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# Valuing the Capacity Contribution of Renewable Energy Systems with Storage

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## Abstract

The growth of renewable energy technologies creates significant challenges for the stability of the system because of their intermittency. Nonetheless, we can value these technologies with storage systems. We model the supply by a renewable technology, wind, into a storage facility using the leaky bucket mechanism. The bucket is synonymous with storage while the leakage is equivalent to meeting load. Modelica is used to capture: (i) the time-dependence of the state of the bucket based on a physical model of storage; (ii) the stochastic representation of wind energy using wind speed data that is fed into a physical model of a wind technology; and (iii) the load, modeled as a resistor-inductor circuit. The strength of Modelica in using non-causal equations for basic sub-systems that are linked together is harnessed through its libraries. We find that there is a diminishing return to storage. Beyond a certain level of storage, the integration of a reliable baseload power supply is required to diminish the risk due to reduced reliability. The need for storage systems as a hedge against intermittency is dependent on the interplay between the supply volatilities and the stochastic load to guarantee an acceptable level of quality of service and reliability.

## Keywords
Renewable energy, Intermittency, Wind energy, Modelica, Reliability, Leaky bucket

## 1. Introduction

The Energy Information Administration (EIA) recently released the 2020 version of the short-term energy outlook indicating that the share of generation from renewable sources will increase from 17% in 2019 to 19% this year and to 22% in 2021 [1]. Globally, it is estimated that the electricity from wind energy, for example, will peak at 8% this year [2]. The increasing capacity addition of renewable electricity holds the potential to impose a cocktail of implications. On the one hand, economic incentives may mitigate the need for load-following and the sequential cost increases that significant renewable penetration may impose on base load power plants through energy storage [3]. On the other hand, there are crucial impacts of the growing capacity and significance of renewable electricity on grid reliability and variability [4]–[6]. Of the solutions proffered to address the intermittence of wind electricity including demand response, storage and ramping of conventional supplies, storage is receiving significant attention because of the characteristic it shares with conventional technologies on dispatch. The value of storage is not limited to dispatch, it may also be used to minimize grid variability. In fact, some studies have shown that the availability of storage could reduce energy supply costs by 30% [7].

This paper uses a system of systems modeling approach to evaluate the capacity contribution of renewable technologies with the aid of storage systems. At the intersection of supply capacity for renewable technologies and load is storage. We model the supply by renewable technologies into a storage facility using its synonymous properties with the leaky bucket mechanism as shown in **Figure 1** below. The bucket is synonymous with storage while the leakage is equivalent to supply from the storage resource. A prior approach [8] that employs the leaky bucket mechanism to evaluate the variability of electricity supply and demand uses an envelope-based modeling effort adapted from Network Calculus theory (NetCal) for queuing systems [9]. The method captures the zero-sum game between capacity and Quality-of-Service (QoS) as a measure of system performance. However, the method is not cognizant of the underlying physical systems producing and consuming the electricity nor is the method cognizant of the interactions between the subsystems as captured using Modelica.

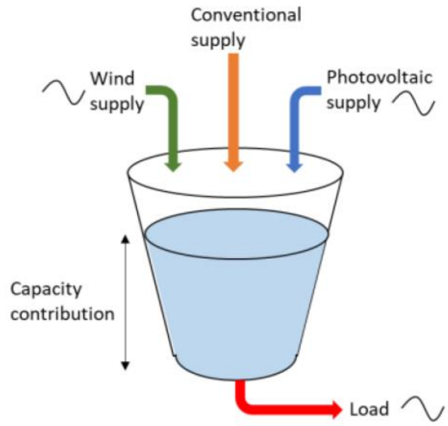


**Figure 1:** Leaky-bucket illustration of storage mechanism

Modelica programming language [10] is used to capture the time-dependence of the evolution of the state of the bucket. The strength of Modelica is harnessed based on its inherent ability to offer time-varying information not only on the average state of the system, but also on the physical state of the sub-systems as represented by intertemporal and dynamic non-causal mathematical modules.

We find that there is a diminishing return to storage. Beyond a certain level of storage, the integration of a reliable baseload power supply is required to diminish the risk due to reduced reliability. The need for storage systems as a hedge against intermittency is dependent on the interplay between the supply volatilities and the stochastic load to guarantee an acceptable level of service and reliability. The contribution of this paper is two folds. The first is on the modeling construct – the model endogenizes the variability in wind speed for wind electricity and load with the physical representation of the underlying technologies to value the optimal threshold for storage. The second is on the counter-intuitive result highlighting that there is diminishing returns to storage capacity relative to the load and supply fluctuations. To the best of our knowledge, while the first contribution builds on existing Modelica libraries, the second is an unexpected outcome, and their intersection offers insights for policymakers.

## 2. Model

The elements of the model include the following:

- stochastic representation of wind electricity based on a time history of available wind speed data.
- physical model of a wind power plant
- physical model of a storage sub-system
- simple resistance-inductance (R-L) load
- power system for wind to storage and storage to load

The system model generates data providing insights to characterize the capacity contribution of storage for intermittent generation. This contribution is evaluated at different QoS or confidence levels ranging from 85% to 95% as the thresholds for "acceptable" supply.

We employ Modelica [10], a standard object oriented modeling language that allows the combination of sub-systems into a single complex system. The value of Modelica for this analysis is based on two factors. First, it has a graphical user interface with readily available component libraries. Second, the mathematical representations of the time-varying parameters that drive the components have been developed. However, the main task lies in integrating the components or subsystems into a single system with the right controls and flows. The model of how the subsystems are combined is represented in **Figure 2**.

The model used in this study, represented in **Figure 2,** was adapted from the "RenewableSources" framework within the Building Library in the Modelica Standard Library to include battery storage and charging controls.

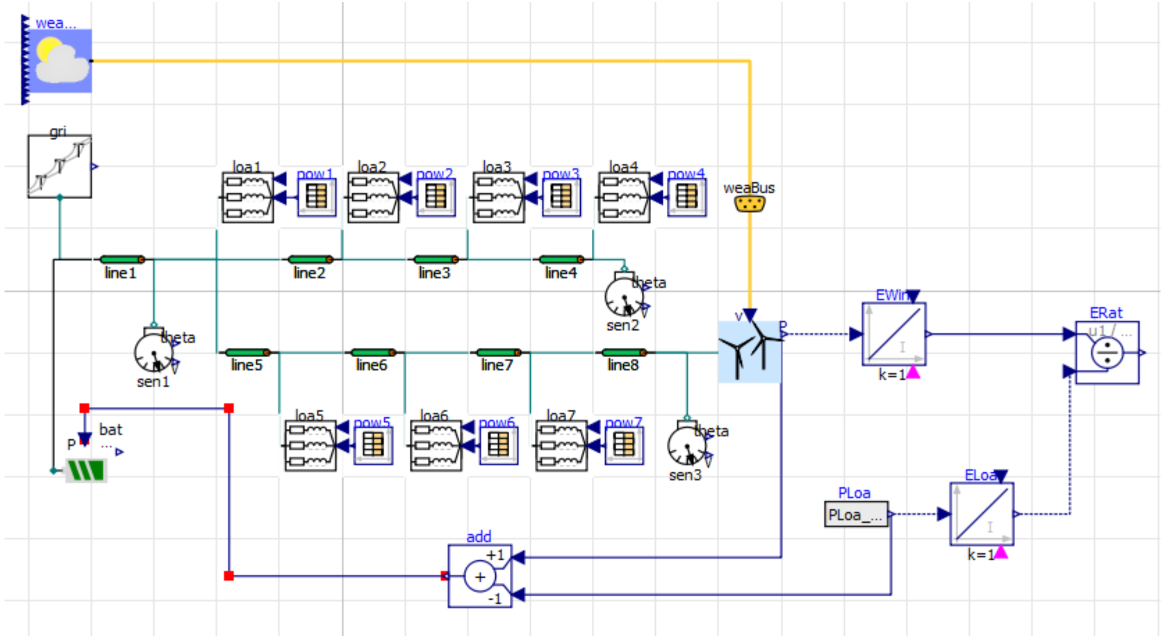


**Figure 2:** Modelica scheme of the system (adapted from [11]).

The loads (loa1, loa2, etc) are defined by 24-hour periodic power consumption. They are each fed by a conductor (line1, line2, etc). The renewable generation is given by a simplified wind turbine, which takes wind velocity as its input, and outputs phase and power. The battery subsystem (bat) consists of an idealized battery component, controlled by an ideal peak-shaving controller. Finally, the larger electrical grid (gri) to which this hybrid system connects to is an infinite sink/source for power. The reason for including the grid component is to introduce slack into an otherwise stiff model for solving purposes. It serves the added benefit of providing an intuitive reference for the gap between the power provided by the wind/battery system, and the total power demanded by the loads.

## 3. Results

In determining the QoS contributions of the storage or battery system, the absolute sizing of the generation, storage, and load is less important than the relative sizing. Thus, the wind system was arbitrarily scaled so that over the 30-day period of analysis, the energy generated was equal to the energy consumed. In this scenario, there will be a value for energy storage that closes the energy gap between the load and renewable curves. The envelope curve is shown in **Figure 3**. To achieve the balance of energies, the load was given a nominal power of 350W, the installed wind capacity was 8,400W, and the battery capacity ranged from 1kWh to 4,000kWh.

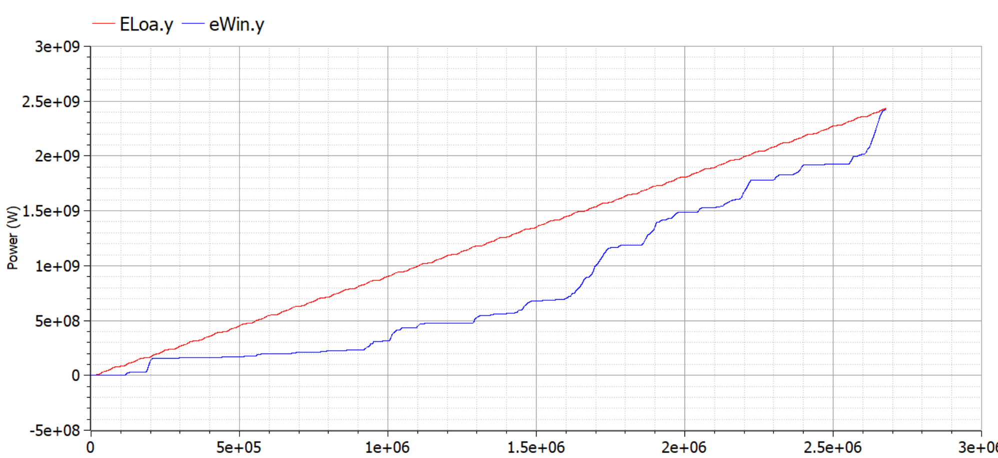


**Figure 3:** Energy Envelope

**Figure 4** shows the time histories for wind and demand. It can be seen that the wind availability for the given location is less than ideal, with long periods of low wind and short spikes or periods of high wind speed.

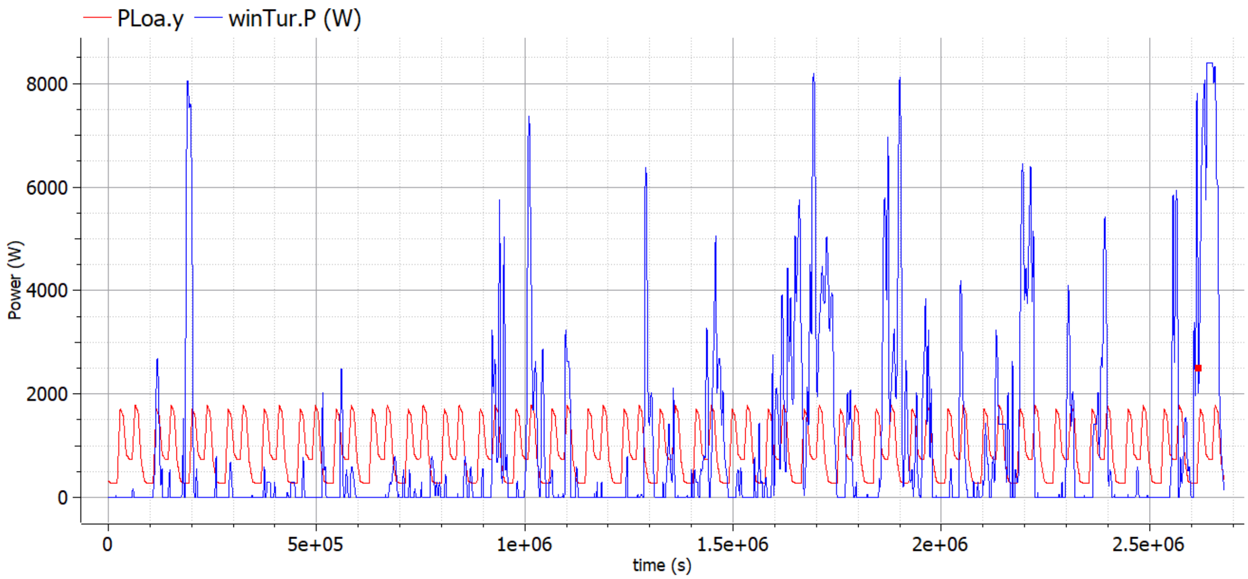


**Figure 4:** Plot of load and wind

The model was validated by assessing component performance under known scenarios. **Figure 5** shows a time segment including the battery power, wind surplus, and grid power. The wind energy is scaled from an hourly wind velocity dataset from San Francisco International Airport for thirty days. The difference between the wind power and the load demand is given as WindSurplus. This serves as the control signal for the battery. **Figure 5** shows a period of time in which the battery power (bat.P) very closely follows the Wind Surplus. Note that the convention used for battery power is positive for charging, and negative for discharging. The opposite is true for the grid power and wind power. When the battery is unable to provide power, the grid (gri.P.real) is forced to generate the deficit.

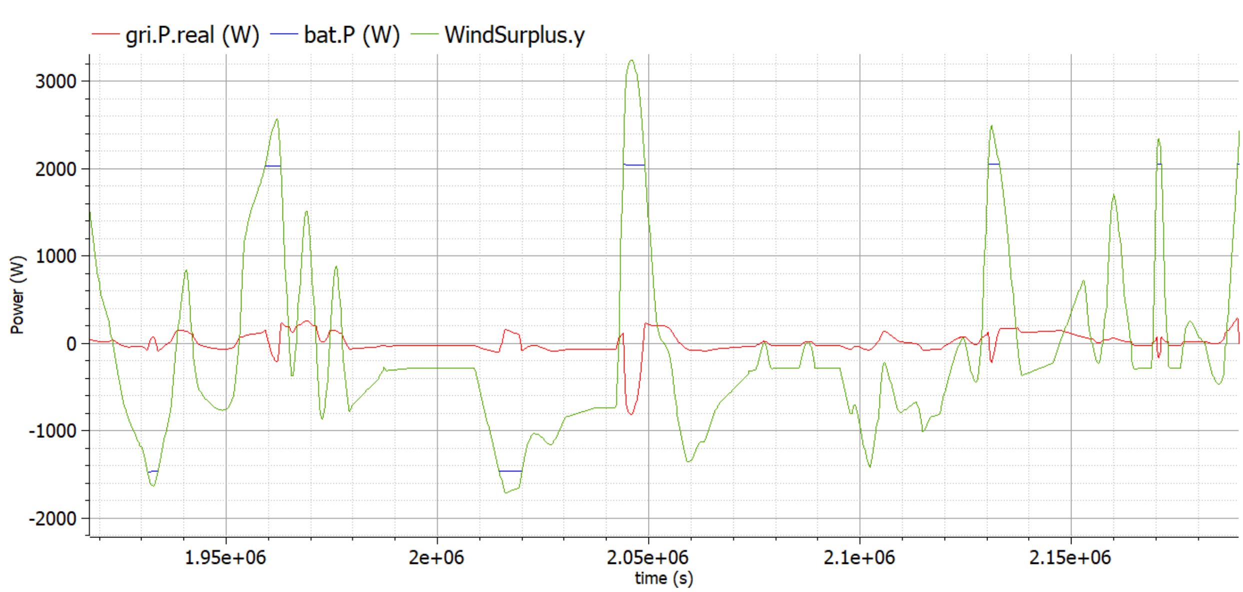


**Figure 5:** Operational validation of the model

The grid also provides phase and voltage stabilization. In this configuration, the large capacity of the battery means that makeup power is rarely required from the grid. It can be observed that all signals behave as expected, with wind providing the primary power, the battery making up the difference as best it can, and the grid providing the slack to maintain the conservation of power.

Results were generated for some scenarios with varying battery capacity. To assess the impact of increasing storage, the grid contributions were used as a proxy for load that was not covered by either the battery or wind generator. In this case it is a very close proxy, but it should be noted that a small error is introduced by the grid contributions for voltage and phase stabilization. Because this error is constant between cases, it is negligible in this study.

**Figure 6** shows that in the given scenario, the QoS reaches the 85% threshold when the storage capacity is ~275 times greater than the installed wind capacity. This indicates that for the given installation, the potential for renewables to reliably satisfy grid on their own would be a costly proposal. Luckily, the connection to the grid makes it more viable, but with higher levels of intermittent supply coming online in the future, there is a clear need for flexible, dispatchable energy sources such as storage.

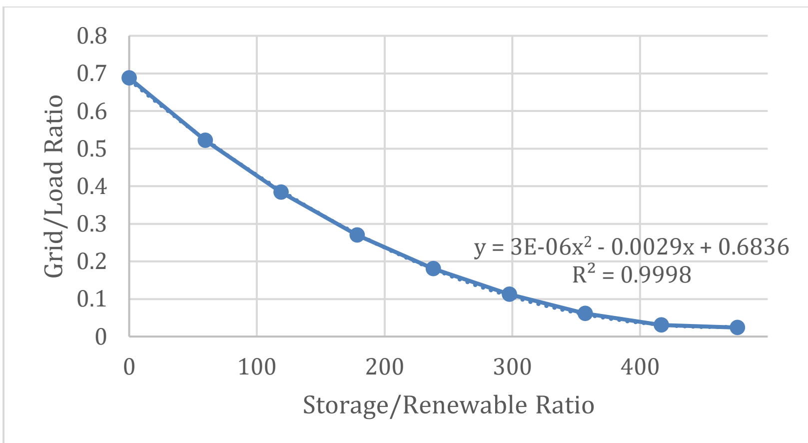


**Figure 6:** Diminishing returns for increasing storage capacity

## 4. Conclusion

This study reconfirms the long-held notion that energy storage can mitigate the volatility and variability of renewables [12]. However, as we rightly postulated, beyond a certain capacity, the QoS contributions diminish. When the cost of investment into storage systems is considered, then it becomes paramount to elicit what the optimum capacity should be. The inherent value in this approach is the inclusion of the physical characteristics of the system. Nonetheless, this study initiates a set of tasks aimed at providing a more robust QoS assessment of storage systems. In this exploration, the next steps include: (i) improving the resolution of the modeling components to better represent physical limitations of the system; (ii) incorporating the stochastic nature of not only production, but also of load signals simultaneously to better understand how the quality of those signals relates to storage QoS systems. One important consideration for future work is a comparison of how storage contributions vary between areas with high availability factor for wind capacity versus areas with low availability factor, as well as between wind resource locations with higher variances. In the data leveraged for this work, the high volatility and unreliable quality of the available wind resource likely drove the need for storage capacity much higher than it would be for a more consistent wind resource. More work is needed to provide answers to how the relationship between predictability (variance) and availability affect capacity decision making.

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