What Properties of Grid Energy Storage are Most Valuable?

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Abstract

While energy storage technologies have existed for decades, grid-level storage is still an immature industry and is experiencing relatively rapid improvements in performance and cost across a variety of technologies. In this innovation cycle, it is important to determine which energy storage properties are most valuable. Decreased capital cost, increased power capability, and increased efficiency all would improve the value of an energy storage technology and each has cost implications that vary by application, but there has not yet been an investigation of the marginal rate of technical substitution between storage properties. We use engineering-economic models of four energy storage technologies and examine their cost-effectiveness for four specific applications. We determine which properties have the greatest effect on cost-of-service by performing an extended sensitivity analysis on the storage properties for combinations of application and storage type. We find that capital cost of storage is consistently important, and identify applications for which power/energy limitations are important. Each combination is different and blanket statements are not always appropriate.

Key Words: Energy storage; Sensitivity analysis; Frequency regulation; Peak shaving; Wind integration; Capital cost

1. Introduction

There has been significant interest in grid-tied energy storage in recent years. The costs of storage have been decreasing for many technologies while the performance has been improving [1,2]. These trends suggest that a substantial quantity of energy storage is likely to be installed on the grid in the next few decades. But energy storage technologies are not interchangeable, due to the differing limitations, operations, and capabilities. The applications served by energy storage are not equivalent to one another due to the different types of charge/discharge profiles required from the storage. Thus, in order to properly evaluate energy storage technology for electrical grid applications, it is necessary to examine particular technologies being used for particular applications.

Previous work has compared the properties of different energy storage technologies and matched them to the most appropriate applications, and that work is not reproduced here [3-8]. Instead, we examine the effects that improving the attributes of energy storage will have on the cost of providing different energy services, and compare the results across different technologies and applications.

We developed engineering-economic models of four energy storage technologies and examine their cost-effectiveness for different applications. We then performed extended sensitivity analysis on the "cost-of-service" for each energy storage technologies in each realistic applications, where cost-of-service is defined as the annual cost of delivering an energy service from a storage technology[1]. From this, we calculate the marginal rate of technical substitution[2] between battery properties and determine which energy storage properties are the most limiting and thus the most important to improve, using the cost of delivering a realistic energy service as the objective criteria.

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[1] The cost-of-service includes fixed costs, variable costs, and amortized capital costs.
[2] If output is held constant, the decrease in one production input factor that is reduced when another input is increased is the marginal rate of technical substitution.

We find that the most common limiting energy storage property is capital cost. This result is consistent across different storage technologies and applications and is robust to changes in energy storage parameters. The power limit of the energy storage device is important for high power applications, such as frequency regulation, while the energy capacity is found to be limiting for energy intensive applications like peak shaving.

This paper is organized as follows: first, we describe the modeling methodology for the storage technologies and applications and the method used to determine which storage properties are most limiting. Second, we present the results and examine how these results are affected by changes to the storage parameters. Third, we discuss how these results can be used to inform decision-making over future energy storage research and development.

2. Methodology

We examine four battery technologies as applied in four applications: sodium sulfur (NaS) batteries, lithium ion batteries, flywheels, and supercapacitors. The applications are frequency regulation, wind smoothing in a generation block producing baseload power, wind smoothing in a generation block producing load-following power, and peak shaving. We determine the effect that changes in storage parameters have on the cost of providing a specific service. Each energy storage technology was modeled separately, since energy storage technologies differ in more than just operational parameters. A model was developed individually for each of the four applications. The result is a matrix of sixteen different models, for the four storage technologies applied to the four different applications. The more important aspects of the storage and applications modeling are described below and greater detail can be found in the Appendix.

2.1. *Energy Storage Modeling*

The four energy storage types represent an operationally diverse set of storage technologies that have potential for significant market share in the coming decades. We developed an engineering-economic model for each of the four energy storage technologies; each is modeled with its own set of operational and cost parameters, including round trip efficiency, energy capacity, fixed operating cost, capital cost, and expected duration of capital investment.

Because NaS batteries are commercially available only in a pre-defined modular form, their power-to-energy ratio is fixed [9]. NaS batteries require a temperature of around 325 degrees Celsius to operate and thus require an continual "maintenance power" to maintain that temperature (accounted for in this model). NaS batteries have a continuous power rating of 0.05 MW, and have a manufacturer-defined pulse power capability under which they can provide up to five times the normal power rating for 30 seconds, making their maximum power output 0.25 MW.

Table 1: NaS battery properties examined and their base-case values.

NaS Battery Parameter	Base-Case Value
Round-trip Efficiency	80%
Module Energy Capacity	0.36 MWh
Module Power Limit	0.25 MW
Module Maintenance (Heating) Power	2.2 kW
Module Capital Cost	$240K ($670K / MWh)
Module Fixed Operating Cost	$8K / module - year ($22K / MWh-year)
Length of Capital Investment	20 years

Li-ion batteries are modeled without modularization and we make the assumption that a system could be created with a wide range of power-to-energy ratios, as required for each application. A generic Li-ion battery is modeled, with parameters close to existing units but not taken from any particular product.

Table 2: Li-ion battery properties examined and their base-case values.

Li-ion Battery Parameter	Base-Case Value
Round-trip Efficiency	80%
Capital Cost of Batteries	$500K / MWh
Capital Cost of Power Electronics	$300K / MW
Fixed Operating Cost	$8K / MW - year
Length of Capital Investment	10 years

Flywheel energy storage, like NaS batteries, is assumed to come in discrete modules with pre-defined properties and is based on Beacon Power's Smart Energy 25 flywheel [10]. In addition to round trip efficiency limitations, the flywheel model accounts for friction losses which reduce the stored energy over time.

Table 3: Flywheel energy storage properties examined and their base-case values.

Flywheel Energy Storage Parameters	Base-Case Value
Round-trip Efficiency	90%
Module Energy Capacity	0.025 MWh
Module Power Limit	0.1 MW
Flywheel Friction Losses	3% of max power (3 kW)
Module Capital Cost	$200K
Fixed Operating Cost	$5K / module - year
Length of Capital Investment	20 years

Supercapacitors are modeled with no power limitation and are not modularized, allowing the model to choose the quantities of power electronics and energy capacity independently [11].

Table 4: Supercapacitor properties examined and their base-case values.

Supercapacitor Parameters	Base-Case Values
Round-trip Efficiency	70%
Capital Cost of Supercapacitors	$143M / MWh
Capital Cost of Power Electronics	$60K / MW
Fixed Operating Cost	$13K / MW - year
Length of Capital Investment	20 years

2.2. *Applications Modeling*

Four applications were chosen as representative of the types of energy services provided by energy storage in the coming decades. Both energy-limited (peak shaving) and power-limited (frequency regulation and wind integration) applications are represented. The applications examined have been identified as some of the most beneficial (in a $/kW basis) and represent a subset of the services energy storage may provide on the grid [1]. Each application was modeled using a time-series analysis, as shown schematically in Figure 1.

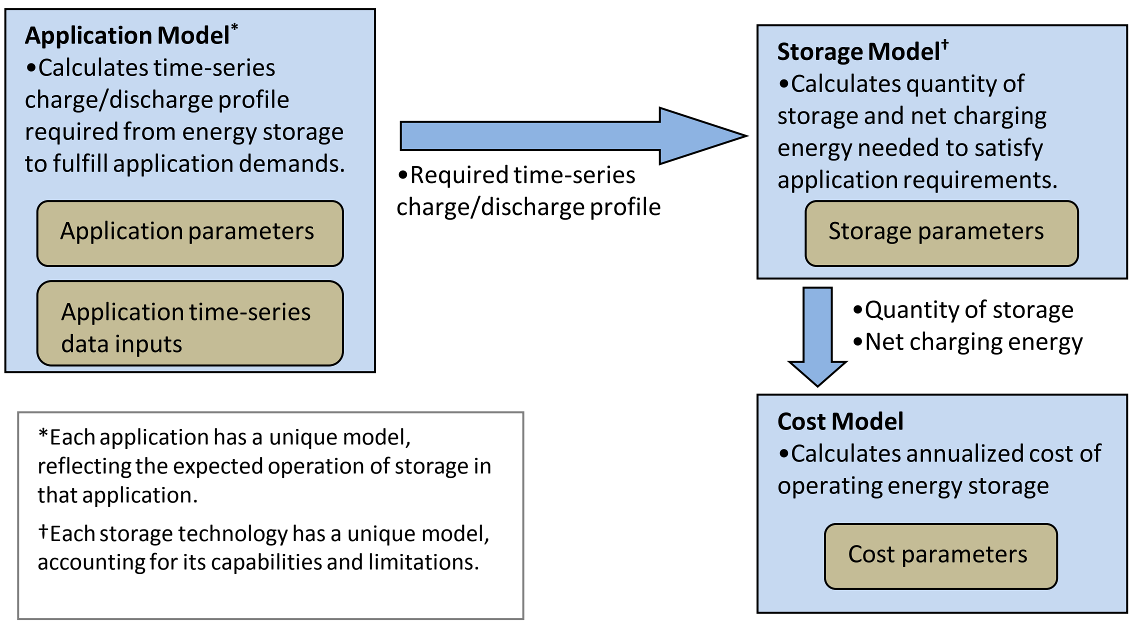

Figure 1: Method used to calculate average cost-of-service. The application model determines the time-series charge/discharge profile that energy storage must satisfy in order to meet the pre-defined requirements of that application. The storage model determines the quantity of energy storage needed to fulfill the requirement of the application and also tracks the charging energy required by the energy storage. The cost model calculates the annualized cost of providing the required energy service. This block diagram describes the general method used to calculate annualized cost-of-service. Input data for the applications are described in Tables 5-8, and greater detail can be found in the Appendix.

The frequency regulation application calculates the cost of providing a year of frequency regulation service using a particular energy storage technology. Frequency regulation is an ancillary service that follows a signal from the system operator and normally requires rapid changes in power output from a generation asset. For storage, this is implemented by scaling each energy storage device to the minimum size at which it can successfully follow the regulation signal for the entire period. The frequency regulation data set consists of five days of 2-second resolution signal made available by the PJM Interconnection [12]. Because the storage provides frequency regulation service continuously, resulting in a roughly constant energy demand, an average electricity cost of $50/MWh is used for the net electricity consumed. During the period covered by the signal released by PJM, the dispatched regulation power up/down went to the contracted maximum power several times, but it is not safe to assume that the maximum possible 15-minute energy deviation was experienced in the five days of data PJM released. Thus, the power requirement of the energy storage is used as determined directly from the model, but the energy capacity requirement is doubled from what the model determines as the minimum possible energy capacity. The model calculates the total cost of providing a year of 100 MW frequency regulation service, and forces the storage to pay for energy lost to inefficiency. This internalizes the cost of the charging energy and allows a fair comparison between storage technologies with differing round-trip efficiencies and losses.

Table 5: Key frequency regulation parameters.

Frequency Regulation Parameter	Value
Modeled Period	5 days
Modeled Time Increment	2 seconds
Balancing Energy Bid Interval	15 minutes
Balancing Energy Cost	$50 / MWh

The peak shaving application models the use of an energy storage technology to provide power during the peak load each day, charging at night when electricity production costs are lower. Peak shaving is commonly used to defer capital investment in generation or transmission capacity. It is modeled by assuming that a system operator wants to reduce the annual maximum load (in MW) in a particular area by 5%. The energy storage is then scaled to provide that reduction from maximum. Given the 2008 Bonneville Power Authority (BPA) load data used (5 minute sampling), this would result in the energy storage being used only for a few peak days each year [13]. Because the high capital cost of the storage has already been spent to mitigate the highest loads, it is further assumed that an operator would additionally use the storage for peak shaving on all days of the year. Thus, while the battery is scaled to reduce the highest peaks, it is also used to effectively transfer load to off-peak hours for each day in the year up to its energy limitations. While discharge is performed as required by the load, charging is distributed evenly between the hours of 11 PM and 4 AM. The model calculates the cost of performing the peak shaving service, moving load from peak hours to nighttime. A price of $40 per MWh is assumed for this nighttime charging, necessary in order to fairly compare storage technologies with different efficiencies. Additionally, it should be noted that while the motivations are different, the peak shaving application is functionally very similar to an energy arbitrage application, at least as far as the battery operation is concerned, and thus the conclusions about energy storage properties for peak shaving should be applicable to energy arbitrage as well.

Table 6: Key peak shaving parameters.

Peak Shaving Parameter	Value
Modeled Period	1 year
Modeled Time Increment	5 minutes
Peak Shaving Requirement	5% of peak load
Charging Period	5 hours (11 PM to 4 AM)
Charging Energy Cost	$40 / MWh

The application described as wind integration in a wind/natural gas/storage baseload system utilizes a small amount of fast-ramping energy storage to remove the sharpest power spikes and drops from a wind farm to facilitate grid integration of that wind energy [14]. Conceptually, the energy storage acts as a shock absorber for the wind power and allows for a defined ramp rate limitation on the wind power. Actual 10-second time resolution wind data is used to model the wind generation (Southern Great Plains United States wind farm, sum of 7 turbines, 15 days, 10 second resolution, 46% capacity factor during this period). For this research, a ramp rate limitation for wind power of 6% per 10-second interval (36% per minute) is used. Energy storage is scaled to the minimum size required to provide the smoothing service. The modeling for this application has been described in a previous paper, where a natural gas turbine is modeled as the remainder of the system [14]. This wind/natural gas/energy storage generation block operates to deliver flat, baseload power within a small deadband range (0.5%).

Table 7: Key baseload wind integration parameters.

Baseload Wind Integration Parameter	Value
Modeled Period	15 days
Modeled Time Increment	10 seconds
Maximum Wind Ramp Rate	6% per 10 second interval

The final application, described as wind integration in a wind/natural gas/storage load-following system, is similar to wind integration in a baseload system described above, except that this application produces a load-following generation profile, while the baseload application has a flat power output. The load data set, sampled at 5-minute intervals, is the same BPA load data used in the peak shaving application. The load data set is chronologically aligned with the wind data, although the wind data is from a different region (Southern Great Plains). The load-following application is examined in this research because it requires a different charge/discharge pattern than the baseload application and thus produces different results.

Table 8: Key load-following wind integration parameters.

Load-following Wind Integration Parameter	Value
Modeled Period	15 days
Modeled Time Increment	10 seconds
Maximum Wind Ramp Rate	6% per 10 second interval

2.3. *Calculations of Marginal Rate of Technical Substitution between Battery Properties*

Each of the four application models has, as an output, the annualized cost of providing that particular energy service. By changing the value of one energy storage property and re-running the model, we can determine the effect that this change has on the cost of providing a service. This allows us to calculate the sensitivity of cost to that storage parameter, and the process is repeated for each of the energy storage properties listed in Tables 1-4. Normally, sensitivity analysis is used to determine the effect of using uncertain parameter values. In this research we make the assumption that the parameters are known and determine the effect that improving them would have on the annual cost of providing different energy services.

For each energy storage parameter and each application, we calculate the sensitivity of the cost of an energy service to the parameter by comparing the cost-of-service from the base-case assumptions to that when the studied property is slightly improved. Conceptually, the cost of providing a particular energy service is a function of the input parameters describing the studied energy storage technology (Equation 1). The marginal physical product[3] of parameter i (MP_{p_i}) shows the sensitivity of cost-of-service to parameter i (Equation 2), where c is the cost-of-service and p_i is the value of parameter i. The approximation in Equation 2 holds for small changes in p_i or cases where the relationship between p_i and c is linear, of which at least one is true for all cases studied. For each storage property, several alternative values are calculated to determine if the sensitivity is roughly linear, even though only two points are used in the calculation. The marginal product is also referred to below as the sensitivity and is always reported as a positive number. Additionally, all figures are in percentage terms to facilitate comparisons across properties (i.e., we determine the percentage decrease in cost-of-service resulting from a percentage increase in energy capacity rather than the decrease in cost-of-service dollars from a MWh increase in energy capacity). Thus the results shown in Figures 3 through 6, showing the marginal product of various storage properties, are between zero (indicating a parameter that has no effect on cost-of-service) and one (indicating a parameter where a 1% improvement results in a 1% decrease in capital cost).

$$c = f(p_i, p_j, \ldots p_n) \qquad (1)$$

[3] The marginal physical product of a production input is the additional output gained by employing one additional unit of that input while holding other inputs constant.

$$MP_{p_i} = -\frac{\partial c}{\partial p_i} \approx -\frac{\Delta c}{\Delta p_i} \tag{2}$$

$$RTS_{p_i,p_j} = \frac{MP_{p_i}}{MP_{p_j}} \tag{3}$$

The relative importance (effect on annualized cost of providing an energy service) of different storage properties can be compared using the marginal rate of technical substitution (RTS_{p_i,p_j}), which is the ratio of the marginal products of the two input parameters (Equation 3). The rate of technical substitution gives the ratio of parameters i and j that must be exchanged in order to keep the overall cost-of-service constant. Alternately, over small changes in parameters, it indicates the ratio of improvements to parameters i and j that would have an equal effect on cost-of-service. Because the production function in Equation 1 is not perfectly elastic across different parameter combinations, the results will be increasingly inaccurate as the base-case parameters are changed, and cannot be considered applicable to all possible combinations of parameters. The effect that changes to the base-case parameters have on the results is discussed in Section 3.

Figure 2 is an example of the method used. This figure shows a sensitivity plot of four flywheel energy storage properties. 100% on the x-axis, where the lines all meet, is the base case result. As a single parameter is changed (along the x-axis), this results in a change in the cost of providing the energy service (on the y-axis). Some properties, such as module energy capacity in this example, have little or no effect on the cost of service while others, such as module capital cost, are far more important. This figure shows data only for flywheels providing frequency regulation service. The sensitivities of all four storage technologies applied to all four applications are collected, normalized, and presented in the Results section below.

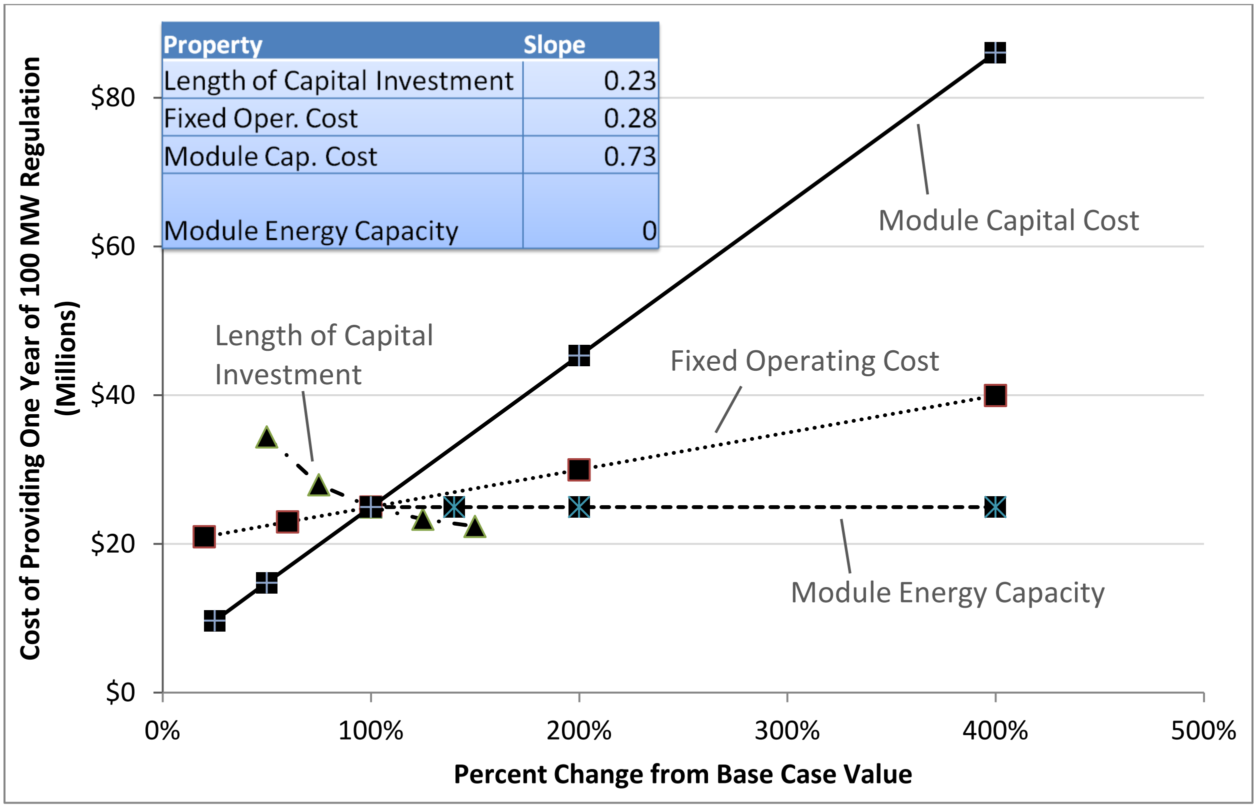

Figure 2: Sensitivity plot of flywheel energy storage properties. As a single parameter is varied (along the x-axis), the cost of providing 100 MW of frequency regulation service changes (along the y-axis). The cost of energy service is most sensitive to those parameters with a higher slope (such as module capital cost). The inset box gives the slope or sensitivity of the four lines in percent decrease in cost-of-service per percent improvement in the examined parameter.

3. Results

We focus on the relative importance of improvements in storage properties for decreasing cost-of-service. Using the four energy storage technologies and the four applications, sixteen different technology/application combinations were modeled. For each combination, sensitivity analysis was performed over each of the energy storage properties studied (between five and seven for each technology).

The results for NaS batteries are shown in Figure 3. We draw two conclusions. First, while each application is different, there are some general trends. Module capital cost is important in every application, while module maintenance power is found to have little effect on cost in all cases. Improvement of efficiency is found to be a relatively insensitive parameter in all applications. Second, the power and energy limitations are very important but their relative importance depends on the type of application. For the power-intensive services, such as frequency regulation, the power limit is the most important NaS battery property, while the existing energy capacity is non-binding and thus unimportant. On the other hand, for an energy-intensive application such as peak shaving, energy capacity is the property that most affects the cost of service, while the power limitation is non-binding.

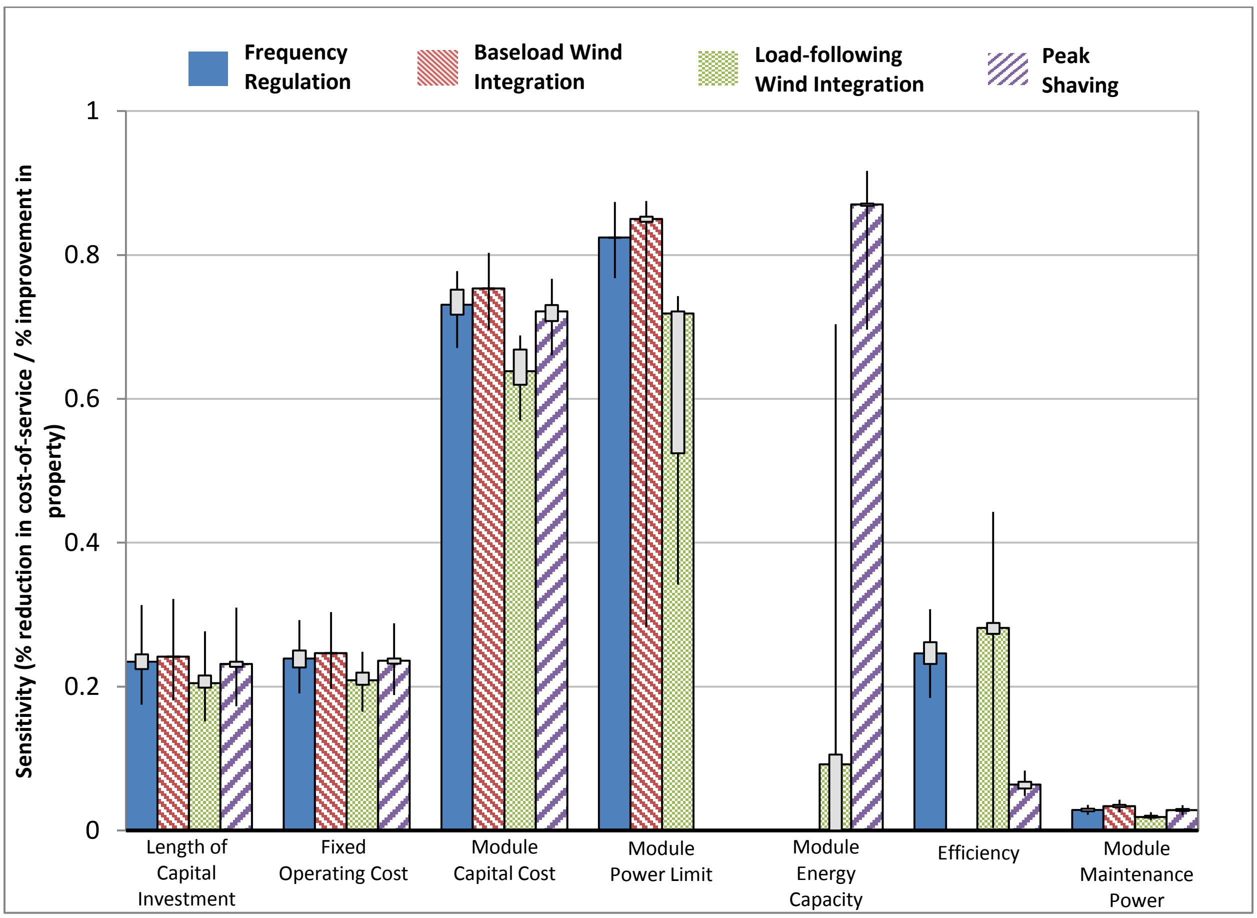

Figure 3: Sensitivities of NaS Battery properties across four applications. Properties with higher sensitivity have a greater effect on the cost of providing energy services. The box and whisker plots summarize the results of sensitivity analysis, described in the sensitivity analysis section. The box range indicates the 25th and 75th percentile values and the whiskers show the minimum and maximum values obtained in sensitivity analysis.

The results for Li-ion batteries are shown in Figure 4. In contrast with NaS batteries, Li-ion batteries do not have as many properties that are highly sensitive. This is due partially to the fact that Li-ion battery systems were not constrained to NaS' pre-defined modular design. As a result, the optimal power-to-energy ratio can be chosen in each case. For Li-ion batteries, the fixed operating cost was found to have a small effect on cost of energy services, while capital cost and lifetime were relatively important. The sensitivity to efficiency depends strongly on the application.

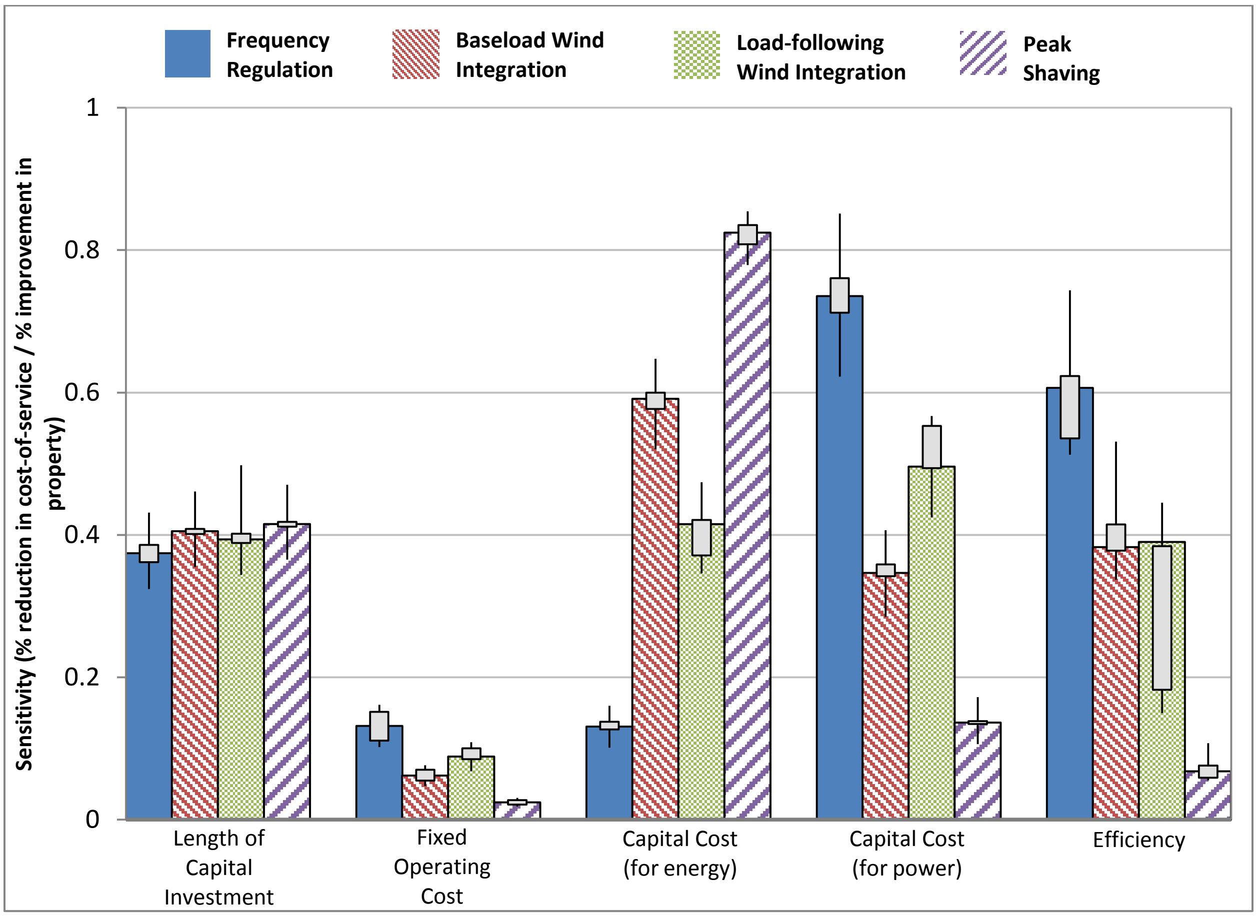

Figure 4: Sensitivities of Li-ion Battery properties across four applications. Properties with higher sensitivity have a greater effect on the cost of providing energy services. The box and whisker plots summarize the results of sensitivity analysis, described in the sensitivity analysis section. The box range indicates the 25th and 75th percentile values and the whiskers show the minimum and maximum values obtained in sensitivity analysis. Because the main bars represent base case values rather than median values, they do not always fall within the interquartile range of sensitivity analysis results.

The results for flywheel energy storage are shown in Figure 5. For all applications, the most limiting energy storage property, and thus the property that most affects cost, is module capital cost. The efficiency and friction losses of the system are found to be of little importance in all applications except load-following wind smoothing. In this instance, the base-case system is very close to requiring one less flywheel module, thus slight improvements in efficiency or friction losses cause the system to decide upon one less module, resulting in an unexpectedly strong effect on cost. This non-linear effect is entirely due to the requirement for discrete flywheel modules, and is discussed further in the sensitivity analysis section. As in the previous results, the relative importance of flywheel energy capacity and power limit vary by application.

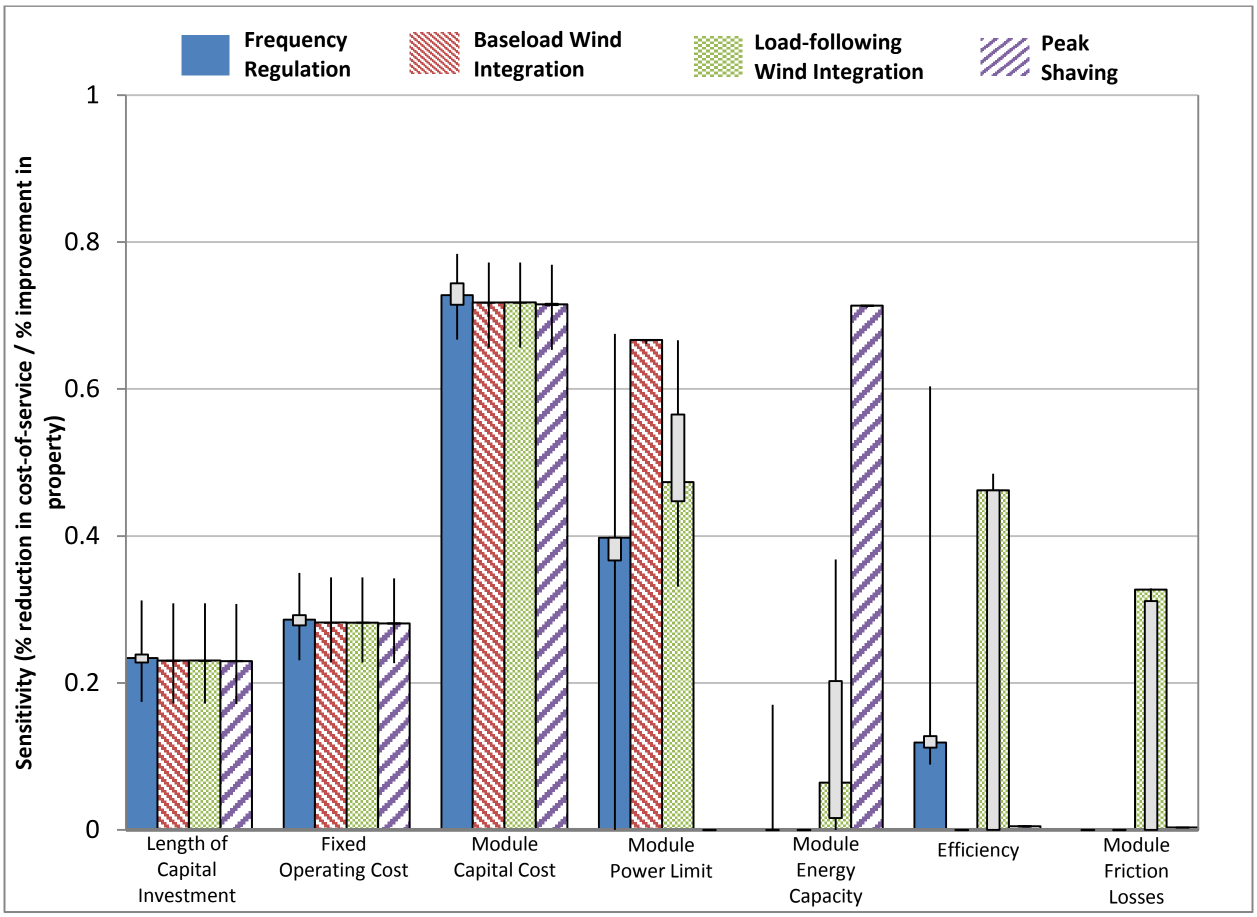

Figure 5: Sensitivities of flywheel energy storage properties across four applications. Properties with higher sensitivity have a greater effect on the cost of providing energy services. The box and whisker plots summarize the results of sensitivity analysis, described in the sensitivity analysis section. The box range indicates the 25th and 75th percentile values and the whiskers show the minimum and maximum values obtained in sensitivity analysis. Because the main bars represent base case values rather than median values, they do not always fall within the interquartile range of sensitivity analysis results.

The results for supercapacitor energy storage are shown in Figure 6. These results are driven largely by the high capital cost per energy capacity of supercapacitors. This causes the capital cost for energy capacity and the duration of capital investment (which is linked to it through the discount rate) to overshadow the capital cost of power electronics and the fixed operating cost. Efficiency is found to be relatively important, as it affects the amount of energy storage required.

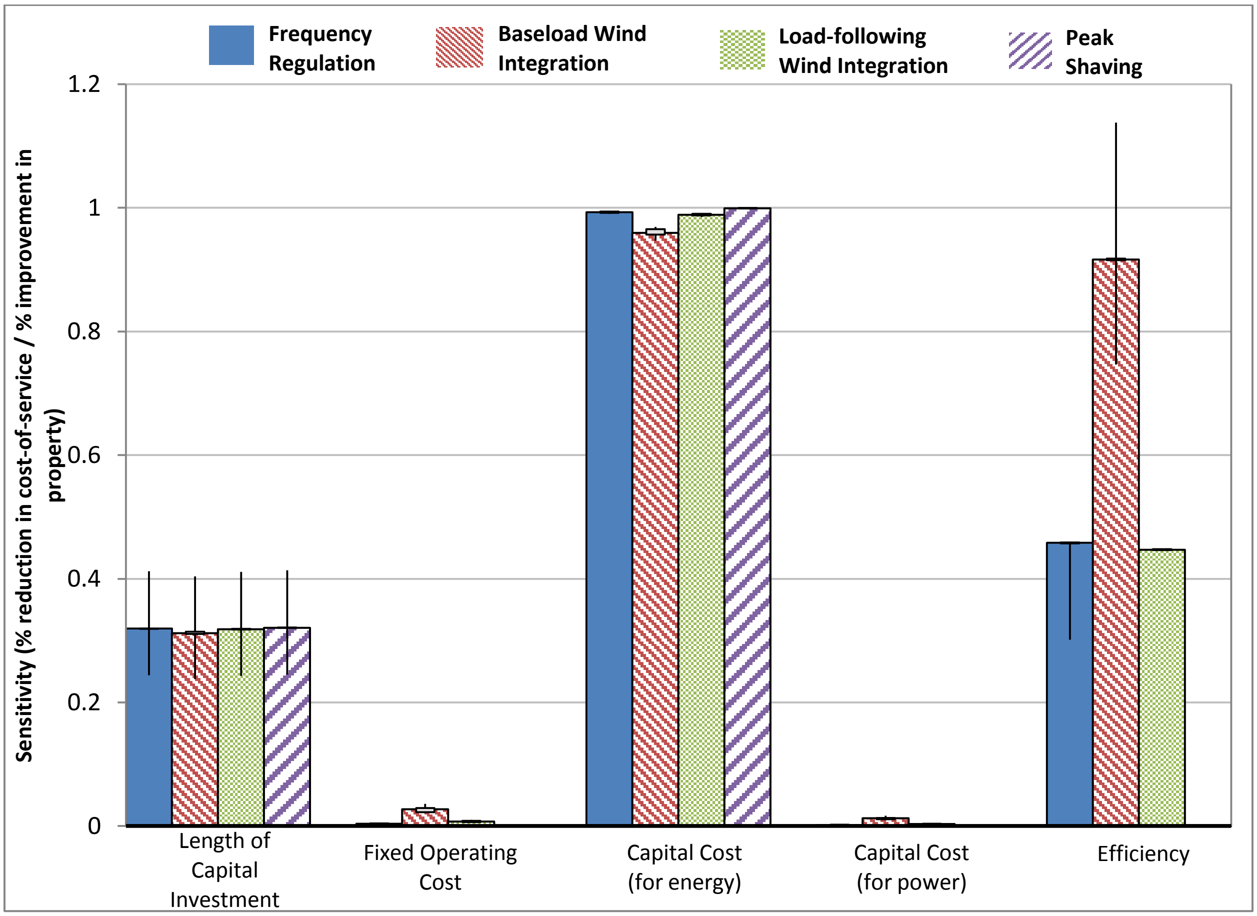

Figure 6: Sensitivities of supercapacitor energy storage properties across four applications. Properties with higher sensitivity have a greater effect on the cost of providing energy services. The box and whisker plots summarize the results of sensitivity analysis, described in the sensitivity analysis section. The box range indicates the 25th and 75th percentile values and the whiskers show the minimum and maximum values obtained in sensitivity analysis. These results are largely driven by the very high capital cost for energy of supercapacitors.

Sensitivity analysis is commonly used to test the robustness of results, by determining the effect that changes in input parameters have on those results. Since many of the parameters used here are uncertain or are continually being improved, sensitivity analysis an appropriate tool for ensuring that small changes in energy storage parameters do not greatly affect the conclusions described above.

For each storage technology/application combination, we determine the effect that changing each input parameter has on the sensitivity of all parameters. Each storage parameter is reset to 75% and 125% of the base-case value with the exception of efficiency, which is not permitted to go above 100%. Then, the entire analysis is run again, calculating the sensitivity of all parameters. This process is performed for each of the sixteen storage technology/application combinations, and produces 1200 data points, most of which do not deviate much from the base-case results. Over all storage technologies and applications, a 25% change in a single storage parameter results in an average change of 0.02 to the calculated sensitivities, which is small considering that these sensitivities range from zero to one (see Figures 3-6). A 25% modification in a parameter generally has the strongest effect on the sensitivity towards that parameter (i.e., reducing the capital cost of storage normally has the greatest effect on the sensitivity towards capital cost), but even the modified parameters experience an average change in sensitivity of only 0.05. In almost all cases examined, changing any single parameter by 25% has little effect on the general shape of the results or the relative importance of different storage properties. The sensitivity analysis results are summarized in Figures 3 - 6 and discussed in greater detail in the appendix.

4. Discussion

While each technology/application combination produces different results, there are some general trends. Capital cost, for either fixed modules or storage/power electronics combinations, is consistently a key limitation for the technologies examined. While researchers that study grid-level energy storage applications certainly understand this, there is sometimes an inconsistency between this understanding and funded research efforts, which may focus on less useful but more technically exciting improvements, such as efficiency or energy capacity. This could be due partly to the reasonable expectation that production costs of energy storage will naturally decrease over time for a variety of reasons, and that deliberate additional efforts are not required. While capital cost reductions can be expected, this does not necessarily mean that investment that further accelerates cost reductions would be imprudent. We find that, at least for the examined technologies and applications, small improvements in capital costs are the most consistent and effective way to improve the value proposition of energy storage.

Several entities have defined capital cost targets for energy storage. The US Department of Energy Office of Electricity Delivery & Energy Reliability Energy Storage Program has a target of $250/kWh for existing battery technologies (NaS, lead-acid, Li-ion, and flow batteries) [15]. American Electric Power has identified a cost target of $500/kWh for residential energy storage, where small energy storage devices are placed below the substation level in order to provide peak shaving and emergency backup services to small groups of residential customers [16]. The US Department of Energy Advanced Research Projects Agency - Energy (ARPA-E) Grid-Scale Rampable Intermittent Dispatchable Storage (GRIDS) Funding Opportunity Announcement seeks "revolutionary new technology approaches to grid-scale energy storage" that have the potential for capital costs as low as $100/kWh [17].

We can use our models to calculate the sensitivities of storage properties if the capital cost of storage technologies met a $250/kWh target while holding other properties constant. For Li-ion systems, this reduces the capital cost of the batteries by 50%, but the sensitivity of cost-of-service to battery capital cost only drops by ~ 20% (on average across the four applications). This suggests that there is still significant value in reducing the capital cost of Li-ion batteries even after the target of $250/kWh has been met. Using $300/kW as the capital cost of power electronics, a NaS battery module would cost $165K (a 30% decrease). At this capital cost, the sensitivity to module capital cost decreases by ~ 12% and module capital cost is the second most sensitive parameter for each of the four applications (the same ranking as the base case results). If flywheel module capital cost were reduced by 50% (a similar reduction to the batteries above), sensitivity of cost-of-service to module capital cost is reduced by ~ 25% and module capital cost is still either the first or second most sensitive parameter in all of the four applications. The cost targets discussed above provide an estimate of what capital cost is required for the deployment of storage to be profitable, but do not necessarily mean that further improvement would be imprudent. While meeting existing technology targets may allow certain storage applications to break even, the value of energy storage will continue to increase as capital costs decrease. These results suggest that reducing capital cost will continue to be a practical strategy for reducing annualized energy service costs from storage even when current capital cost targets have been met.

Apart from capital cost, the other properties of high value are the power/energy limitations of energy storage. This manifests itself differently in the storage technologies that are modeled as modularized (NaS batteries and flywheels) and configurable (Li-Ion batteries and supercapacitors). In the modularized technologies, which have a fixed power/energy ratio, the power and energy limits are found to be quite important, but only one at a time depending on application. The power limit of the energy storage device is important for high power applications, such as frequency regulation, while the energy capacity is found to be limiting for energy intensive applications like peak shaving. In the technologies that are modeled as configurable, with power electronics and storage quantities independently selectable, the relative importance of power and energy limits shows up in the sensitivities for energy-related and power-related capital costs. While the value of increasing the energy capacity and power limit depends on the technology and application studied, improvements in these areas can be valuable if chosen appropriately.

While we can state which properties most strongly drive cost-of-service, there are other considerations that may determine how research efforts should be allocated due to uncertain and presumably unequal development costs for improving different properties. It may be the case, for example, that marginal improvements in a relatively insensitive property are far cheaper to implement and thus would be preferable. On the other hand, if it is determined that small improvements in sensitive properties (such as capital cost) are easiest to attain, this would provide a strong incentive to pursue those improvements.

While we do not attempt to calculate the costs of improving different storage properties, we do provide results that can aid entities making decisions about the development of energy storage technologies. This includes manufacturers of energy storage devices, agencies that must make decisions about funding energy storage research, and entities that define technology targets for energy storage. Although government funding is traditionally focused on relatively basic science, there has been a recent trend towards funding research with the specific goal of improving near-term marketability of energy products, such as the Office of Electricity Delivery & Energy Reliability at the US Department of Energy, who recently initiated an Energy Storage Program that will "ensure that the technologies live up to their potential, and will assist in bringing these solutions into the commercial market" [15]. These results are focused on firm-level profitability of energy storage; government entities that want to encourage the commercialization of energy storage should consider funding the development of manufacturing and process improvements (with the goal of lowering capital cost) in addition to funding performance improvements.

5. Conclusion

We demonstrate that the energy storage properties that are most limiting to profitability for different storage technology/application combinations are capital cost and power/energy limits. Capital cost of storage is found to be consistently important, while the sensitivity to power/energy limits depends on the technology and application. Though there are some strong trends, we show that each combination of technology and application is different, allowing for few universal statements. While significant research funding has been put towards improving the performance of energy storage, decreasing the capital cost through manufacturing process improvements may be far more valuable. These results suggest that entities seeking to improve energy storage technologies should carefully consider how this would affect the adoption of the technology, since different improvements have greatly different effects on the profitability of energy storage. Decision makers responsible for determining the future of energy storage can use these results to make more informed decisions regarding research funding and technology targets and improve the value proposition of energy storage for grid applications.

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Appendix

A.1. Modeling of storage technologies

Energy storage is modeled slightly differently for each technology, as appropriate to the way that the technology is operated and marketed commercially. For NaS batteries and flywheels, the systems come in modules with fixed power limitation and energy capacity. Thus, for these technologies, the amount of storage needed is the maximum of the amount required to provide the capacity needs and the amount required to provide the power needs, as only one of these constraints will be binding for a particular application model run. Li-ion batteries and supercapacitors are not offered exclusively in particular configurations, and the power and energy capacity requirements are considered separately for these technologies. Capacity fade of storage over time is not included in the model.

The round-trip efficiency (RTE) for the energy storage devices is defined as the ratio of AC energy in to AC energy out and applies to all storage technologies. NaS batteries and flywheels both require a fixed maintenance power which is unrelated to the round-trip efficiency of energy through the storage. The maintenance power requirement is a constant power required to keep the batteries hot (NaS batteries) or to overcome the friction losses (flywheels). In all applications, the storage is required to conclude the studied period with a charge state equal to or greater than the initial state. All energy required for charging/maintenance is required to come from the remainder of the system (for wind integration applications) or through the purchase of balancing energy (for frequency regulation and peak shaving).

The power out of the energy storage device comes at an efficiency penalty (Equation A1), and round trip efficiency of the energy storage device is divided geometrically between the charge and discharge portions of the cycle (Equation A2). $E_{batt}(t)$ is the charge state of the battery at time t, $E_{batt,out}$ is the energy discharged from the energy storage device, η_{batt} is the round-trip efficiency of the energy storage device, and $E_{batt,in}$ is the charge energy put into the energy storage device.

$$E_{batt}(t) = P_{batt,out}(t) * T_{step} * \sqrt{\eta_{batt}} - P_{batt,in}(t) * T_{step} / \sqrt{\eta_{batt}} \quad \text{(A1)}$$

$$E_{batt}(t) = E_{batt}(t-1) - E_{batt,out}(t) * \sqrt{\eta_{batt}} + E_{batt,in}(t) / \sqrt{\eta_{batt}} \quad \text{(A2)}$$

A.2. Modeling of applications

A.2.1. Frequency Regulation

For this application, the average cost of delivering 1 MW of frequency regulation service from an energy storage device is calculated. 5 days of 2-second frequency regulation signal were used. For frequency regulation, the amount of power output from the grid asset can vary between zero and the bid power of the asset. For example, if an asset bids 10 MW of frequency regulation, the dispatch signal will vary between 0 MW and 10 MW, with an average dispatched power of ~ 5 MW. As is normal for a frequency regulation signal, this signal requires the grid asset to rapidly change the power output within the agreed range.

Because energy storage is a net consumer of energy (due to inefficiency), we assume that some arrangement is made to allow the average frequency regulation power requirement to be slightly negative. This could be either through arrangement with the grid operator or through the purchase of balancing energy (at $50/MWh) to displace the net discharge required by the storage. The average required power and the total losses from storage inefficiency are calculated in advance and used to determine the zero point of the frequency regulation signal. By this strategy, the storage is able to choose the ratio of up and down regulation so that the average power requirement is slightly negative (on average, energy is going into the energy storage device) and offsets the losses of the storage.

A.2.2. Peak Shaving

The peak shaving model calculates the average cost of delivering a peak shaving service. It uses one year of 5-minute load data from BPA (which is scaled down to 100 MW) and determines the average cost of storage required to reduce the peak power requirement by 5% (a maximum of 95 MW). Because the annual peak is more than 5% higher than the daily peak on most days, using storage to reduce the power requirement to 95 MW would result in it only being used a few days each year. We assume that the operator of a capital-intensive energy storage system would also use it to shave the peak demand on other days to reduce generator startup costs or help reduce the day/night energy cost differential. Conceptually, this application is meant to simulate the operation of a storage system deployed in an area of growing demand in order to defer the need for new capital investment (such as a new, larger transmission line). While the storage is used every day in this application, the annual peak demand determines the scale of the storage.

The storage is sized so that it can reduce the annual peak demand by 5%, bringing the 100 MW maximum demand down to a 95 MW maximum demand. The storage is recharged at night at a constant rate between the hours of 11PM and 4AM. Because the transfer of energy from night to peak hours is the service provided by this application, the value of this transfer is not calculated, though the system is required to pay $40 / MWh for all net energy consumed in the process (through losses and inefficiency). On days other than the peak demand day, the storage is also used to capacity to reduce the daily peak to a flattened plateau and is charged at night.

A.2.3. Wind smoothing in a generation block producing baseload power

The modeled system consists of a co-located gas turbine, wind farm, and energy storage which is constrained to produce baseload power within a 0.5% deadband. The gas turbine has a maximum power output of 100 MW and the wind farm has a capacity of 67 MW. The storage is scaled to the minimum size required to meet the baseload power requirement. To identify the system that can produce power at lowest cost, a scenario analysis framework is used. The objective of the scenario analysis is to identify the system with the lowest average cost of power, given a particular fraction of delivered energy from wind. The lowest-cost system is always taken as the studied system. Parameters for this system are shown in Table A1.

Operational Inputs	Base-Case Value
Natural Gas (NG) Low Operating Limit	40% of nameplate capacity
NG Start-up Time	10 min
NG Ramp Rate Limit	25%/min
NG Minimum Run Time	60 min
NG Lifetime	30 years
Wind Lifetime	20 years

Cost Inputs	Base-Case Value
Blended Cost of Capital	8%
NG Capital Cost	\$620 / kW
NG Price	\$5/MMBTU
NG Variable Cost	\$0.0014 / MWh
NG Fixed Operating Cost	\$10 / kW-year
Wind Capital Cost	\$1500 / kW
Wind Variable Cost	\$0.015 / kWh
CO_2 Price	\$25 / tonne
NO_x Price	\$750 / tonne

Table A1: Parameters for wind smoothing in a generation block producing baseload power and wind smoothing in a generation block producing load-following power

The first cycle of the scenario analysis consists of 10 runs of the operational and cost models. The scenario analysis varies the target power output from 10% of total system generation capacity (gas capacity plus wind capacity) to 100% of total system generation capacity in 10% increments (10 levels). The scenario analysis collects data on each run of the model including average cost of power, energy from wind, energy from gas, CO_2 and NOx emissions, and magnitude of required energy storage.

In the second cycle of the scenario analysis, the target power output that resulted in the lowest average cost of electricity is identified. This "areas of interest" is investigated in finer detail in the second cycle by re-running the model as the system power output is varied +/- 10% around the lowest average cost point in 2% increments (10 levels). This results in another 10 runs of the operational and cost models. The relevant data are again extracted from each run and saved for later analysis.

For each system examined, the gas generator is modeled to operate such that it provides maximum fill-in power for the varying wind resource in an effort to bring the combined wind+gas power output to the target power output. If the gas turbine is unable to provide all of the required fill-in power due to insufficient ramping capability or cold-start limitations, the residual power is provided by an energy storage device. This residual power includes both positive and negative power requirements from the energy storage, which represent both the discharge energy from the device as well as the required charge energy. Actual 10-second time resolution wind data is used to model the wind generation (Southern Great Plains United States wind farm, sum of 7 turbines, 15 days, 10 second resolution, 46% capacity factor during this period). When necessary, the model allows for curtailment of wind energy (if the storage is fully charged but the combined wind+gas output is higher than the target) by assuming a communications link between the system control and the wind farm control station.

The model assumes a single gas turbine, which operates to provide fill-in power for the wind generation within its operational limitations and within the defined deadband. The gas turbine limitations are a high operating limit, a low operating limit, a ramp rate limit, a minimum run time, and a start-up time. The turbine is forbidden to operate above the high operating limit or below the low operating limit. The ramp rate limitation is applied by converting the ramp rate constant (in percent per minute) to a maximum power change per step, and restricting the power output change per step to that value. The minimum run time defines the minimum amount of time that the gas turbine must operate before it can shut down. If the gas turbine has been running for the required period and gets a signal to provide a power output of zero, then it immediately shuts down and ceases to deliver any power. Thus, as the power required from the gas turbine decreases, the gas turbine ramps down to the low operating limit then holds at that point until it is prompted to turn off completely. If the gas turbine is off and gets a signal to deliver any amount of power, then it begins the start-up process. This process is modeled as delivering no power for the duration of the start-up time and then immediately jumping to the low operating limit. The start-up process is not cancelled if the gas turbine ceases to receive a signal to produce power. The start-up and shut down processes are the only exceptions to the ramp rate limitation.

Once the gas turbine has provided all of the smoothing allowable by its operational constraints, the minimum size of the required energy storage device can be directly determined. Given the wind+gas generation, the residual power that must be handled by an energy storage device is calculated, including both charge and discharge energy. From this residual power profile, the power and energy capacity capabilities required from the energy storage can be calculated. When sizing the energy storage, the power requirement is equal to the maximum power required to/from the energy storage during the operational period. The energy capacity requirement is derived from the maximum energy span (difference between highest and lowest energy state) required from the energy storage. This is equivalent to assuming a battery with infinite capacity, then observing the maximum energy span (which is also the minimum possible storage capacity) and using that value for the required storage capacity. The power requirement of the energy storage is used as determined directly from the model, but the energy capacity requirement is doubled from what the model determines as the minimum possible energy capacity. This reflects the understanding that the 15 days of wind data used might not present the worst case energy cycle to the storage device, as well as a conservative design stance towards this relatively unproven technology.

The model requires that the energy storage charge state at the end of the studied period be equal to or greater than its initial state. To do this, the model determines whether the defined residual power, given the round-trip efficiency of the energy storage, is sufficient to achieve a concluding charge state greater than the initial charge state. If the concluding state is determined to be lower, than the gas generation is adjusted to provide more charge energy.

If it is required that the gas turbine produce more power, this is done in a non-forward looking way that attempts to maximize the efficient use of the turbine. As long as more charge energy is required, the model first increases any local minima in the gas turbine power output. If there are no local minima, then it increases the lowest global point. If the gas turbine is at maximum power output at all points when it is operational, then the model extends the periods of operation. The energy output of the gas turbine is increased in this manner until there is sufficient energy through the energy storage device to meet the described constraints. If the gas turbine is operational at all points in time and is at the high operating limit the entire time, then the system is declared "insufficient", model execution is ceased, and no data is returned to the scenario analysis for that system.

In order to keep the study simple and general, the model is constrained to produce power with a small "deadband", allowing for the system output power to vary within 0.5% of the target power output. This is intended as a realistic simulation of the small allowable variation in real power systems (if the allowable deadband is set to zero, then the system is constrained to produce perfectly "flat" power).

The objective function of a single run of the model is to meet the target power output (within the deadband) while minimizing the Power (P_{batt}) and Energy (E_{batt}) requirements of the energy storage device (Equations A3 and A4), in order to prevent over-sizing of this expensive resource.

$$\textit{Minimize } \mathrm{E_{batt}} = \mathrm{E_{batt,max}} - \mathrm{E_{batt,min}} \tag{A3}$$

and

$$\textit{Minimize } \mathrm{P_{batt,max}} \tag{A4}$$

such that, at all points in time (t), the sum of wind, gas, and battery power minus curtailment and storage maintenance energy is within the deadband around the target power level (Equation A5). The gas generator has a ramp rate limitation (Equation A6), high and low operating limits (Equations A7 and A8), and a minimum run time (Equation A9).

$$P_{\mathrm{target}} \pm P_{\mathrm{db}} = P_{\mathrm{wind}}(t) + P_{\mathrm{gas}}(t) + P_{\mathrm{batt}}(t) - P_{\mathrm{maint}}(t) - P_{\mathrm{curt}}(t) \qquad (A5)$$

$$\left|P_{\mathrm{gas}}(t) - P_{\mathrm{gas}}(t-1)\right| \leq \dot{P}_{\mathrm{gas,max}} * T_{\mathrm{step}} \qquad (A6)$$

$$P_{\mathrm{gas}}(t) \leq P_{\mathrm{gas,max}} \qquad (A7)$$

$$P_{\mathrm{gas}}(t) \geq P_{\mathrm{gas,max}} * C_{\mathrm{lol}} \qquad (A8)$$

$$P_{\mathrm{gas}}(t) > 0 \text{ if } \exists x \text{ s.t. } t - T_{\mathrm{mr}} < x < t-1,\ P_{\mathrm{gas}}(x) = 0 \qquad (A9)$$

where P_{target} is the target power output, P_{db} is the deadband power, P_{wind} , P_{gas} , P_{batt} and are the power outputs of wind, gas, and energy storage, P_{maint} is the maintenance power for the energy storage device, P_{curt} is the curtailed power, T_{step} is the step time (10 sec in this study), $P_{gas,max}$ is the maximum power output of the gas turbine, C_{lol} is the low operating limit constant, and T_{mr} is the minimum run time of the gas turbine.

Once the operation of the wind generation, natural gas turbine, and energy storage device has been determined, the emissions and costs of the system over the studied timeframe can be calculated. The emissions calculation uses results from Katzenstein and Apt showing the effect of partial load conditions on efficiency and CO_2 and NO_x emissions of a Siemens-Westinghouse 501FD gas turbine [18]. Capital, variable, and average costs of electricity are also calculated for each potential composite system, including amortized capital costs, other fixed costs, and variable costs of the wind generation, the gas turbine, and the energy storage device. NO_x and CO_2 prices are included in the cost calculation. Emissions allowance prices are applied directly to the emissions, and do not account for seasonal or regional variation, and thus present an upper bound on the cost of emissions.

A.2.4. Wind smoothing in a generation block producing load-following power

The modeling for the load-following application is identical to the above application except that the system is constrained to meet a load-following profile (within a 0.5% deadband) instead of a flat, baseload profile. Except what is described below, all modeling, parameters, and constraints are the same as the wind smoothing in a generation block producing baseload power application.

The load data used is 5-minute data from BPA, which was smoothed to 10-second increments by linearly interpolating the 5-minute data. The wind and load data are from different geographical areas, but were chronologically aligned so that daily cycles would be properly addressed. A scenario analysis structure is again used, scaling the load data to determine the least expensive way to operate the system under the load-following constraint. The scenario analysis varies maximum power of the load data from 10% of total system generation capacity (gas capacity plus wind capacity) to 100% of total system generation capacity in 10% increments (10 levels) and calculates the average cost of power at each point. As in the system above, the area around the lowest cost point is investigated in finer detail in the second cycle by re-running the model with the load data scaled +/- 10% around the lowest average cost point in 2% increments (10 levels).

A.3. Sensitivity Analysis

The sensitivity analysis results for NaS batteries are shown in Figure A1. The most modified result is a single point for module energy capacity in the load-following wind integration application. This point is for the sensitivity analysis case of efficiency at the unrealistically high value of 100%. In this case, due to the modular nature of the NaS batteries, the system is close to requiring one less module. A slight improvement in module energy capacity allows this to happen, resulting in capital savings and a higher sensitivity for module energy capacity. Some of the other divergent points also represent cases where a module is added or removed, but none have as large an effect as the case described above.

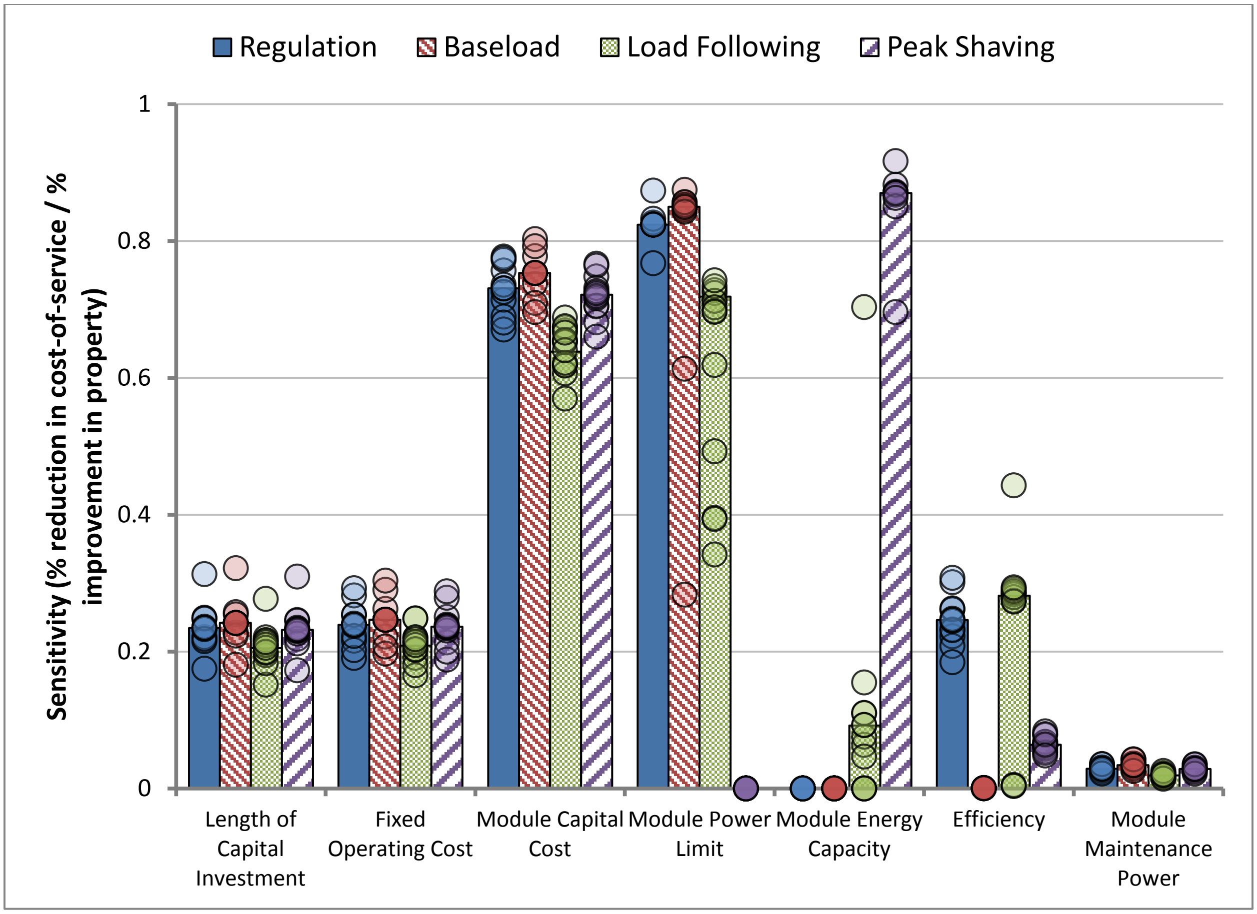

Figure A1: Sensitivity analysis results for NaS batteries. The bars show the base-case results, and display the same data as Figure 3. Each circle represents the result from one run of the sensitivity analysis. The circles are slightly transparent to allow stacked points to be discerned.

The sensitivity analysis results for Li-ion batteries (Figure A2), flywheels (Figure A3), and supercapacitors (Figure A4) produce similar results as those seen for NaS batteries. The sensitivity analysis results for flywheels show significant variability for several of the applications, which is due to two factors. As described in the results section, the base-case scenario for the load-following application was close to requiring one less flywheel module, which allows small improvements in the efficiency and friction loss parameters to have disproportionate effects on cost. The sensitivity analysis shows that in cases where the system is not close to such an boundary efficiency and friction losses are found to be much less important. Due to the quantity of sensitivity analysis runs, some of them will inevitably fall at a point where a slight improvement in performance will require one less module, affecting results for both

NaS batteries and flywheels. In order to neutralize this discontinuous effect and determine more accurate values, the sensitivities for efficiency and friction losses were measured over large changes in their values, which averages out the discontinuities. By varying efficiency from 60% to 90% in the load-following application, the normalized sensitivity is found to be around 0.3, while the normalized sensitivity for friction losses is found to be around 0.16 when varied between 1% and 3%. As expected, these values are around the average of the values found in sensitivity analysis, and lower than the unexpectedly high base-case values (Figure A3).

The second effect that is causing variability in the sensitivity analysis results for flywheels providing frequency regulation is the fact that flywheels have an appropriate power/energy ratio for this application. While module power was found to be the limiting factor in this study, a 25% increase in module power or a 25% decrease in module energy capacity caused the sensitivity towards module power limit to drop to zero and sensitivity to energy capacity to rise significantly. These results suggest that the flywheels studied are relatively well optimized for proving frequency regulation, which is currently a common application for the technology.

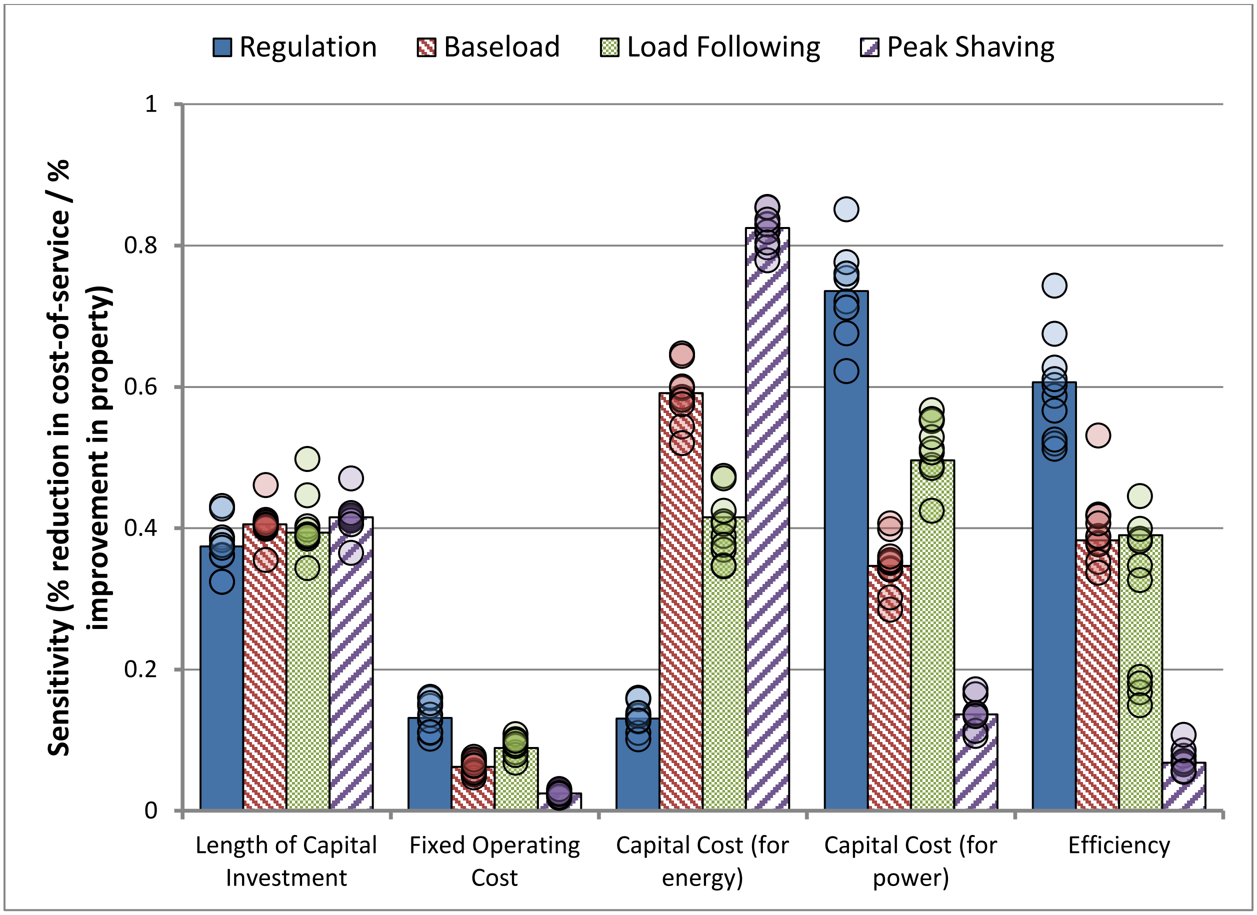

Figure A2: Sensitivity analysis results for Li-ion batteries. The bars show the base-case results, and display the same data as Figure 4. Each circle represents the result from one run of the sensitivity analysis. The circles are slightly transparent to allow stacked points to be discerned.

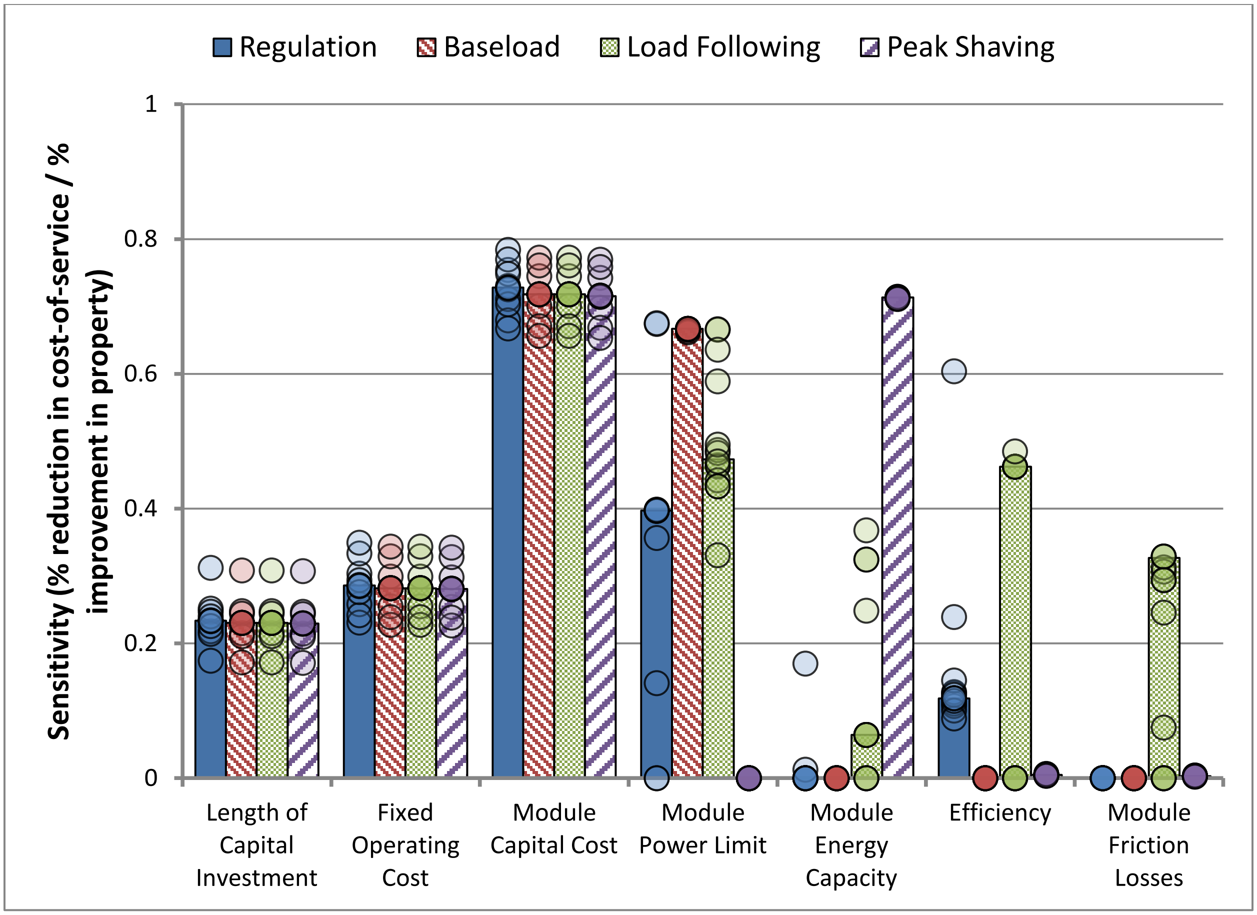

Figure A3: Sensitivity analysis results for flywheels. The bars show the base-case results, and display the same data as Figure 5. Each circle represents the result from one run of the sensitivity analysis. The circles are slightly transparent to allow stacked points to be discerned.

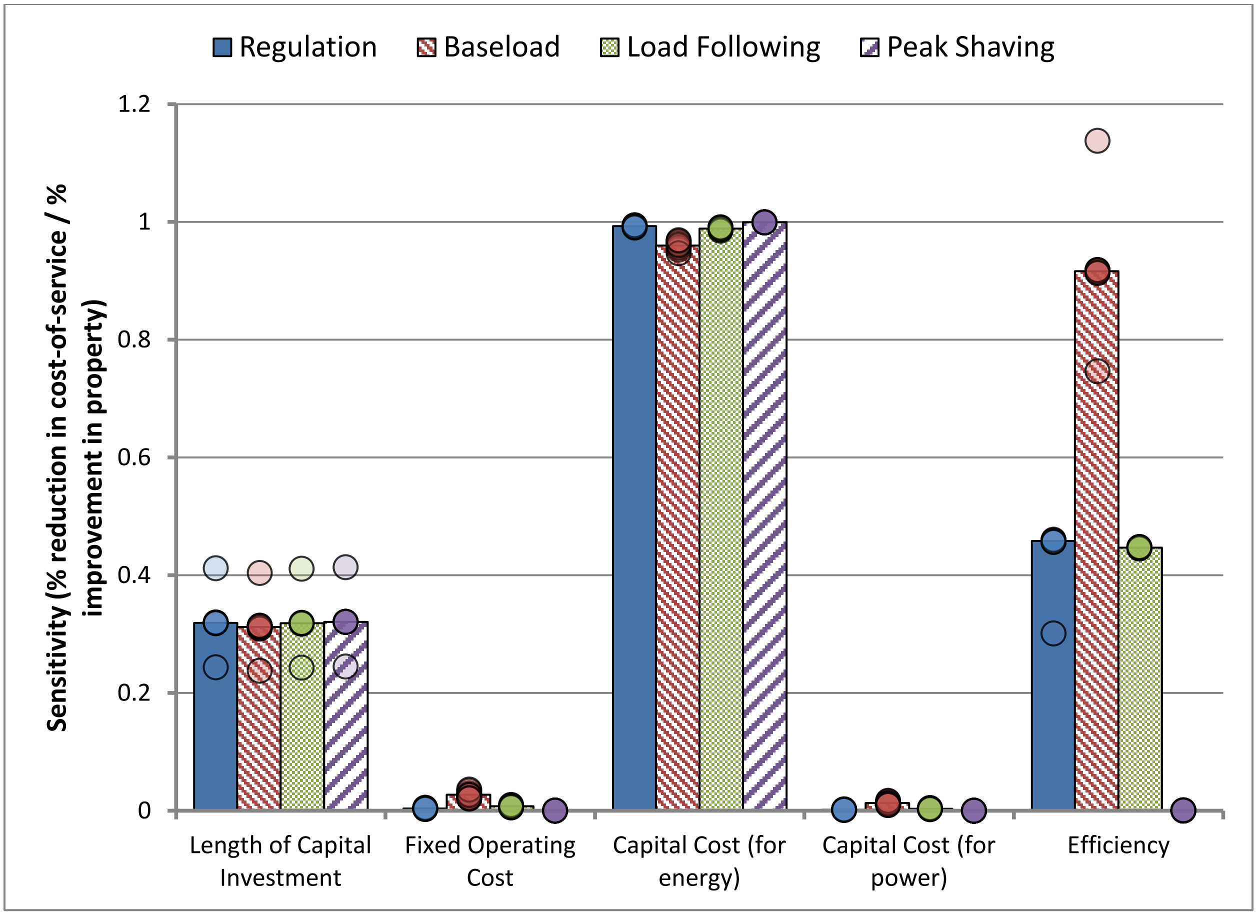

Figure A4: Sensitivity analysis results for flywheels. The bars show the base-case results, and display the same data as Figure 6. Each circle represents the result from one run of the sensitivity analysis. The circles are slightly transparent to allow stacked points to be discerned.

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