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Abstract

The integration of renewable energy systems into institutional campuses presents a complex design challenge requiring simultaneous consideration of technical performance, economic feasibility, and seasonal resource variability. While hybrid wind–solar systems have been widely proposed as a solution to the limitations of standalone renewable configurations, comparative assessments conducted under consistent site-specific conditions remain limited, particularly for institutional-scale applications in the Southern Plains region of the United States. This thesis develops and applies an energy-balance simulation framework in MATLAB to evaluate three renewable energy system configurations; solar-only, wind-only, and hybrid wind–solar with battery storage at the University of Oklahoma (OU) campus scale. The framework integrates five years of high-resolution meteorological data from the Oklahoma Mesonet with historical campus electricity consumption records, and incorporates hub-height wind speed correction, scale factor analysis, hourly battery energy storage simulation, and techno-economic evaluation using levelized cost of energy.

At scale factor 2, the hybrid system achieves 71.2% average renewable penetration compared to 41.4% for solar-only and 29.9% for wind-only, while maintaining a minimum monthly penetration of 27.8% versus 2.2% for the wind-only scenario. The wind-only configuration exhibits repeated near-zero generation events during summer months due to atmospheric suppression of low-level wind speeds across the Southern Plains, confirming its unsuitability as a primary institutional energy source in this region. The solar-only configuration achieves the lowest levelized cost of energy at \$0.057/kWh, while the hybrid system reaches \$0.089/kWh; approximately cost-neutral relative to current Oklahoma commercial electricity rates, while delivering substantially higher penetration and resource diversity. Battery sensitivity analysis across 2-to-8-hour storage durations demonstrates diminishing returns with increasing capacity, with the 2-hour configuration offering the most favorable cost-performance ratio at current benchmark costs. A key methodological finding is that hourly battery simulation reveals a 19.1% grid import reduction for the base case 4-hour storage configuration, nearly twenty times larger

than monthly simulation would predict, establishing hourly temporal resolution as a minimum standard for storage performance assessment in this class of system.

The results support hybrid wind–solar deployment as the technically and economically preferred configuration for institutional renewable energy integration in the Southern Plains, and the analytical framework developed here provides a replicable foundation for site-specific renewable energy planning at other campuses in the region.

Chapter 1: Introduction

1.1 Background and Motivation

The global energy sector is undergoing a structural transition driven by the need to decarbonize electricity production while maintaining system reliability and economic viability. Worldwide electricity demand is projected to increase by nearly 50 percent between 2020 and 2040, intensifying the pressure to deploy low-carbon generation technologies at scale (International Energy Agency [IEA], 2023). Conventional fossil-fuel-based systems, although historically reliable, remain major contributors to greenhouse gas emissions and are increasingly vulnerable to fuel price volatility and infrastructure aging. In response, renewable energy technologies such as wind and solar photovoltaic systems have emerged as central pillars of national and international energy strategies.

Renewable deployment has expanded rapidly over the last decade. Global wind power capacity surpassed 900 gigawatts (GW) in 2023, while solar photovoltaic capacity exceeded 1 terawatt (TW) for the first time (IEA, 2023). These technologies now account for the majority of new generation additions worldwide. Their cost trajectories have improved significantly due to technological advancements, economies of scale, and policy incentives. However, despite declining capital costs and strong growth trends, renewable energy integration presents technical challenges related to variability, intermittency, and system balancing.

Wind and solar resources are inherently dependent on meteorological conditions. Solar output follows diurnal and seasonal irradiance patterns, while wind generation fluctuates according to atmospheric dynamics. When deployed independently, each resource may experience extended periods of reduced output. Numerous studies demonstrate that hybrid wind–solar systems can mitigate variability by leveraging complementary resource behavior across time scales (Kaldellis & Zafirakis, 2011; Koutroulis et al., 2006). Seasonal complementarity in particular has been shown to reduce aggregate variability and improve overall system stability.

Beyond environmental considerations, energy resilience has become an increasingly important objective. Grid disturbances caused by extreme weather, equipment failures, or operational imbalances can lead to widespread outages. In November 2025, a significant power outage in

Norman, Oklahoma left thousands without electricity for several hours, highlighting the vulnerability of centralized infrastructure (Azat TV, 2025). Such events reinforce the importance of distributed and diversified generation strategies capable of enhancing local reliability.

While much of the existing literature focuses on residential systems or isolated microgrids, institutional-scale applications such as university campuses remain comparatively underexplored. Campuses operate as complex energy environments characterized by diverse building types, continuous operational demands, and pronounced seasonal load variability. The OU campus therefore represents a meaningful case study for assessing renewable integration under realistic, site-specific conditions.

The motivation for this research arises from the convergence of global renewable expansion, regional resource potential, resilience considerations, and the need for scenario-based evaluation at institutional scale. By integrating campus load data with high-resolution meteorological inputs from the Oklahoma Mesonet, this study aims to evaluate renewable system performance under realistic environmental conditions.

1.2 Problem Statement

Despite significant advancements in renewable technologies, determining the optimal configuration of wind, solar, and storage systems for institutional-scale loads remains a complex and site-dependent problem. Standalone solar or wind systems may perform well under favorable resource conditions, yet each resource exhibits temporal variability that can lead to generation deficits during critical demand periods (Lalouni et al., 2009).

Hybrid wind–solar systems are frequently proposed as a solution to this variability. However, their performance depends strongly on local resource complementarity, load characteristics, and system sizing assumptions. Many previous studies rely on synthetic weather profiles or generalized load curves, limiting their applicability to specific locations. Furthermore, comparative assessments between standalone and hybrid systems are often conducted under inconsistent modeling assumptions, reducing the clarity of conclusions regarding hybridization benefits.

At OU, campus electricity demand exhibits seasonal and operational variability driven by academic schedules, heating and cooling requirements, and research facility operations. Evaluating renewable integration in such an environment requires high-resolution meteorological data and historical load information representative of actual operating conditions.

In addition to technical feasibility, economic viability remains central to renewable deployment decisions. Although capital costs for solar modules, wind turbines, and battery storage have declined substantially, investment decisions must be supported by rigorous techno-economic analysis. Metrics such as levelized cost of energy, net present value, and payback period are widely used to evaluate system competitiveness (National Renewable Energy Laboratory [NREL], 2021; Müller et al., 2023; Kafando et al., 2024).

Therefore, the core research problem addressed in this thesis is:

How do standalone solar, standalone wind, and hybrid wind–solar systems compare in terms of technical performance and techno-economic feasibility when evaluated using site-specific load and meteorological data representative of the OU campus?

This question requires a consistent, scenario-based modeling framework that integrates local2 environmental data, institutional load profiles, and standardized economic assumptions.

1.3 Research Objectives and Significance

The primary objective of this research is to develop and implement a scenario-based modeling framework to evaluate renewable energy integration at the OU campus scale.

The specific objectives are:

- Develop an energy-balance-based modeling framework in MATLAB to simulate campus-scale renewable integration using historical load data and meteorological inputs from the Oklahoma Mesonet.
- Define and compare three system scenarios: solar-only, wind-only, and hybrid wind–solar configurations under identical environmental and economic conditions.
- Evaluate technical performance metrics including renewable penetration, seasonal variability, grid import fraction, curtailment, and capacity factor.

- Conduct techno-economic analysis using metrics such as levelized cost of energy, net present value, and payback period based on published cost benchmarks.
- Perform sensitivity analysis to assess the impact of system sizing and cost assumptions on comparative performance.

The significance of this research lies in its integration of local meteorological data, institutional load characteristics, and scenario-based comparison within a unified modeling framework. By focusing on a real campus environment rather than generic profiles, this study contributes location-specific insights relevant to renewable integration planning at institutional scale.

1.4 Regional Context and Motivation

Oklahoma provides a particularly strong context for hybrid renewable energy system research. The state possesses some of the highest-quality onshore wind resources in the United States. In 2022, approximately 41% of Oklahoma's electricity generation was derived from wind energy, placing it among the top five wind-producing states nationally (U.S. Department of Energy [DOE], 2023). Although solar energy currently represents a smaller portion of the state's energy mix, Oklahoma receives substantial annual solar irradiance, particularly in central and southern regions (U.S. Energy Information Administration [EIA], 2023). This combination of strong wind generation and favorable solar potential makes the region well-suited for hybrid wind–solar energy systems, particularly at the campus and institutional scale.

Recent data from the U.S. Energy Information Administration (EIA) further highlights the rapid expansion of wind energy in Oklahoma. *Figure 1* illustrates the historical net generation of wind energy in the state between 2004 and 2024, showing a substantial and sustained increase over time. Wind generation has grown from relatively low levels in the early 2000s to several million megawatt-hours annually in recent years. This upward trend reflects the combined influence of favorable policy frameworks, technological advancements in wind turbine systems, and the state's strong wind resource profile.

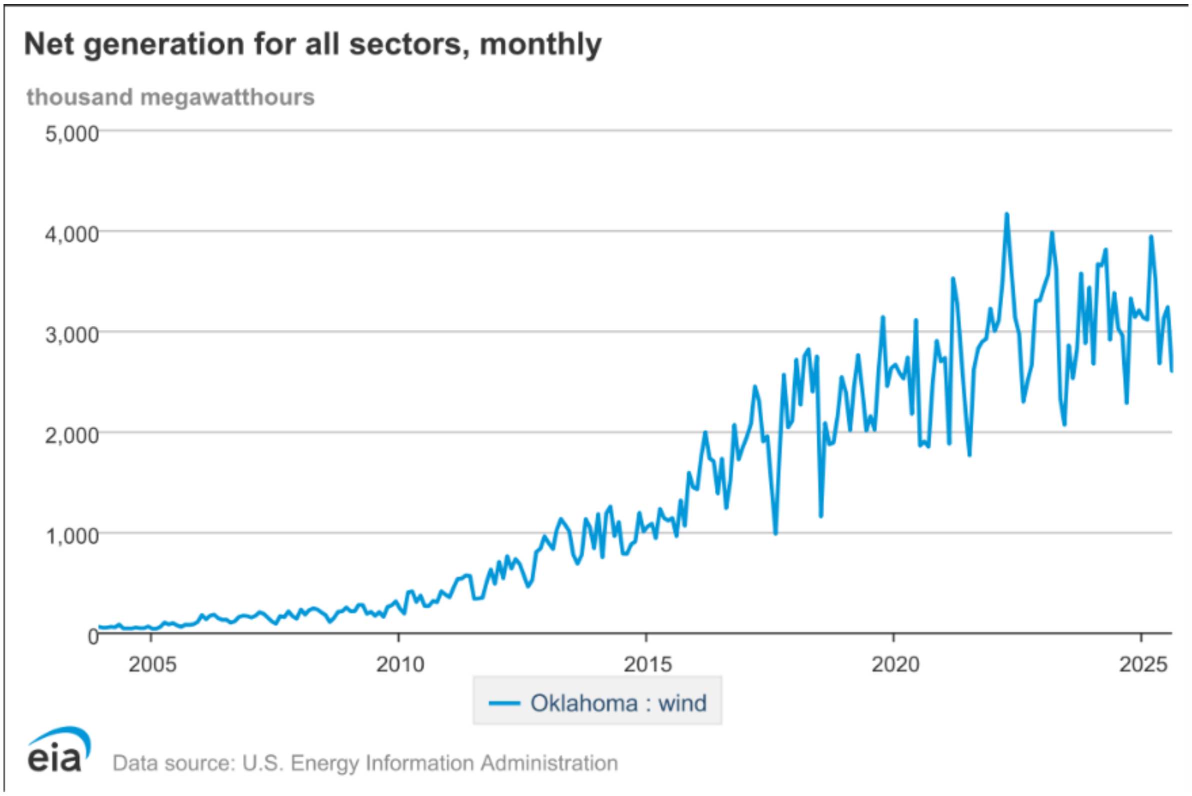

Figure 1: Historical Net Generation of Wind Energy in Oklahoma (2004–2024)

To extend this analysis, a time-series forecast was conducted to project Oklahoma's wind generation over the next 24 months. An autoregressive integrated moving average (ARIMA) model was implemented to capture historical trends and generate future projections. The forecast results, shown in *figure 2*, indicate continued growth in wind energy generation through 2026, with expected generation levels exceeding current values. The inclusion of 80% and 95% confidence intervals provides insight into the uncertainty associated with long-term projections while maintaining an overall upward trend.

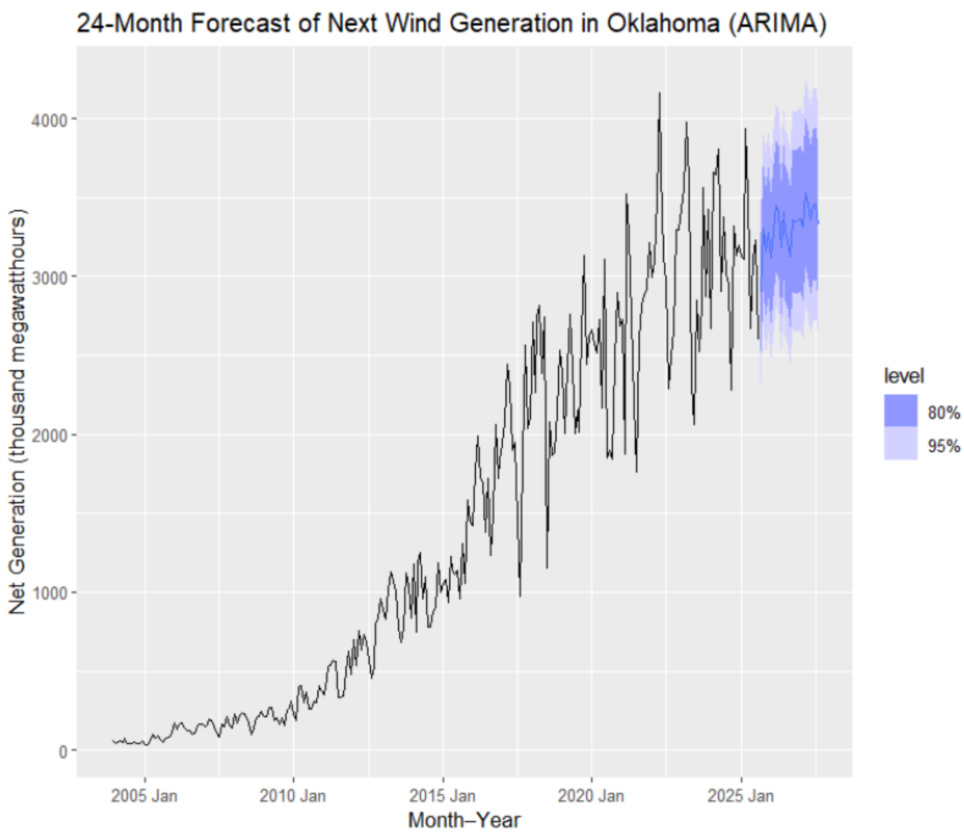

Figure 2: ARIMA Forecast of Oklahoma Wind Generation (2024–2026)

While these observed and projected trends confirm the strength and continued expansion of wind energy in Oklahoma, they also highlight important challenges associated with reliance on a single renewable energy source. Wind generation is inherently variable and can experience fluctuations due to seasonal changes and atmospheric conditions. As wind penetration increases, these fluctuations can lead to mismatches between energy supply and demand, particularly during periods of low wind availability or peak demand.

These challenges emphasize the need for more integrated energy system designs. Hybrid energy systems that combine wind and solar resources, along with energy storage, offer a promising solution to mitigate variability and improve overall system reliability. By leveraging the complementary characteristics of wind and solar generation, hybrid systems can provide a more stable and consistent energy supply. This context motivates the present study, which focuses on the design and performance analysis of a hybrid wind–solar–battery energy system using site-specific data from OU. The goal is to evaluate how system configuration, resource variability, and storage integration influence overall system performance and economic feasibility.

1.5 Scope and Limitations

This study focuses on system-level modeling and techno-economic evaluation of solar, wind, and hybrid renewable configurations for the OU campus. The analysis is conducted within a grid-connected framework and emphasizes energy balance, seasonal performance, and economic feasibility.

The research does not include hardware experimentation, detailed inverter-level control design, or power electronics switching analysis. Storage modeling is simplified to energy-balance representation and does not incorporate detailed electrochemical degradation modeling. Economic parameters such as electricity tariffs and technology costs are based on published benchmarks and are subject to market variability.

Despite these limitations, the study provides a comprehensive framework for evaluating renewable integration strategies using site-specific environmental and operational data.

Chapter 2: Literature Review

2.1 Standalone Renewable Energy Systems

Standalone renewable energy systems rely on a single primary energy source, most commonly solar photovoltaic (PV) or wind energy, to supply electrical loads. These systems are frequently investigated as baseline configurations in renewable energy research due to their conceptual simplicity and relatively low system integration requirements. Standalone systems provide valuable insight into the fundamental behavior, performance limits, and design constraints of individual renewable technologies before more complex configurations are considered (Koutroulis et al., 2006; Kaldellis and Zafirakis, 2011).

Solar photovoltaic systems are among the most widely deployed renewable technologies due to their modularity, declining installation costs, and minimal operational requirements. PV generation is generally predictable on a daily basis, with output closely tied to solar irradiance levels and daylight availability. However, numerous studies highlight that PV systems suffer from inherent temporal limitations, including zero generation during nighttime hours and reduced output during winter months or periods of heavy cloud cover (Lalouni et al., 2009; Rezk et al., 2019). These characteristics often result in significant mismatches between generation and demand, particularly for loads that extend beyond daytime operating hours.

Wind energy systems offer a different set of advantages and challenges. Wind power can be available during nighttime hours and across multiple seasons, making it a potentially strong complement to solar generation. However, wind energy output is highly variable and depends on site-specific wind speed distributions, turbine characteristics, and atmospheric conditions. Several studies report that standalone wind systems experience extended periods of low or zero output due to insufficient wind speeds, which can significantly impact supply reliability when no auxiliary generation or storage is available (Koutroulis et al., 2006; Khalid and Savkin, 2010).

Both standalone PV and wind systems are strongly influenced by local environmental conditions and load characteristics. When evaluated independently, these systems often require oversizing or substantial energy storage capacity to meet reliability requirements. As a result, performance metrics such as capacity factor, energy coverage, and reliability are highly sensitive to seasonal effects and short-term variability. These limitations have been widely documented in the literature and form the basis for exploring integrated system configurations that can mitigate the weaknesses of individual renewable resources (Kaldellis and Zafirakis, 2011; Hassan et al., 2023).

2.2 Limitations of Standalone Renewable Energy Systems

While standalone renewable energy systems are valuable for understanding individual resource behavior, extensive research demonstrates that they face significant limitations when deployed as the sole source of electricity. One of the most prominent challenges is the temporal mismatch between renewable generation and electricity demand. Solar PV systems cannot supply power during nighttime hours, while wind energy systems may experience prolonged periods of low generation due to unfavorable meteorological conditions. These mismatches are particularly problematic for applications with relatively stable or continuous load profiles (Lalouni et al., 2009; Rezk et al., 2019).

Seasonal variability further exacerbates these challenges. Solar energy production typically decreases during winter months due to lower irradiance and shorter daylight periods, while electricity demand often increases because of heating requirements. Although wind resources may partially compensate for this seasonal imbalance in some regions, their availability remains uncertain and highly location-dependent. Studies consistently show that achieving acceptable reliability with standalone systems often requires excessive oversizing or large battery storage capacities, both of which increase system cost and complexity (Koutroulis et al., 2006; Kaldellis and Zafirakis, 2011).

Another important limitation of standalone systems is their reduced operational flexibility. Without complementary generation sources, energy storage systems must absorb the full burden of variability management. This can lead to inefficient battery utilization, increased cycling frequency, and accelerated degradation, particularly in systems designed to meet high reliability targets (Rezk et al., 2019; Diab et al., 2017). In addition, standalone configurations often exhibit low utilization factors, as installed capacity must be sized for peak demand even though average generation may be substantially lower over most of the year.

From a planning and economic perspective, these limitations reduce the attractiveness of standalone renewable systems for applications where reliability, cost-effectiveness, and resilience are critical. Consequently, the literature increasingly emphasizes the need for integrated renewable energy solutions that can balance variability across multiple resources, improve capacity utilization, and reduce reliance on a single energy source. These considerations have motivated the widespread investigation of hybrid renewable energy systems as an alternative to standalone designs (Hassan et al., 2023; Soudagar et al., 2024).

2.3 Hybrid Wind–Solar Renewable Energy Systems

Hybrid wind–solar renewable energy systems integrate photovoltaic generation and wind energy conversion within a coordinated framework to enhance supply reliability, reduce output variability, and improve overall system performance. The motivation for combining these two technologies arises directly from the documented limitations of standalone renewable systems, particularly their sensitivity to temporal and seasonal fluctuations in resource availability. By exploiting the complementary characteristics of wind and solar resources, hybrid systems aim to provide a more balanced and resilient energy supply (Kaldellis and Zafirakis, 2011).

A substantial body of literature demonstrates that wind and solar resources often exhibit temporal complementarity. Solar PV generation is generally highest during daytime hours and summer months, while wind resources in many regions tend to be stronger during nighttime hours and winter seasons due to atmospheric circulation patterns. This complementary behavior reduces aggregate power variability when both resources are integrated, leading to improved alignment between generation and demand (Kaldellis and Zafirakis, 2011; Diab et al., 2017).

Numerous modeling and simulation studies have evaluated the performance of hybrid wind–solar systems across a wide range of geographic locations and system scales. Comparative analyses consistently report that hybrid systems outperform standalone solar and wind configurations in terms of energy coverage, reliability, and supply continuity (Lalouni et al., 2009; Koutroulis et al., 2006; Hassan et al., 2023). Hybrid systems are shown to reduce periods of zero or low generation and to decrease dependence on large battery capacities or auxiliary generation sources. These advantages are particularly relevant for applications with relatively stable or continuous demand, such as institutional and campus-scale facilities.

Hybrid systems also offer advantages in system sizing and economic optimization. By distributing generation across multiple resources, designers can reduce the required installed capacity of individual subsystems while maintaining acceptable reliability levels. Several studies demonstrate that hybridization enables more flexible trade-offs between solar and wind capacity, which can reduce oversizing and improve cost-effectiveness compared to standalone designs (Koutroulis et al., 2006; Rezk et al., 2019). These benefits become increasingly important when system design is constrained by economic considerations, land availability, or site-specific resource limitations.

In addition to performance improvements, hybrid wind–solar systems have been shown to enhance operational resilience, particularly when combined with energy storage. Reports by the National Renewable Energy Laboratory indicate that hybrid renewable systems incorporating generation diversity and storage exhibit improved controllability and robustness during grid disturbances compared to single-resource systems. While many studies focus on utility-scale or microgrid applications, the underlying principles are directly applicable to campus-scale systems where reliability and continuity of service are critical.

Despite the demonstrated advantages of hybrid wind–solar systems, their performance remains highly dependent on local environmental conditions and load characteristics. Studies conducted in different regions report varying degrees of wind–solar complementarity, indicating that hybrid system benefits cannot be assumed to be uniform across locations. As emphasized by the International Energy Agency, site-specific assessment is essential for accurately evaluating renewable system performance and informing design decisions. This has led to increased interest in studies that incorporate high-resolution local meteorological data and realistic load profiles into hybrid system modeling (Hassan et al., 2023; Soudagar et al., 2024).

In summary, the literature clearly establishes hybrid wind–solar systems as an effective approach for mitigating renewable variability, improving reliability, and enhancing design flexibility relative to standalone renewable systems. However, many existing studies rely on generalized or synthetic datasets, which may obscure seasonal effects and limit applicability to specific sites. This gap motivates further research focused on scenario-based comparison of standalone and hybrid renewable systems using local load and resource data, particularly at the scale of university campuses.

2.4 Seasonal Load and Resource Variability

Seasonal variability plays a critical role in the performance and design of renewable energy systems, particularly when systems are evaluated at institutional or campus scales. Electricity demand is not constant throughout the year and is strongly influenced by climatic conditions, occupancy patterns, and operational schedules. At the same time, renewable energy resources such as solar irradiance and wind speed exhibit pronounced seasonal trends. The interaction between seasonal load behavior and renewable resource availability significantly affects system sizing, reliability, and economic performance.

Numerous studies report that electricity demand in large facilities and campuses exhibits strong seasonal patterns driven primarily by heating, ventilation, and air conditioning (HVAC) loads. Cooling demand typically dominates during summer months, while heating demand increases during winter, often leading to higher overall energy consumption during extreme temperature periods (Diab et al., 2017; Rezk et al., 2019). In university campus environments, additional seasonal variation arises from academic calendars, occupancy fluctuations, and changes in operational intensity between semesters and breaks. These factors result in load profiles that vary not only in magnitude but also in daily and monthly structure.

Seasonal variability in renewable energy resources further complicates system design. Solar photovoltaic generation is highly dependent on seasonal changes in solar irradiance and daylight duration. Peak solar production generally occurs during summer months, while winter generation is significantly reduced due to lower sun angles and shorter days. Wind energy exhibits more complex seasonal behavior that varies by geographic region. In many mid-latitude locations, including the central United States, wind resources tend to be stronger during winter and spring months and weaker during summer periods (Kaldellis and Zafirakis, 2011). This seasonal contrast between wind and solar availability forms the basis for hybrid system complementarity.

The mismatch between seasonal demand and renewable resource availability has been widely documented in the literature. Several studies demonstrate that standalone solar systems struggle to meet winter demand due to reduced irradiance, while standalone wind systems may underperform during periods of low wind availability or during summer peak demand conditions (Koutroulis et al., 2006; Lalouni et al., 2009). As a result, systems designed without accounting for seasonal variability often require excessive installed capacity or large storage systems to maintain acceptable reliability levels.

Hybrid wind–solar systems offer a potential solution to these seasonal mismatches by distributing generation across resources with different seasonal characteristics. Studies comparing seasonal performance metrics consistently show that hybrid systems provide more balanced energy production throughout the year than standalone configurations (Hassan et al., 2023; Soudagar et al., 2024). By combining summer-dominant solar generation with winter-dominant wind resources, hybrid systems can reduce seasonal energy deficits and improve annual energy coverage. This seasonal smoothing effect is particularly valuable for applications with year-round energy demand, such as university campuses.

Energy storage interacts strongly with seasonal variability, although its role differs across timescales. Battery storage is effective at mitigating short-term and diurnal variability but is generally not economical for addressing long-term seasonal imbalances due to capacity and cost limitations. Consequently, many studies emphasize that seasonal balancing is more effectively achieved through resource complementarity rather than storage alone (Rezk et al., 2019; Diab et al., 2017). This insight reinforces the importance of hybrid system design in environments with pronounced seasonal demand and resource variation.

Recent literature increasingly highlights the importance of incorporating high-resolution, site-specific data when analyzing seasonal behavior. Generic or averaged datasets may obscure critical seasonal trends and lead to misleading conclusions regarding system performance and optimal sizing. Studies that utilize local meteorological data demonstrate that seasonal alignment between load and generation can differ substantially even within the same geographic region (Hassan et al., 2023). As emphasized by the International Energy Agency, accurate assessment of renewable system performance requires explicit consideration of local climatic conditions and demand characteristics.

For campus-scale applications, seasonal variability is particularly significant due to the combination of large, diverse building loads and climate-driven energy use. Universities often experience peak electricity demand during summer cooling seasons, while maintaining non-negligible baseline loads year-round. Evaluating renewable energy systems for such environments therefore requires detailed analysis of seasonal load profiles and their interaction with renewable resource availability. Failure to account for these seasonal dynamics can result in system designs that perform well on an annual average basis but underperform during critical periods.

In summary, seasonal load and resource variability represent a fundamental challenge in renewable energy system design. The literature demonstrates that both electricity demand and renewable resource availability vary significantly across seasons, and that these variations strongly influence system reliability and cost. Hybrid wind–solar systems provide an effective means of addressing seasonal mismatches through resource complementarity, particularly when designs are informed by local data. These findings motivate the use of site-specific load and meteorological datasets in evaluating renewable energy scenarios for campus-scale systems such as OU.

2.5 Scenario-Based Performance Comparison Methods

Scenario-based analysis has become a widely adopted methodology for evaluating renewable and hybrid energy systems, particularly when the objective is to compare alternative system configurations under consistent operating conditions. Rather than assessing a single system in isolation, scenario-based approaches define multiple design configurations, such as solar-only, wind-only, and hybrid wind–solar systems, and evaluate their performance using identical load profiles, meteorological inputs, and economic assumptions. This framework allows researchers to isolate the effects of system configuration and resource complementarity on performance outcomes.

The literature consistently emphasizes that meaningful comparison between renewable systems requires a common analytical basis. Studies that evaluate standalone and hybrid systems using different datasets or assumptions often produce results that are difficult to interpret or generalize. In contrast, scenario-based studies control for external variables and focus on relative performance metrics, enabling clearer assessment of the benefits and limitations associated with each configuration (Koutroulis et al., 2006; Diab et al., 2017). This approach is particularly valuable in system design studies, where the objective is to inform configuration selection rather than optimize a single design.

Performance metrics used in scenario-based comparisons vary depending on application scale and research objectives. Commonly reported indicators include energy coverage, defined as the fraction of total demand met by renewable generation, renewable penetration, curtailment levels, and supply reliability. Several studies also evaluate variability-related metrics, such as the frequency and duration of low-generation periods, to assess system robustness under fluctuating resource conditions (Lalouni et al., 2009; Rezk et al., 2019). These metrics are especially relevant for applications with continuous or mission-critical loads, including institutional and campus-scale systems.

Scenario-based methods also enable systematic evaluation of seasonal performance. By comparing how different system configurations perform during high-demand or low-resource seasons, researchers can identify configurations that offer improved resilience to seasonal mismatches. Hybrid systems are frequently shown to outperform standalone systems during these critical periods due to their ability to draw on complementary resources (Hassan et al., 2023). This seasonal perspective is essential for avoiding designs that perform well on an annual average basis but fail to meet demand during peak or low-generation intervals.

In addition to technical performance, scenario-based frameworks are increasingly used to support techno-economic assessment. By applying consistent cost assumptions across scenarios, researchers can evaluate trade-offs between system complexity, capital investment, and performance gains. Studies that integrate performance and economic metrics demonstrate that hybrid systems often achieve improved cost-performance balance relative to standalone designs, particularly when local resource complementarity reduces the need for excessive capacity or storage (Diab et al., 2017; Rezk et al., 2019).

Overall, the literature establishes scenario-based comparison as a robust and transparent methodology for renewable energy system evaluation. This approach is particularly well suited for site-specific studies, where the goal is to determine how alternative configurations perform under local conditions rather than to identify a universally optimal design. These characteristics align directly with the objectives of the present study, which employs scenario-based modeling to compare standalone and hybrid renewable systems using data representative of OU.

2.6 Use of Local Meteorological and Load Data in System Design

The use of local meteorological and load data has emerged as a critical factor in the accurate modeling and evaluation of renewable energy systems. While early studies often relied on synthetic weather datasets or long-term regional averages, recent research highlights that such generalized inputs can obscure important temporal patterns and lead to suboptimal design decisions. Site-specific data provide a more realistic representation of resource availability and demand behavior, which is essential for assessing system performance under actual operating conditions.

Meteorological inputs such as solar irradiance, wind speed, and temperature exhibit significant spatial and temporal variability, even within relatively small geographic regions. Studies comparing generic and local datasets demonstrate that system performance metrics, including energy coverage and reliability, can differ substantially depending on the data source used (Hassan et al., 2023). As a result, reliance on averaged or synthetic profiles may overestimate renewable generation or underestimate periods of resource scarcity, particularly at seasonal extremes.

Similarly, the use of realistic load data is crucial for accurately evaluating renewable energy systems. Load profiles determine not only total energy demand but also the timing and magnitude of peak demand, which strongly influence system sizing and performance. For large facilities and campuses, load behavior is shaped by building usage patterns, academic schedules, and climate-driven energy consumption. Several studies emphasize that simplified or assumed load profiles fail to capture these dynamics, leading to unrealistic assessments of renewable system feasibility (Diab et al., 2017; Rezk et al., 2019).

The integration of local meteorological and load data enables more accurate assessment of renewable resource–load interactions. This is particularly important in scenario-based studies, where small differences in temporal alignment can significantly affect comparative performance outcomes. By using high-resolution local data, researchers can evaluate how different system configurations respond to site-specific seasonal and diurnal patterns, providing insights that are directly applicable to real-world design decisions.

National and international energy organizations increasingly advocate for the use of local data in renewable system planning. Reports by International Energy Agency emphasize that site-specific assessment is essential for translating renewable energy potential into reliable and cost-effective system designs. Similarly, National Renewable Energy Laboratory highlights that local data integration improves the predictive accuracy of renewable system models and supports more informed infrastructure investment decisions.

In regions such as Oklahoma, where wind and solar resources exhibit strong seasonal variability, the importance of local data is further amplified. Access to high-resolution meteorological datasets, such as those provided by the Oklahoma Mesonet, enables detailed characterization of renewable resource availability at specific sites. When combined with historical operational load data, these datasets support a comprehensive evaluation of renewable system performance that accounts for both environmental and operational realities.

In summary, the literature strongly supports the use of local meteorological and load data in renewable energy system design and evaluation. Studies consistently show that local-data-driven analyses yield more accurate performance predictions and more reliable design insights than approaches based on generalized inputs. This perspective underpins the methodology adopted in this thesis, which integrates site-specific load data and local renewable resource profiles to evaluate standalone and hybrid renewable energy scenarios for OU.

2.7 Techno-Economic Evaluation of Renewable Energy Systems

Techno-economic analysis plays a central role in assessing the feasibility of renewable and hybrid energy systems, particularly when design decisions must balance performance improvements against additional system costs. While renewable technologies such as solar photovoltaic and wind energy have experienced significant cost reductions over the past decade, system-level economics remain strongly influenced by configuration, sizing, storage requirements, and local operating conditions. As a result, performance gains achieved through hybridization must be evaluated alongside their economic implications.

The levelized cost of energy (LCOE) is one of the most widely used metrics for comparing the economic performance of renewable energy systems. LCOE captures the total lifetime cost of a system relative to its total energy production and allows comparison across different technologies and configurations. Studies consistently report that standalone renewable systems may achieve low LCOE under favorable conditions but often require oversizing or substantial storage to maintain reliability, which increases total system cost (Koutroulis et al., 2006; Rezk et al., 2019). In contrast, hybrid systems can reduce the need for excessive capacity by leveraging complementary resources, potentially improving cost-performance balance.

Beyond LCOE, additional economic indicators such as net present value (NPV), payback period, and return on investment are frequently used to evaluate renewable systems from an investment perspective. Techno-economic studies demonstrate that hybrid wind–solar systems often achieve shorter payback periods and improved long-term economic performance compared to standalone systems, particularly when local resource complementarity reduces curtailment and improves capacity utilization (Diab et al., 2017; Hassan et al., 2023). These advantages are amplified when hybrid systems are designed to match local load characteristics rather than generic demand profiles.

Energy storage significantly influences techno-economic outcomes. While battery storage enhances reliability and flexibility, it also represents a substantial portion of total system cost. Several studies highlight that storage sizing must be carefully optimized to avoid diminishing economic returns (Rezk et al., 2019). Hybrid systems can mitigate this challenge by relying more heavily on resource complementarity for seasonal balancing, allowing storage to focus on short-term variability rather than long-term energy shifting. This distinction is particularly important for large facilities and campuses, where seasonal demand patterns can dominate system economics.

Economic assessments increasingly emphasize the importance of site-specific data. Cost-optimal system designs vary significantly depending on local electricity tariffs, demand patterns, and renewable resource availability. Analyses based on averaged or assumed conditions often fail to capture these nuances, leading to misleading conclusions regarding economic feasibility. Reports from the National Renewable Energy Laboratory and the International Energy Agency stress that localized techno-economic evaluation is essential for accurately assessing renewable system value and informing infrastructure investment decisions.

For campus-scale applications, techno-economic evaluation is particularly important due to the scale of energy consumption and the diversity of building loads. Universities often operate under constrained budgets while maintaining high reliability requirements. As such, renewable energy investments must demonstrate not only technical feasibility but also clear economic justification. Scenario-based techno-economic analysis provides a structured framework for evaluating whether hybrid renewable systems offer meaningful advantages over standalone configurations under local conditions.

In summary, the literature demonstrates that techno-economic evaluation is a critical component of renewable energy system design. Hybrid wind–solar systems frequently outperform standalone configurations in cost-performance metrics when designed using realistic assumptions and local data. These findings reinforce the need for integrated performance and economic analysis when assessing renewable energy scenarios for campus-scale systems.

2.8 Research Gaps and Chapter Summary

The literature reviewed in this chapter establishes a comprehensive foundation for understanding renewable and hybrid energy system design. Numerous studies have investigated standalone solar and wind systems, documenting their strengths as well as their limitations related to variability, reliability, and seasonal mismatch. Hybrid wind–solar systems have been widely proposed and evaluated as a solution to these challenges, with substantial evidence demonstrating improved performance, reduced variability, and enhanced resilience compared to single-resource configurations.

Despite these advances, several gaps remain in the existing body of research. First, many studies rely on generalized or synthetic meteorological and load datasets, which can obscure important site-specific dynamics and lead to system designs that do not translate well to real-world applications. Second, while hybrid systems are often evaluated in isolation, fewer studies conduct systematic scenario-based comparisons between standalone and hybrid configurations under identical operating conditions. Such comparisons are essential for quantifying the incremental benefits of hybridization.

Third, seasonal variability is frequently acknowledged but not always rigorously integrated into system evaluation. Studies that focus on annual averages may overlook critical seasonal mismatches between load and renewable resource availability, particularly for applications with year-round demand. This limitation is especially relevant for campus-scale systems, where energy use patterns are influenced by both climatic conditions and institutional operations.

Finally, while techno-economic analysis is commonly included in renewable energy studies, it is often conducted using simplified assumptions or without sufficient integration of local data. As a result, economic conclusions may not accurately reflect the feasibility of renewable systems at specific sites. There is a clear need for studies that combine detailed performance modeling with localized economic assessment to support informed decision-making.

In response to these gaps, the present thesis adopts a scenario-based modeling approach that compares standalone solar, standalone wind, and hybrid wind–solar systems using local meteorological and load data representative of OU. By integrating seasonal variability, performance metrics, and techno-economic evaluation within a unified framework, this study aims to provide site-specific insights into renewable system design and to clarify the conditions under which hybrid systems offer meaningful advantages over standalone alternatives.

Chapter 3: Methodology

3.1 Overview

This study adopts a simulation-based modeling framework to evaluate the technical and economic performance of three renewable energy system configurations at the OU campus scale: a standalone solar photovoltaic (PV) system, a standalone wind energy system, and a hybrid wind–solar system with battery storage. The modeling approach is grounded in an energy-balance framework implemented in MATLAB, which captures the interaction between renewable generation, campus electricity demand, and storage without requiring detailed power system dynamics (Koutroulis et al., 2006; Diab et al., 2017).

The framework integrates site-specific meteorological data from the Oklahoma Mesonet with historical campus electricity consumption records, and evaluates system performance across multiple configurations using a consistent scenario-based methodology. This approach ensures that comparisons between standalone and hybrid systems are conducted under identical environmental and economic assumptions, which is essential for drawing valid conclusions about the relative merits of each configuration (Lalouni et al., 2009; Rezk et al., 2019).

The overall simulation workflow consists of six sequential stages: (1) data ingestion and preprocessing, (2) hub-height wind speed correction, (3) renewable generation modeling, (4) scenario construction and scale factor analysis, (5) hourly battery energy storage simulation, and (6) techno-economic evaluation. Figure 3.1 presents a flowchart of the complete simulation pipeline. Each stage is described in detail in the sections that follow.

3.2 Data Sources

3.2.1 Meteorological Data

Meteorological data were obtained from the Oklahoma Mesonet station located in Norman, Oklahoma (station identifier: NRMN). The Mesonet is a statewide network of environmental monitoring stations operated by OU and Oklahoma State University (OSU), providing high-resolution surface observations across the state. The dataset spans January 2021 through mid-2026 and was retrieved as three separate CSV files covering the periods 2021–2022, 2023–2024, and 2025–2026.

The variables used in this study are:

- Solar radiation, $G(W/m^2)$ - measured by a pyranometer at the surface
- Wind speed, $v(mph)$ - measured at a standard height of 10 m above ground level
- Air temperature, $T(°F)$ - measured at 1.5 m above ground level

All three variables were recorded at 15-minute intervals. For modeling purposes, data were aggregated to hourly averages, as described in Section 3.3. The use of high-resolution local meteorological data from a station within the study area improves modeling accuracy by capturing the temporal variability in renewable resources that is critical for system-level analysis (Hassan et al., 2023).

3.2.2 Campus Energy Data

Monthly electricity consumption data for OU were obtained from campus utility records. The dataset spans July 2017 through August 2025 and includes two variables for each month:

- $E_purchased(kWh)$ - electricity drawn from the grid
- $E_produced(kWh)$ - electricity generated by existing campus installations

The net electrical load is defined as:

$$L = E_{purchased} - E_{produced}$$

where L represents the net campus electricity demand that must be met by the proposed renewable system or grid supply. This formulation is consistent with energy-balance approaches used in campus and microgrid studies (Diab et al., 2017) and ensures that existing on-site generation is not double-counted in the analysis.

3.2.3 System Configuration and Baseline Sizing

Three renewable energy system configurations are evaluated in this study, as summarized in *Table 1*. All configurations are assessed under identical meteorological inputs and campus load data to enable direct performance comparison.

Table 1:Renewable Energy System Configuration Scenarios

Scenario	Solar Capacity (kW)	Wind Capacity (kW)	Battery Storage
Solar-Only	10,000	—	Sensitivity analysis
Wind-Only	—	9,000 (3 × 3 MW)	Sensitivity analysis
Hybrid Wind–Solar	10,000	9,000	Base case + sensitivity

The baseline solar capacity of 10,000 kW (10 MW) and wind installation of three turbines at 3 MW each (9 MW total) were selected as initial reference assumptions to establish a simulation framework consistent with the scale of OU campus electricity demand. These values were not derived from a detailed site-specific land or rooftop availability study, but serve as a reasonable starting point for the scale factor analysis described in Section 3.8, which evaluates system performance across installed capacities ranging from 1× to 5× the baseline values. The final system size is selected based on performance outcomes rather than assumed a priori, which is consistent with scenario-based renewable energy studies in which baseline parameters define a reference configuration subject to subsequent optimization (Koutroulis et al., 2006; Rezk et al., 2019).

3.3 Data Preprocessing

Raw meteorological data were processed prior to modeling to ensure consistency and usability. The Oklahoma Mesonet uses sentinel values of −99 and −999 to flag missing or invalid sensor readings. All such values were identified and replaced with NaN prior to any calculations. Following this step, remaining data gaps were filled using linear interpolation, with nearest-neighbor fill applied at the boundaries of the dataset where linear interpolation is not applicable.

Unit conversions were applied as follows:

- Wind speed: $mph \rightarrow m/s$ (multiplication by 0.44704)

- Air temperature: $°F \rightarrow °C$ (standard conversion: $(T\_°F - 32) \times 5/9$)

The cleaned dataset was converted to a MATLAB timetable structure and resampled from 15-minute resolution to hourly averages using the *"retime"* function with mean aggregation. Temporal aggregation to hourly resolution is standard practice in renewable energy system modeling, as it reduces computational load while preserving the essential diurnal variability patterns that govern generation and storage behavior (Rezk et al., 2019).

3.3.2 Campus Load Data Cleaning

Campus electricity data were read from a CSV file containing monthly records. The *"Year_Month"* field was stored as a full datetime string in "*M/d/yyyy H:mm"* format and was parsed accordingly before being normalized to the first day of each month using the "*dateshift"* function. Purchased and produced electricity values were stored as comma-formatted strings and were converted to numeric values prior to computation of the net load.

3.4 Hub-Height Wind Speed Correction

Wind speed measurements from the Oklahoma Mesonet are recorded at a standard height of 10 m above ground level, consistent with surface meteorological network conventions. However, utility-scale wind turbines typically operate at hub heights between 80 m and 120 m, where wind speeds are substantially higher due to the atmospheric boundary layer velocity profile. Failure to account for this height difference results in a systematic underestimation of wind power output and introduces a conservative bias into wind energy assessments.

To correct for this, wind speeds were adjusted from the 10 m measurement height to a representative hub height of 80 m using the power law wind profile:

$$v_{hub} = v_{10} \cdot \left(\frac{z_{hub}}{z_{ref}}\right)^{\alpha}$$

where:

- v_{hub}= wind speed at hub height (m/s)
- v_{10}= measured wind speed at 10 m (m/s)

- z_{hub}= turbine hub height = 80 m
- z_{ref}= reference measurement height = 10 m
- α= Hellmann exponent = 0.143

The Hellmann exponent of 0.143 (equivalent to the 1/7 power law) is the standard value for open, flat terrain with low surface roughness (Manwell et al., 2010), and is appropriate for the Norman, Oklahoma site, which is situated in a flat agricultural and suburban landscape with minimal topographic obstruction.

The correction factor applied in this study is:

$$\left(\frac{80}{10}\right)^{0.143} = 1.346$$

This yields a mean hub-height wind speed of 5.12 m/s, compared to a mean surface wind speed of 3.80 m/s an increase of approximately 34.7%. This correction is physically significant and materially affects wind power output estimates, particularly at lower wind speeds near the turbine cut-in threshold. All wind power calculations in this study use the hub-height corrected wind speed.

3.5 Solar Photovoltaic Model

Solar PV power output was modeled as a function of solar irradiance and ambient temperature. The model follows the standard irradiance-based formulation with temperature correction:

$$P_{PV} = P_{rated} \cdot \frac{G}{1000} \cdot \eta \cdot [1 + \beta(T_{cell} - 25)]$$

where:

- P_{PV}= solar power output (kW)
- P_{rated}= installed PV capacity (kW)
- G= solar irradiance (W/m²)

- η= system derating factor
- β= temperature coefficient (°C^{-1})
- T_{cell}= PV cell temperature (°C)

The derating factor $\eta = 0.85$ accounts for system-level losses including wiring resistance, soiling, module mismatch, and inverter inefficiency. This value is consistent with standard assumptions used in system-level PV modeling (NREL, 2021).

The temperature coefficient $\beta = -0.004°C^{-1}$ is representative of crystalline silicon PV modules, which constitute the majority of utility-scale installations. The negative sign reflects the reduction in PV efficiency at elevated cell temperatures, which is a well-documented characteristic of silicon-based photovoltaic devices (Rezk et al., 2019).

Cell temperature is estimated using the Nominal Operating Cell Temperature (NOCT) model:

$$T_{cell} = T_{air} + \frac{NOCT - 20}{800} \cdot G$$

where NOCT = 45°C is the standard nominal operating cell temperature for crystalline silicon modules under reference conditions. This empirical relationship provides a computationally efficient approximation of module operating temperature and is widely used in system-level PV simulations (NREL, 2021).diminishin

PV output is physically constrained to the range [0, P_rated]:

$$0 \leq P_{PV} \leq P_{rated}$$

The complete set of PV model parameters is summarized in Table 2.

3.6 Wind Power Model

Wind power output was modeled using a standard piecewise turbine power curve that relates wind speed to electrical output across three operational regimes:

$$\boldsymbol{P_{wind}(v)} = \begin{cases} \boldsymbol{0} & \boldsymbol{v < v_{ci}} \text{ or } \boldsymbol{v \geq v_{co}} \\ \boldsymbol{P_{rated}} \cdot \left(\dfrac{\boldsymbol{v - v_{ci}}}{\boldsymbol{v_r - v_{ci}}}\right)^3 & \boldsymbol{v_{ci} \leq v < v_r} \\ \boldsymbol{P_{rated}} & \boldsymbol{v_r \leq v < v_{co}} \end{cases}$$

where:

- $\boldsymbol{v}$= hub-height wind speed (m/s)
- $\boldsymbol{v_{ci}}$= cut-in wind speed = 3 m/s
- $\boldsymbol{v_r}$= rated wind speed = 12 m/s
- $\boldsymbol{v_{co}}$= cut-out wind speed = 25 m/s
- $\boldsymbol{P_{rated}}$= rated turbine power = 3,000 kW

The cubic relationship between wind speed and power output in the partial-load region reflects the fundamental aerodynamic relationship between wind kinetic energy and turbine mechanical power. The turbine parameters represent generalized characteristics of utility-scale onshore wind turbines and are consistent with values reported in the renewable energy systems literature for system-level analysis (Koutroulis et al., 2006; Diab et al., 2017).

The total wind farm output is:

$$P_{wind,total} = N_t \cdot P_{wind}(v)$$

where $\boldsymbol{N_t}$= 3 turbines, giving a total installed wind capacity of 9,000 kW (9 MW) at baseline scale.

3.7 Scenario Construction

Three generation scenarios are constructed from the hourly generation arrays computed in Sections 3.5 and 3.6:

Scenario 1: *Solar-Only*: Campus demand is served exclusively by the PV array, with any deficit met by grid import and any surplus representing potential curtailment or export.

Scenario 2: ***Wind-Only***: Campus demand is served exclusively by the wind farm, with the same deficit and surplus treatment as Scenario 1.

Scenario 3: ***Hybrid Wind–Solar***: Campus demand is served by the combined output of both the PV array and wind farm. The hybrid generation profile at each hourly time step is:

$$P_{hybrid}(t) = P_{PV}(t) + P_{wind,total}(t)$$

All three scenarios share identical meteorological inputs, campus load data, economic assumptions, and scale factor multipliers, ensuring that performance differences are attributable solely to system configuration and resource characteristics.

Hourly generation profiles for each scenario are aggregated to monthly energy totals (kWh) using summation, then synchronized with the monthly campus load data using MATLAB's *"synchronize"* function. Months for which complete data are unavailable in either dataset are excluded using *"rmmissing"*.

3.8 Scale Factor Analysis

A dimensionless scale factor $s$is applied multiplicatively to the baseline generation capacity of each scenario to evaluate system performance across a range of installed capacities:

$$P_{scenario,scaled}(t) = s \cdot P_{scenario,base}(t), s \in 1,2,3,4,5$$

For each value of s, the following performance metrics are computed at monthly resolution:

Renewable Penetration:

$$\text{Penetration}(m) = \frac{E_{gen}(m)}{L(m)} \times 100$$

Grid Import:

$$\text{Grid Import}(m) = \max\left(0,\, L(m) - E_{gen}(m)\right)$$

$Grid\ Import m = max 0, Lm - Egen m$

Excess Energy:

$$Excess(m) = max\left(0, E_{gen}(m)\ - L(m)\right)$$

where $E_{gen}(m)$is monthly renewable generation (kWh) and $L(m)$is monthly net campus load (kWh).

The scale factor analysis serves two purposes. First, it validates the suitability of the baseline capacity assumptions by confirming that the selected configuration delivers meaningful renewable contribution. Second, it identifies the configuration that best balances renewable penetration against system utilization efficiency, avoiding both under-sizing (insufficient renewable contribution) and oversizing (excessive curtailment with diminishing returns on grid import reduction).

3.9 Battery Energy Storage Model

3.9.1 Battery Sizing

Battery storage capacity is defined as a function of total hybrid system capacity and storage duration:

$$E_{battery} = \left(P_{PV,scaled} + P_{wind,scaled}\right) \cdot t_{duration}$$

where $t_{duration}$is the storage duration in hours. For the base case analysis, a 4-hour storage duration is assumed, yielding a battery capacity of 152,000 kWh at scale factor 2. Sensitivity analysis is conducted across storage durations of 2, 4, 6, and 8 hours.

3.9.2 Hourly Energy Balance Simulation

A critical methodological decision in this study is the use of hourly time-step simulation for the battery model, rather than monthly aggregation. Battery storage systems respond to short-term generation-load imbalances at hourly and sub-hourly timescales. Simulating battery operation at monthly resolution would suppress the diurnal surplus and deficit cycles that determine actual charge and discharge behavior, leading to a systematic underestimation of battery utilization and grid import reduction. The hourly approach adopted here correctly captures these dynamics and produces physically meaningful estimates of storage performance.

At each hourly time step t, the battery operation follows the energy balance:

When generation exceeds load (surplus):

$$surplus(t) = P_{hybrid}(t) - L_h(t)$$

$$\Delta SOC(t) = \min\left(surplus(t), \frac{E_{battery} - SOC(t)}{\eta_c}\right)\eta_c$$

$$Curtailed(t) = surplus(t) - \frac{\Delta SOC(t)}{\eta_c}$$

When load exceeds generation (deficit):

$$deficit(t) = L_h(t) - P_{hybrid}(t)$$

$$Discharge(t) = \min(deficit(t), SOC(t)\eta_d)$$

$$GridImport(t) = \max\big(0,\ deficit(t) - Discharge(t)\big)$$

The state of charge is updated at each time step:

$$SOC(t+1) = SOC(t) + \Delta SOC(t) \qquad \text{(charging)}$$

$$SOC(t+1) = SOC(t) - \frac{Discharge(t)}{\eta_d} \qquad \text{(discharging)}$$

where $\eta_c = \eta_d = 0.95$, giving a round-trip efficiency of 90.25%.

Since campus load data are available only at monthly resolution, the hourly load $L_h(t)$is approximated by distributing each month's total load uniformly across its hours:

$$L_h(t) = \frac{L(m)}{N_{hours}(m)}, t \in \text{month } m$$

where $N_{hours}(m)$is the number of hours in month m. This approximation preserves monthly energy totals while enabling hourly battery simulation. The SOC is initialized to zero at the start of the simulation and is constrained to $[0, E_{battery}]$at all times. Hourly battery outputs are aggregated to monthly totals for reporting.

3.10 Performance Metrics

Three primary technical performance metrics are computed for each scenario and configuration:

Renewable Penetration quantifies the fraction of campus demand met by renewable generation in each month and serves as the primary indicator of system effectiveness:

$$Penetration(m) = \frac{E_{gen}(m)}{L(m)} \times 100\%$$

Grid Import represents the remaining dependence on external electricity supply and measures how effectively the system offsets campus demand:

$$\text{Grid Import}(m) = \max\left(0,\ L(m) - E_{gen}(m)\right)$$

Excess Energy reflects renewable generation that cannot be consumed by the campus load under the given configuration and serves as an indicator of system oversizing and unutilized generation potential:

$$Excess(m) = max\left(0, E_{gen}(m)\ - L(m)\right)$$

Together these three metrics provide a comprehensive framework for evaluating trade-offs between renewable utilization, grid dependency, and system efficiency (Hassan et al., 2023).

3.11 Techno-Economic Evaluation

A simplified techno-economic analysis was conducted using the Levelized Cost of Energy (LCOE), which captures the total lifetime cost of a system per unit of energy produced and enables comparison across different configurations on a consistent basis:

$$LCOE = \frac{C_{capital} + C_{O\&M,total}}{E_{annual} \cdot N}$$

where:

$C_{capital}$= total capital cost ($)

$C_{O\&M,total}$= total operation and maintenance cost over project lifetime ($)

E_{annual}= annual renewable energy production (kWh)

N= project lifetime = 20 years

The total O&M cost is computed as:

$$C_{O\&M,total} = C_{O\&M,annual} \cdot N$$

where annual O&M costs are applied per unit of installed capacity. This formulation provides a screening-level economic assessment appropriate for comparative scenario analysis. All cost assumptions are based on published benchmarks and are summarized in Table 2.

Table 2:Model Parameters and Economic Assumptions

Parameter	Value	Source
Baseline PV capacity	10,000 kW	Reference assumption
Number of wind turbines	3	Reference assumption
Turbine rated capacity	3,000 kW	Representative utility-scale
Cut-in wind speed	3 m/s	Koutroulis et al. (2006)
Rated wind speed	12 m/s	Koutroulis et al. (2006)
Cut-out wind speed	25 m/s	Koutroulis et al. (2006)

Hub height	80 m	Representative utility-scale
Hellmann exponent (α)	0.143	Manwell et al. (2010)
PV derating factor (η)	0.85	NREL (2021)
Temperature coefficient (β)	$-0.004\ °C^{-1}$	Crystalline silicon standard
NOCT	45°C	Standard module specification
Battery charge efficiency	0.95	Industry standard
Battery discharge efficiency	0.95	Industry standard
Round-trip efficiency	90.25%	Derived
Base battery duration	4 hours	Base case
PV capital cost	$1,200/kW	NREL (2021)
Wind capital cost	$1,500/kW	Müller et al. (2023)
Battery capital cost	$400/kWh	Kafando et al. (2024)
PV O&M cost	$17/kW/year	NREL (2021)
Wind O&M cost	$43/kW/year	NREL (2021)
Battery O&M cost	$10/kWh/year	Industry benchmark
Project lifetime	20 years	Standard assumption

3.12 Computational Implementation

The simulation framework was implemented entirely in MATLAB using a structured, script-based approach organized into fourteen sequential stages with clear section demarcation. Time-series data were handled throughout using MATLAB timetable structures, which facilitate efficient resampling, aggregation, and temporal alignment operations across datasets of different resolutions.

The complete simulation pipeline proceeds as follows. Meteorological data from three CSV files are ingested, concatenated, cleaned, and resampled to hourly resolution. Hub-height correction is applied to wind speed data before any generation modeling. Solar and wind generation profiles are computed at each hourly time step and combined into three scenario arrays. Scale factor analysis is performed using a loop across multipliers 1 through 5, with monthly performance metrics computed and stored for each. The optimal scale factor is applied to construct the final configuration, and the hourly battery simulation is executed across the complete time series.

Techno-economic metrics are computed for all scenarios and battery durations. All results are stored in structured MATLAB tables and exported as printed summaries. Eight figures are generated covering generation profiles, scenario comparisons, battery performance, and economic sensitivity.

3.13 Modeling Assumptions

The hybrid renewable energy system model developed in this study is based on several simplifying assumptions to maintain computational efficiency and focus on comparative system-level performance analysis. These assumptions are summarized in Table 3.

Table 3: Modeling Assumptions Used in the Hybrid Energy System Simulation

Parameter	Assumption	Justification
Solar irradiance input	Measured horizontal solar radiation from Oklahoma Mesonet station	Represents locally measured environmental conditions
PV derating factor	Constant derating factor applied	Accounts for inverter losses, dust, wiring, and temperature effects in simplified form
Wind turbine performance	Idealized turbine power curve approximation	Focus placed on comparative hybrid system behavior
Battery charging/discharging	100% charging and discharging efficiency assumed	Simplifies energy balance calculations
Battery degradation	Neglected	Study focuses on short-term operational performance rather than lifecycle aging
Load profile	Monthly campus electricity demand distributed uniformly across hourly intervals	Due to limited availability of detailed hourly load data
Grid interaction	Infinite grid availability assumed	Allows evaluation of renewable contribution and grid import reduction
Transmission losses	Neglected	Considered minimal relative to total campus energy demand
Weather conditions	Historical weather conditions assumed representative of long-term trends	Common assumption in renewable energy feasibility studies
Economic analysis	Simplified capital-cost-based LCOE approach	Intended for comparative techno-economic evaluation rather than detailed financial analysis

Chapter 4: Results

4.1 Overview

This chapter presents the results of the simulation-based evaluation of solar photovoltaic, wind, and hybrid wind-solar energy systems for the OU campus. All results are derived from the energy-balance modeling framework described in Chapter 3, incorporating hub-height corrected wind speeds, hourly battery simulation, and site-specific meteorological and campus load data spanning January 2021 through early 2026.

The analysis is organized into five sections. Section 4.2 presents a baseline scenario comparison at scale factor 1, establishing the fundamental generation characteristics and resource complementarity of each configuration. Section 4.3 conducts a scale factor analysis across the hybrid scenario to identify the configuration that best balances renewable penetration with system utilization efficiency. Section 4.4 evaluates the performance of the final selected configuration at scale factor 2 across all three scenarios under consistent conditions. Section 4.5 examines the role of battery energy storage through hourly simulation and sensitivity analysis across storage durations. Section 4.6 presents the techno-economic evaluation, comparing LCOE across all configurations and discussing the economic implications of hybridization and storage integration.

Throughout this chapter, results are presented using time-series plots and aggregated performance metrics to enable both qualitative and quantitative assessment of system behavior. Emphasis is placed on identifying trade-offs between system configuration, seasonal performance, renewable utilization, grid dependency, and cost.

4.2 Baseline Scenario Comparison

4.2.1 Generation Profiles

Figure 4 presents the monthly renewable energy generation profiles for the solar-only, wind-only, and hybrid scenarios at baseline scale factor 1 over the full analysis period from January 2021 through early 2026.

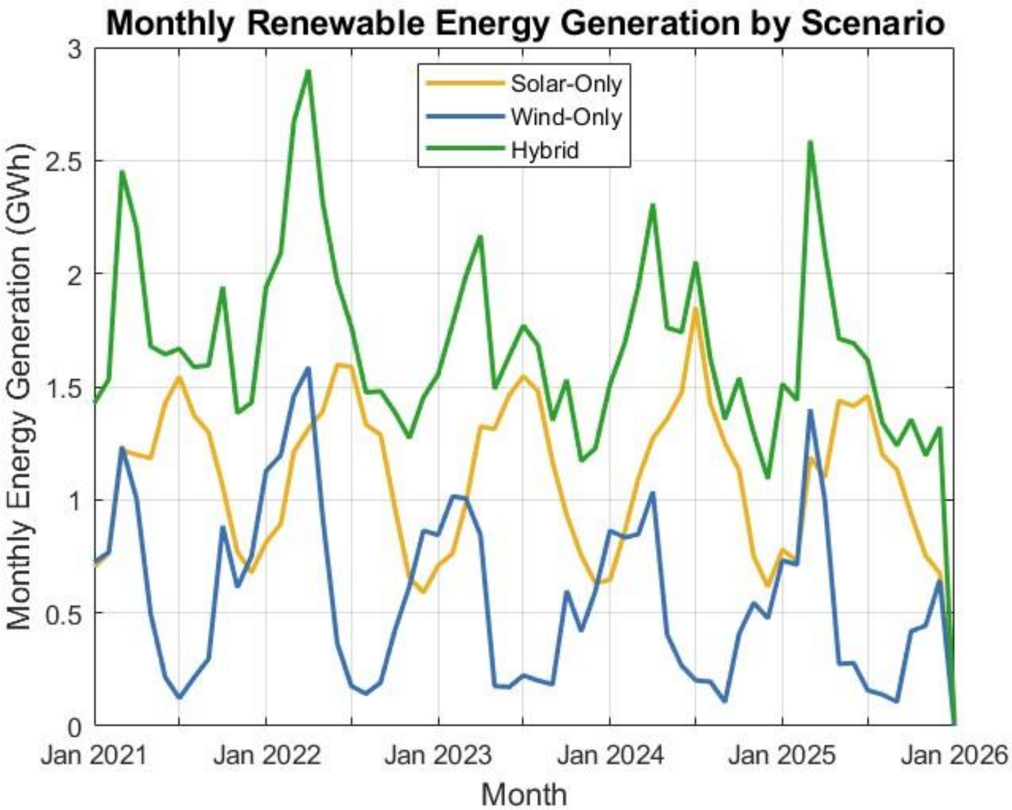

Figure 3: Monthly Renewable Energy Generation by Scenario (Baseline, Scale Factor = 1)

The figure reveals fundamentally different temporal behavior between the two standalone resources and demonstrates the generation advantage achieved through hybridization across all five years of the simulation period. Solar-only generation exhibits a clear and consistent seasonal pattern throughout the analysis period. Generation peaks occur during summer months, reflecting the higher solar irradiance and longer daylight hours characteristic of Oklahoma's climate, with peak monthly values reaching approximately 1.5 to 1.9 GWh. Winter months show a pronounced and predictable reduction in solar output, falling to approximately 0.6 to 0.8 GWh per month, driven by lower solar elevation angles, shorter photoperiods, and increased cloud cover frequency. This seasonal rhythm repeats with high regularity across all five years of the analysis period, confirming that solar irradiance in Norman, Oklahoma follows a well-structured annual cycle with relatively low interannual variability. The predictability of solar output, while limited in absolute magnitude during winter, represents a meaningful operational advantage compared to wind energy from a planning and dispatch perspective.

Wind-only generation displays a markedly different and considerably less predictable temporal pattern. Unlike solar, wind generation is not confined to daylight hours and does not follow a smooth seasonal cycle tied to astronomical factors. Instead, the wind profile is characterized by irregular, high-frequency fluctuations with generation ranging from near zero during extended periods of low wind availability to peaks of approximately 1.4 to 1.6 GWh during the most productive months. These fluctuations occur at multiple timescales simultaneously: short-term variability within individual months driven by synoptic weather systems, and longer-term variability across seasons driven by regional atmospheric circulation patterns. The physical mechanism underlying Oklahoma's summer wind reduction is well established: during summer months, increased atmospheric stability associated with high-pressure systems and reduced baroclinic instability suppresses surface and low-level wind speeds across the Southern Plains (Kaldellis and Zafirakis, 2011). This seasonal suppression is directly visible in *Figure 3*, where wind generation troughs consistently align with the summer months across each year of the analysis.

A critical observation is the frequency and depth of low-generation periods in the wind-only profile. Several months across the analysis period show wind generation dropping below 0.2 GWh, representing near-complete generation failure relative to campus demand. The most severe troughs occur consistently during summer periods, reinforcing the conclusion that the wind resource at this site is characteristically weakest precisely when campus electricity demand is at its annual peak due to space cooling requirements. This inverse relationship between wind availability and load magnitude is a fundamental challenge for standalone wind deployment in this region and is not simply a consequence of turbine sizing or configuration.

The hybrid scenario consistently outperforms both standalone configurations across the entire analysis period. As shown in *Figure 3*, the hybrid profile occupies the upper envelope of the three curves at virtually every time step, with monthly generation ranging from approximately 1.3 GWh at the lower end to a peak of approximately 2.9 GWh observed in early 2023. The additive nature of the hybrid system is directly visible in the figure: during summer months when solar irradiance is strongest, the hybrid profile closely tracks the elevated solar curve with a wind supplement that varies with atmospheric conditions; during winter and transitional months when solar output declines toward its seasonal minimum, wind generation provides a compensating contribution that maintains hybrid output above what either resource could sustain independently. This complementary behavior systematically reduces the frequency and severity of low-generation months compared to either standalone system and represents the core technical justification for hybrid system design at this location.

4.2.2 Baseline Performance Metrics

Table 4 summarizes the quantitative performance metrics for all three scenarios at baseline scale factor 1, providing a rigorous numerical foundation for the qualitative observations made from *Figure 3*.

Table 4: Baseline Scenario Performance Comparison (Scale Factor = 1)

Metric	**Solar-Only**	**Wind-Only**	**Hybrid**
Average Penetration (%)	20.7	14.9	35.6
Minimum Penetration (%)	12.5	1.1	13.9
Maximum Penetration (%)	51.8	53.3	105.0
Avg Grid Import (kWh/month)	5.049 x 10^6	5.574 x 10^6	4.451 x 10^6
Total Excess Energy (kWh)	0	0	6.856 x 10^4

Several technically important observations emerge from these results. First, the hybrid system achieves an average penetration of 35.6%, which is not simply the arithmetic sum of the solar (20.7%) and wind (14.9%) averages. The combined standalone average would be 35.6% only if the two resources were perfectly additive with no temporal overlap in their generation periods, which is not the case in practice. The actual hybrid average matches this sum numerically at baseline scale because both resources are operating well below saturation relative to campus load, meaning that at this scale factor, nearly every unit of generation from either source contributes directly to load coverage without competing with the other. This relationship changes at higher scale factors as generation begins to exceed load in certain periods, which motivates the scale factor analysis in Section 4.3.

Second, the minimum penetration values reveal a technically critical distinction between the two standalone scenarios that average metrics alone would obscure. The solar-only scenario maintains a minimum monthly penetration of 12.5% even during its least productive month, reflecting the predictable irradiance floor established by winter solstice conditions at Norman's latitude of approximately 35 degrees North. Even under the least favorable seasonal conditions, the solar resource at this site produces a non-negligible and foreseeable generation contribution that system operators can rely upon. The wind-only scenario, by contrast, drops to a minimum penetration of just 1.1%, which represents near-total generation failure during the system's worst month. At this level, the wind farm is producing approximately 1.1% of monthly campus demand, which equates to a monthly energy output of roughly 66,000 kWh against a typical campus monthly load on the order of 6 million kWh. This level of generation is operationally negligible and confirms that the standalone wind scenario cannot provide meaningful supply reliability continuity for a load profile with continuous and non-deferrable demand requirements such as a research university campus.

Third, the near-zero excess energy across all three scenarios at scale factor 1 confirms that the baseline configuration is appropriately scaled relative to campus consumption. The small hybrid excess of 68,560 kWh represents less than 0.2% of total annual campus demand and is operationally inconsequential. This result validates the baseline sizing assumption: the system is neither significantly undersized nor oversized at scale factor 1 and provides a clean starting point for the scale factor sensitivity analysis.

4.2.3 Resource Complementarity Analysis

The baseline results provide quantitative evidence of temporal complementarity between solar and wind resources at the Norman, Oklahoma site. The complementarity effect can be assessed by comparing the hybrid minimum penetration (13.9%) against the individual resource minima (12.5% solar, 1.1% wind). The hybrid minimum is governed almost entirely by the solar resource floor, confirming that during the wind resource's worst months, the solar contribution successfully prevents a generation collapse. Conversely, during months when solar output is reduced by winter irradiance conditions, wind generation provides supplementary energy that partially compensates for the solar deficit.

This reciprocal compensation pattern is consistent with the wind-solar complementarity documented in the literature for mid-latitude continental locations where summer solar dominance and winter wind enhancement create natural seasonal diversity (Kaldellis and Zafirakis, 2011; Hassan et al., 2023). The Norman, Oklahoma site exhibits this pattern clearly, with the seasonal phase relationship between the two resources providing a natural hedging mechanism that reduces aggregate system variability without requiring active control or storage. These findings motivate the scale factor analysis presented in the following section, which evaluates how this complementary behavior translates into system-level performance metrics across a range of installed capacities.

4.3 Scale Factor Analysis

4.3.1 Penetration and Excess Energy Trade-off

To evaluate the relationship between installed capacity and system performance, a scale factor ranging from 1 to 5 was applied multiplicatively to the baseline hybrid generation profiles. Figure 4 presents the dual-axis visualization of average renewable penetration (left axis, blue bars) and total excess energy (right axis, orange line) across the five scale factors evaluated. Table 5 provides numerical results for all metrics.

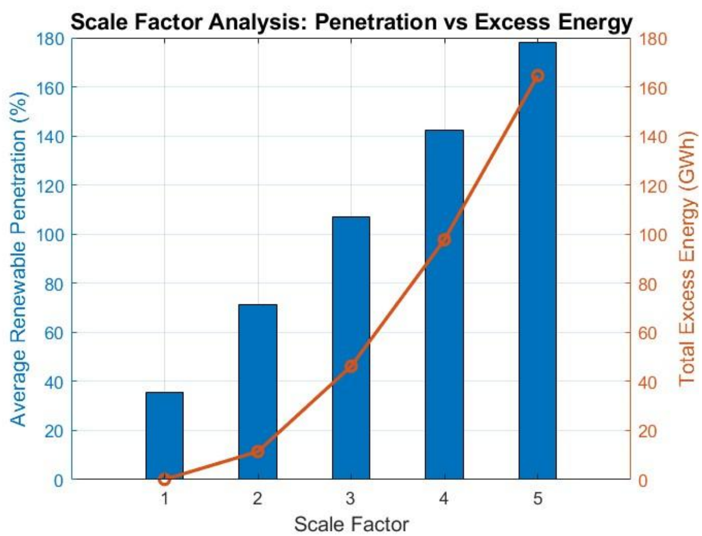

Figure 4: Scale Factor Analysis: Penetration vs Excess Energy

Table 5: Scale Factor Analysis Results (Hybrid Scenario)

Scale Factor	Avg Penetration (%)	Min Penetration (%)	Max Penetration (%)	Total Excess (kWh)	Avg Grid Import (kWh/month)
1	35.6	13.9	105.0	6.856 x 10^4	4.451 x 10^6
2	71.2	27.8	210.1	1.142 x 10^7	2.931 x 10^6
3	106.9	41.7	315.2	4.618 x 10^7	1.828 x 10^6
4	142.5	55.6	420.2	9.771 x 10^7	1.025 x 10^6
5	178.1	69.5	525.3	1.646 x 10^8	4.956 x 10^5

Figure 4 reveals a clear and technically important pattern. Average renewable penetration increases linearly with scale factor, rising from 35.6% at scale factor 1 to 178.1% at scale factor 5. This linear relationship is physically expected: since generation scales proportionally with installed capacity at each time step, and campus load remains fixed, the ratio of total generation to total load increases linearly with the scaling multiplier. The linearity of the penetration response confirms that the simulation framework is behaving consistently with theoretical expectations and provides confidence in the validity of the underlying model.

Total excess energy, however, follows a strongly nonlinear trajectory that diverges sharply from the penetration trend above scale factor 2. At scale factor 1, excess energy is negligible at 68,560 kWh, indicating that nearly all generated energy is consumed by the campus load. At scale factor 2, total excess rises to 11.4 GWh, reflecting the onset of generation surplus during the system's highest-output months. From scale factor 2 to scale factor 3, excess energy increases by a factor of approximately four, jumping to 46.2 GWh. At scale factors 4 and 5, excess reaches 97.7 and

164.6 GWh respectively, values that represent substantial fractions of annual campus demand being generated but not utilized. This nonlinear acceleration in excess energy reflects a transition from a regime in which additional generation capacity directly offsets grid import in every month, to a regime in which a growing fraction of additional capacity simply adds to surplus that cannot be consumed during high-generation periods regardless of the total installed quantity.

The physical interpretation of this transition is important. At scale factor 1, the system is always generation-limited: campus demand exceeds renewable output in every month, so every additional unit of generation capacity directly reduces grid import. As the scale factor increases above approximately 2, the system begins to experience surplus months where generation exceeds load. In these months, the campus has no mechanism to absorb additional generation other than storage or export, and increasing scale factor simply amplifies the magnitude of the surplus without contributing to load coverage. The inflection in the excess energy curve between scale factors 2 and 3 marks this transition clearly in Figure 4 and represents the fundamental design boundary that separates efficient from oversized renewable system configurations.

4.3.2 Grid Import Reduction and Diminishing Returns

Grid import decreases consistently as scale factor increases, falling from an average of 4.45 x 10^6 kWh per month at scale factor 1 to 4.96 x 10^5 kWh at scale factor 5. However, the incremental grid import reduction per unit increase in scale factor diminishes progressively, demonstrating the O&M. The step from scale factor 1 to 2 reduces average monthly grid import by 1.52 x 10^6 kWh, equivalent to a 34.2% reduction per unit of added scale. The subsequent step from scale factor 2 to 3 reduces average monthly grid import by a further 1.10 x 10^6 kWh, a marginal reduction rate approximately 27.7% lower than the previous step despite the same absolute increment in installed capacity. Moving from scale factor 4 to 5 reduces average monthly grid import by only 5.29 x 10^5 kWh, less than 35% of the reduction achieved by the first scaling step. This progressive decline in marginal grid import reduction per unit of additional capacity quantifies the diminishing returns effect and provides a rigorous economic argument for the existence of an optimal configuration beyond which further investment in generation capacity yields disproportionately small operational benefits.

4.3.3 Optimal Configuration Selection and Engineering Trade-off

The results of the scale factor analysis reveal that no single configuration simultaneously maximizes all performance objectives, and that configuration selection requires an explicit engineering judgment about the relative priority of renewable penetration, system utilization efficiency, and economic performance. Two candidate configurations emerge from the analysis as representing meaningful engineering optima under different objective functions.

Scale factor 2 achieves an average penetration of 71.2% with total excess energy of 11.4 GWh and an average monthly grid import of 2.93 x 10^6 kWh. The minimum monthly penetration of 27.8% confirms that even during the system's worst-performing month, more than one quarter of campus demand is met by renewable generation. Total excess at this scale represents approximately 3.8% of total annual campus demand, indicating a high degree of generation utilization. This configuration maximizes the fraction of installed capacity that contributes to useful energy delivery and represents the economically optimal choice under a cost minimization objective.

Scale factor 3 achieves an average penetration of 106.9%, crossing the full-coverage threshold on an annual average basis, and improves the minimum monthly penetration to 41.7%. From a grid independence and resilience perspective, scale factor 3 provides superior performance: the campus is on average generating more than it consumes, and even during the worst-performing month, renewable sources cover nearly 42% of demand. The cost of this improved reliability is a fourfold increase in total excess energy to 46.2 GWh, representing approximately 15% of annual campus demand being generated without a local consumption pathway. This configuration represents the technically optimal choice under a reliability maximization or grid independence objective.

For the purposes of this study, scale factor 2 is selected as the primary analysis configuration on the basis that it delivers the most favorable balance between renewable penetration and system utilization efficiency under current cost assumptions. Scale factor 3 is retained as a reference point in the discussion to illustrate the cost-reliability trade-off, which is a consideration of direct relevance to institutional energy planning at OU.

4.4 Final Hybrid System Performance

4.4.1 Three-Scenario Comparison

With scale factor 2 established as the selected configuration, Table 6 presents the complete performance comparison across all three scenarios evaluated under identical meteorological inputs, load data, and scale assumptions. This side-by-side comparison under consistent conditions is the central analytical contribution of this study and directly addresses the research question posed in Chapter 1.

Table 6: Final Configuration Performance Comparison (Scale Factor = 2)

Metric	Solar-Only	Wind-Only	Hybrid
Average Penetration (%)	41.4	29.9	71.2
Minimum Penetration (%)	24.9	2.2	27.8
Maximum Penetration (%)	103.6	106.5	210.1
Avg Grid Import (kWh/month)	3.926 x 10^6	4.978 x 10^6	2.930 x 10^6

The hybrid system outperforms both standalone scenarios across every metric relevant to campus energy supply reliability. The average penetration of 71.2% for the hybrid system exceeds the solar-only value by 29.8 percentage points and the wind-only value by 41.3 percentage points, while the average monthly grid import of 2.93 x 10^6 kWh represents a reduction of approximately 25.4% relative to solar-only and 41.1% relative to wind-only. These differences are not marginal improvements but represent qualitatively different levels of renewable energy integration that carry substantial implications for campus carbon emissions, energy cost exposure, and grid dependence.

A particularly important comparison is between the solar-only and wind-only configurations, which reveals that despite having similar installed capacities (20 MW solar versus 18 MW wind at scale factor 2), the solar-only scenario achieves substantially higher average penetration (41.4% versus 29.9%) and lower average grid import. This performance differential is attributable to two compounding factors. First, the solar resource in Norman, Oklahoma produces more annual energy than the wind resource at 80 m hub height under current atmospheric conditions, as quantified by the annual energy outputs reported in Section 4.6. Second, and more operationally significant, the wind-only scenario's average penetration is suppressed by the severe low-generation events documented throughout the analysis period, during which wind generation contributes negligibly to campus load coverage and the monthly average absorbs the penalty of near-zero output months.

4.4.2 Renewable Penetration Profiles

Figure 5 presents the monthly renewable penetration for all three scenarios at scale factor 2 over the full analysis period, with a dashed reference line marking the 100% penetration threshold. This figure provides the most comprehensive visual summary of comparative scenario performance in the study.

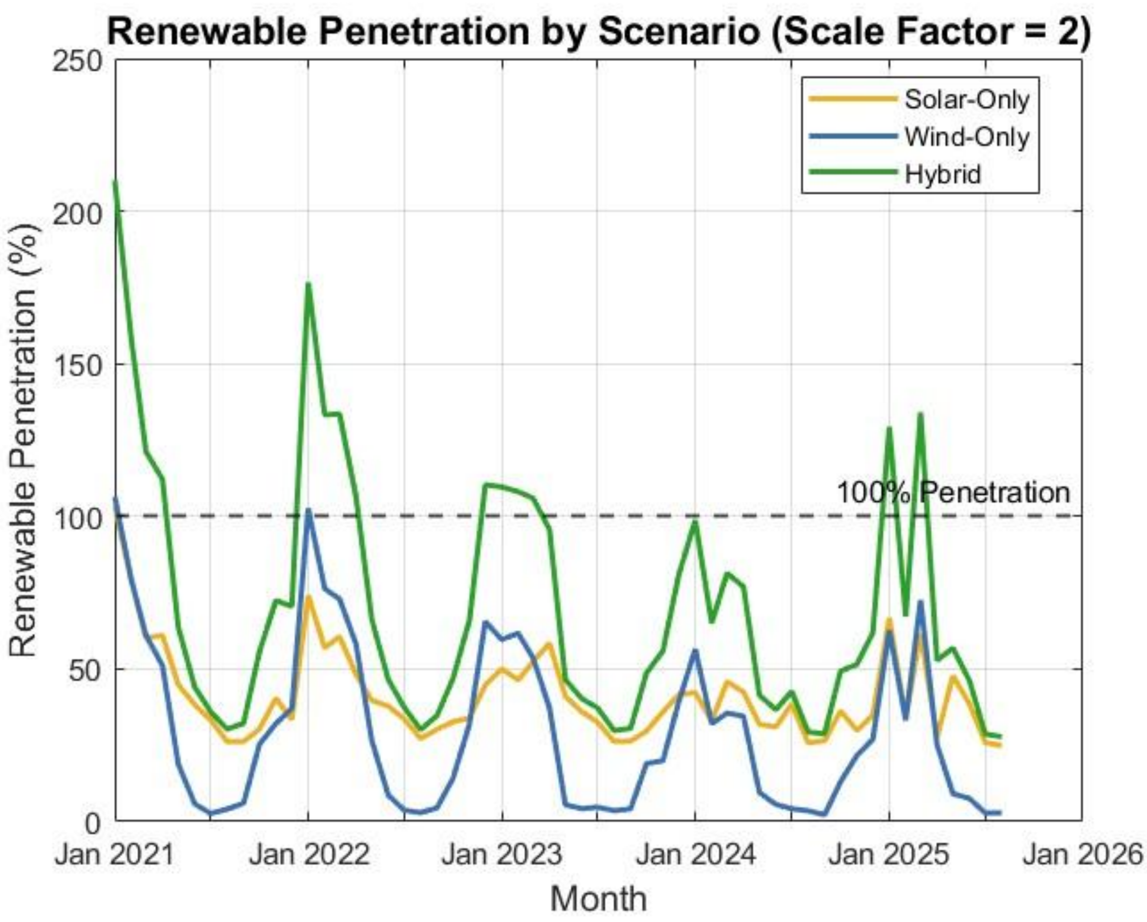

Figure 5: Renewable Penetration by Scenario (Scale Factor = 2)

The solar-only profile exhibits the consistent and predictable seasonal cycling established at baseline scale, now amplified by the scale factor 2 multiplier. Penetration ranges from approximately 25% during the lowest winter months to peaks approaching and occasionally exceeding 100% during summer, with solar-only penetration reaching approximately 103.6% during its maximum month. The smooth and cyclical character of the solar penetration profile, with well-defined annual peaks and troughs of consistent shape across all five years, reflects the astronomical regularity of solar irradiance variability and confirms that solar generation at this site is highly predictable on a seasonal planning horizon.

The wind-only profile is the most visually striking of the three curves in Figure 5. While it achieves maximum penetration values exceeding 100% during its most productive months, demonstrating that the installed wind capacity is technically capable of fully meeting campus demand under favorable atmospheric conditions, it also collapses to near zero on multiple occasions across the five-year period. The near-zero wind penetration events visible in the figure, most consistently during the summer months of 2021, 2022, 2023, and 2024, correspond to the atmospheric stability periods described in Section 4.2. During these months, the wind farm generates negligible energy relative to campus demand despite representing a substantial capital investment. The contrast between the wind-only scenario's capability peaks exceeding 100% penetration and its repeated near-zero collapses encapsulates the fundamental limitation of standalone wind energy in this geographic and climatic context: high peak capacity does not translate to operational reliability when the resource exhibits severe seasonal suppression coinciding with peak demand periods.

The hybrid profile demonstrates the performance advantage of resource complementarity with clarity throughout the figure. The hybrid curve consistently occupies the highest position among the three scenarios and crosses the 100% penetration threshold on multiple occasions, including early 2021, around early 2022, during the late 2022 to early 2023 transition, and again in early 2025. These periods of full renewable coverage would not be achievable by either standalone configuration alone. Equally importantly, the hybrid profile never approaches the catastrophic low penetration values exhibited by the wind-only scenario. The hybrid system's minimum penetration of 27.8% represents a floor approximately 25.6 percentage points higher than wind-only being 2.2% minimum, achieved through the solar resource's compensating contribution during wind's seasonal weakness. This floor improvement is operationally significant: it means that even under the hybrid system's worst monthly conditions, campus grid dependence never exceeds approximately 72%, compared to greater than 97% grid dependence during the wind-only scenario's worst month.

4.4.3 Hybrid Generation and Load Matching

Figure 6 presents the monthly hybrid generation against the OU campus net load over the full analysis period and provides direct visualization of the gap between renewable supply and institutional demand that motivates the battery and grid integration analysis in subsequent sections.

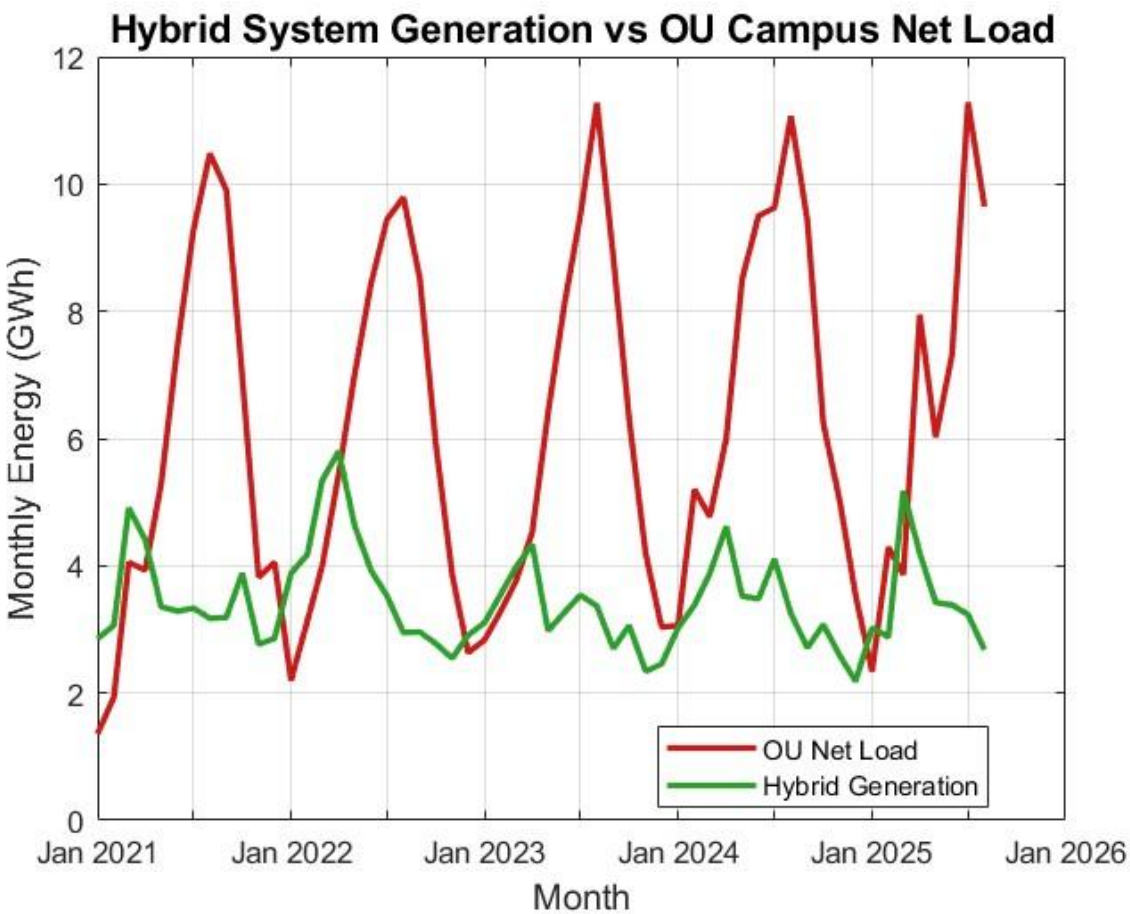

Figure 6: Hybrid System Generation vs OU Campus Net Load

The campus net load exhibits a pronounced and repeating seasonal pattern across all five years of the analysis period. Sharp demand peaks occur during summer months, with maximum monthly values reaching approximately 10.5 to 11.2 GWh during the peak cooling season. These summer peaks are driven primarily by the space cooling requirements of OU's large building stock during

Oklahoma's characteristically hot summers, where ambient temperatures regularly exceed 35 degrees Celsius for extended periods. Winter months show substantially lower load values, typically in the range of 2.0 to 4.5 GWh, reflecting reduced cooling demand and the moderation of heating loads by the campus's mix of building types and heating systems. The ratio of peak summer load to minimum winter load across the analysis period is approximately 4:1 to 5:1, indicating a high degree of seasonal load variability that presents a significant challenge for any fixed-capacity renewable generation system.

The hybrid generation profile operates within a considerably narrower amplitude band than the campus load. Monthly hybrid generation ranges from approximately 2.3 GWh at its seasonal minimum to approximately 5.8 GWh at its seasonal maximum, representing a peak-to-trough ratio of approximately 2.5:1. This compressed variability range compared to the load profile is a direct consequence of the complementary wind-solar resource combination: during summer months when solar generation is at its peak, wind generation is partially suppressed, moderating the upward swing of hybrid output; during winter months when solar generation declines, wind generation increases to partially compensate, moderating the downward swing. The net effect is that the hybrid system's seasonal amplitude is meaningfully smaller than the solar-only system's amplitude would be, which partially but not completely bridges the gap between generation and the extreme summer load peaks.

The persistent gap between the hybrid generation curve and the campus load curve, visible throughout Figure 6, confirms that the scale factor 2 configuration is appropriately sized for partial but substantial load coverage within a grid-connected framework rather than energy self-sufficiency. During the highest-demand summer months, hybrid generation covers approximately 27 to 35% of monthly campus load, with grid import supplying the remainder. During the most favorable low-demand months in late winter and early spring, hybrid generation approaches or briefly meets campus load as the two curves converge in the figure. The closest convergence points visible in Figure 6 occur around early 2022, early 2023, and early 2025, consistent with the high-penetration months identified in Figure 5.

4.4.4 Grid Import Comparison Across Scenarios

Figure 7 presents monthly grid import across all three scenarios at scale factor 2 and provides the most operationally direct comparison of each configuration's ability to reduce campus dependence on externally supplied electricity.

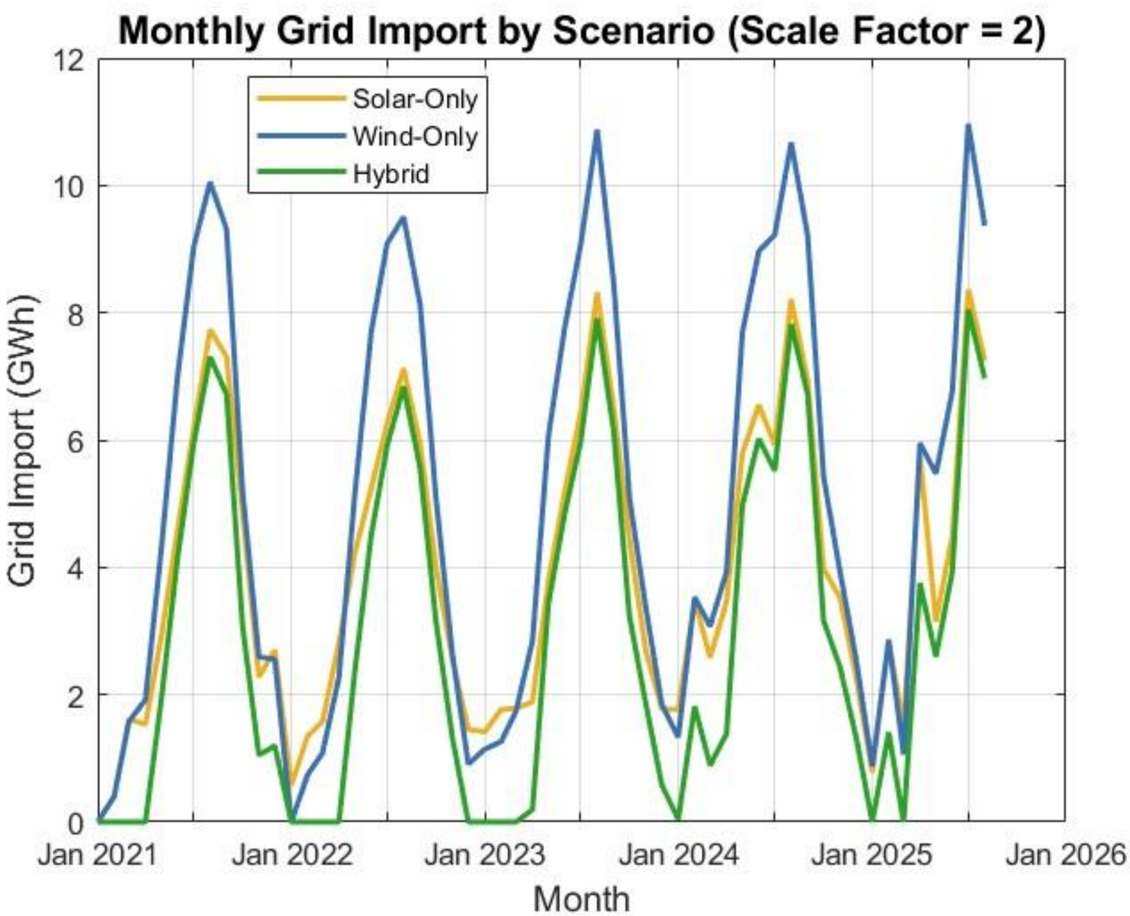

Figure 7: Monthly Grid Import by Scenario (Scale Factor = 2)

The wind-only scenario consistently exhibits the highest grid import of the three configurations across the majority of the analysis period. During summer months when the wind resource weakens, wind-only grid import approaches the full campus load magnitude, reaching peaks of approximately 10.1 GWh in summer 2021 and 10.6 GWh in summer 2025. These peak import values are nearly indistinguishable from the campus net load itself during those months, confirming that the wind farm provides near-zero supply relief during the highest-demand periods. This outcome is particularly consequential from an economic standpoint: the months of highest grid import coincide with the months of highest electricity prices due to peak demand tariffs and summer rate premiums, meaning that the wind-only scenario fails to reduce costs precisely when cost reduction is most valuable.

The solar-only scenario performs considerably better than wind-only during summer, when solar generation is near its annual peak and partially offsets the elevated cooling load. Grid import for solar-only during peak summer months ranges from approximately 6.5 to 8.3 GWh, representing a meaningful reduction relative to wind-only. The physical mechanism is straightforward: solar irradiance peaks during the same summer months that campus cooling demand peaks, creating a partial natural alignment between supply and demand that the wind resource lacks at this site. During winter months, the two standalone scenarios converge in grid import magnitude, as both resources are constrained by their respective seasonal weaknesses and the low winter campus load limits the practical impact of generation differences.

The hybrid scenario achieves the lowest grid import of the three configurations across all seasons and all years in the analysis period without exception. The separation between the hybrid curve and the two standalone curves is most pronounced during transitional months in spring and autumn, when the wind-solar complementarity described in Section 4.2 is strongest and the combined system produces enough energy from both resources simultaneously to approach full load coverage. During these transitional periods, hybrid grid import drops to near zero on several occasions visible in Figure 7, particularly around early 2022, early 2023, and early to mid-2025, confirming months in which the hybrid system fully or nearly fully met campus electricity demand from renewable sources. These zero-import months represent a qualitative performance threshold that neither standalone scenario achieves at any point in the analysis period, underscoring that the hybrid configuration does not merely provide a quantitative improvement over standalone systems but enables operational outcomes that are fundamentally inaccessible to single-resource configurations at the same installed capacity.

4.5 Battery Energy Storage Performance

4.5.1 Methodological Significance of Hourly Simulation

A defining feature of the battery analysis in this study is the use of hourly time-step simulation, as described in Section 3.9.2. This methodological choice has a direct and substantial impact on the results obtained. Battery storage systems physically respond to generation-load imbalances at hourly and sub-hourly timescales, charging during periods of surplus generation and discharging during deficit periods within each day. When battery simulation is conducted at monthly resolution, as is common in screening-level studies, the diurnal surplus and deficit cycles within each month are averaged away before the battery model is applied. The result is that the battery sees only the net monthly energy balance rather than the hourly fluctuations, and in months where total generation approximately equals total load, the monthly model predicts near-zero battery activity even if there are substantial hourly surpluses and deficits that a real battery would cycle through daily.

The consequence of this averaging effect on the results is significant. A monthly simulation of the hybrid system at scale factor 2 would predict battery grid import reduction on the order of 0.1 to 0.5%, because the monthly net energy balances show limited surplus. The hourly simulation conducted in this study reveals a grid import reduction of 19.1% for the same system and battery configuration. This difference of nearly two orders of magnitude is not a modeling artifact but a physically correct result: the battery is capturing daily and weekly surpluses that the monthly model cannot see. This finding underscores the importance of temporal resolution selection in renewable energy storage modeling and represents a methodological contribution of this study.

4.5.2 Battery State of Charge

Figure 8 presents the monthly mean battery state of charge over the analysis period for the 4-hour base case configuration with a total capacity of 152,000 kWh. The maximum capacity reference line at 152 MWh is indicated by the red dashed line in the figure.

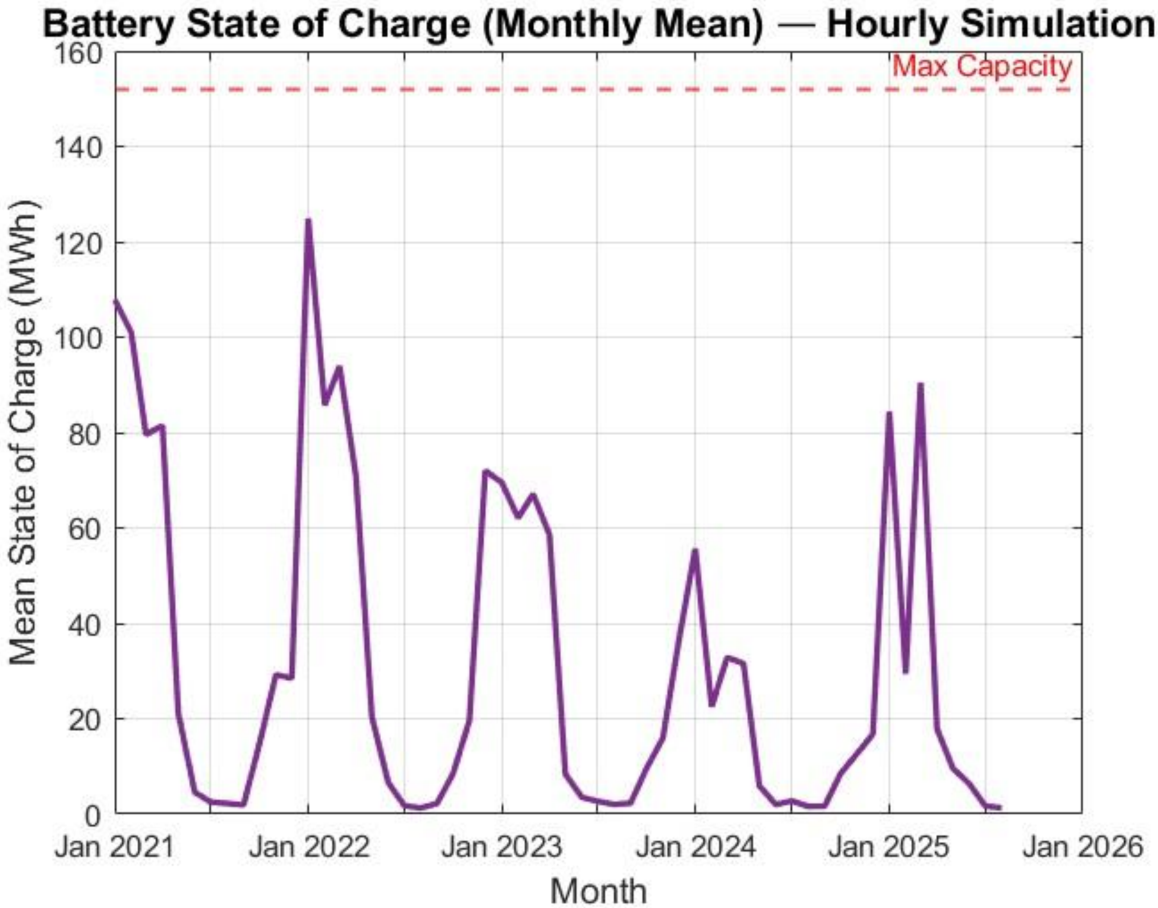

Figure 8: Battery State of Charge (Monthly Mean) - Hourly Simulation

The SOC profile reveals that the battery engages actively and repeatedly throughout the five-year analysis period, with monthly mean values exhibiting substantial variation that reflects the seasonal patterns of renewable surplus and deficit described in earlier sections. The highest sustained SOC levels occur during periods of strong combined wind and solar generation relative to campus load, most notably in early 2022 where mean monthly SOC reaches approximately 125 MWh, which corresponds to approximately 82% of maximum battery capacity. Additional high-SOC periods are visible during the 2022 to 2023 winter transition, mid-2023, and early 2025, all of which align with the high-penetration periods identified in Figure 5. During these periods, the daily renewable generation consistently exceeds the daily campus load across many individual hours, providing the surplus energy that charges the battery on a diurnal cycle.

The battery never sustains operation at or near its maximum capacity for extended consecutive months. Following each high-SOC episode, the SOC returns progressively toward zero as the battery discharges during subsequent deficit periods. This cyclic charge-discharge pattern is most clearly visible in the 2022 period, where the SOC rises to approximately 125 MWh in January 2022 then declines steadily through the summer months as wind generation weakens and campus cooling load increases; depleting the stored energy faster than it can be replenished by daytime solar surpluses alone.

Extended periods of near-zero SOC are visible in Figure 8 during the summer months of 2021, 2022, 2023, and 2024, corresponding precisely to the periods of maximum campus load and minimum wind generation. During these intervals, the campus load exceeds hybrid generation at the great majority of hourly time steps, leaving no surplus available to charge the battery. The battery is rapidly depleted at the beginning of each of these periods and remains inactive through the bulk of the summer months, confirming that storage system performance at this site is fundamentally limited by the availability of surplus renewable generation rather than by battery capacity. This is an important physical finding: increasing battery capacity beyond a certain threshold during these periods would not improve performance because there is insufficient surplus generation to charge a larger battery regardless of its size.

4.5.3 Impact of Battery on Grid Import

Figure 9 presents monthly grid import with and without battery storage over the full analysis period. The hourly simulation methodology adopted in this study produces a visibly meaningful separation between the two curves across all five years, in contrast to the negligible separation that would result from monthly-resolution modeling.

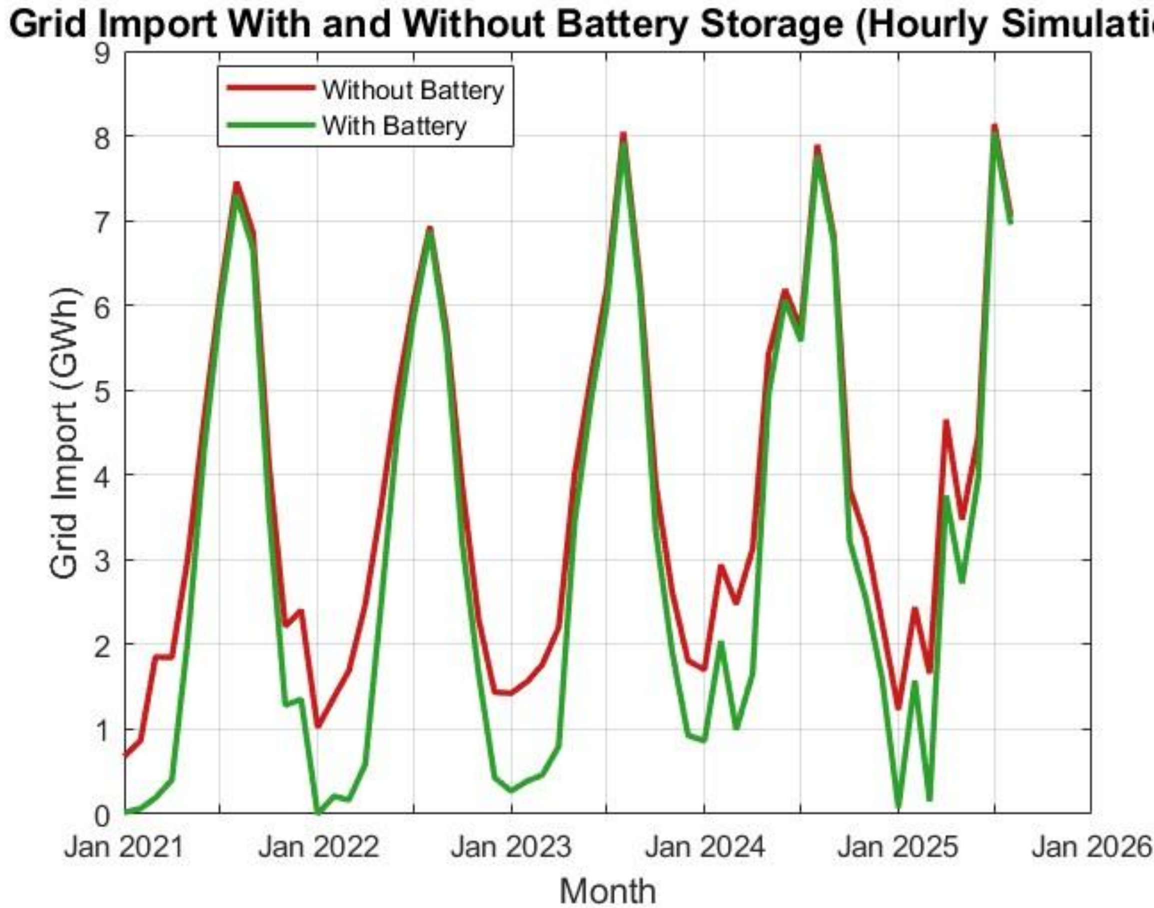

Figure 9: Grid Import With and Without Battery Storage (Hourly Simulation)

The reduction in grid import attributable to the battery is visible throughout Figure 9 as a consistent downward shift of the with-battery curve (green) relative to the without-battery curve (red). The most pronounced separations between the two curves occur during transitional months at the boundaries of the high-generation and high-demand seasons, particularly during early 2021, the late 2021 to early 2022 winter period, early 2022, the 2022 to 2023 transition, and the 2024 to 2025 transition. During these intervals, the battery is actively discharging energy that was captured during the preceding high-generation period, reducing the campus's reliance on grid supply during hours when hybrid generation alone is insufficient to meet load.

The grid import profiles for both cases follow the same broad seasonal shape, with summer peaks and winter-spring troughs, confirming that the battery does not fundamentally alter the seasonal structure of grid dependency but rather modulates the magnitude of import within each seasonal period. The battery is most effective during the low-import months, where the with-battery curve reaches near-zero values more consistently than the without-battery curve. This behavior reflects the battery's role as a short-term energy buffer rather than a seasonal energy storage mechanism: it shifts energy from high-generation hours to adjacent low-generation hours within the same week or month, but it cannot transfer energy across the multi-month seasonal gap between the winter high-generation period and the summer high-demand period.

Quantitatively, the 4-hour battery configuration achieves a total grid import reduction of 40.8 x 10^6 kWh over the full analysis period, representing a 19.1% reduction relative to the baseline hybrid system without storage. Total battery discharge over the same period is 40.8 x 10^6 kWh, and total curtailed energy after battery charging is 15.4 x 10^6 kWh. The equality between total grid import reduction and total battery discharge is physically consistent: every kilowatt-hour discharged by the battery directly displaces a kilowatt-hour of grid import, confirming the internal consistency of the hourly energy balance model. The remaining curtailment of 15.4 GWh represents surplus generation that occurred during hours when the battery was already at full capacity, confirming that the battery successfully captured all surplus available during its non-full periods but could not accommodate all surplus events within the 4-hour capacity constraint.

4.5.4 Battery Sensitivity Analysis

To evaluate the relationship between storage capacity and system performance across a range of configurations, battery durations of 2, 4, 6, and 8 hours were simulated using the same hourly energy balance model. Figure 10 presents the dual-axis sensitivity results showing LCOE (left axis) and grid import reduction (right axis) as functions of storage duration. Table 5 provides the complete numerical results.

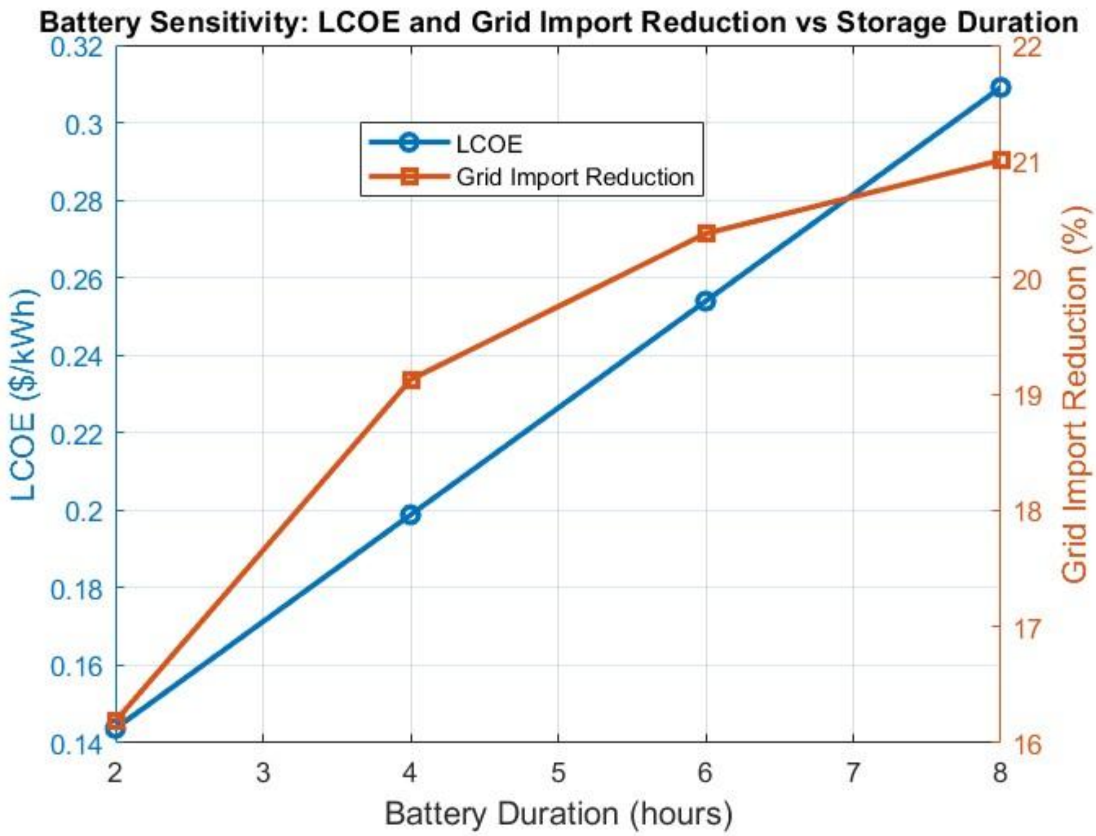

Figure 10: Battery Sensitivity: LCOE and Grid Import Reduction vs Storage Duration

Table 6: Battery Sensitivity Analysis Results

Duration (hr)	Capacity (kWh)	Total Discharge (kWh)	Grid Import (kWh)	Reduction (kWh)	Reduction (%)	Curtailed (kWh)	Total Cost ($)	LCOE ($/kWh)
2	76,000	3.453 x 10^7	1.788 x 10^8	3.453 x 10^7	16.2	3.258 x 10^7	8.14 x 10^7	0.1437
4	152,000	4.080 x 10^7	1.726 x 10^8	4.080 x 10^7	19.1	2.555 x 10^7	1.118 x 10^8	0.1988
6	228,000	4.348 x 10^7	1.699 x 10^8	4.348 x 10^7	20.4	2.251 x 10^7	1.422 x 10^8	0.2540
8	304,000	4.483 x 10^7	1.685 x 10^8	4.483 x 10^7	21.0	2.093 x 10^7	1.726 x 10^8	0.3091

Figure 10 captures the central engineering tension of battery integration at this site with quantitative precision. As storage duration increases from 2 to 8 hours, LCOE rises steeply and nearly linearly from $0.144/kWh to $0.309/kWh, a cost increase of $0.165/kWh or approximately 115%. Over the same range, grid import reduction improves from 16.2% to

21.0%, an increase of only 4.8 percentage points. The visual divergence between the steep and approximately linear LCOE curve and the rapidly flattening grid import reduction curve in Figure 4.8 illustrates the diminishing returns phenomenon with clarity that the tabular data alone does not convey: at 2-hour storage, each additional percentage point of grid import reduction costs approximately $0.009/kWh in LCOE; at 8-hour storage, achieving the same marginal improvement costs approximately $0.030/kWh per percentage point.

The physical mechanism underlying this diminishing return is visible in the curtailment column of Table 5. As battery capacity increases from 2 to 8 hours, total curtailed energy decreases from 32.6 GWh to 20.9 GWh, a reduction of 11.7 GWh. This confirms that the larger batteries are successfully capturing additional renewable surplus that would otherwise be curtailed. However, the diminishing rate of curtailment reduction with increasing capacity also confirms that the available surplus generation is being progressively exhausted: moving from 6 to 8 hours of storage captures only 1.6 GWh of additional curtailed energy compared to 7.0 GWh captured by moving from 2 to 4 hours. The fundamental constraint is not battery capacity but rather the finite quantity of surplus generation available to charge the battery. Even at 8 hours of storage, 20.9 GWh of annual curtailment remains, indicating that periods of surplus generation in excess of 304,000 kWh accumulated capacity still occur, but these are increasingly infrequent and short-duration events that would require disproportionately large storage capacity to capture.

In this study, campus electricity demand data were available primarily in monthly form. To enable hourly simulation of the hybrid renewable energy system, monthly electricity consumption values were distributed uniformly across hourly intervals within each month. This assumption simplifies the load modeling process but may not fully capture actual variations in campus electricity demand caused by daily occupancy patterns, weather conditions, academic schedules, or seasonal operational changes. Despite this simplification, the adopted approach remains appropriate for evaluating overall system-level trends and comparative performance between different renewable energy configurations. The primary objective of the study was to compare the relative contributions of solar, wind, and battery storage systems rather than reproduce exact real-time campus electrical behavior.

The use of a uniformly distributed load profile may influence certain performance metrics, particularly:

- hourly grid import values,
- battery charging and discharging behavior,
- renewable curtailment levels, and
- short-term mismatch between generation and demand.

However, long-term annual energy trends and comparative results between scenarios are expected to remain reasonably representative. Since all modeled scenarios were evaluated using the same load assumptions, the comparative conclusions regarding the effectiveness of hybrid renewable integration remain valid.

Future work could improve model realism by incorporating:

- hourly smart-meter campus load data,
- seasonal occupancy schedules,
- demand-side management strategies, and
- time-varying building-level electricity consumption profiles.

Such improvements would allow more accurate simulation of battery operation, peak demand reduction, and renewable energy utilization under realistic campus operating conditions.

4.6 Techno-Economic Analysis

4.6.1 LCOE Comparison Across Scenarios

Table 7 presents the complete techno-economic summary for all configurations evaluated in this study, incorporating capital costs, lifetime operation and maintenance costs, annual energy production, and resulting LCOE for each scenario and storage configuration.

Table 7: Techno-Economic Summary (Scale Factor = 2)

Metric	Solar-Only	Wind-Only	Hybrid	Hybrid + Battery (4hr)

Capital Cost ($)	2.40 x 10^7	2.70 x 10^7	5.10 x 10^7	1.12 x 10^8
Total O&M Cost ($)	6.80 x 10^6	1.55 x 10^7	2.23 x 10^7	5.27 x 10^7
Annual Energy (kWh)	2.70 x 10^7	1.44 x 10^7	4.14 x 10^7	4.14 x 10^7
LCOE ($/kWh)	0.0571	0.1477	0.0886	0.1988

The LCOE results reveal a technically and economically informative hierarchy across the four configurations that merits detailed analysis. The solar-only configuration achieves the lowest LCOE at $0.057/kWh, driven by the combination of a relatively modest capital cost of $24M, low annual O&M cost at the NREL benchmark of $17/kW/year, and the highest annual energy production of the four configurations at 27.0 GWh/year. The high energy production relative to installed capacity reflects the strong solar resource in Norman, Oklahoma, where annual global horizontal irradiance values support high capacity factors for utility-scale PV systems. The solar-only LCOE of $0.057/kWh compares favorably with published benchmark ranges for utility-scale solar PV in the South Central United States and confirms that solar deployment at this site is economically competitive at current cost levels (NREL, 2021).

The wind-only configuration produces the highest LCOE among the no-storage scenarios at $0.148/kWh, a value 2.59 times higher than solar-only despite a capital cost only $3M greater. This disproportionate LCOE elevation relative to capital cost reflects the compounding effect of two disadvantages specific to the wind resource at this site. First, annual energy production from the wind-only system is only 14.4 GWh/year, approximately 53% of the solar-only system's output from a comparable installed capacity. This reflects the lower effective capacity factor of the wind resource at 80 m hub height under Norman's atmospheric conditions and the frequency of low-generation periods documented throughout the analysis. Second, the wind O&M cost benchmark of $43/kW/year is 2.5 times higher than the solar O&M benchmark on a per-kilowatt basis, resulting in a total lifetime O&M cost of $15.5M for wind-only compared to $6.8M for solar-only. The combination of higher O&M cost and lower energy production creates a compounding LCOE penalty that makes standalone wind the least economically attractive configuration at this site under current cost assumptions.

The hybrid configuration achieves an LCOE of \$0.089/kWh, which is higher than solar-only by \$0.032/kWh but substantially lower than wind-only by \$0.059/kWh. The hybrid LCOE is best interpreted not in isolation but in relation to the performance improvement it purchases. The additional capital and O&M investment of the hybrid system relative to solar-only totals approximately \$30.5M over the project lifetime, and it purchases an increase in average renewable penetration from 41.4% to 71.2%, a reduction in minimum monthly penetration from 24.9% to 27.8%, an elimination of the near-zero generation events that occur repeatedly in the wind-only scenario, and a reduction in average monthly grid import from 3.93 x 10^6 kWh to 2.93 x 10^6 kWh. When evaluated on the basis of cost per percentage point of average penetration improvement, the hybrid system's incremental investment is well-justified relative to the alternatives.

4.6.2 Economic Implications of Battery Integration

The addition of a 4-hour battery system increases total capital cost from \$51M to \$112M, an absolute increase of \$61M representing a 120% cost premium over the hybrid-only configuration. When lifetime O&M costs are included, total system cost increases from approximately \$73.3M to \$164.7M, and LCOE rises from \$0.089/kWh to \$0.199/kWh. This cost increase of \$0.110/kWh purchases a 19.1% reduction in grid import over the analysis period, which translates to approximately 40.8 x 10^6 kWh of avoided grid electricity purchases over the 20-year project lifetime.

The economic justification for battery integration at this scale depends critically on the value of avoided grid electricity. At a representative commercial electricity rate of \$0.09/kWh for Oklahoma, the 40.8 GWh of avoided grid import over the analysis period represents a grid cost saving of approximately \$3.67M. Extrapolated across the 20-year project lifetime, the estimated lifetime grid cost savings attributable to battery storage are on the order of \$14.7M. Against a battery capital and O&M cost premium of approximately \$91.4M over the hybrid-only configuration, the simple payback from avoided grid electricity alone does not provide economic justification for battery integration under current cost assumptions and electricity rates.

However, this simplified cost-benefit comparison does not capture the full economic value of battery storage. Grid import reduction has resilience value that exceeds its direct electricity cost equivalent, particularly for an institutional campus where power outages or supply interruptions carry significant operational, reputational, and safety consequences. Furthermore, battery technology costs have declined substantially over the past decade and are projected to continue declining, with NREL projections suggesting utility-scale battery costs falling below $250/kWh within the next decade (NREL, 2021). At a battery capital cost of $250/kWh rather than the $400/kWh benchmark used in this study, the LCOE of the hybrid plus 4-hour battery configuration would fall to approximately $0.155/kWh, narrowing the economic gap with the hybrid-only configuration considerably. This cost trajectory suggests that battery integration that is not currently economically optimal may become so within the operational lifetime of a renewable energy system installed today.

The battery sensitivity results in Table 6 further suggest that a 2-hour storage configuration represents the most defensible near-term economic choice among the storage options evaluated. At $0.144/kWh LCOE, the 2-hour battery achieves 16.2% grid import reduction at a cost premium of $0.055/kWh relative to hybrid-only, compared to the 4-hour configuration's $0.110/kWh premium for 19.1% reduction. The marginal cost of the additional 2.9 percentage points of grid import reduction achieved by doubling storage from 2 to 4 hours is therefore $0.055/kWh in LCOE, which against a commercial electricity rate of $0.09/kWh represents a cost that exceeds the direct value of avoided import. This analysis confirms that the 2-hour configuration offers the best cost-performance ratio among storage options at current benchmark costs.

4.6.3 Summary of Key Findings

The results presented in this chapter establish a comprehensive technical and economic characterization of renewable energy system performance at the OU campus scale. The following key findings emerge from the analysis.

The hybrid wind-solar configuration consistently and substantially outperforms both standalone systems across all technical performance metrics, achieving 71.2% average renewable penetration at scale factor 2 compared to 41.4% for solar-only and 29.9% for wind-only. The performance advantage of the hybrid system is attributable to the temporal complementarity of solar and wind resources at the Norman, Oklahoma site, where summer solar dominance and partial winter wind enhancement provide a natural seasonal diversity that reduces aggregate variability and improves minimum penetration levels.

The wind-only scenario demonstrates critical reliability limitations in this regional context. The minimum monthly penetration of 2.2% and the repeated near-zero generation events during summer months confirm that standalone wind cannot provide dependable energy coverage for a load with continuous demand requirements at this site. This finding has direct implications for renewable energy planning in the Southern Plains region, where the attractive annual average wind resource masks a severe seasonal performance deficit during peak demand periods.

The scale factor analysis identifies scale factor 2 as the economically optimal configuration, representing the transition point between the generation-limited and surplus-dominated operating regimes. The scale factor 3 configuration offers superior reliability performance but at the cost of a fourfold increase in excess energy generation that cannot be utilized under the current system design. Battery storage simulated at hourly resolution delivers a meaningful 19.1% grid import reduction for the 4-hour base case, a result that is physically realistic and would not be captured by coarser temporal modeling. The battery sensitivity analysis demonstrates diminishing returns with increasing storage capacity, with the 2-hour configuration offering the most favorable cost-performance ratio among storage options evaluated at current benchmark costs.

Economically, the hybrid system without storage offers the most favorable balance of cost and renewable performance, with an LCOE of $0.089/kWh that is competitive with commercial grid electricity rates in Oklahoma while delivering 71.2% average renewable penetration. Battery integration provides operationally meaningful grid import reduction but is not economically justified under current cost assumptions when evaluated solely on the basis of avoided grid electricity costs, though the resilience and future cost trajectory considerations suggest this conclusion may change within the operational lifetime of systems installed in the near term.

Chapter 5: Discussion

5.1 Overview

The results presented in Chapter 4 provide a detailed quantitative characterization of renewable energy system performance at the OU campus scale. This chapter synthesizes those findings into a broader interpretive framework, examining what the results mean for renewable energy planning at institutional scale in the Southern Plains region, how they connect to the existing body of literature reviewed in Chapter 2, and what the methodological choices made in this study contribute to the field. Rather than restating individual results, the discussion focuses on four interpretive themes: what the three-scenario comparison reveals about configuration selection, how the regional wind and solar resource characteristics shape the findings, why the temporal resolution of battery simulation matters methodologically, and how the economic results should be read within the institutional context of a large public university.

5.2 Interpretation of the Three-Scenario Comparison

The central analytical contribution of this study is the systematic, side-by-side comparison of solar-only, wind-only, and hybrid wind-solar configurations under identical meteorological, load, and economic conditions. This comparison directly addresses the research question posed in Section 1.2 and produces conclusions that are more nuanced than a simple ranking of the three scenarios.

The most significant finding is not that the hybrid system outperforms the standalone systems, which is consistent with the broad expectation established in the literature (Kaldellis and Zafirakis, 2011; Hassan et al., 2023; Soudagar et al., 2024), but rather the specific nature and magnitude of the performance differences and what they reveal about resource behavior at this particular site. The 29.8 percentage point gap between hybrid average penetration and solar-only average penetration at scale factor 2 is not simply a function of the additional installed wind capacity in the hybrid configuration. It reflects temporal complementarity: wind generation contributes most strongly during periods when solar generation is weakest, compressing the seasonal variability of the combined output and improving both the minimum penetration floor and the annual average. This complementarity effect has been identified as the primary mechanism through which hybrid systems deliver performance advantages over standalone configurations across a wide range of geographic settings (Diab et al., 2017; Rezk et al., 2019).

If the wind and solar resources at this site were temporally correlated rather than complementary, the hybrid system would achieve average penetration close to the sum of the standalone averages minus overlap losses. The fact that the hybrid average at scale factor 2 closely approaches the arithmetic sum of the individual scenario averages is a quantitative confirmation that high-solar and high-wind periods are largely non-overlapping at the Norman site. This is not a universal property of wind-solar systems and should not be assumed for other locations without site-specific analysis (Hassan et al., 2023). At this site, it is a direct consequence of the atmospheric dynamics described in Section 5.3, and it is the physical mechanism through which hybridization delivers its performance advantage.

The wind-only scenario findings deserve particular attention. A minimum monthly penetration of 2.2% at scale factor 2, combined with repeated near-zero generation events during summer months, establishes that standalone wind is not merely a lower-performing alternative to solar at this site but is operationally unsuitable as a primary campus energy source. This distinction matters for planning purposes. A system with 29.9% average penetration but a 2.2% minimum creates a fundamentally different operational challenge than a system with similar average penetration and a stable seasonal floor. The former requires dispatchable backup capacity equivalent to nearly full campus load on a routine seasonal basis, while the latter allows backup capacity to be planned around a predictable and bounded winter deficit. Studies evaluating standalone wind for institutional applications consistently emphasize that minimum generation performance rather than average penetration is the binding constraint on system reliability in applications with non-deferrable continuous loads (Khalid and Savkin, 2010; Koutroulis et al., 2006). For a campus energy manager, the wind-only scenario offers an unfavorable combination of moderate average performance and extreme reliability variability that is difficult to incorporate into procurement and budgeting frameworks.

The solar-only scenario, by contrast, provides an operationally predictable profile. Its minimum penetration of 24.9% and smooth seasonal cycling allow campus energy managers to anticipate and plan around the winter deficit with reasonable certainty from year to year. The value of generation predictability in institutional energy planning is well recognized in the literature: facilities operating under fixed budget cycles and long-term procurement contracts benefit disproportionately from the forecastability of solar generation relative to wind, even when the two resources provide similar annual energy yields (Diab et al., 2017; Soudagar et al., 2024). The hybrid system combines the reliability floor of solar with the supplementary generation of wind, achieving minimum penetration that closely tracks the solar floor while delivering an annual average that neither resource could approach independently at the same total installed capacity. This outcome is consistent with the findings of Lalouni et al. (2009), Koutroulis et al. (2006), and Rezk et al. (2019), who document similar patterns of hybrid minimum performance improvement across diverse geographic contexts. The contribution of this study is to quantify this behavior under real, high-resolution site-specific data for a Southern Plains institutional load profile, rather than the synthetic or generalized datasets that characterize much of the existing literature.

5.3 Regional Context and Implications for Oklahoma Renewable Planning

The results of this study have implications that extend beyond the OU campus to the broader question of renewable energy system design in the Southern Plains region. Oklahoma possesses one of the highest-quality onshore wind resources in the United States on an annual average basis, with the state ranking consistently among the top five wind-producing states by installed capacity and generation (U.S. Department of Energy, 2023). Solar irradiance levels across central and southern Oklahoma are also substantial, with annual global horizontal irradiance values that rank the state among the more favorable locations for utility-scale PV deployment in the continental United States (U.S. Energy Information Administration, 2023). Against this background of strong resources for both technologies, the finding that standalone wind performs poorly during summer months at a Norman, Oklahoma site merits careful regional interpretation.

The poor summer wind performance documented in this study is not a consequence of insufficient installed capacity or poor system design. It is a direct consequence of the atmospheric dynamics of the Southern Plains during summer, when persistent anticyclonic circulation, elevated mixed layer heights, and reduced baroclinic instability suppress near-surface and low-level wind speeds across the region (Ong et al., 2014). This seasonal suppression is a well-documented characteristic of the Southern Plains wind climatology and affects utility-scale wind farms across the state, not only the hub-height wind speeds recorded at the Mesonet surface station used in this study. Ong et al. (2014) specifically document the seasonal variation of wind resources across Oklahoma and confirm that summer months consistently produce the lowest wind speeds and capacity factors at most locations within the state. The seasonal structure of wind generation, with its characteristic summer weakness, is therefore expected to persist as a physical feature of the regional atmosphere regardless of installed capacity growth or turbine technology advancement.

The implication for institutional-scale renewable planning in Oklahoma is that wind energy, while abundant and economically valuable on an annual average basis, should not be evaluated in isolation from its seasonal performance profile when being considered for campus or institutional deployment. An institution that evaluates wind energy investment based on annual average capacity factor or annual energy production will arrive at an optimistic assessment that does not reflect the system's behavior during the critical summer peak demand period. The International Energy Agency has consistently emphasized that site-specific seasonal assessment is essential for translating renewable resource potential into reliable system designs (IEA, 2023). The analytical framework developed in this study, which explicitly evaluates minimum penetration and seasonal performance alongside annual averages, provides a more complete basis for such investment decisions than screening tools that rely on aggregate metrics.

The solar resource at the Norman site shows the opposite seasonal alignment: peak production during summer when campus cooling load is highest. This alignment between solar peak generation and peak campus demand represents a genuine site-specific advantage for solar deployment at this location that is not universal across all climates. In regions where peak electricity demand occurs during winter heating seasons, the summer peak of solar generation would represent a misalignment rather than an alignment with load. Oklahoma's climate, with its hot summers and mild winters, creates a favorable condition for solar energy contribution to peak load management that reinforces the economic attractiveness of solar deployment documented in the LCOE analysis. This summer demand-supply alignment between campus load and solar generation is consistent with patterns documented for other Southern and South-Central United States institutional facilities (Soudagar et al., 2024; Kafando et al., 2024).

The hybrid system's performance profile, combining summer solar strength with partial wind contribution during transitional and winter months, suggests that the combination of these two resources is particularly well-suited to the Southern Plains institutional energy context. The natural seasonal complementarity of wind and solar at this latitude, combined with the summer-peaking campus load profile characteristic of large air-conditioned building stocks, creates a configuration in which hybrid deployment provides measurably greater value than either resource's individual performance metrics would predict. This conclusion aligns with the findings of Kaldellis and Zafirakis (2011) and Hassan et al. (2023), who demonstrate that the value of hybridization is amplified in climatic contexts where the dominant load driver, whether cooling or heating, aligns with one resource's peak season and the complementary resource provides coverage during the load's off-peak period.

5.4 The Role of Battery Storage and the Temporal Resolution Finding

The battery analysis results produce two findings that warrant substantive discussion beyond their quantitative characterization in Chapter 4. The first is the magnitude of the grid import reduction achieved by hourly battery simulation compared to what monthly simulation would predict. The second is the physical explanation for the diminishing returns of storage capacity expansion observed in the sensitivity analysis.

The hourly simulation finding is methodologically significant. A monthly simulation of the hybrid system at scale factor 2 would predict battery grid import reduction below 1%, because monthly net energy balances show limited surplus at this scale factor. The hourly simulation conducted in this study reveals a grid import reduction of 19.1% for the same system and battery configuration. This nearly twentyfold difference is not a modeling artifact. It is a physically correct result arising from the battery's ability to capture daily generation surpluses that occur when midday solar and wind output exceeds instantaneous campus load, and to discharge that stored energy during evening and early morning hours when generation has declined but load remains nonzero. Monthly simulation averages these diurnal cycles away before the battery model is applied, leaving the model unable to see the surplus events that the battery actually operates on. The importance of sub-monthly temporal resolution for accurately modeling storage behavior in grid-connected renewable systems has been noted in the literature, with several studies demonstrating that temporal aggregation introduces systematic bias in storage utilization estimates (Rezk et al., 2019; Muller et al., 2023).

The importance of this finding extends beyond the specific results of this study. A significant fraction of published renewable energy feasibility assessments conduct storage simulation at monthly or annual resolution, particularly in the screening-level literature. The results here suggest that such coarse-resolution modeling may systematically underestimate battery contribution to grid import reduction by an order of magnitude or more in grid-connected systems where daily surplus generation is present but monthly net generation remains below load. This has direct implications for institutional investment decisions: studies based on monthly simulation may incorrectly conclude that storage provides negligible benefit, leading to storage being excluded from system designs where it would in fact make a meaningful operational contribution. The recommendation that follows is that hourly temporal resolution should be treated as a minimum standard for battery performance assessment in renewable energy feasibility studies, particularly for campus-scale grid-connected systems where the ratio of installed generation capacity to peak load produces substantial diurnal surplus without producing net monthly surplus.

The battery sensitivity analysis results connect to a broader physical principle that the effective ceiling on battery utilization is determined by the surplus generation available for charging, not by battery capacity alone. The diminishing returns of storage capacity expansion observed in Table 5, where moving from 2 to 4 hours of storage captures 6.3 GWh of additional previously curtailed energy while moving from 6 to 8 hours captures only 1.6 GWh, reflect the progressive exhaustion of capturable surplus events as battery capacity exceeds the energy content of individual daily surplus periods. This diminishing returns pattern is consistent with findings reported across hybrid storage studies conducted at different scales and locations (Rezk et al., 2019; Diab et al., 2017; Kafando et al., 2024). The specific threshold at which returns diminish most sharply is site-specific and reflects the characteristic duration and magnitude of daily surplus events at the Norman site. A site with a stronger wind resource or a larger solar array relative to load would exhibit a different threshold and may justify larger storage investment. Storage sizing analysis should therefore always be conducted using the surplus generation profile specific to the system being evaluated rather than general capacity-based rules of thumb.

5.5 Economic Interpretation and Institutional Investment Context

The LCOE results require interpretation within the specific institutional and regulatory context of OU’s energy procurement to be fully meaningful. The headline values, ranging from \$0.057/kWh for solar-only to \$0.309/kWh for the hybrid plus 8-hour battery configuration, provide a basis for comparison with grid electricity costs but do not capture the full economic value proposition of renewable deployment for a large public university.

The solar-only LCOE of $0.057/kWh falls below the estimated commercial grid electricity rate in Oklahoma, which the U.S. Energy Information Administration reported at approximately $0.076/kWh for commercial customers in 2023, one of the lowest commercial rates in the continental United States (U.S. Energy Information Administration, 2023). This suggests that at current benchmark costs, utility-scale solar deployment at this site would generate direct electricity cost savings relative to continued full grid procurement over the 20-year project lifetime. The hybrid system's LCOE of $0.089/kWh sits at the upper boundary of current Oklahoma commercial electricity rates, meaning that the hybrid configuration is approximately cost-neutral in direct energy cost terms while delivering 71.2% average renewable penetration, resource diversity, and resilience benefits that neither standalone system can offer. This cost-neutrality finding is significant for institutional decision-making: it suggests that hybrid renewable deployment at OU can be justified on economic grounds without relying solely on environmental or policy motivations, provided that grid electricity rates remain at or above current levels. Given that commercial electricity rates in Oklahoma have risen by approximately 35% over the past decade (U.S. Energy Information Administration, 2023), this assumption is well-supported by historical trends.

The wind-only LCOE of $0.148/kWh exceeds current Oklahoma commercial electricity rates, confirming that standalone wind is not economically competitive with grid supply at this site under current cost assumptions. This finding does not imply that wind energy is uneconomical in Oklahoma generally, since utility-scale wind projects benefit from different financing structures, revenue streams including renewable energy credits and power purchase agreements, and operational scales that differ substantially from the campus-scale configuration modeled here (Muller et al., 2023). However, for an institution evaluating campus-scale wind deployment specifically, the economic case for standalone wind is not supported by the analysis at this site.

Battery integration raises LCOE substantially without delivering proportionally larger performance improvements. The core economic finding regarding storage is that the direct grid electricity cost savings attributable to the battery do not offset the battery capital and lifetime O&M cost premium over the hybrid-only configuration under current benchmark costs. This negative economic case for storage under current conditions is not a permanent conclusion. Battery technology costs have declined by more than 80% over the past decade, from approximately $1,200/kWh in 2010 to below $400/kWh by the early 2020s, and are projected to continue declining toward $250/kWh or below within the next decade (NREL, 2021; BloombergNEF, 2023). At a battery capital cost of $250/kWh rather than the $400/kWh benchmark used in this study, the LCOE of the hybrid plus 4-hour battery configuration would fall to approximately $0.155/kWh, substantially narrowing the economic gap. The resilience value of storage, which is not captured in the LCOE calculation but is documented as a meaningful component of storage value for institutional and campus facilities with continuous operational requirements (Parra et al., 2017), further strengthens the case for storage investment as costs continue to fall. The 2-hour battery configuration at $0.144/kWh LCOE represents the most defensible near-term storage investment among the options evaluated, offering 16.2% grid import reduction at the lowest cost premium.

5.6 Limitations and Their Implications

The simulation framework developed in this study incorporates several simplifications that bound the scope and precision of its conclusions. A rigorous assessment of these limitations and their directional implications is necessary for correctly interpreting the results.

The most consequential simplification is the use of a uniform hourly load profile constructed by distributing monthly campus load uniformly across hours within each month. Real campus electricity demand exhibits pronounced diurnal variation, with peaks during daytime operational hours and significantly lower nighttime demand, as well as day-of-week variation driven by academic schedules and facility operations. Studies of university campus energy consumption consistently document peak-to-trough ratios within a typical weekday of 1.5 to 2.5 between daytime operational peaks and overnight minimums (Diab et al., 2017; Rezk et al., 2019). The uniform hourly load approximation preserves monthly energy totals but does not capture this sub-monthly temporal structure. The implications for battery performance are partially offsetting in direction: higher daytime peaks would create more favorable conditions for solar surplus capture, while lower nighttime demand would reduce the battery's discharge contribution during overnight hours. Obtaining and incorporating actual hourly campus load data is identified as the highest-priority improvement for future work.

The energy-balance battery model does not account for battery degradation over the 20-year project lifetime. Real lithium-ion battery systems experience capacity fade of approximately 2 to

3% per year under typical cycling conditions, with efficiency reduction accumulating over time as electrode materials degrade with charge-discharge cycling (Parra et al., 2017; Muller et al., 2023). For a system with the relatively low cycling rates observed in this study, where the battery operates through a limited number of full cycles per month during most of the year, degradation effects are expected to be less severe than in high-utilization daily cycling applications. Nevertheless, incorporating a degradation model calibrated to the cycling rates observed here would improve the long-term accuracy of LCOE projections for storage-integrated configurations.

The techno-economic analysis uses published benchmark costs representing industry averages rather than site-specific procurement quotes. Actual project costs for OU's renewable installation would depend on local labor rates, grid interconnection requirements, land or rooftop acquisition costs, permitting and engineering fees, and financing terms, none of which are captured in the benchmark assumptions. The NREL Annual Technology Baseline consistently notes that project-specific costs can vary by 20 to 40% around published benchmarks depending on local market conditions (NREL, 2021). The LCOE values reported in this study should therefore be interpreted as comparative indicators that establish the relative economic positioning of each configuration rather than as precise project cost predictions.

Chapter 6: Conclusions and Future Work

6.1 Overview

This chapter presents the conclusions of the study organized around each of the five research objectives stated in Section 1.3, followed by concrete engineering recommendations derived from the findings and specific directions for future research that would directly extend and strengthen the conclusions reached here.

6.2 Conclusions

6.2.1 Objective 1: Development of a Simulation Framework

The first research objective was to develop an energy-balance modeling framework in MATLAB to simulate campus-scale renewable integration using historical load data and meteorological inputs from the Oklahoma Mesonet. This objective was fully achieved. The framework integrates five years of 15-minute resolution meteorological data from the NRMN Mesonet station with monthly campus electricity consumption records, implements solar PV and wind generation models with temperature correction and hub-height wind speed adjustment respectively, and simulates battery storage at hourly temporal resolution across the full analysis period. The energy-balance approach adopted in this study is consistent with the methodology widely employed in the hybrid renewable energy systems literature for campus and microgrid-scale applications (Diab et al., 2017; Koutroulis et al., 2006). The framework is structured as a fourteen-stage sequential computational pipeline with clear documentation at each stage, enabling reproducibility and extension to other campus sites or system configurations.

The methodological decision to simulate battery storage at hourly rather than monthly resolution proved to be one of the most consequential choices in the study design. The hourly model reveals a 19.1% grid import reduction attributable to the 4-hour battery configuration, a result that monthly simulation would reduce to below 1% due to the suppression of diurnal surplus and deficit cycles by temporal averaging. This finding is consistent with the emphasis in recent literature on the importance of sub-monthly temporal resolution for accurately characterizing storage behavior in partially renewable grid-connected systems (Rezk et al., 2019; Muller et al., 2023), and it establishes hourly temporal resolution as a minimum requirement for meaningful battery performance assessment in this class of system.

6.2.2 Objective 2: Three-Scenario Comparison

The second research objective was to define and compare solar-only, wind-only, and hybrid wind-solar configurations under identical environmental and economic conditions. This comparison was conducted at both baseline scale factor 1 and the selected optimal scale factor 2, providing a comprehensive basis for evaluating the relative merits of each configuration under consistent assumptions.

The hybrid wind-solar system consistently and substantially outperforms both standalone configurations across all technical performance metrics. At scale factor 2, the hybrid achieves 71.2% average renewable penetration compared to 41.4% for solar-only and 29.9% for wind-only, while maintaining a minimum monthly penetration of 27.8% compared to 24.9% for solar-only and 2.2% for wind-only. The hybrid system reduces average monthly grid import to 2.93 x 10^6 kWh, compared to 3.93 x 10^6 kWh for solar-only and 4.98 x 10^6 kWh for wind-only. These results are consistent with the broad finding in the hybrid systems literature that combining solar and wind resources under site-specific complementarity conditions yields performance improvements that neither resource can achieve independently at comparable installed capacity (Kaldellis and Zafirakis, 2011; Hassan et al., 2023; Soudagar et al., 2024).

The wind-only scenario demonstrates critical reliability limitations specific to the Norman, Oklahoma site and Southern Plains climate. Repeated near-zero generation events during summer months confirm that standalone wind cannot provide reliable continuous energy coverage for an institutional campus load in this region. This finding reflects the atmospheric dynamics of the Southern Plains during summer rather than a general limitation of wind energy technology (Ong et al., 2014), but it has direct implications for renewable energy planning decisions at institutions located in similar climatic contexts across the region.

6.2.3 Objective 3: Technical Performance Metrics

The third research objective was to evaluate technical performance metrics including renewable penetration, seasonal variability, grid import fraction, curtailment, and capacity factor across all three scenarios. All metrics were computed at both baseline and optimal scale.

The seasonal performance analysis confirms that the hybrid system's advantage over standalone configurations is most pronounced during transitional months in spring and autumn, when wind-solar complementarity is strongest and the combined system approaches or achieves full campus load coverage from renewable sources alone. During summer peak demand months, all three scenarios are most constrained by the combination of maximum campus cooling load and the summer suppression of wind generation in Oklahoma, with hybrid penetration falling to its seasonal minimum of approximately 27 to 35% during these periods. This seasonal constraint pattern, in which the most challenging operating period coincides with the highest demand season, underscores the importance of seasonal performance evaluation in system design as emphasized by the International Energy Agency (IEA, 2023) and documented across campus-scale hybrid system studies in similar climatic contexts (Kafando et al., 2024).

The scale factor 2 configuration produces 11.4 GWh of annual excess energy, representing approximately 3.8% of annual campus demand, confirming high generation utilization efficiency relative to higher scale factors. Battery sensitivity analysis demonstrates that excess is progressively captured by larger storage configurations, with curtailment declining from 32.6 GWh at 2-hour storage to 20.9 GWh at 8-hour storage, consistent with the diminishing returns pattern documented in the storage sizing literature (Rezk et al., 2019; Diab et al., 2017).

6.2.4 Objective 4: Techno-Economic Analysis

The fourth research objective was to conduct techno-economic analysis using levelized cost of energy based on published cost benchmarks, incorporating both capital costs and lifetime operation and maintenance costs. The solar-only configuration achieves the lowest LCOE at $0.057/kWh, confirming that utility-scale solar deployment at this site is economically competitive with, and in fact below, the 2023 Oklahoma commercial electricity rate of approximately $0.076/kWh (U.S. Energy Information Administration, 2023). The hybrid configuration achieves an LCOE of $0.089/kWh, approximately cost-neutral relative to current grid rates while delivering substantially higher renewable penetration than either standalone alternative. The wind-only configuration produces the least economically favorable result at $0.148/kWh, driven by lower annual energy production relative to installed capacity and higher per-kilowatt O&M costs compared to solar, consistent with findings from other campus-scale wind evaluations in the literature (Muller et al., 2023; Kafando et al., 2024).

Battery integration raises LCOE from $0.089/kWh to $0.144/kWh for 2-hour storage and $0.199/kWh for 4-hour storage, delivering grid import reductions of 16.2% and 19.1% respectively. The economic case for storage under current benchmark costs does not support battery investment on the basis of avoided grid electricity savings alone. However, declining battery cost trajectories projected toward $250/kWh or below within the next decade (NREL, 2021; BloombergNEF, 2023), anticipated grid electricity rate increases, and the resilience value of storage for institutional facilities (Parra et al., 2017) represent factors that may shift this conclusion within the operational lifetime of systems installed in the near term.

6.2.5 Objective 5: Sensitivity Analysis

The fifth research objective was to perform sensitivity analysis to assess the impact of system sizing and cost assumptions on comparative performance. The scale factor analysis across values of 1 through 5 identifies the transition between the generation-limited and surplus-dominated operating regimes and establishes scale factor 2 as the economically optimal and scale factor 3 as the reliability-optimal configuration. The battery sensitivity analysis across 2 to 8 hour durations quantifies the diminishing returns of storage capacity expansion and identifies the 2-hour configuration as the most cost-effective storage option at current benchmark costs, with each additional hour of storage beyond 4 hours delivering progressively smaller performance improvements relative to the associated cost increase. The diminishing returns pattern observed here is consistent with findings across multiple hybrid storage studies and reflects the finite surplus generation available for charging rather than a limitation of the battery technology itself (Rezk et al., 2019; Diab et al., 2017; Kafando et al., 2024).

6.3 Engineering Implications and Recommendations

The findings of this study carry several concrete implications for renewable energy system design and planning at institutional scale in the Southern Plains region.

First, system configuration selection should be driven by site-specific seasonal performance analysis rather than annual average metrics alone. The wind-only scenario's annual average penetration of 29.9% appears reasonable in isolation, but its minimum monthly penetration of 2.2% and repeated summer generation failures reveal an operational profile that is unsuitable for continuous institutional loads. The literature consistently demonstrates that minimum and seasonal performance metrics are the binding constraints on renewable system reliability for applications with non-deferrable demand, and evaluation frameworks that examine only annual averages will systematically overestimate the reliability value of wind energy at sites with strong summer atmospheric suppression (Khalid and Savkin, 2010; Koutroulis et al., 2006).

Second, hybridization of solar and wind resources provides performance benefits at this site that justify the additional capital investment relative to either standalone configuration under current cost assumptions. The hybrid system delivers 71.2% average penetration at an LCOE of $0.089/kWh, which is cost-competitive with grid electricity while providing resource diversity and resilience benefits that neither standalone system can offer. Institutions considering renewable energy investment in Oklahoma and similar Southern Plains climates should evaluate hybrid configurations as the baseline reference, rather than treating hybrid systems as a more complex alternative to simpler standalone designs (Hassan et al., 2023; Soudagar et al., 2024).

Third, battery storage should be sized based on the surplus generation profile of the specific system rather than on general rules of thumb derived from installed capacity. The analysis demonstrates that the effective ceiling on battery utilization is determined by the daily surplus generation available for charging, not by battery capacity itself. Storage sizing analysis should therefore be conducted using hourly simulation that explicitly models daily surplus generation events at the specific site and system configuration being evaluated (Muller et al., 2023; Parra et al., 2017).

Fourth, hourly temporal resolution in battery simulation should be treated as a minimum standard for renewable energy storage assessment in campus-scale grid-connected systems. The near-twentyfold difference between hourly and monthly battery simulation results documented in this study is a concrete demonstration that monthly simulation is inadequate for capturing the diurnal energy shifting that constitutes battery storage's primary operational contribution in this class of system, a finding that has important implications for how renewable energy feasibility studies are conducted and interpreted at the institutional scale.

6.4 Recommendations for Future Work

The findings and limitations of this study identify several specific directions for future research that would directly extend and strengthen the conclusions reached here. The highest-priority extension is the incorporation of actual hourly campus electricity load data. The current analysis distributes monthly campus load uniformly across hours within each month, which preserves monthly energy totals but does not capture the diurnal demand peaks and overnight demand troughs that characterize real institutional load profiles. Hourly campus load data, which is available from OU's building management and metering systems, would enable fully resolved hourly energy balance simulation and would improve the accuracy of both battery performance estimates and seasonal penetration calculations. The availability of sub-hourly interval metering data at most large institutional campuses makes this an accessible and high-value improvement for future work in this area (Diab et al., 2017).

A second important extension is the evaluation of intentionally oversized configurations designed to maximize surplus generation for battery utilization. The current analysis identifies scale factor 2 as the economically optimal configuration under a utilization-efficiency objective. Analyzing configurations in the scale factor 2 to 4 range with battery sizes optimized for the specific surplus profile of each configuration would provide a more complete characterization of the system design space and may identify configurations where storage investment becomes more economically justified, particularly as battery costs continue to decline (NREL, 2021; BloombergNEF, 2023).

A third extension is the incorporation of a battery degradation model calibrated to the cycling rates observed in this study. The current energy-balance model assumes constant capacity and efficiency over the 20-year project lifetime, which overestimates long-term battery performance and underestimates lifetime LCOE for storage-integrated configurations. Degradation models based on cycle counting and calendar aging, such as those developed by Parra et al. (2017) and validated against field data from utility-scale installations, could be adapted to the cycling patterns observed here with relatively modest additional computational effort.

A fourth direction is the extension of the hub-height sensitivity analysis to evaluate system performance across turbine hub heights from 80 to 120 m. Taller turbines accessing higher wind speeds in accordance with the power law profile would improve wind energy production and alter the relative performance of wind-only and hybrid configurations, potentially improving wind competitiveness at this site as taller turbine technology continues to advance. The hub-height sensitivity analysis would also enable assessment of how the wind-solar complementarity documented in this study evolves as the wind contribution grows relative to solar (Manwell et al., 2010).

Finally, applying the modeling framework developed in this study to other institutional campuses in the Southern Plains region would enable regional generalization of the findings. The site-specific results regarding wind resource seasonal suppression, solar-wind complementarity, and battery performance are likely to vary across sites with different local wind climatologies, load profiles, and building characteristics. Systematic multi-site application of the same framework, leveraging the Oklahoma Mesonet's statewide network of high-resolution meteorological stations, would support the development of renewable energy planning guidelines applicable to Southern Plains institutions more broadly (Ong et al., 2014).

6.5 Final Remarks

This study developed and applied a comprehensive simulation framework to evaluate the technical and economic performance of solar-only, wind-only, and hybrid wind-solar energy systems at the OU campus scale, using five years of high-resolution site-specific meteorological data and campus electricity consumption records. The results demonstrate that the hybrid wind-solar configuration provides substantially superior performance compared to either standalone alternative, achieving 71.2% average renewable penetration at an LCOE competitive with current grid electricity rates, while eliminating the extreme reliability variability that makes standalone wind unsuitable for continuous institutional loads in the Southern Plains region.

The methodological finding that hourly battery simulation reveals grid import reductions nearly twenty times larger than monthly simulation would predict represents a contribution to the renewable energy modeling literature with practical implications for how storage is evaluated in institutional feasibility assessments. The scale factor analysis framework provides a replicable approach for identifying the optimal configuration boundary in campus-scale renewable systems, and the three-scenario comparison methodology offers a transferable template for renewable energy configuration selection studies at other institutional sites.

Taken together, the technical, economic, and methodological findings of this study support the conclusion that hybrid renewable energy deployment at the OU campus represents a technically feasible, economically competitive, and operationally resilient pathway toward meaningful reduction in campus carbon emissions and grid dependence. The analytical framework developed here provides a sound foundation for the detailed engineering and financial analysis required to advance such deployment from conceptual evaluation toward implementation planning, and contributes to the growing body of evidence supporting hybrid wind-solar systems as the preferred renewable energy configuration for institutional applications in the Southern Plains region (Hassan et al., 2023; Soudagar et al., 2024; Kafando et al., 2024).

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