for every time slice *d*. In this case, *d* is one hour:

$$Obj = \min \sum_t \sum_v (Capacity[t,v] * CostFixed[t,v] + \sum_d^{8760} Activity[d,t,v] * CostVariable[t,v]) \tag{6}$$

Due to the exponential increase in computational complexity from modeling multiple years at high temporal resolution (Lara et al, 2018), this analysis includes least-cost operational dispatch for a single year with hourly resolution. In this database, capacity expansion is prohibited, and instead solar and storage assets were added parametrically. While Temoa was originally developed to perform capacity expansion, it has also been used to evaluate dispatch and has been benchmarked against a unit-commitment and dispatch model (de Queiroz et al., 2019).

Several constraint sets define energy storage in Temoa. The Temoa energy storage algorithm works such that energy storage is initialized at a full charge and must be completely discharged at the end of the year. Storage duration is represented as a fraction of a year, either a value of (2/8,760) for a two-hour battery or (4/8,760) for a four-hour battery. Roundtrip efficiency losses are modeled as 15% of nameplate capacity and are counted on charge only. Storage has explicit constraints preventing the stored energy in a given hour from exceeding the energy capacity or dropping below zero. The charge and discharge rates cannot exceed power capacity, nor can throughput.

3.4 Modeled Scenarios

Since the estimated capacity credit is a function of the deployment level, solar capacity credits were evaluated in the absence of energy storage at 20 different solar PV capacity levels. Eleven were chosen based on DEC and DEP capacity value results in DEC (2018) and DEP (2018) and the remaining 9 were chosen to offer a more complete range of values. Adefarati (2017) concluded that the reliability of solar plus storage is highly dependent on the capacity of the storage system, so it was important to choose a few different storage capacities. Thus, to evaluate the capacity credit of lithium-ion battery storage, storage dispatch patterns were obtained from Temoa at two storage power capacities, two storage duration limits, and five PV penetration levels, totaling 20 storage scenarios:

$$\text{Storage trials: } \begin{bmatrix} 0.08 \\ 0.5 \\ 2 \end{bmatrix} (GW) X \begin{bmatrix} 2 \\ 4 \end{bmatrix} (hr) X \begin{bmatrix} 0 \\ 3 \\ 5 \\ 10 \\ 13 \end{bmatrix} (GW Solar)$$

The chosen storage durations were based on commonly observed configurations of solar plus storage projects. Common lithium-ion battery system durations installed in the United States are two and four hours (GTM, 2018). The storage power capacities were chosen to provide bounds ranging from relatively modest to highly ambitious storage investments. Sioshansi et al. (2014), the study used in DeCarolis et al. (2018), calculated storage capacity credits for 80 MW systems. Thus, an 80 MW battery was modeled in order to benchmark results presented here with those in the existing literature. Trials with 0 GW solar were conducted to observe how storage would behave in the absence of solar. Approximately 3 GW of solar were on Duke Energy’s grid in 2017 and around 5 GW of solar were on the grid at the beginning of 2020. Trials including of 10 and 13 GW of solar were also conducted to assess how storage would perform with additional solar capacity beyond currently planned solar investments.

3.5 References

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4. RESULTS AND DISCUSSION

In Section 4.1, I discuss the results of the solar capacity credit analysis without energy storage, and then in Section 4.2 I compare my results with those reported in Duke Energy's IRPs. In Section 4.3, I explain how energy storage impacted the net load curves of multiple days with high demand and provide energy storage capacity credit estimates for the scenarios described in Chapter 3. Finally, in Section 4.4, I discuss limitations of the analysis and introduce a revised method to address one of these limitations.

4.1 Solar Capacity Value in the Absence of Energy Storage

Incremental additions of solar generation showed diminishing reliability value, consistent with what has been observed in the DEC and DEP IRPs as well as other literature mentioned earlier (Gami et al, 2017; Samadi & Singh, 2014; Frew et al, 2017; Richardson & Harvey, 2015). Figures 1a and 1b illustrate this trend for the incremental solar capacity credit and cumulative solar capacity credit, respectively. The box and whisker diagrams represent the average, first and third quartiles, minimum, and maximum measured capacity credits for each PV addition. The quartiles are the gray or red boxes, the averages are the colored lines, and the minimum and maximum values are shown as whiskers. In the context of Equations 4 and 5 which explain the calculation of LOLP, a diminishing capacity credit means the ratio between load added (L_s) and solar added (G_s) becomes larger, as less load can be added with each additional investment in solar. A qualitative illustration of this trend is in the Appendix section as Figure A4.

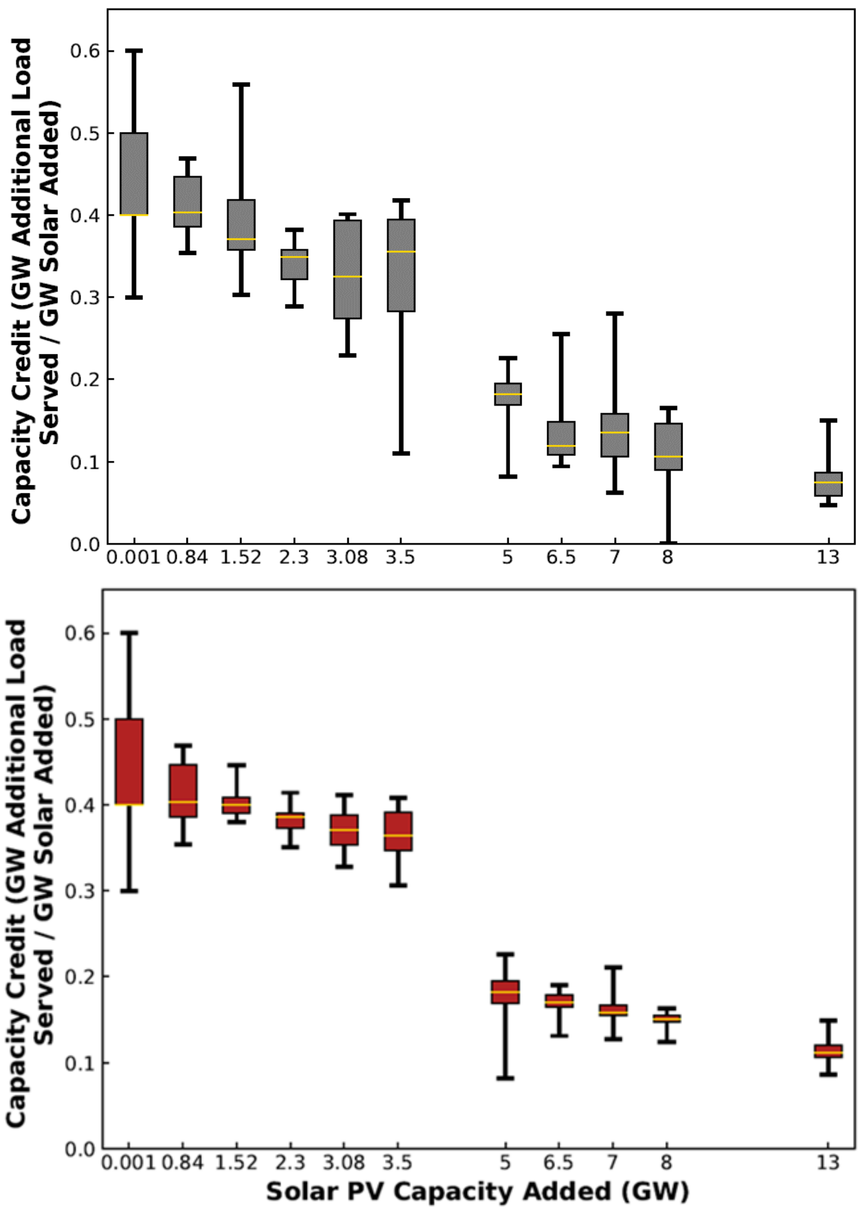


Figure 1: (a) Incremental and (b) cumulative capacity credit ranges by solar photovoltaic nameplate capacity

As noted in Chapter 3, the incremental capacity credit refers to the value assigned to the next increment of solar capacity added to the system, while the cumulative capacity credit refers to the value assigned to the aggregated solar capacity up to a specified capacity level. The solar PV capacity additions used in Duke's IRPs are included in Figure 1 along with several higher capacity levels to examine the impact of continued solar deployment. The hours in which the solar resource is weak or nonexistent gradually become the hours of highest net load as solar capacity is increased, which is why additional solar capacity shows diminishing returns. Increasing solar penetration changes the net load curve in two ways: first, solar pushes high summer net load into the late afternoon and early evening, when the solar resource declines in intensity; second, as higher solar generation shaves summer peaks more effectively than winter peaks, the peak net load hour shifts to the winter, where the solar resource is weaker. In general, the seasonal shift in net load is more impactful on capacity credit.

The incremental capacity credit was often close to the capacity factor of solar at the marginal hour for which the LOLP changed from a reliable to unreliable value. When the amount of additional solar capacity increased but the specific hour where the critical outage occurs did not change, the incremental solar capacity credit did not significantly change, if at all. In some cases, the capacity factor at the critical outage hour was higher, a result of an hour with high demand getting peak shaved to a larger degree than other hours. This effect is illustrated twice in Figure 1a, from 3.08 to 3.5 GW and from 6.5 to 7 GW which explains why there is a slight increase in capacity value with an increase in solar capacity.

Before comparing my results with those drawn from the Duke Energy IRPs, I will discuss the approach Duke used to evaluate solar capacity value. DEC and DEP provided summer (June, July, August) and winter (January, February) LOLE weighting values in no-solar scenarios and at various PV penetrations. They represent the likelihood that a loss of load event will occur in a particular season with varying amounts of solar on their respective grids. In DEC, loss of load events in a no-solar scenario occur 59% of the time in summer and 41% in winter. The peak net load with only 1 MW of solar occurs on a summer afternoon, unchanged from when there is 0

MW of solar. After the planned solar capacity additions from all four tranches in the DEC 2018 IRP are considered, LOLE occurs 93% of the time in winter and 7% of the time in summer. The DEP no-solar scenario has a seasonal LOLE weighting of 85% in winter and 15% in summer. After the planned solar capacity addition from all four tranches in the DEP IRP are considered, seasonal winter LOLE weighting is over 99%, such that solar capacity value is dictated solely from the winter capacity contribution.

I found that some values in my analysis were similar to those reported in DEC's IRP. The value of the first MW is highest with an average value of 44%, the same value reported in Table 9-C of DEC's 2018 IRP when only considering summer loss of load events. However, since DEC allocated a 59% LOLE weight to the summer season and 41% in the winter, and DEC assigned a 2.5% capacity credit to the first MW of solar in the winter, the resultant weighted average capacity credit for the first MW of solar is 27.2%. Loss of load events were much more prevalent in July and August hours in my analysis. For example, at 5 GW of solar, loss of load occurs in the winter 36% of the time, even though the two highest peak net load hours are in January. Tables from the 2018 DEC and DEP IRPs detailing their measured capacity values are provided in the Appendix.

The more evenly distributed loss of load events in this analysis may have contributed to the consistently higher capacity credit values compared to those presented in the Duke IRPs. As solar penetration increases, the incremental capacity value of solar decreases, but declined at a slower rate compared to Duke's estimates. In my analysis, the average capacity credit is below 10% as solar PV exceeds 7 GW of installed capacity; comparatively, DEC estimates that capacity credit falls below 10% by 1.52 GW of solar PV. At 8 GW solar, I found that the lowest incremental solar capacity credits are near 0%. While Duke did not examine this level of solar penetration, my results are in line with Duke's estimate of less than 1% capacity credit for additions past 7 GW. In general, my estimated capacity values are higher than Duke's, but an overall similarity in the declining trend of capacity credit values is observed.

4.2 Uncertainty in Capacity Value

Given that the Duke service territory has several large coal and nuclear power plants with assumed low forced outage rates, minimum cumulative available generation occurs when several of these plants are offline at once. This "lumpiness" is acknowledged in literature such as Ryan (2018), where the conclusion that a grid with a large number of smaller generators would have different levels of reliability and capacity values than one with fewer, larger generators is true in this analysis as well.

In the context of my analysis, I observed infrequent but impactful system realizations where multiple large units were simultaneously unavailable, creating extreme events where a cumulative generation value was much lower than even the second or third lowest generation values. These events were so infrequent that they occurred less than once per 50,000 iteration trial on average. In the trials with one or two extremely low cumulative generation values, capacity values for solar were higher. My analysis required a total of 16 loss of load events to occur out of every 50,000 iterations, and load was continuously added after the solar capacity was installed until the grid reached that level of reliability again. With one or two extremely low cumulative generation values stemming from the unavailability of multiple large generators, several hours will experience a loss of load event. Therefore, one extremely low generation value causes loss of load events across a wider range of hours. Many of the sub-peak, high load hours were in July and August, so solar capacity values were comparatively higher when cumulative generation was low because more loss of load events associated with conventional plants occurred during these summer hours.

Other times, the lowest cumulative generation values were close to each other, making a smoother tail in the cumulative generation distribution. In trials without extremely low cumulative generation values where the “lumpiness” between cumulative generation values was lower, fewer hours experienced loss of load. This outcome resulted in dual-peaking behavior (i.e., the magnitude of the peak summer hour and peak winter hour were less than 100 MW between each other). In these cases, the solar PV capacity value remained relatively low as solar PV capacity increased. Each of the 12 trials exhibited a relatively wide range in capacity values at each solar penetration level, mostly the result of the simulated grid experiencing high or low spreads between minimum generation values.

4.3 Impact and Capacity Credit of Energy Storage

Using Temoa, hourly energy storage and dispatch across a single year was determined for each storage duration, storage capacity, and PV penetration combination, and the resultant dispatch pattern was used to determine the capacity credit of storage under those conditions. Figure A6 in the Appendix section shows a visual representation of storage dispatch behavior throughout the year in one scenario, where the exact hours storage charged and discharged can be identified. Figure 2 shows examples of these operational outputs for select days, with demand (red), net load with 5 GW solar PV (orange), and net load with solar and 2 GW/8 GWh energy storage (dotted blue). Figures 2a and 2c show January 22, the peak winter day on the combined DEC and DEP grid system, and Figures 2b and 2d show July 16, a summer day with high demand. Additional net load curves are provided in the Appendix under Figure A6.

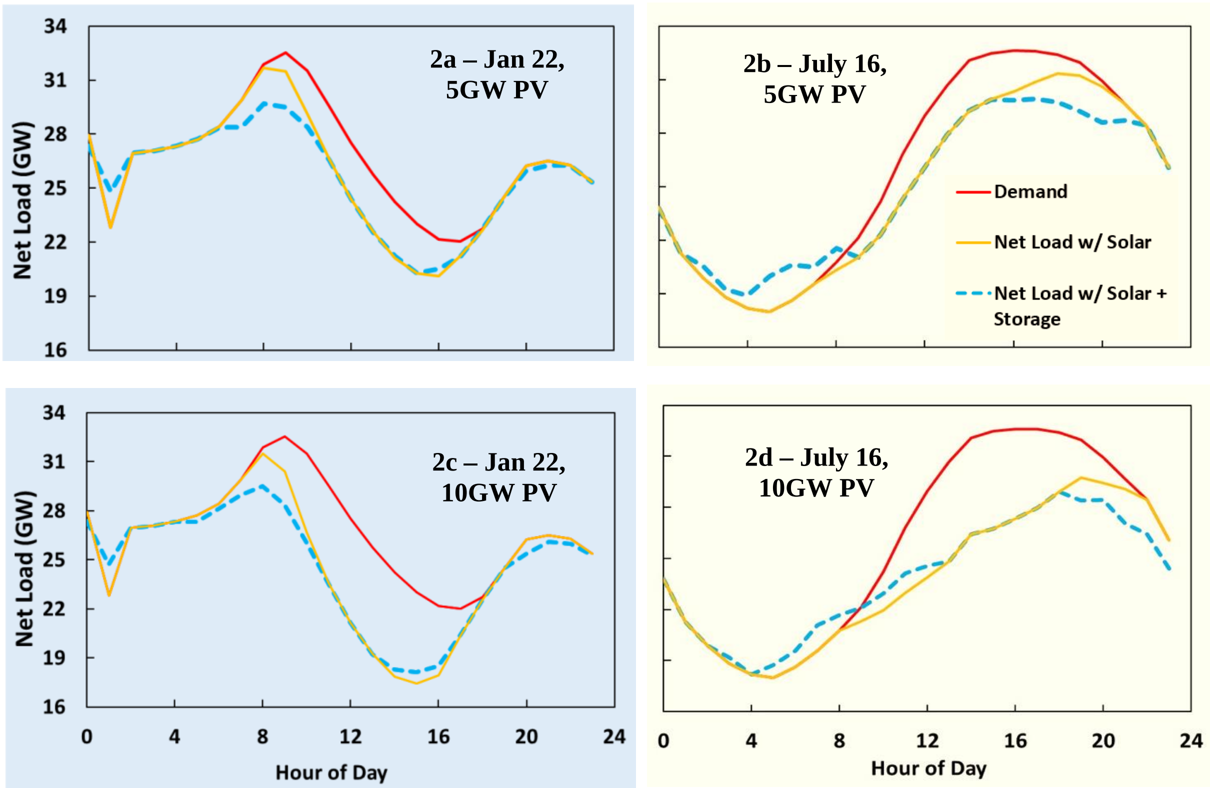


Figure 2: Net load on peak winter and summer days with solar generation and a 2GW/8GWh energy storage system. (2a) January 22 with 5 GW solar; (2b) July 16 with 5 GW solar; (2c) January 22 with 10 GW solar; (2d) July 16 with 10 GW solar

The energy storage systems demonstrated consistent charging and discharging patterns under all combinations of storage capacity and solar penetration, while varying storage duration yielded slightly different operational behaviors. During peak days, in all cases, energy storage charged predominately in the middle of the night and discharged during times of peak net load. Storage reduced overall grid operational costs throughout the year. Higher PV penetrations narrowed the duration of the net peak loads in both winter and summer, which is particularly evident in Figure 2c. Because the energy storage systems have a fixed discharge duration, these narrower peaks allowed the energy storage systems to reduce the new net peak loads more effectively.

The capacity value trends of four storage power capacity and duration combinations at various PV penetrations are shown in Figure 3. Figures 3a and 3b show the results for 500 MW of storage with two- and four-hour maximum discharge durations, respectively, while Figures 3c and 3d show comparable results for 2 GW of storage. Since narrowed peaks still last for multiple hours, longer duration storage is more effective and results in a higher capacity credit allocation for storage. Shorter duration energy storage is more energy limited and therefore cannot participate as effectively in peak shaving during multi-hour periods of high demand.

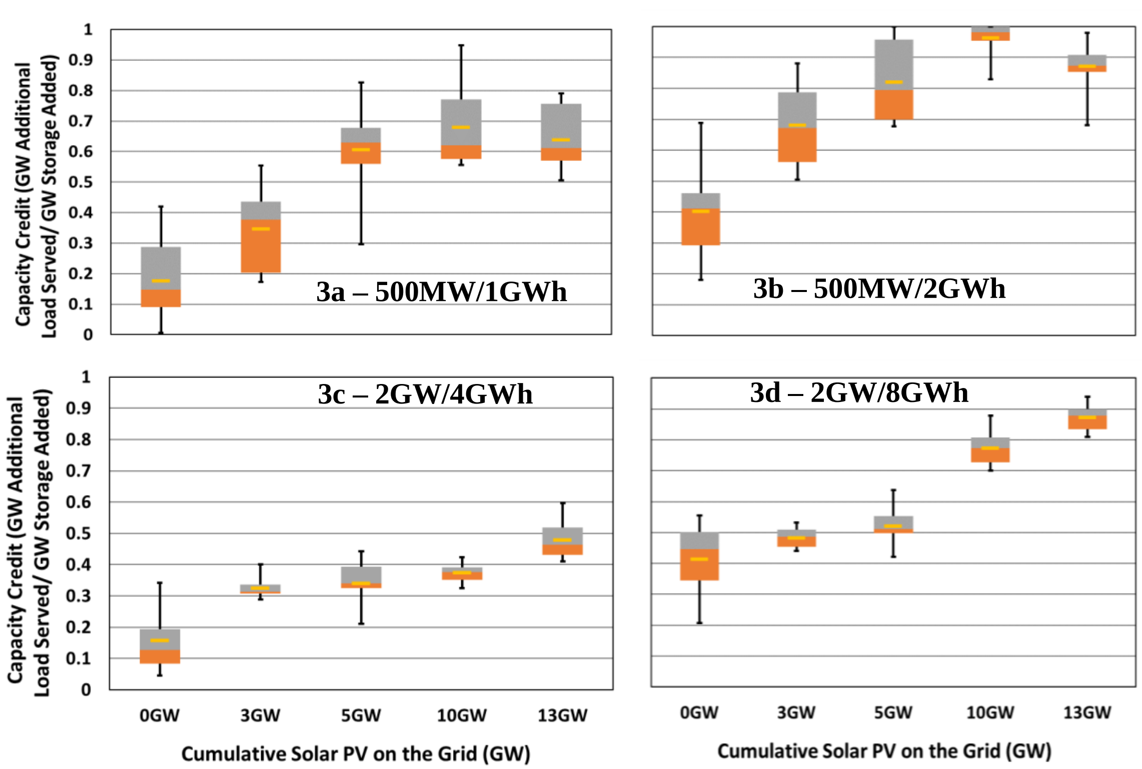


Figure 3: Capacity credit of energy storage as a function of solar PV deployment, given different storage configurations: (a) 500MW/1GWh; (b) 500MW/2GWh; (c) 2GW/4GWh; (d) 2GW/8GWh

I ran additional operational model tests at the 5 different PV capacities with 80 MW, 320 MWh storage to allow us to compare my results to Sioshansi et al (2014), which was used in the North Carolina energy storage report (DeCarolis, 2018). In the 3 GW solar PV cases, the average capacity credit is 75%, the same as presented in Sioshansi et al (2014). However, it is worth noting the spread in results, which ranged from 0% to 100%. Similar to solar capacity value, the storage capacity value is affected by the cumulative generation levels within each trial. Extremely low cumulative generation values made storage less effective. Generally, if the difference between the lowest generation value and the second lowest generation value was small (20 or 70 MW difference), capacity credits were larger (100% and 84%, respectively). Contrarily, a high deviation between the lowest and second lowest generation values (1.21 or 1.24 GW difference i.e. a lumpier grid) resulted in lower capacity credits (10%). This wide range is observed for most PV capacities, as shown in Figure 4. In one case, measured capacity credit was 0%, meaning the 80 MW storage system did not affect the shape of the net load curve, and in another case, capacity credit was 100%.

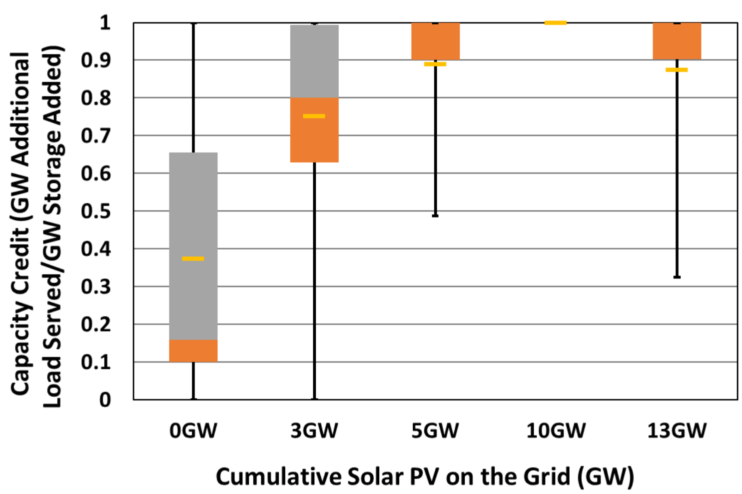


Figure 4: Capacity credit of 80 MW/320MWh energy storage system at five different PV deployments. Uncertainty is much higher than the other tested storage configurations.

At PV deployments greater than 10 GW, solar actually began to broaden winter morning net load peaks. In my analysis, with 10 or 13 GW of PV deployments, overnight and early morning winter net load exceeds afternoon and evening net load. Instead of winter peaks occurring between 8 and 10 am, the net peak hours on a typical winter day shift earlier (5-9 am) in the presence of high penetrations of solar PV. This is a possible reason why there is a slight decline in capacity credit from 10 GW to 13 GW observed in Figures 3a, 3b, and 4. This topic will be elaborated upon in the next subchapter.

Figure 5 highlights the impact of storage discharge on peak net load hours within Duke's territory. In Figure 5, the percentages represent the actual storage discharge in the given hour compared to maximum discharge capability based on the storage system's power capacity. The darker bars show net load without storage and the lighter bars show net load including storage. Figures 5a, 5c, and 5e have the eight highest net load hours without storage plotted in descending order, while Figures 5b, 5d, and 5f have the new eight highest net load hours after considering storage dispatch. Energy storage with 2 GW of rated capacity and a four hour storage duration can shift Duke's grid back to a net load peak in the summer depending on the amount of solar capacity on the grid. This shift to summer net peaking increases the capacity value of additional solar, as the solar resource better corresponds to peak net loads in the summer months. As seen below in Figures 5e and 5f, at 13 GW of PV, the system remained winter peaking, even though the storage system had nearly 100% capacity value. The takeaway here is that storage and solar deployments should move in lockstep to maintain high capacity values from both assets.

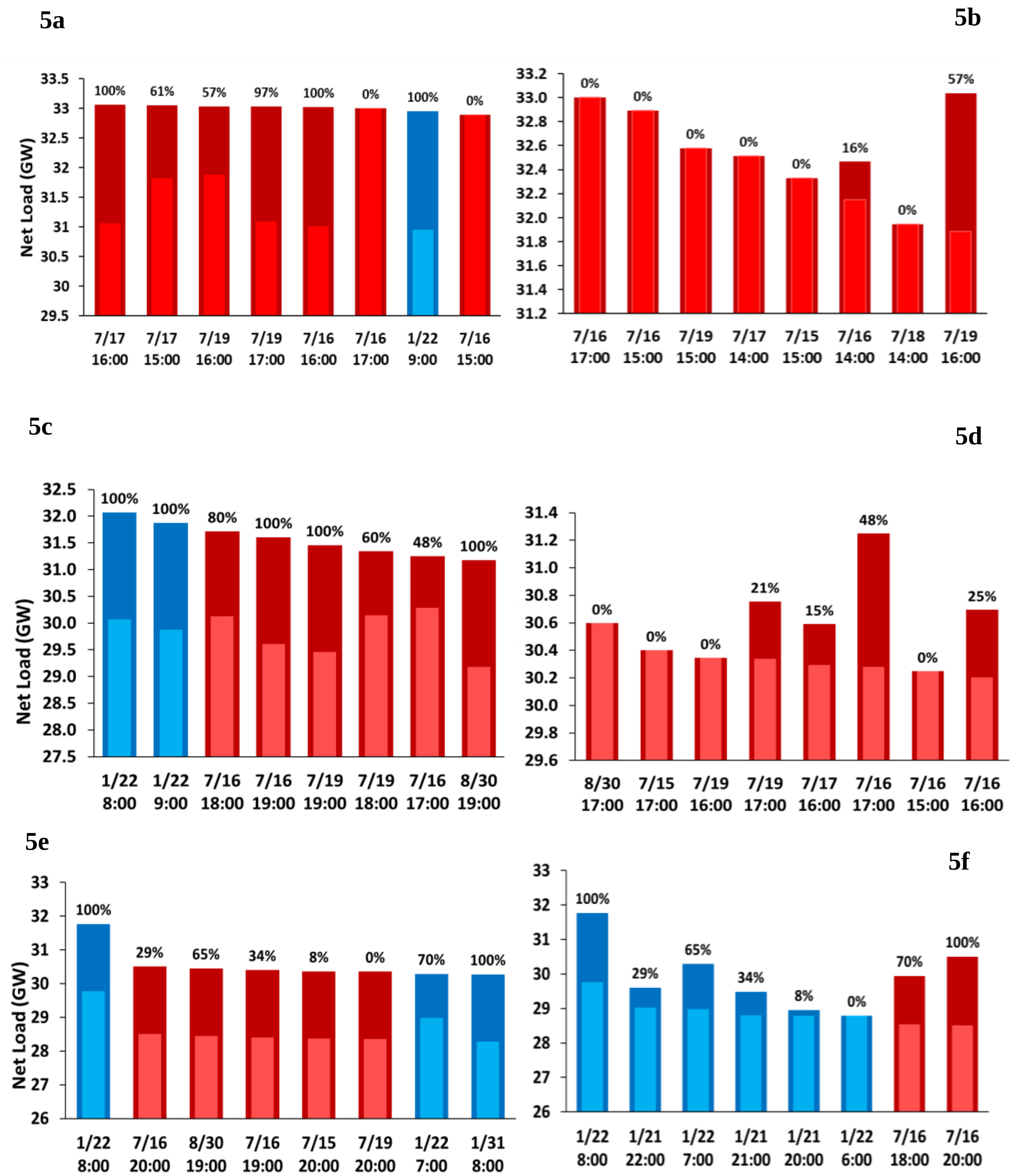


Figure 5: Net load at peak hours without storage (darker bars) and with storage (lighter bars) with (a, b) no solar; (c, d) 5 GW solar; and (e, f) 13 GW solar PV. The peak net load hours are displayed in descending order based on net load before storage (left column) and after storage (right column). The percentages show the storage discharge in the given hour compared to maximum discharge capability.

In some cases, the presence of storage changed the hours of peak net load to ones where there is little to no storage available to dispatch, similarly to how the presence of solar shifts the hours of peak net load to hours with weaker solar resource. This is shown in Figures 5c and 5d. At 5 GW PV levels, the eight highest net peak hours in the year – that is, the peak net load hours once storage has been added to the grid – see little to no actual storage dispatched. An artifact of the energy-limited nature of storage, it is impossible to achieve a perfectly flat net load curve (unless there is an astronomical amount of long duration storage capacity on the grid). During these peak demand hours, PV generation contributed substantially towards reducing peak. In Figure 5a, the hours 7/17 16:00 and 7/16 16:00 are high demand hours and see high storage dispatch with zero solar on the grid, but dispatch less capacity when 5 GW of solar is introduced (15% and 25%, respectively), shown in Figure 5d. Extrapolating from the results in Figure 5, it may be that, at least for Duke Energy's grid, relatively modest energy storage capacity additions would considerably change the capacity value of solar by shifting peak net load towards more favorable hours for solar technologies.

4.4 Analysis Limitations

It is important to note that LOLP analyses (including this study) can lack certain real-world operational constraints, which may affect the actual loss of load distribution. The method utilized here assumes that all available generators are equally able to serve load in all hours. This implicitly disregards operational constraints such as ramping limits of generators. Such ramping limits can be a binding constraint while meeting morning winter peaks, which are narrower and may be less predictable than broader summer peaks. In addition, generator run time and unit commitment constraints are not considered, which could constrain certain generator's availability. Also, my model assumes perfect foresight of demand at every hour since demand was an input to the model.

The objective function in Temoa minimizes grid operational costs throughout the year. In my analysis, Temoa only performed energy arbitrage, charging storage during hours with low electricity production costs and discharging during hours with high marginal electricity production costs. This objective mostly aligns with the objective of my analysis, which is to assess the peak shaving capabilities of energy storage. However, sometimes the storage dispatch results deviated significantly from what "optimal" peak shaving would look like. The storage dispatch pattern has to do with the differences in marginal electricity costs throughout the high demand hours. In scenarios with high solar penetration, hours of peak demand had a lower marginal electricity cost than other high-demand hours because solar PV, which generates electricity with zero marginal cost, contributes to meeting demand. Therefore, the overall marginal cost of electricity is lower, which influenced Temoa to discharge storage during other hours with high demand. These "other" hours have lower solar insolation and therefore require electricity from generating units with higher operational costs. Temoa will effectively perform arbitrage with storage by displacing hours with higher marginal cost electricity, but it does not always result in neatly clipped demand peaks with flat tops, as the model optimizes when it uses storage to offset the highest cost electricity.

There were more times when the energy arbitrage objective misaligned with optimal peak shaving in 13 GW solar scenarios compared to 10 GW solar scenarios, as the additional solar generation during summer days and summer evenings lowered the electricity price during peak hours more significantly. Consider the scenarios with 10 GW and 13 GW of solar and 500 MW/2 GWh of storage on July 16th. On the selected day, the 13 GW solar case produces 1.4 GW more solar than the 10 GW solar case in the net peak hours. The 10 GW solar case has 1200 MW more coal and 200 MW more gas generation in those hours. Since these technologies have higher operational costs than solar, the marginal cost of producing enough electricity to meet demand in the 10 GW solar case is higher at 5pm when compared to the 13 GW solar PV case. This leads to more battery discharge during those hours in the 10 GW case, relative to the 13 GW case. This difference continues over the next four hours until 9pm. During some of this time, it is more cost-optimal for the battery to discharge, and does so for four hours from 7-11pm. Peak net load on July 16th occurred at 7pm in the 10 GW and 13 GW scenarios, so storage meets peak net load in the 10 GW case. In the 13 GW case, solar provides a sufficient amount of generation at 7pm such that storage does not discharge. As solar generation wanes and disappears, storage discharges from 8pm-12am, so this system did not shave the peak net load hour as effectively. Thus, the capacity value is higher at the 10 GW solar penetration level. The net load curves for both 10 GW and 13 GW of solar with 500 MW/2 GWh of storage are shown below as Figures 6a and 6b.

For the most part, 2GW/4GWh and 2GW/8GWh storage systems discharge during periods with both the highest marginal generation costs and highest net peak loads, sufficiently shaving peak but receiving lower capacity credits. As shown earlier in Figures 3 and 4, a 2 GW storage capacity resulted in a lower capacity credit at high PV levels compared to a 500 MW storage capacity. Nearly 100% of a 500 MW system contributed to peak demand economically, whereas with a 2 GW system, dispatching 100% of its power or energy capacity may not be necessary. A high stored energy capacity provided energy arbitrage benefits during on- and off-peak hours, maximizing operational value but not *capacity* value.

Marginal electricity costs may also be lower in the middle of the day than in the evening due to technological constraints such as ramping down of coal plants. In Temoa, coal plants have ramp up and ramp down rates, reflecting the thermodynamic limits associated with quickly increasing or decreasing power generation from coal units. This ramp up and down may be necessary at the beginning and the end of the day as solar generation reduces the need for more expensive coal power. This ramping may be another reason besides optimized energy arbitrage as to why storage discharged at irregular times, such as what is illustrated in Figures 6c and 6d.

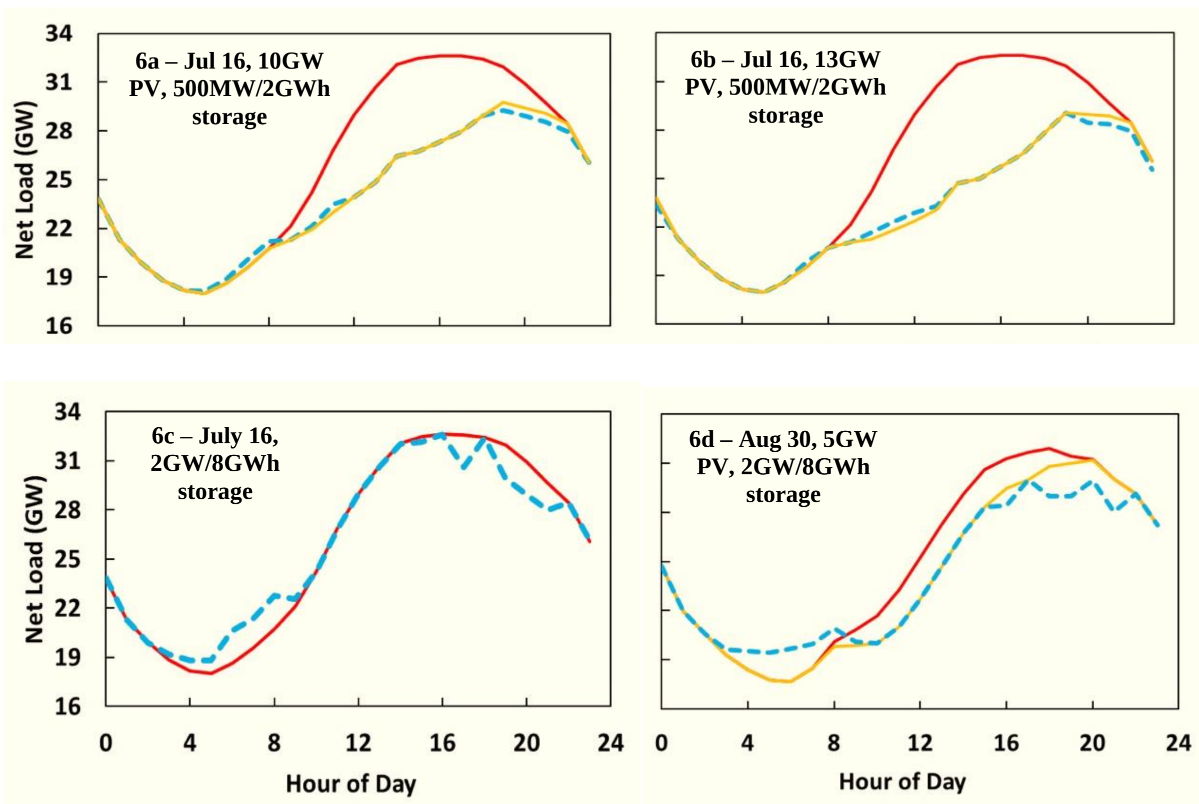


Figure 6: Modeled energy storage dispatch with 500 MW/2GWh storage and 10 GW solar (6a) or 13 GW (6a) and 2GW/8GWh storage on July 16 with no solar (6c) or August 30 with 5 GW solar (6d)

To better understand the impact of using these operational results, I optimized energy storage dispatch separate from Temoa to see how the resultant capacity credit changed. In this new analysis, a simpler energy storage dispatch pattern was created specifically to perform peak shaving instead of energy arbitrage. I modifed the energy storage dispatch behavior for four peak days in the year (one winter and three summer) solely for peak shaving, meaning I chose hours of lowest net load in the day to charge and highest net load in the day to discharge. Storage began and ended the day at zero charge, thus leaving the state of charge throughout the rest of the year unchanged. Because of time limitations, not all hours in the year could be optimized. However, the most important days to modify are those with peak or near-peak net load, since those hours have the highest impact on the measured capacity value of storage. Other days would likely have a diminished to negligible impact on capacity value, analogous to how most days in the year have a negligible impact on the LOLP of a grid. I used the resultant storage dispatch pattern in the LOLP model for two storage configurations at two solar PV penetrations and recalculated the capacity credit for these cases.

Select results from this analysis are in Figures 7a and 7b. These figures show examples of the new net load curves that were created by focusing on peak shaving. Peaks are much flatter in both the winter day (January 22) and the summer day (August 30). No analysis was performed to determine how this impacted grid operational costs. Energy storage configurations with high energy capacity are shown here to more prominently show the resultant differences in net load with storage.

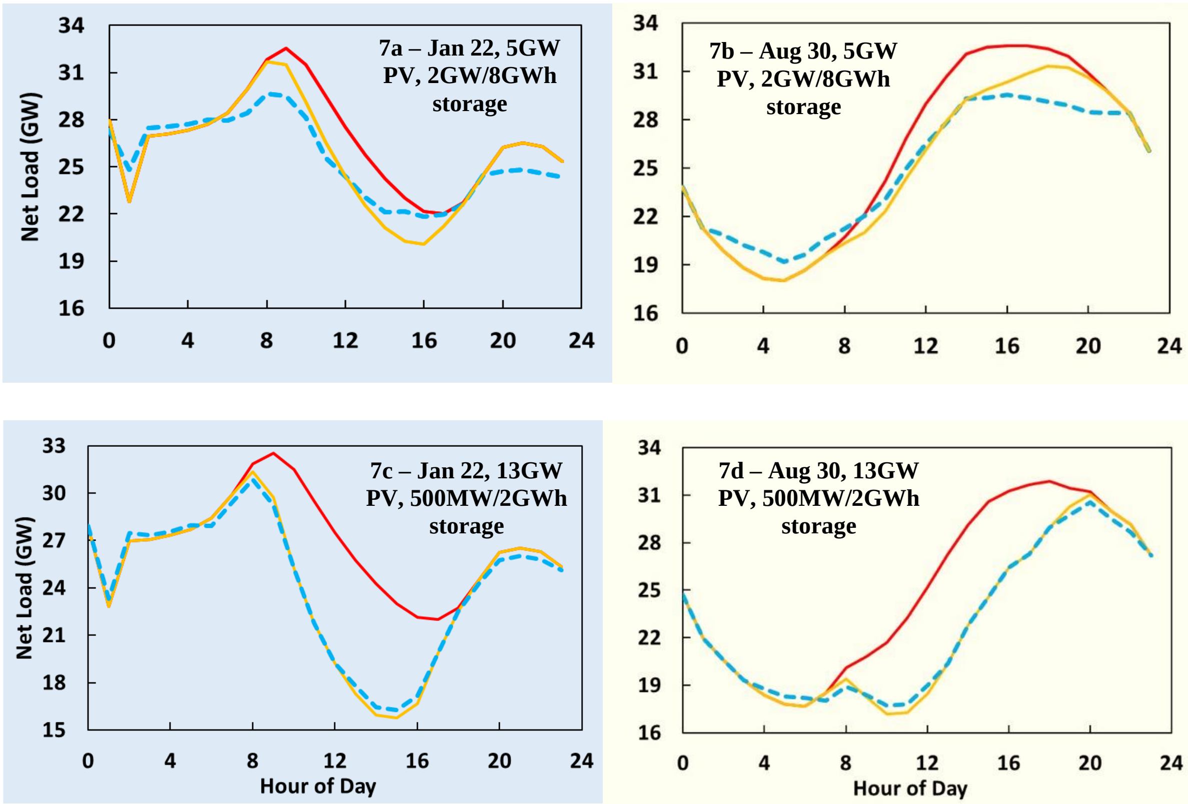


Figure 7: Net load curves of high demand days on January 22 (7a and 7c) and August 30 (7b and 7d) with 5 GW solar and 2GW/8GWh storage (top) or 13 GW solar and 500MW/2GWh storage (bottom). Storage dispatch was adjusted to optimize peak shaving capability

Figure 8 shows how this peak shaving optimization impacted the capacity credit of energy storage in two different scenarios. In the lower storage capacity scenario, the optimization impacted the average capacity credit significantly. Referring back to Figure 3, which illustrated storage capacity credit at four different storage capacity / duration configurations, the 500 MW systems in 3a and 3b showed a decline in allocated capacity credit from 10 GW of solar to 13 GW of solar. After performing this peak shaving optimization, this capacity credit reduction was not observed in the 13 GW case. Instead, capacity credit rose 11% (from 87% to 98%) compared to its original 13 GW value. This is also a 2% increase compared to the 10 GW capacity credit, which is 96%. However, this revised storage dispatch test had a negligible impact on the 2 GW, four-hour duration energy storage system. Only a 3% increase was observed between the Temoa-optimized scenario and the peak shaving storage dispatch scenario (from 77% to 80%). These systems already had a positive correlation between PV penetration and capacity credit with the storage dispatch pattern optimized by Temoa.

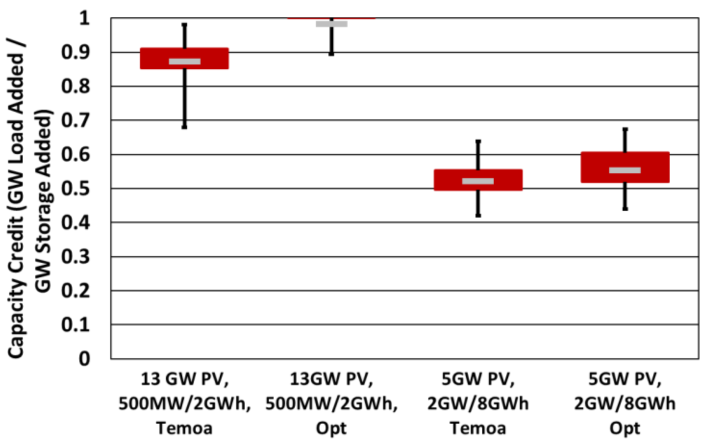


Figure 8: Energy storage capacity credit difference between Temoa optimal dispatch and peak shaving optimal dispatch. “Opt” refers to peak shaving optimization

Based on the results of these two adjusted optimization scenarios, it is reasonable to assume the same pattern would be observed for most or all other storage configurations and solar PV capacity additions, or at the very least, scenarios with four-hour storage duration. Therefore, the results in this analysis may be conservative, as the storage systems were not fully optimized for peak shaving. Additional analysis would be required to fully quantify the divergence between the two optimization methods.

5. CONCLUSION AND FUTURE WORK

The capacity value of solar depends on a multitude of factors, including the penetration level of solar PV on the grid, and should not be reported as a single scalar value. Studies on the capacity value of variable energy resources should include some level of sensitivity analysis or they may miss key insights. The difference between the capacity values estimated by Duke Energy Carolinas and Duke Energy Progress and estimated in my study suggest that a review by Duke Energy on their capacity values may prove worthwhile, especially as they prepare their 2020 Integrated Resource Plan. Since their grid is close to dual-peaking (winter-summer) status, Duke Energy's territory, which has less than 2 MW of battery energy storage currently operating in NC (DeCarolis, 2018), could benefit from energy storage assets installed over the course of several years in order to improve the value of their utility-scale solar assets. In my analysis, investing in 2 GW of four-hour energy storage on Duke's grid with 10 GW of solar PV would result in a grid system with a peak net load in the summer. This can be achieved within the next several years, and additional analysis may find that less solar or less storage is necessary to recreate a summer peak net load grid system to maintain a higher solar capacity value.

Not all energy storage configurations can shift the grid back to a summer peaking system. The same amount of storage as mentioned earlier (2 GW of four-hour storage) on a 13 GW solar grid instead of a 10 GW grid is sub-optimal from a peak shaving perspective and therefore would not be as cost-effective, since both assets provide less value to the grid. Energy storage at some level is inevitable as more VERs come online on every grid system and waiting to invest in energy storage may reduce the value of the initial additions. Every grid is dynamic, and utilities and grid operators must be cognizant of the storage investments they will make relative to PV penetration levels and how it shifts the net load on the grid.

The “lumpiness” of the grid system under analysis is very important when calculating solar or storage capacity credits. A grid with a large number of smaller generators would have different levels of reliability and lower solar capacity values than a grid with fewer, larger generators. The demand profile and resultant net load curve from excluding VER generation are extremely important when evaluation storage capacity value as well. Because energy storage systems have a fixed energy capacity and discharge duration, narrower net load peaks are more favorable for both two- and four-hour duration energy storage systems, as the storage systems can more effectively reduce those net load peaks.

There are limitations in my work that should be considered by those looking to use the methodology or results of this analysis. First, while I used real solar generation and load data from 2018 and 2019, there is no meteorological uncertainty, either in Temoa or the LOLP model. There is an inherent assumption that solar PV hourly irradiance at every hour is known throughout trials. It is unclear if this results in an overestimation or an underestimation of capacity values, but would change the net load curve, given the hourly generation from solar during peak hours would potentially increase or decrease. The perfect foresight assumption for electricity demand and generation is not a unique limitation to this analysis. Few studies consider meteorological uncertainty, assuming static solar PV hourly capacity factors the same way as is presented here.

A second limitation is that geographical factors are not considered in this analysis. There is no incorporation of transmission and distribution infrastructure, shading, system location, or land usage. Again, this is not a unique limitation. Residential, commercial, and industrial scale solar projects connected to the grid at the distribution level could all have separate capacity values from utility-scale projects in the same area, and storage may impact capacity value in different ways. These limitations highlight the importance of sensitivity analysis when interpreting capacity value of variable energy resources.

A third important limitation is that, as discussed in Chapter 4.4, Temoa cost-optimizes storage by minimizing grid operational costs, with no explicit prioritization of using energy storage for peak demand reduction. This means Temoa will solely use energy storage for energy arbitrage. This did not perfectly align with peak reduction benefits due to variations in electricity production costs throughout the day. Sometimes the hours with highest marginal electricity costs were not the highest net load hours of the day. This could have been caused by more expensive generators coming online whenever solar resource availability was low or non-existent. It could have also been caused by coal asset ramping, which is inefficient and increases that asset's operational costs, and therefore storage would dispatch during those hours. Regardless of the cause, the storage capacity credit results would likely be higher if a storage dispatch algorithm were tuned to prioritize peak shaving, an observation made during my offline storage dispatch analysis.

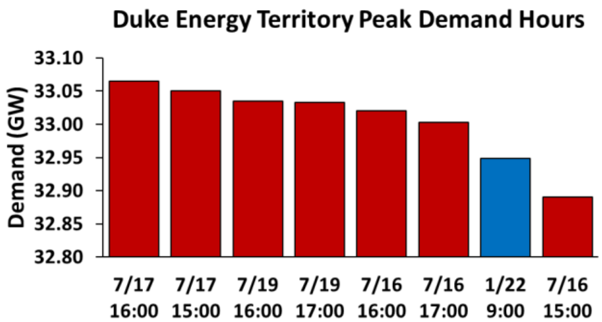
Future work topics include altering the objective function of Temoa to focus on peak shaving. This would yield improved capacity value estimates under specific energy storage configurations. Future work could further incorporate economic considerations related to the capacity value of solar and energy storage, such as additional analysis on the impacts of these resources on annual grid operational costs, and electricity prices. In DeCarolis et al. (2018), the capacity expansion results were highly sensitive to the assumed capacity values. Further work to characterize how more accurate capacity credit estimates affect the deployment levels of solar and storage is warranted. Perhaps the improved accuracy of this aspect of capacity expansion modeling could offer new insights about pathways towards reliable, low-carbon electric grid systems. Finally, it would be interesting to study the environmental impact of using energy storage and solar for peak shaving, similar to Hittinger & Azevedo (2015), but in the context of the Duke territory. While solar PV and energy storage are slowly becoming more attractive assets from an economic standpoint, the moral imperative of reducing anthropogenic greenhouse gas emissions is also critical to consider.

APPENDIX

Solar Capacity at Each Penetration Level (Incremental MW)	Solar Capacity at Each Penetration Level (Cumulative MW)	Penetration Level	Winter	Summer	Annual
0	0	DEC – 0 Solar	2.5%	44.7%	27.2%
840	840	DEC – 840 Existing + Transition	0.9%	33.6%	11.1%
680	1,520	DEC – Tranche 1 – Fixed	0.5%	29.5%	6.5%
780	2,300	DEC – Tranche 2 – Fixed	0.4%	23.1%	2.9%
780	3,080	DEC – Tranche 3 – Fixed	0.2%	19.4%	1.6%
420	3,500	DEC – Tranche 4 – Fixed	0.2%	14.6%	1.2%

Solar Capacity at Each Penetration Level (Incremental MW)	Solar Capacity at Each Penetration Level (Cumulative MW)	Penetration Level	Winter	Summer	Annual
0	0	DEP - 0 Solar	1.2%	35.4%	7.2%
2,950	2,950	DEP - 2950 Existing + Transition	0.6%	12.4%	0.6%
160	3,110	DEP - Tranche 1 – Fixed	0.3%	12.2%	0.3%
180	3,290	DEP - Tranche 2 – Fixed	0.3%	11.6%	0.3%
160	3,450	DEP - Tranche 3 – Fixed	0.2%	8.8%	0.3%
135	3,585	DEP - Tranche 4 – Fixed	0.2%	8.2%	0.3%

Figure A1: Capacity value results from Duke Energy Carolinas (1a) and Duke Energy Progress (1b)



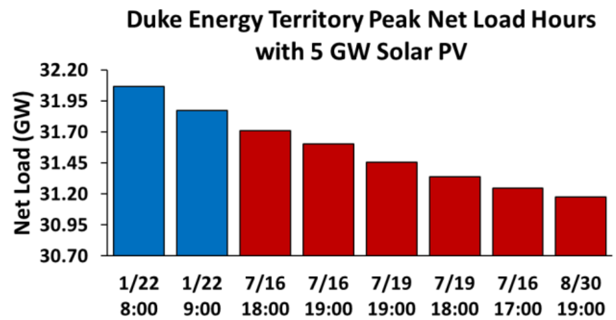


Figure A2: Duke Energy territory peak hours before and after the introduction of 5 GW solar PV. This illustrates how the 2 highest load hours changed from summer to winter, leading to a re-evaluation of the capacity value of solar (From Duke Energy Carolinas' 2018 IRP and Duke Energy Progress's 2018 IRP)

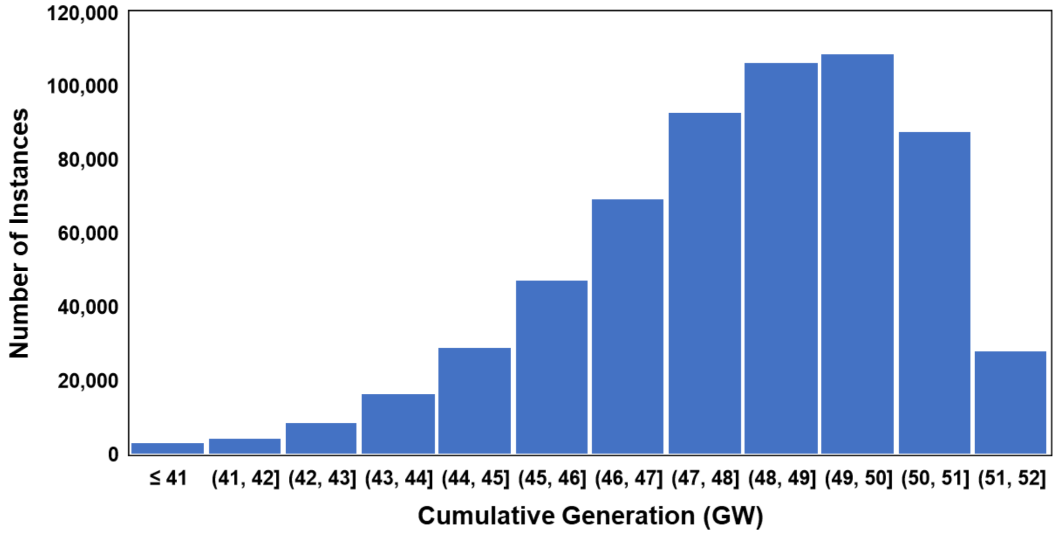


Figure A3: Histogram of all 600,000 cumulative available generation values using a Monte Carlo simulation. Duke Energy's grid is overbuilt so load needed to be added to reduce reliability before LOLP analysis could be conducted.

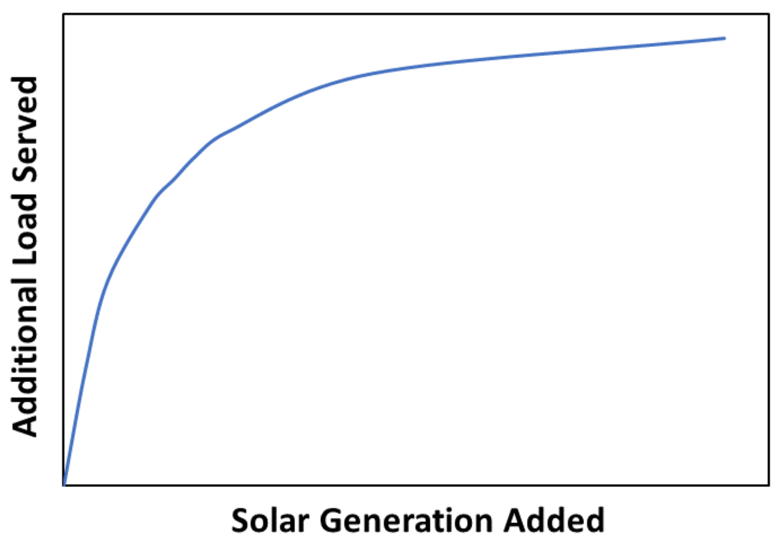


Figure A4: Loss of Load Probability Isovalue Curve. As additional generation is brought online, less additional load can be served to maintain the same level of reliability on the grid

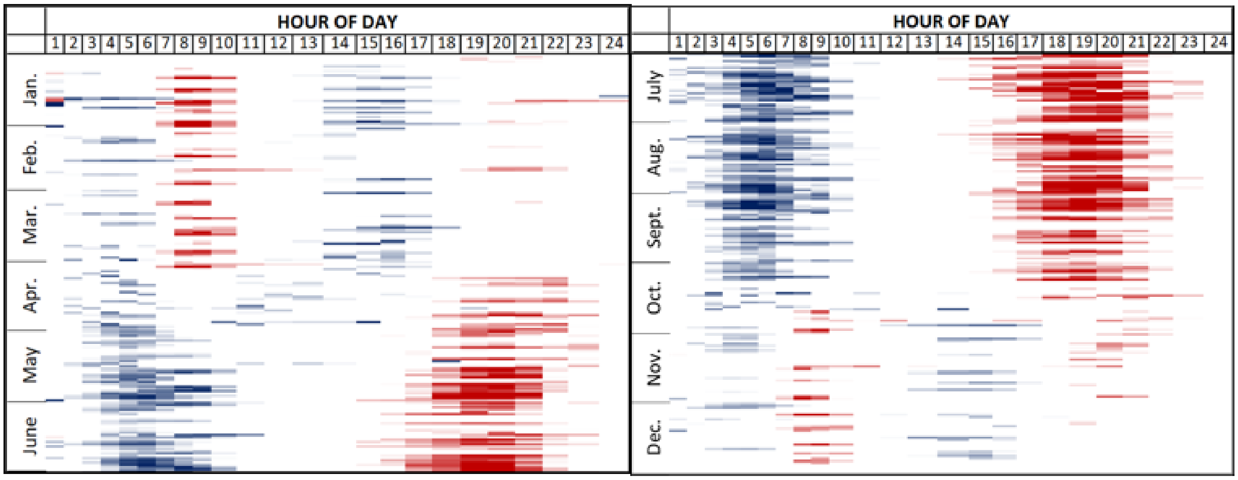


Figure A5: Energy storage dispatch pattern for 2GW/8GWh of storage on a grid with 5 GW solar PV. Blue indicates storage charging, which mostly occurred overnight or in the early morning. Red indicates storage discharging, which mostly occurred winter mornings and early summer evenings.

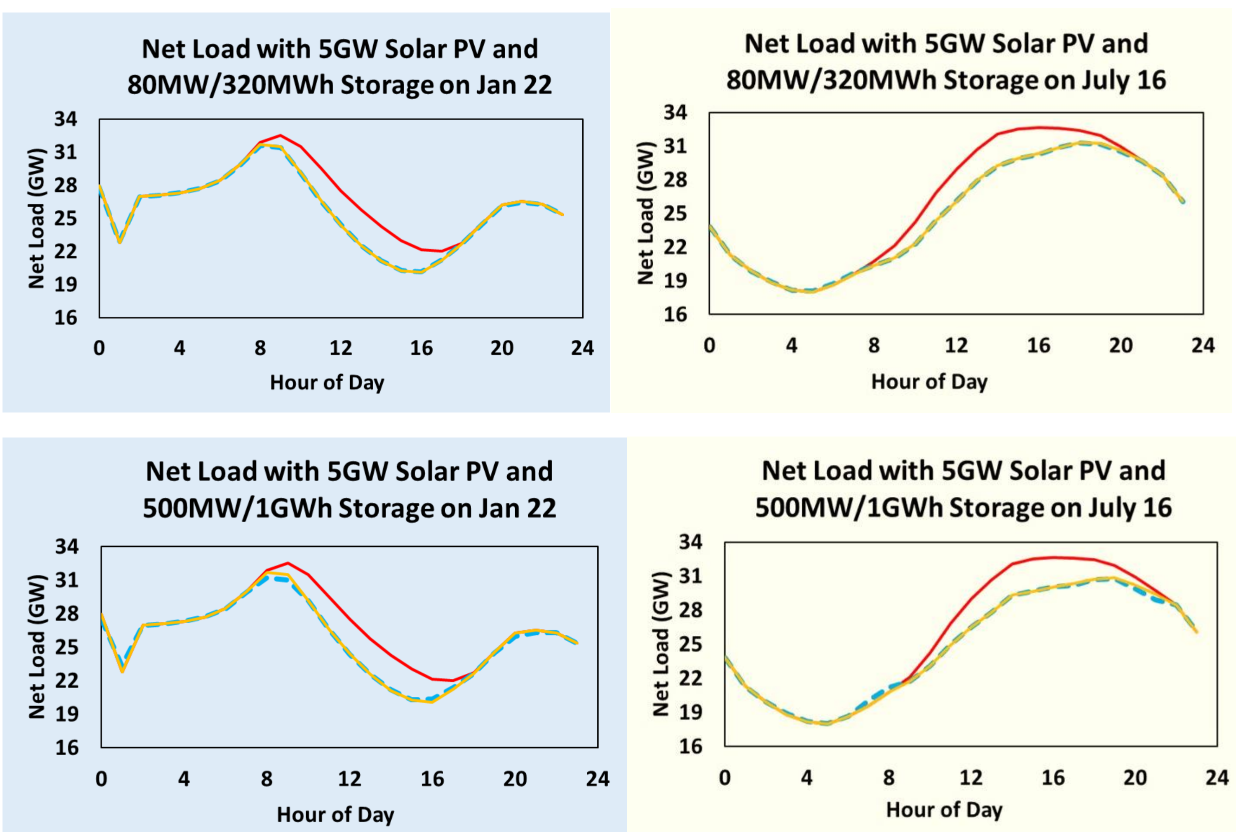


Figure A6: Select Net Load Curves

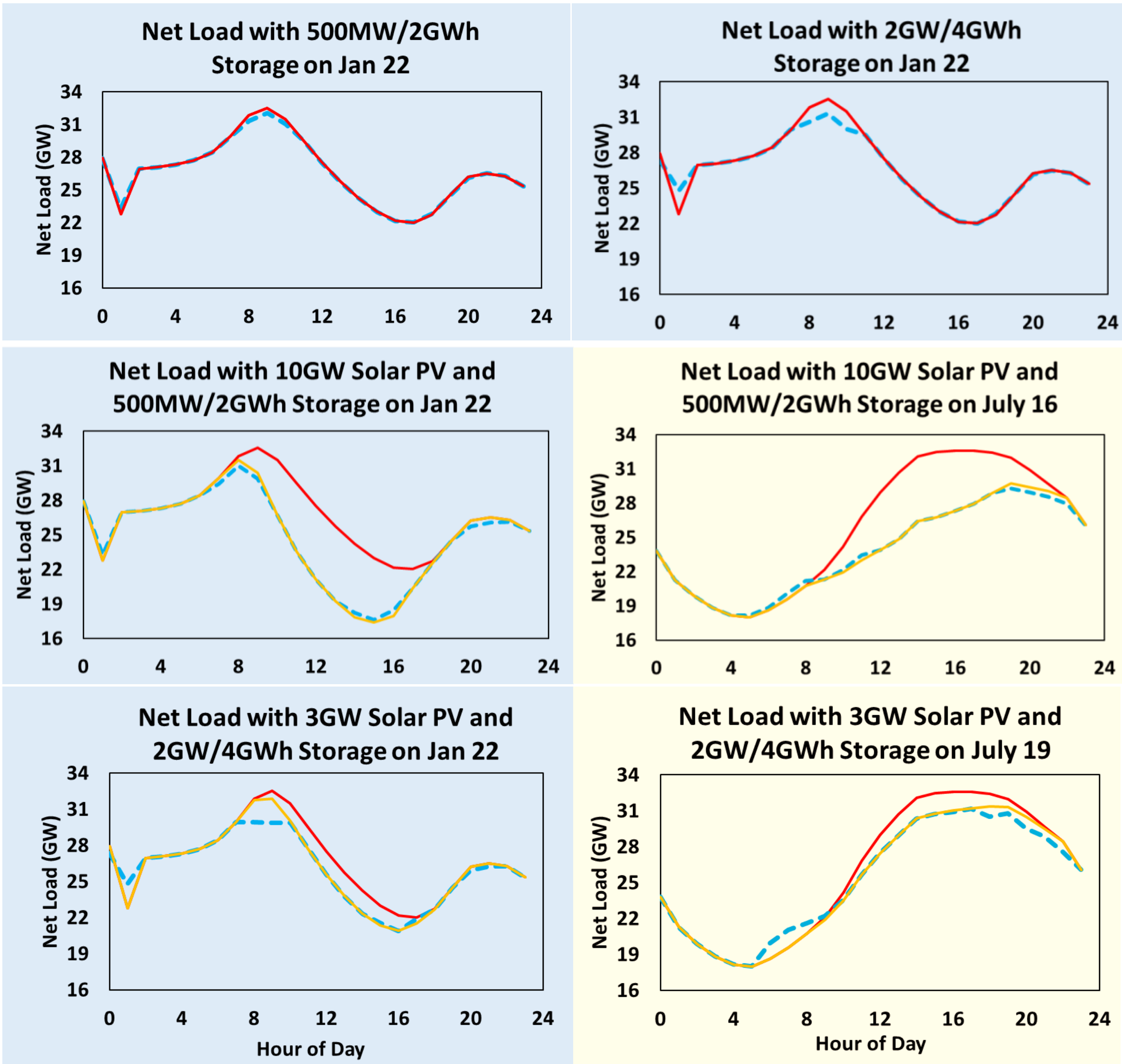
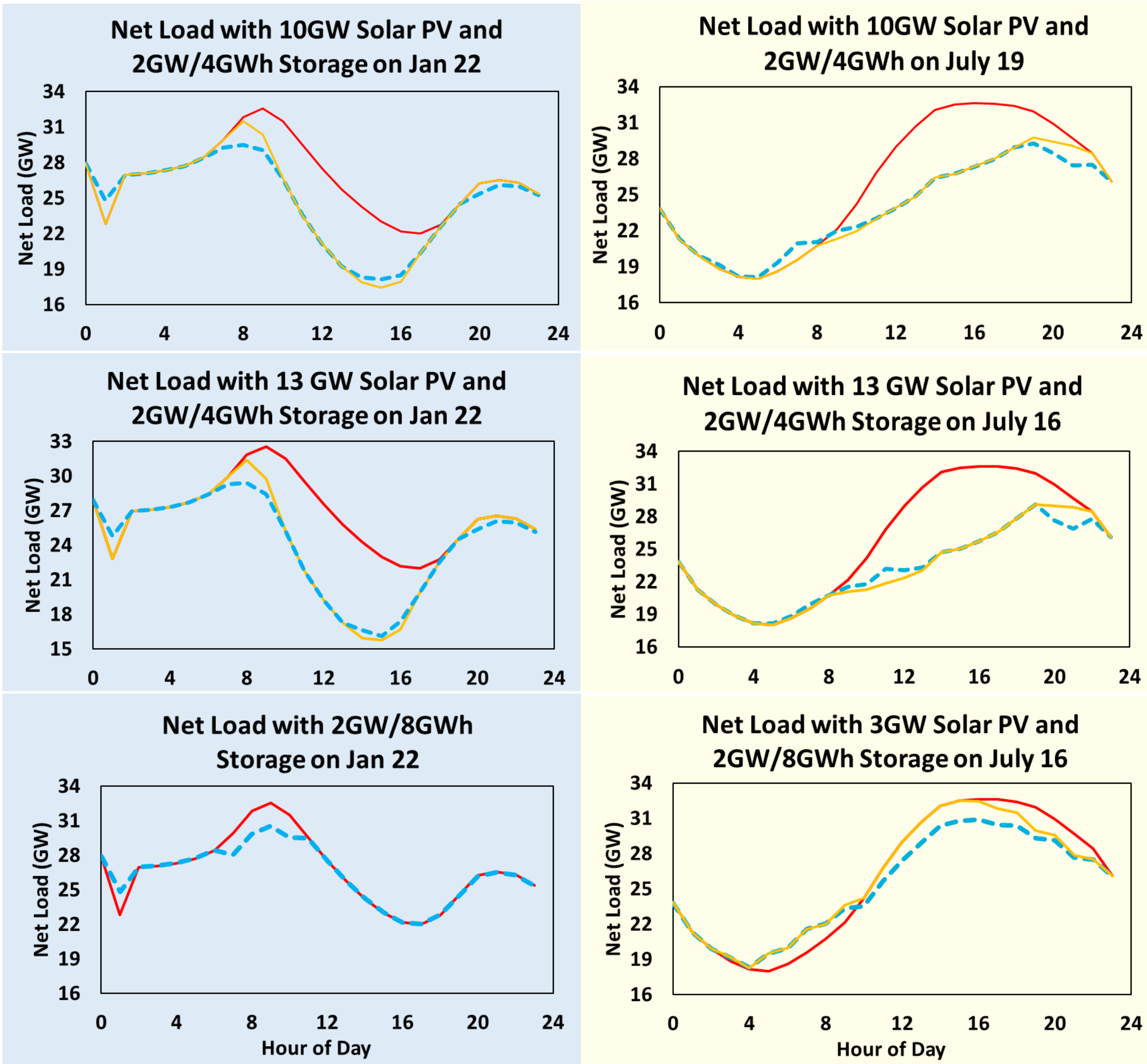


Figure A6 continued



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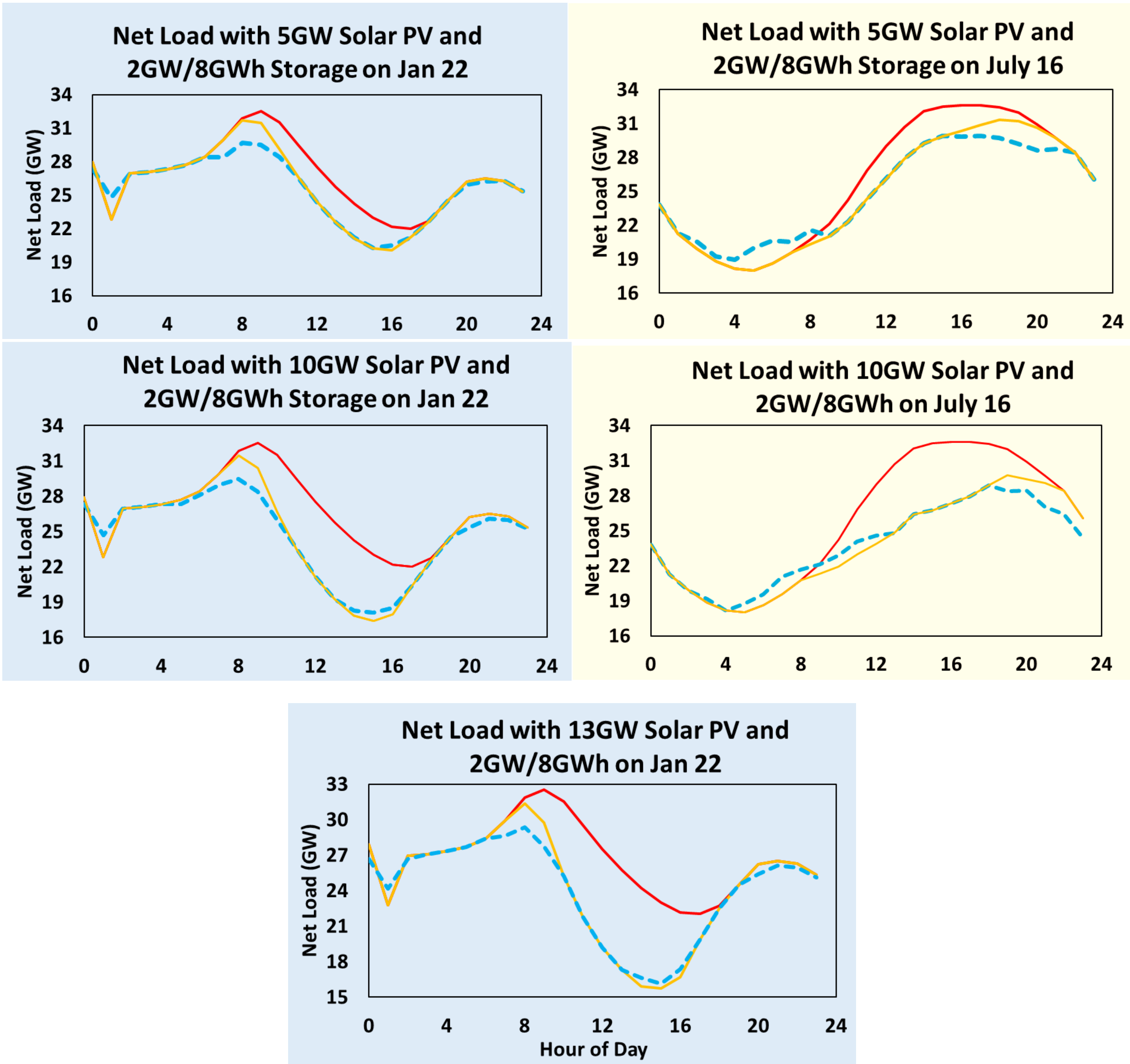

Figure A6 continued