Assessing the Impact of Rising Wind Power with Energy Storage on Grid Resilience in Sweden to Mitigate Volatility and Enhance Grid Flexibility

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Abstract:

This paper assesses the impact of increasing wind power production and energy storage systems on grid resilience in Sweden. Wind power currently makes up 17% of Sweden's electricity mix, and this share is expected to rise significantly in the coming decades as Sweden aims for 100% renewable energy generation by 2040. However, the variable and intermitted output can negatively impact grid stability. A microgrid model is developed, incorporating a wind turbine, battery storage, power grid, and a representative demand profile. Wind speed data is analysed to select profiles representing high and low variability, with variance used as a metric for resilience. Planned production is constructed in 12-hour intervals based on wind speed forecasts. The model compares grid dependency and electricity delivery with and without battery storage of varying capacities. The results show that battery storage reduces grid interactions and grid dependency. Furthermore, it aligns actual wind power production with the planned production profile. Optimisation analyses find that minimising operational costs and battery usage increases grid reliance while minimising costs and grid supplies provides a more stable supply but overuses batteries. Sensitivity analysis demonstrates higher grid dependency in high-variance wind conditions. The paper contributes to understanding how to enhance wind power resilience through improved production planning and battery integration. It proposes using variance analysis in wind profile selection and identifies trade-offs between system stability, costs and battery lifespan under different optimisation strategies.

Keywords: wind power, planned production, battery storage, resilience, Sweden

1. INTRODUCTION

Sweden primarily relies on hydropower and nuclear energy for domestic electricity production (The Swedish Energy Agency, 2023). In 2020, renewable energy sources contributed to 92% of Sweden's electricity production, with hydropower accounting for 45%, nuclear power for 29%, wind power for 17% and solar power for 1%. The remaining 8% was generated through combined heat, power, and industrial processes. Globally, there has been a rapid increase in the adoption of wind power (Benitez, Benitez and van Kooten, 2008), a trend mirrored in Sweden. The installed capacity of wind power in Sweden increased from 3,487 GWh in 2010 to 27,536 GWh in 2020, a growth attributed partly to supportive renewable electricity policies (IEA, 2019). Sweden aims to achieve 100% renewable energy production by 2040, while still retaining nuclear energy as an option (The Swedish Energy Agency, 2023). However, this goal is complicated by the predicted rise in energy demand over the coming decades, driven by various factors including emissions reduction, industry growth, hydrogen production, and the electrification of transportation and the steel industry (Holmberg and Tangerås, 2023). To address this growing demand, it is expected that wind energy production will need to increase over the coming decades (Ministry of the Environment and Energy, 2018). Current projections indicate that the installed capacity of wind power, which stood at 12,100 MW, is expected to rise to 18,500 MW by 2030 and 33,300 MW by 2040 (Swedish Wind Energy Association, 2021). Integrating wind power into the electricity grid presents several challenges due to its inherent weather-dependent nature, which results in variable and unstable power output (Zhao *et al.*, 2015; Reddy, 2017). This variability may adversely affect the stability and performance of the electric power system, causing frequency and voltage disturbances that may lead to system shutdowns (Li *et al.*, 2021). Additionally, the intermittency of wind power affects market mechanisms for electricity trading, as these mechanisms rely on accurate production planning forecasts. Inaccuracies can lead to price fluctuations in electricity prices, particularly as wind power penetration rises (Peizheng Xuan *et al.*, 2019). The primary goal of grid operation is to meet electricity demand, however variable wind power output complicates this objective. Accurate forecasting of production and demand is crucial for determining the required amount of dispatchable electricity. Despite advancements in forecasting techniques, errors are inevitable, necessitating power reserves for grid operators (Michiorri *et al.*, 2018), ultimately hindering the integration of wind power (Zhao *et al.*, 2015). One proposed solution to mitigate these grid issues is combining wind power with energy storage systems (ESS). ESS can provide the necessary flexibility to smooth out the variability in wind power output (Zhao *et al.*, 2015; Michiorri *et al.*, 2018; Barra *et al.*, 2021). Previous research has explored various aspects of ESS integration: Li et al. examined short-term "power-smoothing" applications utilising high-power ESS that rapidly respond to high power outputs (Barra *et al.*, 2021), Sperstad & Korpås et al. investigated the optimal scheduling of ESS in grids with large renewable energy shares, developing a framework to avoid suboptimal operations (Sperstad and Korpås, 2019). Additionally, M. Ghazipour and M. Abardeh et al. developed a stochastic optimisation approach for optimising the location and size of ESS in energy systems (M. Ghazipour and M. Abardeh, 2019). These studies collectively aim to enhance the understanding of ESS from various technological perspectives, addressing the volatile energy output of renewable energy sources (RES) and mitigating their adverse effects on the energy system. However, none of these studies specifically address ensuring a guaranteed electricity supply, a critical factor as the increase in wind power reduces the amount of controllable electricity supply. This aspect is vital in the broader context of energy system resilience. Acknowledging resilience is increasingly crucial within the ongoing energy transition, despite its varied definitions across multiple disciplines. Fundamentally, resilience revolves around the capacity to cope with disruptive events (Gasser *et al.*, 2021; Jasiūnas, Lund and Mikkola, 2021). One definition of resilience involves minimising service disruptions by anticipating, resisting, absorbing, adapting to and recovering from disruptive events (Ahmadi, Saboohi and Vakili, 2021). Gasser et al. define resilience as the capacity of systems to withstand stress, pressure or disturbance without loss of function (Gasser *et al.*, 2021). This research aims to develop a microgrid model that integrates wind power and battery energy storage, assess the role of battery storage in mitigating wind power variability, and analyse the system's resilience. By evaluating performance during disruptive wind events, this study aims to enhance the broader understanding of how ESS can enhance the resilience of renewable energy systems, ensuring a more stable and reliable electricity supply. The central question addressed is: *How can battery energy storage mitigate volatility and increase the integration of wind turbines?*

2. METHODOLOGY

This research employs a case study representative of recent developments in Eskilstuna, Sweden. The primary components of the microgrid model include a wind turbine, battery storage, a power grid and a representative demand profile. Two configurations will be modelled, to assess the value added by battery storage. These configurations are modelled using Modelon Impact, a systems modelling and simulation program. Modelon Impact utilises Modelica's core modelling and simulation capabilities. Modelica is an object-oriented programming language. Modelica allows for a detailed description of the behaviour of physical components and their interactions within the system.

2.1 Components and controls

Fig. 1 illustrates the microgrid model. The Wind and Temperature blocks contain wind speed and air temperature data, respectively. The Temperature block determines the air density, directly affecting the wind power produced in the Turbine block. By incorporating these data, the model accounts for the impact of temperature-induced density variations on wind power generation. The power generated by

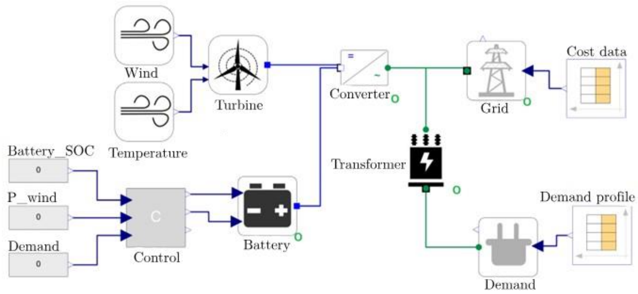

Figure 1: The microgrid model developed with Modelon Impact.

the wind turbine is then directed to the Converter block which converts the alternative current (AC) to direct current (DC). This DC power flows through the transformer- which converts the high voltage to a lower voltage suitable for distribution within the grid. The electricity is delivered to the Demand block, representing a representative demand profile. The Demand and Demand profile blocks represent the forecasted power demand. The Grid block can provide and receive unlimited electricity to balance the grid. This setup facilitates analysis by comparing the actual power output against the planned output. An important component of the microgrid model is the Control unit. The operation of the battery is based on the net amount of power denoted by P_{net}, described in (1).

$$P_{net} = P_{wind} - P_{demand} \tag{1}$$

The Control unit measures P_{net} at each time point and operates according to the following control scheme.

- If $P_{net} < 0$, the required power is generated by discharging the battery, or bought from the grid
- If $P_{net} > 0$, the surplus is either used to charge the battery sold to the grid or both.

2.2 Wind power

The theoretical power that can be extracted from the wind by a wind turbine is proportional to the wind speed to the power of three (Kim, 2013). This relation is described in (2), where P represents the total wind power production by the turbine, measured in watts. The total area the turbine blades cover in one rotation is described by A, the swept area of the wind turbine in m², ρ is the density of the air in kg/m³ and v represents the velocity of the wind in m/s, C_p is the power coefficient, defined as the ratio of power extracted by the wind turbine from the energy available in the wind.

$$P = \frac{1}{2} \mathrm{A}\, \rho\, v^3 C_p \tag{2}$$

In addition to calculating the theoretical wind power, a suitable wind speed profile is required. Moreover, a thorough wind data analysis is needed to capture resilience in a wind speed profile. Rapid and large changes in wind speeds are identified as disruptive events. One example of such events is sudden drops in high wind speeds. These abrupt changes can be quantified through statistical measures such as variance. Variance assesses the spread of data points relative to their average in the data set. Specifically, in wind speed analysis, variance indicates the degree of variability in wind speeds over time. Greater variability, as indicated by a higher variance signifies an increased need for system resilience. A timeframe of one week is selected for the modelling phase to calculate the variance of the wind speed of the dataset. Hence the variance will be calculated for each week of the dataset. The formula for the variance is shown in (3). Where x_i is each value in the data set, x is the mean of all values in the data set and N is the number of all values in the data set (Hui, 2018).

$$\sigma^2 = \frac{(x_i - \bar{x})^2}{N} \tag{3}$$

The selection of wind speed profiles in this research is based on several criteria. First data was sourced from a location of importance to the research region. Additionally, the profiles were chosen to represent a range of scenarios including average, low and high-wind conditions, to assess the system's resilience under diverse operational conditions.

2.3 Planned production

Forecasting wind speed will become increasingly paramount as future wind farms function more like conventional power plants. This transition implies a shift towards more accurate planning of electricity production, leading to the development of guidelines focused on reliability to ensure the safe operation of wind farms. Several factors are driving the shift in the role of wind power. Firstly, wind power's exposure to volatile wholesale electricity prices changes its economic dynamics. Given the relatively low marginal cost of producing wind power, increased wind power tends to decrease electricity prices. Secondly, governmental support schemes, such as feed-in-tariffs (a guaranteed cost-based purchase price for electricity), are being replaced by auctioning systems, incentivising wind farm owners to prioritise profit maximisation over pure electricity production volume. This shift underscores the growing importance of accurate wind speed forecasts in optimising wind farm operations and maximising profitability (Kölle *et al.*, 2022). Wind speed forecasts are constructed for various timeframes depending on the specific application. These include very short-term forecasts (a few seconds to 30 minutes), short-term forecasts (30 minutes to 6 hours ahead), mid-term forecasts (6 hours to a day ahead), and long-term forecasts (1 day to a week or more). Different methods, such as machine learning or statistical approaches are employed for generating these forecasts (Khosla and Aggarwal, 2022). In this research, a mid-term forecast for a half-day ahead is used, with wind speed predictions generated every 12 hours. The variables used in the planned production profile are depicted in (4) and (5), where $v_{average}$ represents the average wind speed, and V_i represents the hourly wind speed values i = 1,2, …, 12. The choice of a 12-hour planning interval aligns with the timeframe of day-ahead wholesale electricity price data, ensuring coherence between the forecasting parameters and pricing data.

$$v_{average} = \frac{1}{12}\sum_{i=12}^{12} v_i \tag{4}$$

$$\rho_{average} = \frac{1}{12}\sum_{i=12}^{12} \rho_i \tag{5}$$

2.4 Optimisation

The optimiser minimises the total cost, as presented in (6). Where L(x,u,p) represents the integral cost depending on the process state x, the controls u, and the plant parameters p. State variables x denote the dynamic state over time, such as the state of charge (SOC) of the battery, the power output of the wind turbine or the electricity consumption of the grid. Control variables u are decision variables that can be adjusted to optimise the system performance, such as the charging and discharging rate of the battery or the import and export to and from the grid. Parameters p are fixed values for a system, including the power efficiency of the turbine, battery capacity, electricity prices, or demand profiles. The cost integrand $L(x, u, p)$ can be further decomposed into two terms, presented in (7). $Cost_y$ typically refers to the operational cost per unit time ($OPEX_{sec}$), while $cost_u$ penalises the controls u (du^2/dt) to promote smoother and more stable operation.

$$min_{u(t),p} cost = \int_0^{T_{Optimization}} L(x, u, p)\, dt \tag{6}$$

$Cost_u$ can be defined as minimising the battery's aggressive charging and discharging behaviour, thus extending its technical lifetime. Generally, the penalty of $cost_u$ is much lower than the operational cost $cost_y$. Dynamic optimisation aims to find the optimal trajectory u(t) while satisfying the system constraints. Modelon Impact utilises the Interior Point OPTimiser (IPOPT) to determine the best next step. IPOPT gradually narrows down search barriers within a feasible region to approach an optimal solution without reaching the boundary until close to finding it.

$$L(x, u, p) = cost_y + cost_u \tag{7}$$

In this research, different objectives are chosen to be minimised. The first scenario combines operational cost and battery controls to minimise total cost while minimising battery operation to extend the technical lifetime. The second scenario considers operational cost and the power output of the grid, aiming to minimise grid dependency. In Table 1 the optimisation scenarios are presented.

Table 1: Optimisation scenarios

Scenario	$Cost_y$	$Cost_u$
$OPEX_{sec}$, controls	$OPEX_{sec}$	Battery(Power charge * Power discharge)
$OPEX_{sec}$, power grid	$OPEX_{sec}$	Grid power

2.5 Data

This section outlines the key properties and sources of the time series data used in the research, which include air temperature, wind speed, electricity prices, and demand profiles. The following tables provide a summary of the data.

Table 2: Demand profile data

Parameter	Resolution	Period	Unit
Demand profile	5 min intervals	Weekly	[MW]

Table 3: Time series data

Parameter	Unit	Range	Period	Source
Air temperature	[K]	01/01/2010 – 01/10/2023	Hourly	(SMHI, 2023)
Wind speed	[m/s]	01/01/2010 – 01/10/2023	Hourly	(SMHI, 2023)
Electricity price	[€/MWh$_e$]	01/01/2015 – 01/12/2023	Hourly	(ENTSO-E, 2023)

2.6 Modelling assumptions

The battery capacity is assumed to remain constant, meaning that the battery's efficiency does not degrade over the simulation period of one week. This assumption is reasonable given the short simulation period, where the number of charging cycles during this time is insufficient to cause the battery capacity to degrade. Additionally, unlimited import and export from and to the grid is assumed. However, in real-life, grid may encounter congestion, where the transmission network cannot meet the demand. In such cases, assets like wind farms may receive compensation from Svenska kräftnat (Transmission System Operator) to adjust production or decrease consumption accordingly (Holmberg and Tangerås, 2022). The total installed cost of batteries decreases as the capacity increases. Most costs are calculated for a battery system with a 2-hour duration, meaning the time it can deliver its full power capacity in MW. For example, a battery with 2 MW and a 2-hour duration has a capacity of 4 MWh. In the case study, the battery system has a 1:1 power ratio (MW:MWh). Data on batteries with a 1-hour duration is limited, therefore it is assumed that the cost of batteries for different capacities is based on 2-hour duration systems. Although the transmission capacity of the power grid is assumed to be unlimited in this research, in reality, exceeding transmission capacity can result in penalties for wind farm owners. For example, if the 220 kV transmission line connecting the wind farm to the grid is exceeded, penalties may be imposed on the wind farm owner for not meeting planned production. To mitigate this, batteries with longer durations and different power ratios could enable more effective operating strategies. A 1:1 power ratio is selected, allowing the battery to discharge completely within one hour.

3. RESULTS

3.1 Wind profile selection

The wind speed variance at hub height is calculated from 2010 to 2023, plotted in Fig 2. Each bar in the plot represents a week and its corresponding variance value. A higher variance indicates greater variability in wind speed, while a lower value suggests more stable wind conditions. The highest and lowest variances are 51 and 0, respectively. It is important to note that the variance is rounded up towards the nearest integer. The variance is calculated at hub height, as the wind speed at this height determines the wind turbine's power output.

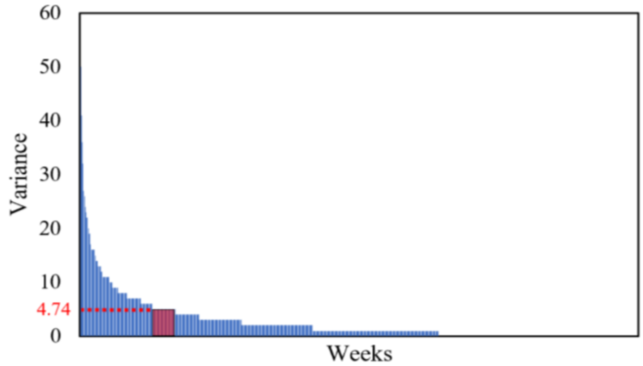

Figure 2: Variance of the wind speed at hub height, from 2010 until 2023. The chosen wind profile is indicated in red.

3.2 Planned production

It is essential to establish a baseline by examining the wind power output generated solely by the wind farm, without any battery storage. This baseline gives insight into how accurate the actual production of the wind turbine is compared to the planned production. Furthermore, the interaction between the wind turbine, power grid, and planned production will be visible. In Fig. 3 the produced power of the wind turbine is presented. The planned power production and the actual power production are not balanced most of the time. During periods of imbalance, the electricity grid functions as a source and sink of electricity. Analysis indicates that 65% of the total exchanged electricity flows into the systems and 35% is delivered to the grid. Integrating battery storage aims to decrease grid interactions, especially the delivered electricity to increase power system autonomy. Battery integration with a wind turbine increases power output. This influences the total amount of electrical energy the grid has to provide. The total electricity delivered is presented in Fig. 4. The blue bar represents the delivered electricity in the scenario when only the wind turbine operates, and the yellow bars indicate the scenario in which both the wind turbine and battery are in operation. With increasing battery capacity, there is a notable decrease in the total energy demand from the grid. For instance, in the wind turbine-only scenario, the grid delivers 430 MWh. However, with 1 MW of installed battery capacity, the grid delivers 37 MWh less. At 30 MW installed capacity, the grid provides a total of 183 MWh.

3.3 Battery storage

The straightforward observation of decreased electricity delivered by the grid with increased battery capacity can be further analysed when looking at capacity efficiency. Capacity efficiency is defined as the difference between the delivered electricity by the grid in a scenario with only wind turbines and the electricity delivered by the grid when batteries are installed, divided by the total battery capacity. It measures how effectively the battery is utilised. For example, in Fig. 4, the total electricity delivered by the grid in the wind turbine scenario is 430 MWh, and the delivered electricity for a 2 MW battery is 382 MWh, resulting in a capacity efficiency of 430−382= 24 MWh/MW. In Fig. 5 the capacity efficiency for each battery size is plotted against the battery capacity. It can

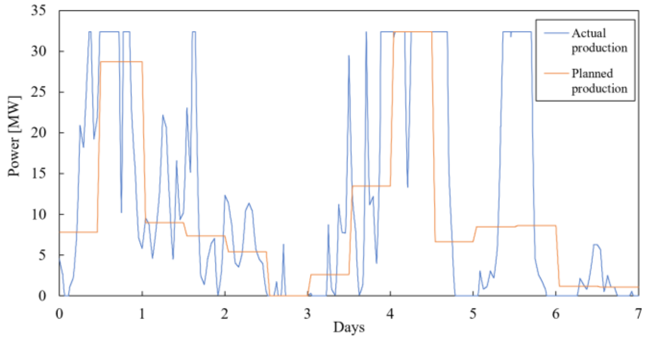

Figure 3: The actual and planned power production of the wind farm.

be observed that as battery capacity increases the capacity efficiency goes down. This implies that increasing battery capacity has diminishing returns in terms of its effectiveness in reducing grid dependency.

3.4 Optimisation

The results of the two optimisation scenarios in Table 1 are presented in Fig. 6 and compared with the main scenario from Fig. 4, which involves the simulation with the microgrid controller. The control strategy of the microgrid controller, as outlined in (1) focuses on maintaining grid balance by prioritising maximum utilising the battery while minimising reliance on the grid. Unlike optimisation strategies, this method does not involve optimising specific variables but rather adopts a more direct approach to grid management. The optimisation analysis reveals that integrating 1 MW of battery capacity reduces grid-supplied electricity when minimising operational cost and battery controls. Grid-delivered electricity shows a steep increase after installing 10 MW battery capacity. This observation suggests a trade-off, wherein efforts to smooth battery controls to extend battery life elevate the reliance on the grid. In the scenario aimed at minimising the operational cost and grid power output, the dependency on grid-supplied electricity remains relatively stable for each additional battery capacity. However, exceptions are noted with the installation of 2 MW and 30 MW battery capacities, where an increase in grid dependency is observed. Fig 7. presents the operational cost across all scenarios. In each scenario, the operational cost of the wind turbine and the battery are constant as they incur fixed operational expenses. Conversely, the grid's operational costs

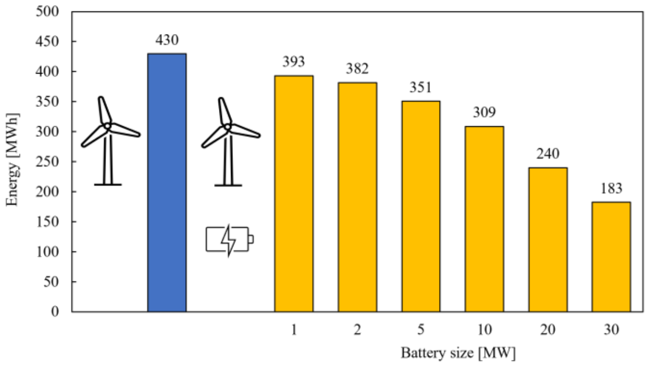

Figure 4: The total electricity delivered by the grid with and without battery storage.

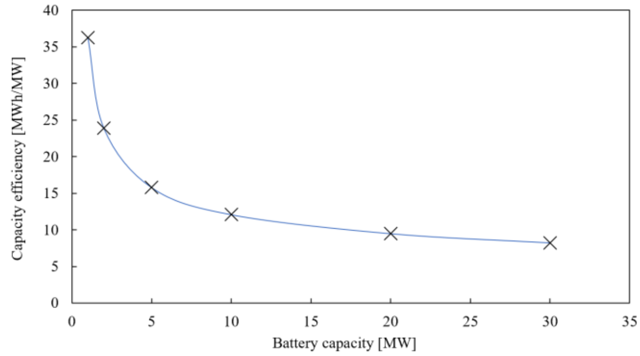

Figure 5: The impact of battery capacity on the total amount of the grid's delivered electricity.

vary and depend on the power output and electricity price. The optimisation analysis reveals that incorporating up to 2 MW of battery storage leads to a small decrease in operational cost. Compared to the main scenario, incorporating 10 MW, 20 MW and 30 MW of battery storage leads to higher operational costs. The SOC of the battery is presented in Fig. 8. In the optimisation scenario aimed at minimising the operational cost and grid supply, the SOC begins at 0.9 and gradually decreases until 0.1 over the simulation period. Although continuous charge and discharging cycles occur, they constitute only a small fraction of the total battery capacity. In the optimisation scenario of the operational cost and battery controls, the SOC exhibits different patterns of battery utilisation. A more regular pattern is observed in the SOC of the battery, especially in the first two days of the simulation. The small operational cycle during day six indicates a degree of flexibility in deviating from the optimised battery controls to minimise operational costs. Compared to battery controls a higher penalty is associated with optimising operational costs. In contrast, the SOC during the simulation with the microgrid controller indicates a more frequent utilisation of the battery, aligning with the result of Fig. 7, which suggests reduced grid dependency. Specifically, the microgrid controller simulation experiences a total of fifteen operational cycles, whereas the battery controls optimisation scenario only experiences a total of eleven operational cycles. This indicates a trade-off wherein the grid can be stabilised at the expense of potentially overusing the battery, or reducing stress on the battery by increasing dependency on the grid.

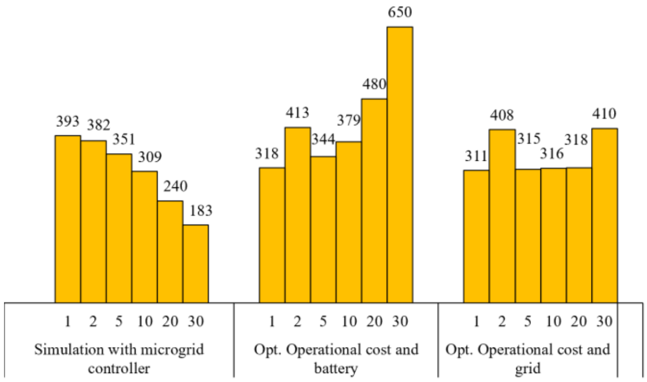

Figure 6: Delivered power grid electricity for the main and Optimisation scenarios.

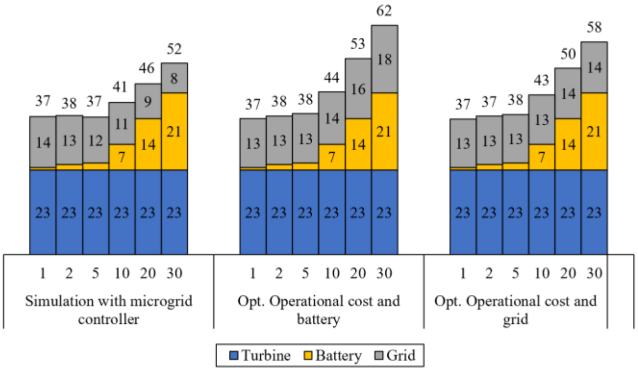

Figure 7: The operational cost of the simulation and Optimisation scenarios for every battery size.

3.5 Sensitivity analysis

To measure the impact of variance on the results, different wind speed profiles and their 12-hour interval average are presented in Fig. 9. What can be observed from this analysis is that the high variance profile exhibits more pronounced peaks and troughs in wind speed throughout the week. High peaks are observed on the first and third days of the simulation. The low-variance profile demonstrates a more stable pattern and gradually increases from 0 m/s on the first day to approximately 5 m/s by the end of the week. Quantitatively, the high variance profile has a variance of 16.01 and the low variance has a value of 2.27. Fig. 10 presents the electricity delivered by the grid in the high and low-variance scenarios, showcasing a similar trend to that of the main scenario. In the high variance scenario, more electricity is delivered by the grid in both the wind turbine-only simulation and the incorporation of each additional battery storage capacity. This observation can be attributed to the deviations between planned and actual production caused by the high variance in wind speed. The grid intervenes to align the actual with planned production, resulting in an increased demand for electricity from the grid. Conversely, in the low variance scenario, less electricity is required from the grid as the actual production closely aligns with the planned production due to lower variance in wind speed. Consequently, there is a reduced need for the grid to intervene

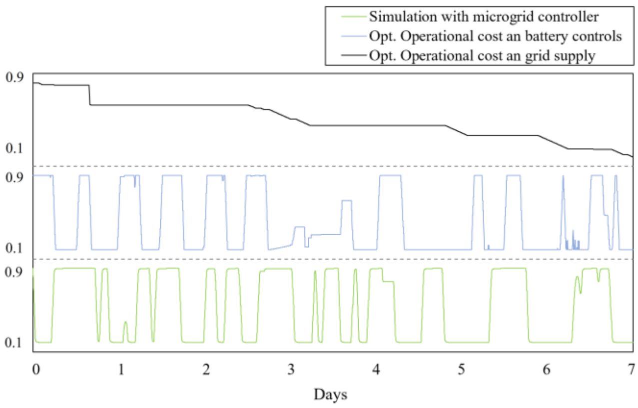

Figure 8: The battery SOC during the simulation run with the microgrid controller and the optimisation runs.

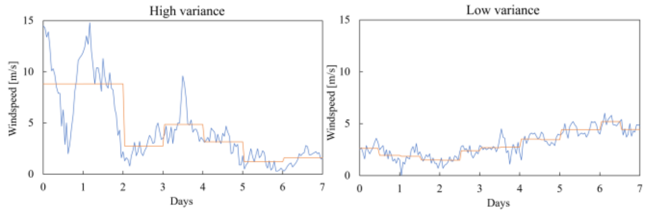

Figure 9: The selected wind speed profiles and their average wind speeds.

to align the two. For instance, in the wind turbine-only simulation, the electricity delivered by the grid is 116 MWh in the low variance scenario but decreases to 0 MWh when 30 MW of battery capacity is installed, this indicates the significant impact of variance on grid dependency and the effectiveness of battery storage mitigating it. In addition to analysing variations in wind speed, it is essential to consider the potential effects of model prediction uncertainties on the system's performance. Prediction errors, whether in wind speed or demand can lead to imbalances in supply and demand, compromising grid stability. Errors in forecasting can lead to inefficient dispatch resulting in increased operational costs and can reduce system efficiency. Storage sizing depends on accurate forecasts, if errors are not accounted for, resilience strategies may be underutilized.

4. DISCUSSION

4.1 Battery optimisation

Michiorrit et al. researched strategies to minimise power errors in wind turbines and optimise battery storage sizing in a 9MW wind farm. The wind farm owner provided to the transmission system operator with 30-minute interval power predictions. A 5 MW power-rated, resulted in high penalties and periods of disconnection. To address this, a sizing methodology was developed that generated error time series characterised by their autocorrelation. This led to an optimal capacity. A smaller-sized battery performed better because it effectively absorbed prediction errors correlated over timescales of around 6 hours, rather than compensating for all the differences between actual and predicted output over time. Consequently, a smaller battery reduced penalties while still achieving the target level of allowable errors, allowing it to be utilised to its full technical potential (Michiorri *et al.*, 2018). In this research, no error range is employed for the operational strategy, resulting in immediate battery utilisation whenever there is a misalignment between predicted and actual power. This complicates the comparison between the study of Michiorri et al and the current research. However, both studies agree that a smaller battery can better utilise its full potential. This is demonstrated in the present research, where the battery capacity increases and the capacity efficiency decreases.

4.2 Production planning interval

This research shows that a 12-hour interval accumulates production planning errors in a high-variance scenario, resulting in increased electricity from the grid. As the variance decreases, the forecast error also decreases, suggesting that a 12-hour forecast interval is more suitable for low-variance wind profiles. In contrast, high-variance wind profiles could

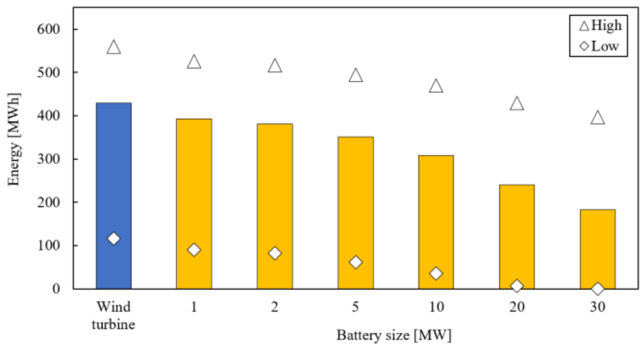

Figure 10: Electricity delivered by the power grid: high and low wind profile.

benefit from a narrower interval. Y et al. investigated the optimisation of a self-disciplined interval of a wind farm. This interval is calculated assuming an error distribution around the mean of
the predicted power output. An estimation technique models the historical error distribution shape between the actual and predicted wind power output. This interval width is optimised using the IPOPT. A case study analyses a 10-minute simulation interval to validate this method. Optimised battery storage technology supplies the necessary power to maintain this interval. It was found that the optimised method can effectively improve the self-disciplined level. Showing shorter intervals is an effective way of constructing robust production planning. A limitation of this research is the exclusion of battery degradation. Furthermore, only one case study is used and the method does not consider any error in actual wind power production (Yu *et al.*, 2020).

4.3 Policy decisions

Policy decisions should focus on resilient energy infrastructure, with investments made in battery optimisation to achieve cost-effective grid independence. Furthermore, policies should address grid congestion and provide compensation mechanisms for energy producers. Increase penalties for overproduction to encourage efficient energy management. Furthermore, high upfront costs and varying electricity prices are barriers to large-scale deployment of battery storage. Governments can provide subsidies for stable pricing mechanisms and long-term contracts to ensure financial security.

5. CONCLUSION

This research aims to investigate how battery storage can mitigate the volatility of wind power and its implications for the resilience of the Swedish energy system upon integration into the power grid. Given the growing trend of wind power with battery storage in Sweden, this study contributes to our understanding of improving wind turbine resilience through better production planning. Presented below are the main findings stemming from this research:

- Incorporating battery storage significantly reduces dependency on the power grid, especially in the lower-variance wind profiles.
- Enhanced utilisation of batteries is observed as battery capacity decreases.
- The research introduces a method for selecting wind speed profiles based on variance analysis, which captures the dynamic nature of wind behaviour. This approach identifies disruptive events through variance, providing a nuanced understanding of wind variability and system resilience.
- Enhancing system resilience by reducing grid dependency can increase capital and operational costs. Consequently, this leads to a higher variability in the SOC of the battery while smoothing the power grid supply. This creates a trade-off between stabilising the grid by heavily using the battery and protecting battery life by relying more on the grid.
- High-variance wind speed profiles lead to greater discrepancies between planned and actual production, requiring more grid intervention. In contrast, low-variance profiles aligned better with forecasts, reducing grid dependency.

The research identifies a clear trade-off between battery usage and grid dependency. While battery integration reduces grid reliance, it also necessitates careful consideration of battery control strategies to prevent increased operational costs and ensure battery longevity. This insight is crucial for optimising microgrid performance and achieving a more autonomous, cost-effective, resilient power system.

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