Title
ANALYTICAL ANALYSIS OF LITHIUM-ION BATTERIES' EFFICIENCY FOR STATIONARY ENERGY STORAGE APPLICATIONS

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ANALYTICAL ANALYSIS OF LITHIUM-ION BATTERIES' EFFICIENCY FOR STATIONARY ENERGY STORAGE APPLICATIONS

A Thesis submitted in partial satisfaction of the requirements for the degree of Master of Science

in

Mechanical Engineering

by

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SYMBOLS

η efficiency

ABBREVIATIONS

CAISO	California independent system operator
EIA	energy information administration
EVs	electric vehicles
LIBs	lithium-ion batteries
RTE	round trip efficiency
SoC	state of charge

ABSTRACT

The accelerating deployment of lithium-ion batteries within stationary energy storage facilities across the United States, notably driven by California, has sparked a notable surge in their usage, giving an opportunity for the first time to analyze their performance. In this thesis, the real-world data reported in Energy Information Administration datasets are used to quantify the efficiency of the plants, investigate parameters that effectively change the efficiencies, and analytically model the efficiencies. By quantifying the efficiencies, it is observed that plants experiencing more than five cycles per month show around 85% efficiencies, while for a lower number of cycles, the efficiency drops severely. Also, by analyzing the change of efficiencies with time, it was observed that the degradation of efficiencies is less than 0.1% per year. Moreover, a model is proposed which expresses efficiency in terms of number of monthly cycles. According to the model, newer plants show slightly higher efficiencies, which could be attributed to technological advancements in making batteries. Additionally, using the model, the drop in the efficiency of some plants with an infrequent number of monthly cycles could be justified by the recorded idle loss values in the literature; however, the drop is more significant for other plants. Therefore, the loss could be related to parasitic losses for the latter plants. Lastly, some plants show slight seasonal variations in the observed efficiencies, which could be related to the cooling and heating of the parasitic loads. However, it also might be associated with seasonal variations in the number of monthly cycles of the plants. More research could be done to analyze the efficiency's seasonal variations by separating the two mentioned factors.

Chapter 1: Introduction

Chapter 1:
Introduction

This chapter provides the overall motivation and context of the thesis work. Chapters 2 and 3 include part of the work that has already been published in peer-reviewed conference proceedings, while Chapter 4 includes the overall conclusion of the research.

1.1. Motivation, background, and context of the work

The earth's average surface temperature is increasing due to carbon emissions from burning fossil fuels. According to Fig. 1, The data show that the earth's average surface temperature has risen by about 1 degree Celsius during the last 50 years, leading to melting glaciers, rising sea levels, and extreme weather events. To stop the temperature increase, we should use more zero-carbon energy resources rather than burning fossil fuels. California is a leading state in this transition, and it could be a good pattern for the rest of the world. In Sep. 2018, Senate Bill 100, known as SB100, was passed, establishing a landmark policy requiring zero-carbon resources to supply 100% of electric retail sales to end-use customers by 2045 [1].

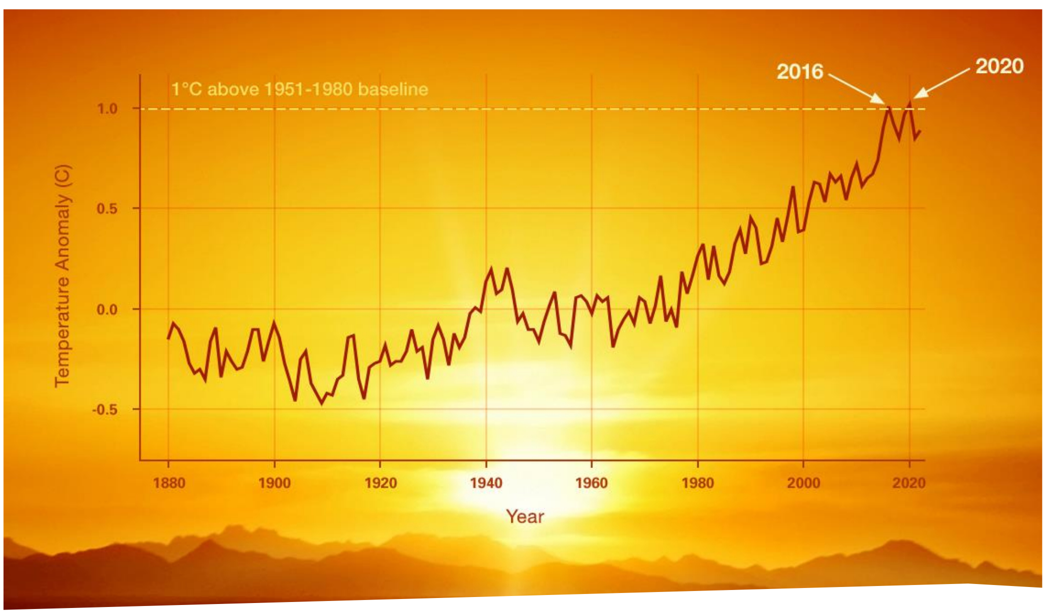

Figure 1. The recorded earth average surface temperature [2]

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These zero-carbon resources could be in different forms, such as solar, wind, geothermal, and biomass, to name but a few. By moving toward deploying more renewables, this question might be asked: “How is it possible to provide green energy at all times?” Some of the resources could provide consistent electricity generation, such as geothermal. However, is it optimal to deploy a large amount of geothermal in terms of cost and practicality? The answer is no; we need a combination of these resources complemented with storage systems. The storage system is charged when the renewables are abundant and discharged when demand is more significant than the generation. Consequently, developing promising storage technologies [3,4] to provide a zero-carbon energy resource when renewables generation is smaller than load is necessary.

1.2. Lithium-ion batteries

Li-ion batteries (LIBs) are widely used as power sources in portable electronic devices like smartphones, tablets, and laptops, to name but a few. However, LIBs have exhibited immense potential to contribute to our modern society beyond their current applications. They can serve as a vital component in achieving sustainable energy practices. LIBs integrated into the existing electricity grid have the capacity to facilitate the seamless integration of high amounts of solar (PV) and wind energy, offering storage capabilities and ancillary services. This combination allows for reliable and sustainable access to electricity, particularly in developing regions [5].

The increase in LIBs’ popularity can be predominantly attributed to several key advantages they offer. First and foremost, LIBs exhibit a comparatively higher energy storage capacity per unit mass, allowing for extended operating times and increased driving ranges in EVs. This enhanced energy density translates into greater overall efficiency, enabling EVs to travel longer distances on a single charge and improving performance for various mobile devices [6]. Another substantial advantage of LIBs is their impressive high-temperature performance. These batteries are designed to withstand and operate efficiently in high temperature conditions. Furthermore, the potential recyclability of most components in LIBs adds to their appeal [6]. LIBs offer the potential for efficient recycling, enabling the recovery and reuse of valuable materials such as lithium, cobalt, nickel, and other metals, thus minimizing environmental impact and resource depletion.

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Table 1. Key advantages of LIBs for storage stationary applications

High efficiencies: typically, 85% at the system level, as described in Chapter 3.
Can be made with a variety of formulations. The lithium ion phosphate formulation uses no rare metals, it is relatively safe and has longer life than other batteries
Plug, play and charge. No watering (maintenance free)
Non-hazardous; no gasses emitted.

While the lightweight construction is less noticeable in stationary applications, the remarkable performance (e.g. high efficiency) exhibited by LIBs makes them the technology of choice, even for stationary purposes. In Table 1, some of the advantages of LIBs are described. These suggest that LIBs are an ideal option for stationary applications.

1.3. Lithium-ion batteries in California: utilization and application

LIBs' utilization has increased significantly in California recently. In Chapter 3, it is mentioned how LIBs application has changed from providing ancillary services to mainly storage purposes in recent years in California. California is the leading state in transition toward renewables, which primarily utilizes solar power. Fig. 2 shows the utility-scale renewable electricity-generation mix for a sample sunny day in California. The data of the figure were obtained from California Independent System Operator (CAISO) [7]. As the figure exhibits, Solar power includes the main provided energy in the day, and after that, wind power has the most share. Other resources, such as geothermal, small hydro, and biomass mostly provide constant base generation. For such a grid, we expect that the diurnal LIBs storage state of charge changes correlating to the solar power generation. Fig. 3, which illustrates a sample day in California, shows that the storage charging and discharging directly correlates with the availability of solar power.

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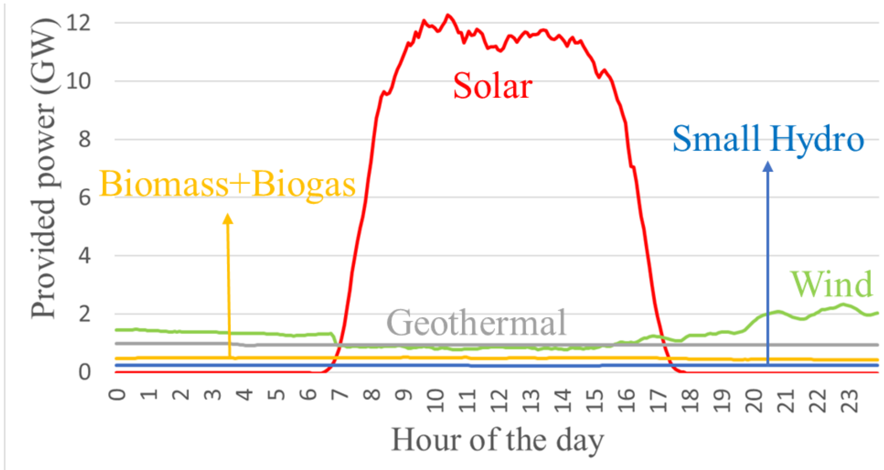

Figure 2. California's grid configuration; a sample day in 2023 [7]

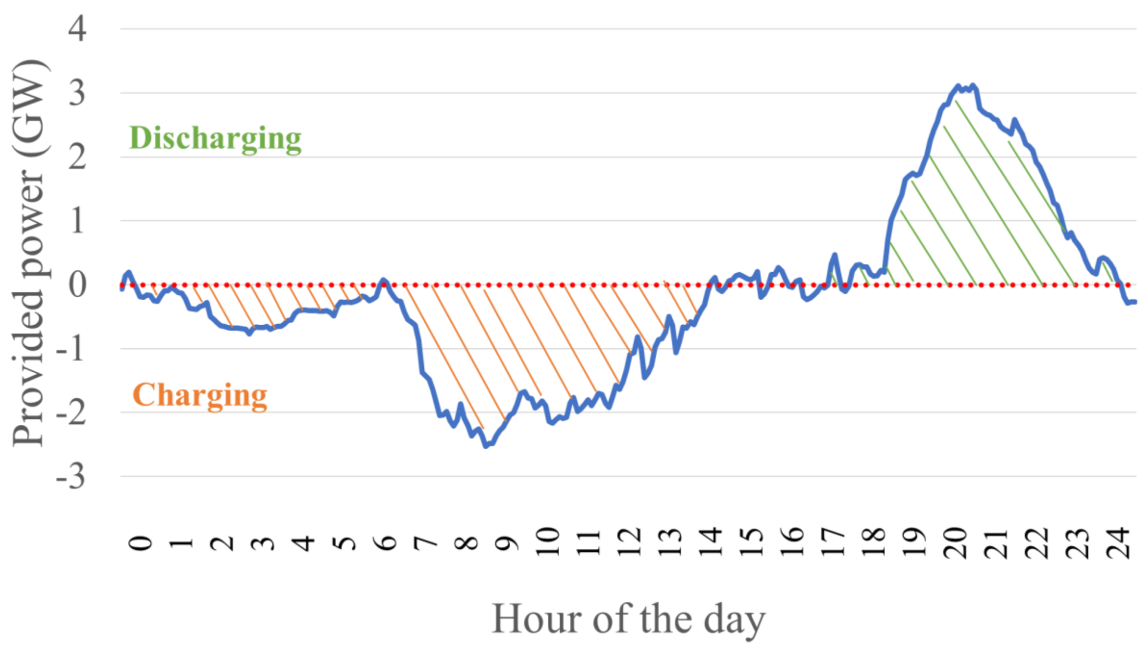

Figure 3. Rate of charge or discharge of batteries in California; a sample day in 2023 [7]

Chapter 1: Introduction

1.4. Lithium-ion batteries' performance metrics: efficiency and capacity degradation

Storage metrics can help us understand the value of a technology. Regarding batteries, round-trip efficiency and capacity degradation are two essential metrics.

A battery charge cycle refers to the complete process of discharging and recharging a battery, draining the battery to 0% and recharging it to 100%. This complete cycle represents the usage and replenishment of the battery's energy. Alternatively, a charge cycle can also be completed by using only 50% of the battery's capacity, recharging it to 100%, and repeating this procedure.

It is important to note that as a battery undergoes more charge cycles, its overall health and performance gradually degrade, ultimately reducing its lifespan. This degradation can be attributed to various chemical mechanisms inherent in LIBs. One particular mechanism involves the loss of mobile lithium ions within the battery. These ions are often lost due to side reactions occurring with the electrolyte, leading to the formation of compounds that effectively trap free lithium ions. Consequently, this reduces the number of lithium ions available for efficient movement between the battery's electrodes during the charging and discharging processes. The loss of these mobile ions subsequently diminishes the maximum capacity that the battery can achieve, impacting its overall performance [8].

Moreover, the structural disordering of the battery's electrode can also contribute to a decrease in its lifespan. During the cycling process, as lithium ions move in and out of the electrodes, the electrode structure can undergo structural disorder. This disordering adversely affects the electrode's ability to accept and accommodate a sufficient number of lithium ions within its structure. Consequently, this depletion of lithium ions within the electrode leads to a reduced overall capacity of the LIB, impacting its energy storage capabilities. These chemical mechanisms, such as the loss of mobile lithium ions and the structural disordering of electrodes, contribute to the gradual degradation of a LIB over its lifetime [9].

Efficiency is a fundamental metric that quantifies the energy losses during the charging and discharging processes of a storage system. High efficiency indicates minimal energy wastage and improved overall system performance. Efficient storage systems enable optimal utilization of available energy resources, leading to reduced environmental impact and enhanced economic returns.

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Round-trip efficiency refers to the proportion of electricity initially stored in an energy storage system that can be subsequently retrieved and utilized. It represents the efficiency of the storage process by indicating the amount of energy lost during charging and discharging cycles. A higher round-trip efficiency signifies a more efficient storage system with reduced energy losses [10]. A high round-trip efficiency is most important in energy storage applications as it directly impacts the system's overall effectiveness and economic viability. By minimizing energy losses during the storage process, a higher round-trip efficiency ensures that a greater percentage of the stored energy can be effectively utilized when needed. This translates into enhanced system performance, improved energy utilization, and increased economic returns.

The round-trip efficiency (RTE) of a single lithium battery pack refers to the ability of the battery to efficiently store and discharge energy without significant losses. Generally, modern lithium-ion batteries exhibit high round-trip efficiencies, often exceeding 90%, which means that the amount of energy returned during discharge closely matches the energy stored during charging. However, when considering a larger lithium battery energy storage system (BESS), such as those used in grid-scale applications, additional components like power converters, cooling systems, and energy management systems come into play. These components introduce some losses during the charging and discharging processes. While the core lithium batteries themselves still maintain high RTEs, the overall efficiency of the entire energy storage system might be slightly lower due to the combined impact of these auxiliary components. Nonetheless, advancements in technology continue to minimize these losses, allowing lithium battery energy storage systems to provide efficient and reliable energy storage solutions for various applications, including renewable energy integration and grid stabilization. Strategies to enhance RTE include optimizing charging and discharging algorithms, utilizing high-quality storage components with reduced internal resistance, and employing advanced power electronics and control systems to minimize energy losses during the storage process [11].

Furthermore, higher round-trip efficiency contributes to the overall sustainability and environmental impact of energy storage systems. By minimizing energy losses, less energy needs to be generated or drawn from the grid to compensate for the inefficiencies. This, in turn, reduces the demand for primary energy sources and decreases greenhouse gas emissions associated with electricity generation [10].

Chapter 2:
Analysis of effective parameters affecting battery efficiency in stationary energy storage power plants

Some contents of this chapter are part of the conference peer-reviewed publications:

Zareafifi, F., Baerwaldt, D., Hour, S., Xie, Y. H., & Kurtz, S. (2022). "Performance investigation of batteries supporting solar power" in U.S. *Conference Record of the IEEE Photovoltaic Specialists Conference*, *2022-June*, 121–125. https://doi.org/10.1109/PVSC48317.2022.9938520

Zareafifi, F., & Kurtz, S. (2022). "Analytical analysis of stationary Li-Ion-battery storage-system efficiency on a large scale." *Proc. of the 2022 IEEE Vehicle Power and Propulsion Conference*. https://doi.org/10.1109/VPPC55846.2022.10003407.

2.1. Introduction

The integration of stationary energy storage power plants into modern electricity grids has proven to be a pivotal solution in meeting the ever-increasing demand for clean, reliable, and sustainable energy. Among the various energy storage technologies available, batteries have emerged as a prominent contender, offering the potential for scalable, efficient, and long-term energy storage. To harness the full benefits of battery technology, it is crucial to thoroughly examine and understand the diverse array of parameters influencing battery efficiency in stationary energy storage applications. In the following, the most significant parameters affecting the performance of the batteries are elaborated upon:

- **Number of Cycles:** One fundamental parameter affecting battery performance is the number of charge-discharge cycles the battery experiences over its operational lifetime. As batteries are cycled, they may undergo gradual capacity fade due to electrode degradation and electrolyte changes [12].
- **Cooling Conditions:** Efficient thermal management is an essential aspect of battery performance in stationary energy storage applications. Inadequate cooling can lead to elevated operating temperatures, accelerating undesired chemical reactions and causing irreversible damage to battery components. Consequently, identifying and implementing effective cooling strategies can mitigate temperature-related degradation and enhance overall battery performance [13].

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- **Battery Chemistry:** The selection of battery chemistry significantly influences the performance of stationary energy storage systems. Various battery chemistries, such as lithium-ion, flow batteries, sodium-ion, and others, exhibit distinct energy densities, charge/discharge characteristics, and degradation patterns [14].
- **Battery Degradation:** Over time, batteries undergo physical and chemical changes that lead to degradation of their electrochemical properties. Factors such as mechanical stresses, electrode dissolution, and electrolyte decomposition contribute to a reduced performance.[15].
- **Rate of Charging and Discharging:** The rate at which batteries are charged and discharged significantly influences their performance. Rapid charging or discharging can exacerbate side reactions within the battery, affecting its electrochemical stability and overall performance.[16].
- **State of Charge (SoC) Management:** Efficiently managing the state of charge within batteries is critical for maintaining overall system performance. Operating batteries at extreme SoC levels can lead to capacity loss and compromise the energy storage system's stability.
- **Environmental Factors:** The geographical location and environmental conditions of a stationary energy storage power plant can significantly impact battery performance. Ambient temperature, humidity, and altitude can influence battery efficiency and degradation rates. Integrating weather and climate data into the analysis enables a more comprehensive understanding of the environmental effects on battery systems.

In conclusion, the performance of batteries in stationary energy storage power plants is influenced by a multitude of parameters that interplay in complex ways. The following analyzes the effect of the potentially important parameters on the efficiency of stationary storage power plants, while the provided information above discusses broader performance, including capacity fade. The capacity analysis is outside this thesis's scope as the data sets introduced in the following do not provide sufficient information for capacity analysis. More specifically, the following aims to explore and analyze the impact of cooling conditions, battery chemistry, and degradation on battery efficiency. The effect of the number of cycles is analyzed in Chapter 3.

Chapter 2: Analysis of effective parameters affecting battery efficiency in stationary energy storage power plants

2.2. Analytical Modeling

In this research, the datasets EIA923 [17] and EIA860 [18] were employed to compute the efficiency of the power plants. The efficiency was determined by calculating the ratio of gross generation to energy consumption. Moreover, the number of monthly cycles was derived by dividing the plant's gross generation by its nameplate energy capacity. The EIA860 [18] dataset provided the initial operating year and nameplate energy capacity of the plants, while the EIA923 [17] dataset supplied the data for gross generation (discharge of the batteries) and energy consumption (energy used to charge and operate the batteries). Gross generation was defined as the total electric energy produced by the generation units, measured at the generating terminal. On the other hand, energy consumption was determined as the electricity drawn from the grid or from a generating unit within the plant, which was utilized to energize the battery or storage technology, following the instructions in the EIA923 report [17].

To explore potential seasonal effects, the efficiencies were plotted against different months. Additionally, a comparison of reported efficiencies was conducted for various battery chemistries. Only power plants present in both the EIA923 and EIA860 datasets and utilizing LIBs (Lithium-ion Batteries) as the primary mover were taken into consideration. Special attention was given to plants experiencing significant outages, warranting further examination.

However, certain performance metrics, such as battery capacity, were excluded from the scope of this study due to inadequate information in the data sets. Similarly, parameters such as environmental factors, state of charge (SoC) management, and charging and discharging rates were not analyzed due to the lack of available data in the datasets. Also, most of the energy storage plants available in the datasets are using LIBs; therefore, the effect of other chemistries is not analyzed in this study.

2.3. Results and Discussion

Figure 4(a) illustrates the frequency of observed cases where the minimum levels of efficiencies occurred within distinct 3-month periods among the studied plants, specifically focusing on those located within California. This geographical restriction aims to reduce the potential effects of varying climates; however, it is still not completely removing it, as California has sixteen climate zones. Additionally, in Figure 4(b), the 3-month rolling efficiency for these plants is depicted. The data showcased in the figures reveals a noteworthy pattern: an increase in the number of plants showing the minimum efficiency level during winter and summer. This could be interpreted as indicative of increased energy losses from the elevated use of heating and air conditioning systems.

Fig. 5 shows a Histogram of the maximum efficiency changes for the same group of plants, which are obtained by subtracting the minimum calculated efficiency in Fig. 4(b) from the maximum one. As the figure shows, the maximum efficiency changes for around 80% of the analyzed plants are smaller than 2%, and the maximum observed efficiency change is around 6%, which is observed for one of the plants.

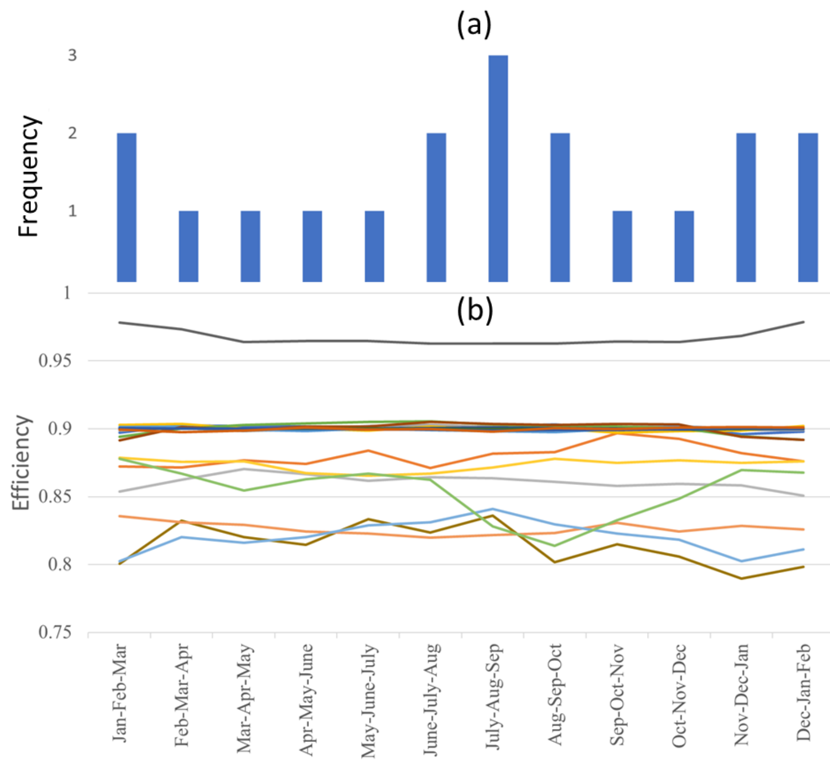

Figure 4. (a) Histogram of the observed minimum number of efficiencies that happened in each 3-month group (b) 3-month rolling efficiencies for plants in California[1]

[1] The data were cleaned by removing those that were suspicious.

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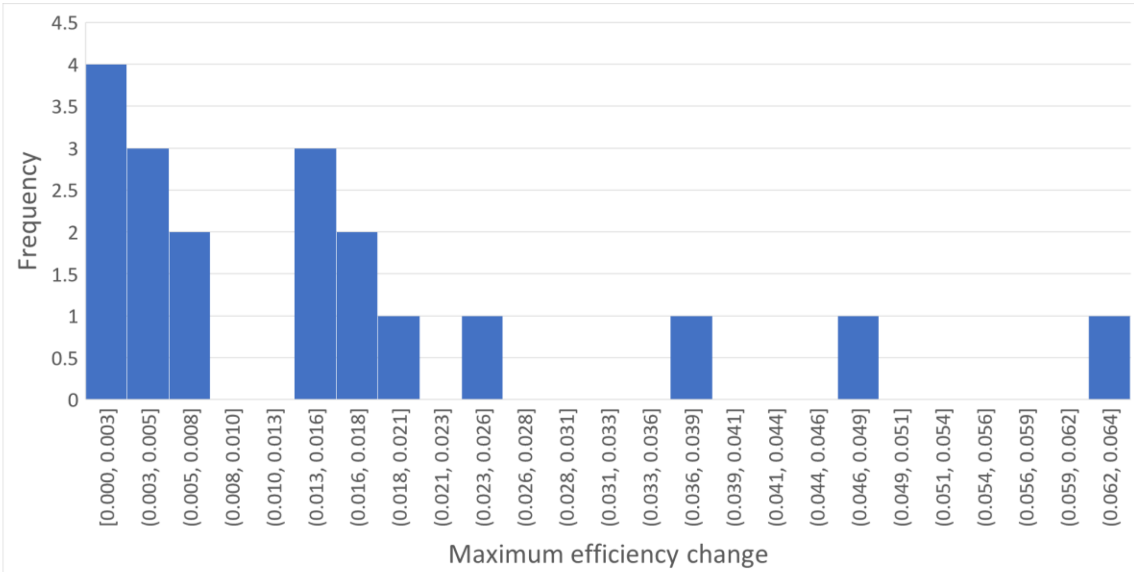

Figure 5. The maximum efficiency change throughout the year obtained by subtracting the minimum calculated efficiency in Fig,4(b) from the maximum value

2.3.1. Degradation of the efficiency

Figure 6 presents a comprehensive analysis of plant efficiencies concerning their initial operating years, specifically focusing on the period from 2017 to 2019, plotted against time. To ensure the availability of substantial data for each plant, the analysis excludes the 2020 and 2021 plants. This careful consideration ensures that at least one full year of data is available for every plant under examination.

In Figure 6(a), the efficiency trends for the 2016 plants reveal an average rate of change of -0.0009 % per month. The rates of change for the subsequent years exhibit varying patterns, as depicted in Figures 6(b), 6(c), and 6(d). For the 2017 plants (Figure 6(b)), the rate of change is +0.0032 % per month, signifying a modest efficiency gain. Additionally, the 2018 plants (Figure 6(c)) display an efficiency decline with a rate of change of -0.049 % per month. Meanwhile, the 2019 plants (Figure 6(d)) showcase a slight improvement in efficiency, with a rate of change of +0.0063 % per month.

For a broader perspective, Figure 7 provides a histogram illustrating the distribution of efficiency changes per month for all plants examined in the

Chapter 2: Analysis of effective parameters affecting battery efficiency in stationary energy storage power plants

study. Notably, the majority of plants exhibit efficiency changes that fall within the realm of uncertainty associated with measurement. This indicates a relatively stable performance for most of the plants under observation.

Nevertheless, it is crucial to highlight that a couple of plants show more substantial efficiency losses, with an observed maximum decline of about 0.2% per month. These outliers warrant further investigation to comprehend the underlying reasons behind such significant efficiency fluctuations. Factors such as maintenance practices, operational strategies, or technology-specific characteristics could potentially contribute to these variations.

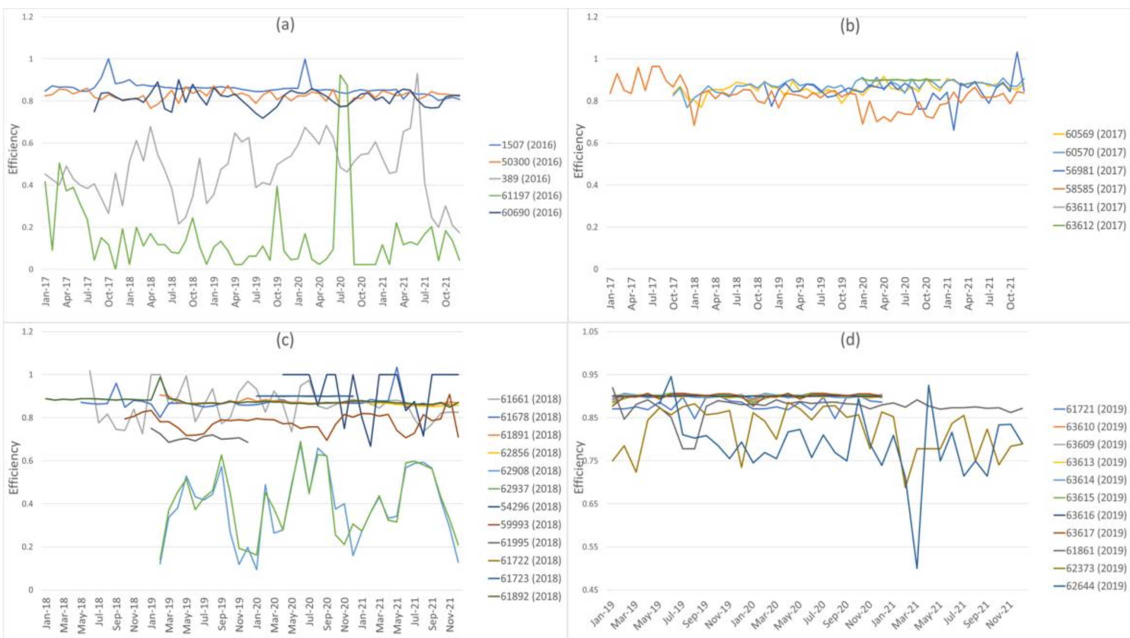

Figure 6. Efficiency versus month for the plants with the initial operating year of (a) 2016 (b) 2017 (c) 2018 (d) 2019

Chapter 2: Analysis of effective parameters affecting battery efficiency in stationary energy storage power plants

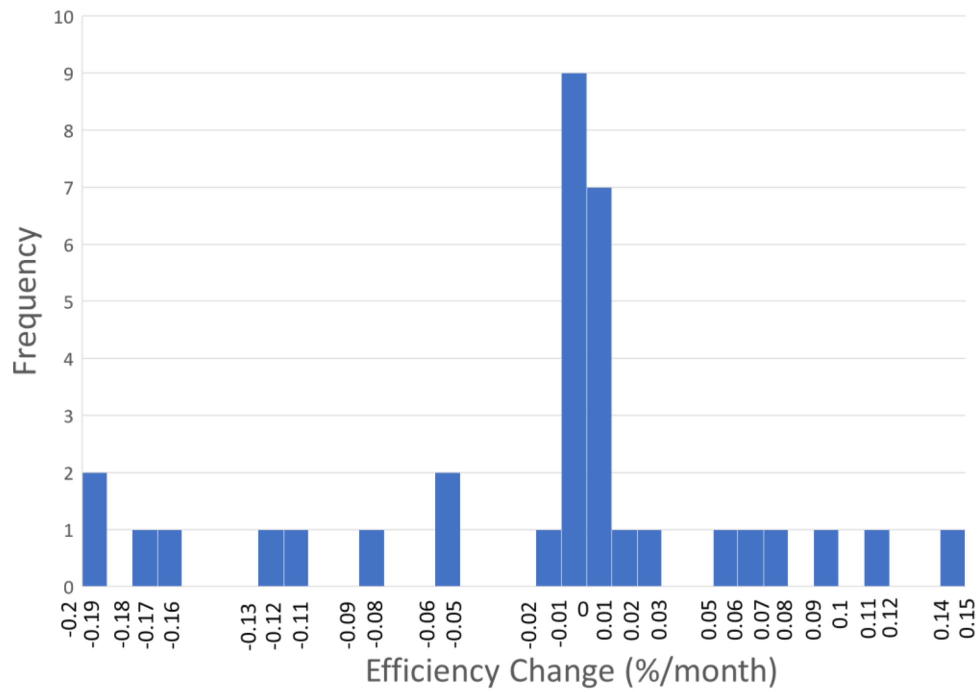

Figure 7. Histogram of the efficiency changes for the 2017 to 2019 plants

2.4. Conclusions

In this study, the monthly efficiencies of various plants from the Energy Information Administration (EIA) datasets were examined, and potential seasonal effects on their performance were explored by presenting a visual representation of the monthly efficiencies for different plants. Some plants experienced efficiency increases, while others encountered decreases as the months progressed.

To investigate the presence of seasonal effects, 3-month rolling efficiency of the plants located in California was analyzed. Some of the analyzed plants show efficiency decrease during the winter and summer months. Typically, the 3-month rolling efficiency changes less than 2%.

Furthermore, to analyze the degradation of the efficiency, a comprehensive analysis of plant efficiencies concerning their initial operating years from 2017 to 2019 was conducted. Most plants exhibited efficiency changes that fell within the uncertainty associated with measurement, indicating relatively stable performance for most of the observed plants.

Chapter 3:
Analytical analysis of stationary Li-ion-battery storage-system efficiency on a large scale

The text of this chapter is a reprint of the material as it appears in Zareafifi, F., & Kurtz, S. (2022). Analytical analysis of stationary Li-ion-battery storage-system efficiency on a large scale. 2022 IEEE Vehicle Power and Propulsion Conference, VPPC 2022 - Proceedings. https://doi.org/10.1109/VPPC55846.2022.10003407.

3.1. Introduction

LIBs are currently used in most EVs and other mobile applications, replacing other types of batteries because they have a relatively higher stored energy per unit mass and higher efficiency. Also, they have a good high-temperature performance, and most of their parts are recyclable [19,20]. Stationary applications have a lower requirement for being lightweight, but the high performance of LIBs is enabling LIBs to also become the technology of choice for stationary applications. Fig. 8 shows how the usage of LIBs in energy storage power plants in California changed from ~ 100 MW for ancillary services in 2019 to ~ 1 GW of energy shifting, allowing solar electricity to be used to power the grid after sunset starting in 2021. The increase in the use of stationary LIB units provides an opportunity to quantify the efficiency of the plants on a large scale using publicly available real-world data.

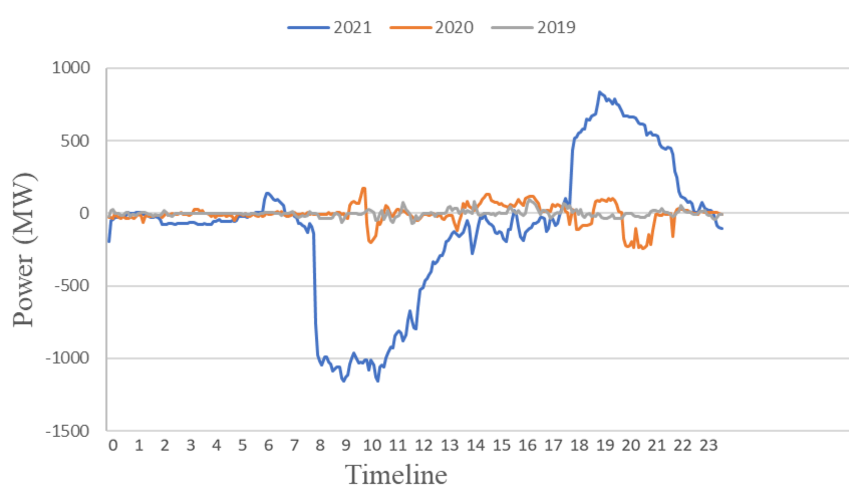

Figure 8. Battery utilization in 2019, 2020, and 2021 using August 18th as a representative day, based on California Independent System Operator (CAISO) data [7,21]

Chapter 3: Analytical analysis of stationary Li-ion-battery storage-system efficiency on a large scale

A study by Choi et al [22] suggests high LIB efficiencies that degrade measurably with cycling based on their studies of two commercial types of LIBs: Lithium Nickel-cobalt-aluminum oxide (NCA) cathode and lithium iron phosphate (LFP) cathode. They reported the round-trip efficiency (RTE) of LFPs as about 94-96%, with that efficiency decreasing by about 0.9% per 100 cycles designed to simulate the type of stress encountered when the batteries are used for frequency response. RTE of NCAs was found to be a little less: about 91.5-93.5%, decreasing by about 0.4% per 100 cycles. These data are summarized in Table 2. These RTEs reflect the efficiency of the batteries rather than the efficiency of an entire system.

Table 2. RTEs measured for LIBs [22]

LIB Type	Application	RTE	RTE change after 100 cycles
LFP	Frequency Regulation	94%	-0.94%±0.1%
	Baseline	96%	-0.85%±0.09%
NCA	Frequency Regulation	93.50%	-0.31%±0.02%
	Baseline	91.50%	-0.45%±0.05%

We anticipate that a system may show a lower efficiency than the batteries alone. Schimpe et al. [23] identified 18 loss mechanisms in a stationary LIB container storage system. A summary of their categorization is shown in Fig. 9. This figure shows the three loss mechanisms associated with the batteries (as in Table 2). Additionally, the system experiences 15 other losses associated with power electronics, thermal management, and control and monitoring, which are not shown here. They showed that the losses associated with the power electronics and with the system consumption are each about half the battery losses for a typical system.

Chapter 3: Analytical analysis of stationary Li-ion-battery storage-system efficiency on a large scale

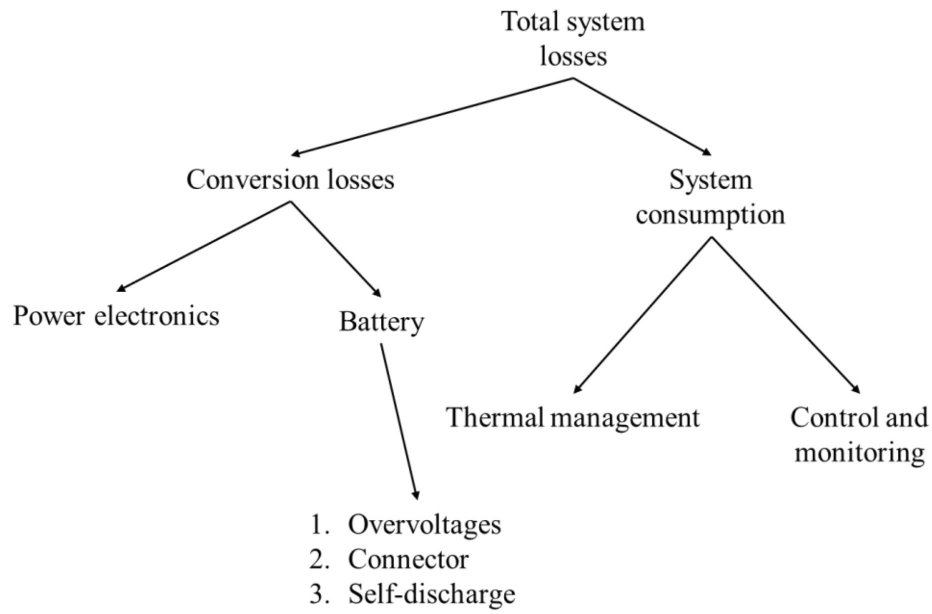

Figure 9. Loss mechanisms presented by Schimpe et al. [23] for a stationary LIB container storage system

An unused battery will slowly discharge even if the current is not being used in an external circuit. According to a LIB test center measurement [24], a typical LIB has a self-discharge of around 5% per month. In addition, according to the estimation provided by Battery University [25], self-discharge in LIBs is about 5% in the first 24 hours and around 1-2% for the rest of the month. DNK company also claims that most of the LIBs have a self-discharge rate of 5-10% per month, depending on their temperature [26]. Thus, we conclude that according to the literature, the self-discharge rate is expected to be < 10%/month. This type of loss is also called idle loss. This means that the average amount of charging and discharging of LIBs in a month might affect the observed average RTE. Other factors like depth of discharge and temperature conditions may also affect the RTE.

The LIBs' capacity to store energy is another important metric for storage systems. Atalay et al. [27] showed that the capacity decreases as a LIB pack experiences more cycles. The capacity is often reported to decrease more than the efficiency as a battery is cycled many times [28].

We previously presented a very short analysis of the EIA datasets showing that the observed efficiencies are around 90% but decrease significantly for systems that are cycled infrequently [29]. That study did not explore the

Chapter 3: Analytical analysis of stationary Li-ion-battery storage-system efficiency on a large scale

question of why lower efficiencies were seen for systems that cycled infrequently. It also did not quantify the degradation of the efficiency, and it did not include the 2021 plants. In this study, we extend our previous study by including the 2021 data in addition to the 2016 to 2020 data. We explore the causes of the losses that our model predicts. We apply this model to storage systems categorized by the initial operating year. After that, we analyze the degradation of the efficiency for the 2016 to 2019 plants.

3.2. Analytical Modeling

In this study, the datasets EIA923 [17] and EIA860 [18] are used to calculate the plants' efficiency, i.e., the ratio of plants' gross generation to the amount of energy consumption, and the number of monthly cycles, calculated as the ratio of the plant's monthly gross generation to the plant's nameplate energy capacity. The plants' initial operating year and nameplate energy capacity can be found in EIA860, and the plant's gross generation and energy consumption are from EIA923. The plant's gross generation is defined as "the total amount of electric energy produced by generation units and measured at the generating terminal," and the plant's energy consumption is defined as "electricity pulled from the grid and/or electricity pulled from a generating unit also located at this plant that is used to energize the battery or storage technology," according to the EIA923 report instructions [17]. Only plants available in both EIA923 and EIA860 and those using LIBs as the prime mover are considered. Those showing significant outages are not studied here as described in the Appendix. The other important performance metric of the batteries, which is capacity, is not in this study's scope since there is insufficient information in the datasets. Also, factors like cycle life, depth of discharge, temperature, and the detailed chemistry of the utilized LIBs are not studied due to the lack of information in the datasets.

To better understand the highly variable efficiencies observed, we proposed a simple function to predict the efficiency as a function of the number of cycles/month [29]. Specifically, eq. 1 relates the efficiency of the plants in terms of two empirical coefficients and the number of monthly cycles [29].

$$\eta = C_1 - \frac{C_2}{Number\ of\ Average\ Daily\ Cycles} \tag{1}$$

Considering 30 days for one month, eq. 1 becomes:

$$\eta = C_1 - C_2 \times \frac{30}{Number\ of\ Monthly\ Cycles} \tag{2}$$

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where (η) is the efficiency for one month, as described before. C_1 represents the maximum efficiency where C_2 (Number of monthly cycles) is subtracted from it. Therefore, C_2 might represent a loss. According to eq. (2), C_2 shows the average efficiency reduction of the battery storage system if a plant experiences 30 cycles in one month. This proposed model is consistent with the observation that increasing the number of monthly cycles increases efficiency. As a result, C_2 may be a loss related to the batteries' idle loss. We explore that possibility in the discussion section.

3.3. Results and Discussion

3.3.1. Observed efficiencies and modeling

Fig. 10 shows the efficiency data versus the number of monthly cycles for 58 plants. According to this graph, as the number of monthly cycles increases, the efficiency also increases. To analyze the rate of this increase more accurately, a Box and Whisker plot of these data is used, shown in Fig. 11. Based on this figure, the loss is significant mainly for the number of monthly cycles smaller than five. After five monthly cycles, the efficiencies mostly range between 80 and 90 percent.

Fig. 12 shows curve fits for plants with initial operating years of 2016 to 2021. In the 2018 group, the excluded points belong to the 2020 months showing efficiencies above 90%, while data for the plant in the previous months show efficiencies around 70%. Thus, most probably, the plant has been updated, and the plant's 2020 data are considered in the 2020 group as summarized in the Appendix.

The fit coefficients are summarized in Figs. 13 and 14. The newer plants show higher efficiencies (i.e., higher C_1) and low level of losses (i.e., low C_2). We do not know the cause of the improved performance for newer systems, but we surmise that the improved performance is from technological advances. In Fig. 13, the reported ranges of LFP and NCA performance in the literature are shown. Not surprisingly, the efficiencies measured for the batteries are higher than the observed system efficiencies because the maximum system efficiency must also include the efficiency of the power electronics, which we noted adds a loss of about half of the loss in the battery itself during the charging/discharging cycle. Thus, from Schimpe et al's paper [23], we predict that the system efficiencies would be lower than reported in Table 2. Specifically, considering the range of 91-96% for the LIBs' efficiencies reported by Schimpe et al [23], the range of power electronics efficiencies will be 95.5-98%. By multiplying the efficiencies, the maximum system efficiencies will be

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between 87% and 94%. This prediction is quite consistent with what we show in Fig. 13.

We turn now to the question of why the systems that are used infrequently show lower efficiencies. According to the literature provided in the introduction, by assuming the idle loss of a LIB equal to 5%/month and considering the amount of $30\times C_2$ appeared in eq. 2 as the idle loss, C_2 will be equal to 0.00167. This number would increase to 0.00334 if the self-discharge rate (idle loss) is 10%/month, the maximum we identified in the introduction. Fig. 15 shows the efficiency versus number of cycles/month for the different values of C_2. In this figure, the value of C_1 for all cases is set to 0.88, which is the same value as the 2017 and 2018 groups. According to Fig. 15, the small values of C_2 calculated from the self-discharge numbers provided in the literature, are much smaller than some of the observed fit values for C_2.

Both Fig. 14 and Fig.15 show that the values of C_2 obtained from the model are bigger than the values reported in the literature for self-discharging. As the data in EIA923 dataset reflect the full generation unit, not just the battery, we surmise that the model is also considering the parasitic system losses (Fig. 9), and that might be the reason why we are getting more losses than the self-discharges reported in the literature.

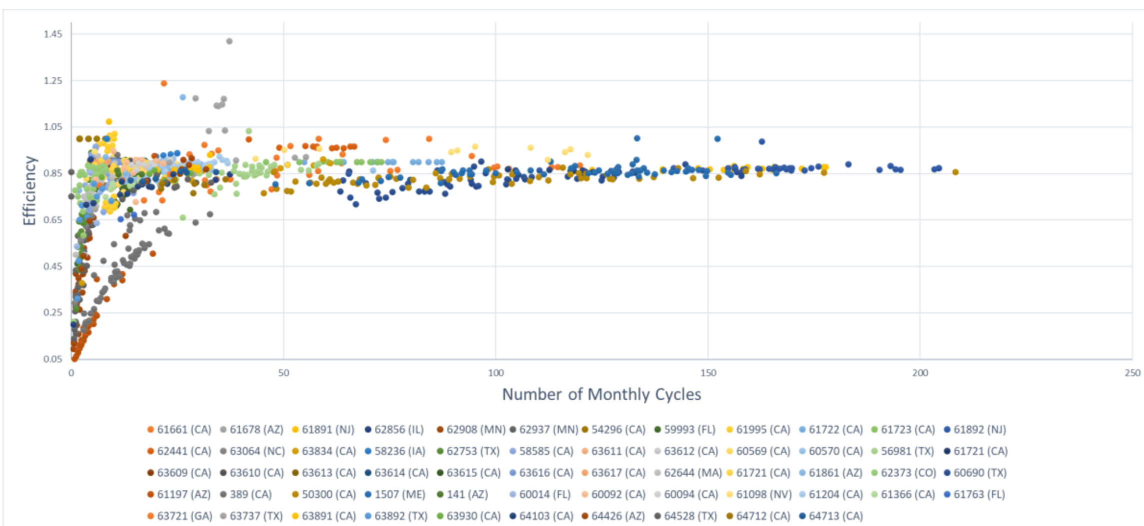

Figure 10. Efficiency versus number of monthly cycles for 58 plants based on the data from the EIA datasets; The state where each plant is located is indicated in the parentheses next to the plant IDs below the graph [29].

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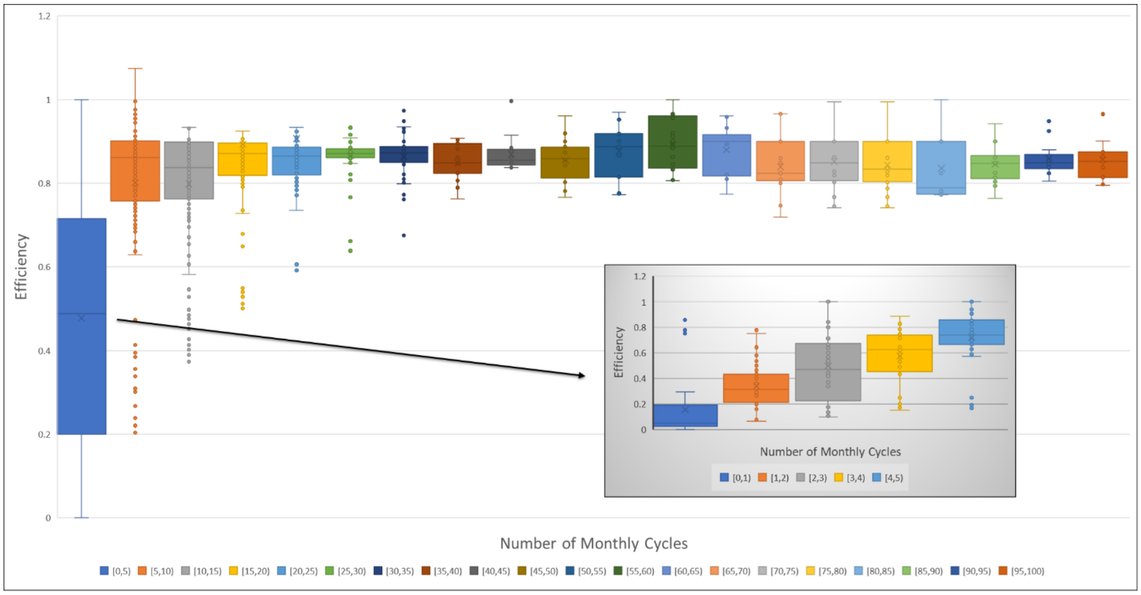

Figure 11. Box and Whisker plot of the data in Fig. 10 with 5 cycles intervals [29]

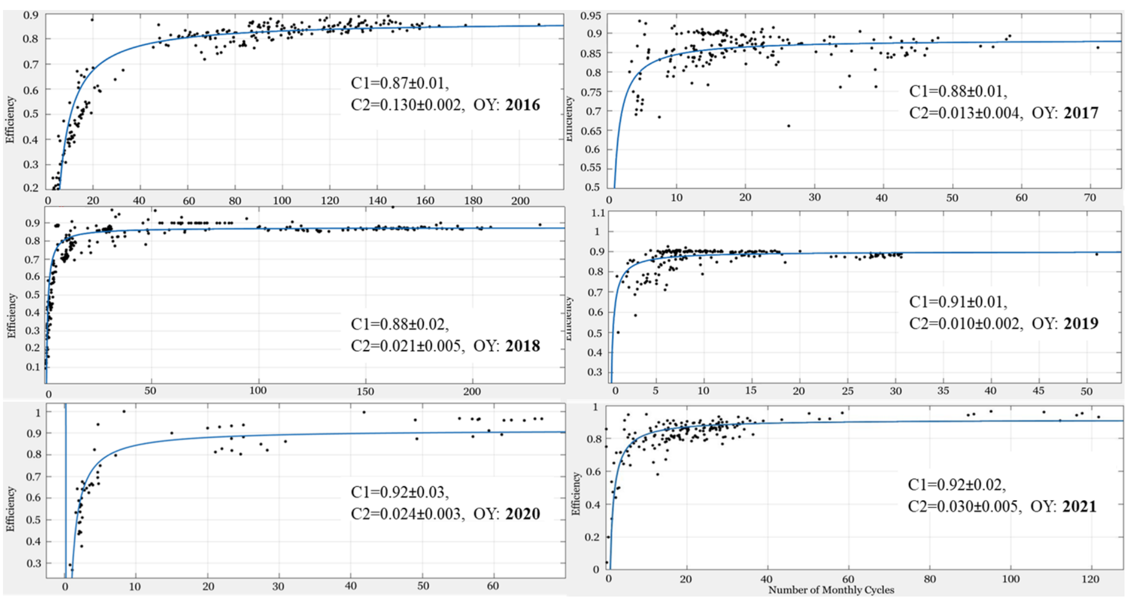

Figure 12. The best curve fits for plants with the installation years of 2016 to 2021

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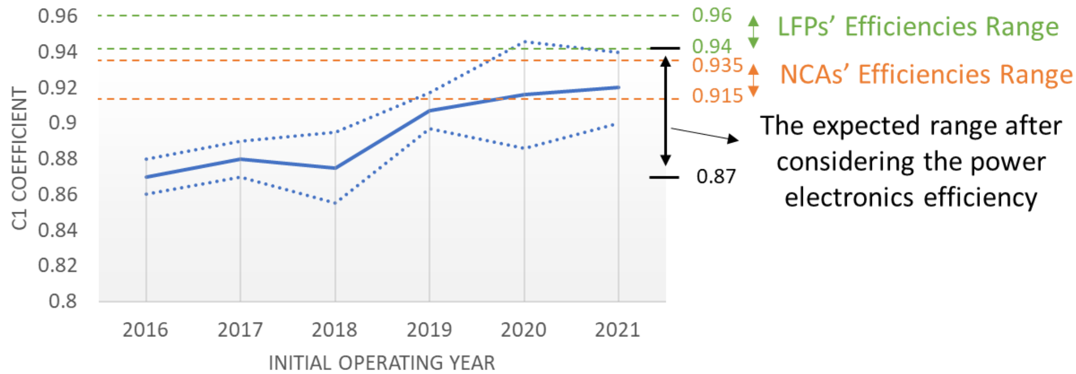

Figure 13. Calculated C_1 coefficients vs the initial operating year, compared with efficiencies measured for the batteries alone [22]

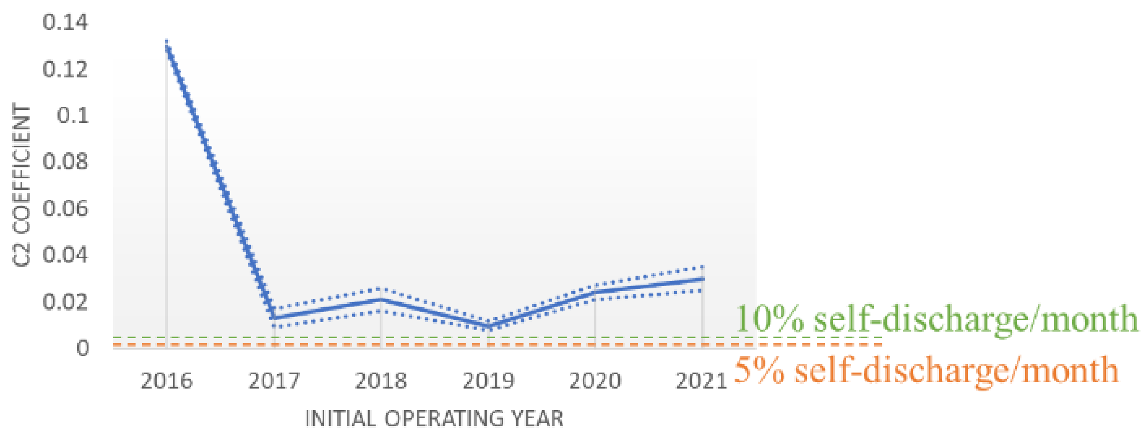

Figure 14. The calculated C_2 coefficients vs the initial operating year, compared with values we would expect for idle losses reported in the literature.

3.4. Conclusions

In this study, the EIA860 and EIA923 datasets are used to quantify the efficiency of energy storage power plants in the U.S. that use LIBs as storage devices. The efficiencies are mostly between 80 and 90% for plants that cycle more than five times/month. An analytical model is used expressing the efficiency of the plants in terms of the number of monthly cycles and two coefficients, one representing the maximum efficiency and the other showing some loss mechanisms.

The analytical expression is implemented separately on plants with the same initial operating year (2016 to 2021). The coefficients are calculated for each group to have the least fitting error. From older to newer plants, the first coefficient, which represents the maximum efficiency, increases. The trend might be attributed to technological advancements in making batteries. Also, the loss predicted by the model is bigger than expected based on the self-discharge losses reported in the literature. Therefore, the model points to losses related to the system, which will decrease the observed efficiency for a battery that cycles infrequently. For a few systems, the efficiency is mostly independent of cycle frequency. For these, the idle loss may be the primary cause of the very small decreased efficiency for low cycles.

Finally, analyzing the efficiency changes by time for the 2016-2019 plants shows almost no change for most of the plants. The efficiency change is about -0.2%/month in the two plants observed to degrade the most.

If more information can be obtained for these plants, it would enable a more complete understanding of why the efficiency decreases for some, but not all, of the infrequently cycled batteries. However, the data are clear that for modeling stationary storage systems that are anticipated to be cycled about once per day, the observed real-world efficiencies are around 85%, providing a real-world data benchmark for modelers who wish a realistic value for the efficiency.

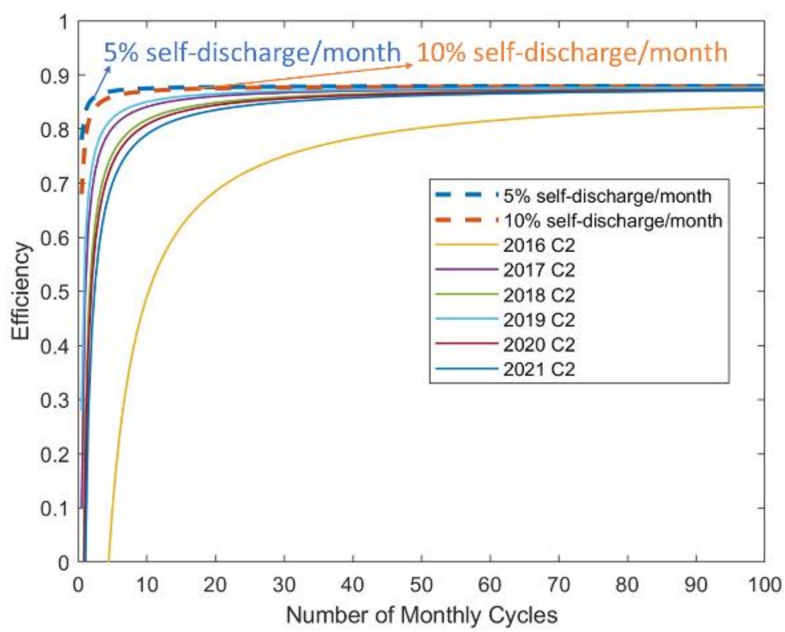

Figure 15. Efficiency predicted by the model for different values of C_2 and for the ones reported in the literature versus the number of cycles/month; C_1 is set to 0.88 for all of the cases

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3.5. Appendix

In the table below, we list the data that were not considered or that were considered with a different year along with the reasons for these decisions [29].

Plant Code in EIA Datasets	Decision	Explanation
62381	Not Considered	Efficiencies much higher than one
62382	Not Considered	Efficiencies much higher than one
62682	Not Considered	Significant outages in the datasets
62683	Not Considered	Significant outages in the datasets
61892	Considered in the 2018 group	In the dataset, the operating year is 2019, but there are some reported data for the plant in 2018
60690	Considered in the 2016 group	In the dataset, the operating year is 2017, but the incorporation date of the plant is 13 April 2016 (Reference)
56981	Considered in the 2017 group	A new generator with a similar description was reported in 2017 (Reference)
61995	Data reported before 2020: considered in the 2018 group Data reported after 2020: considered in the 2020 group	A sudden increase in the efficiencies reported from the year 2020 compared to the previous months; possibly the plant has been updated

Chapter 4: Conclusions

The utilization of lithium-ion batteries in stationary energy storage plants across the United States, spearheaded by California, has witnessed a significant upsurge. This increase gives researchers an excellent opportunity to quantify the energy storage plants' performance on the megawatts scale for the first time. This thesis used data from the Energy Information Administration (EIA) datasets to calculate real-world efficiencies, explore potentially influential factors, and develop a mathematical model for the efficiencies obtained.

For stationary storage systems expected to undergo approximately more than five cycles per month, the real-world observed efficiency is around 85%. This real-world efficiency provides a valuable benchmark for modelers seeking realistic efficiency values for their assessments. The efficiencies were observed to drop significantly for plants with infrequent cycles/month. For some of the plants, this efficiency drop could be justified by the idle loss of the batteries; however, for many of the plants, the observed loss is greater than the recorded idle losses in the literature; therefore, other losses, such as parasitic loads losses should exist in the reported data.

Furthermore, the model shows an improvement in the observed efficiencies for the newer plants, which could be attributed to the technological progress in making batteries. Additionally, the provided data analysis revealed that efficiency degradation was not evident, as most plants exhibited efficiency changes smaller than 0.1%/year.

Moreover, according to Figs. 4(a) and 5 in Chapter 2, there is evidence of slight seasonal variations in efficiency that may arise from heating or cooling parasitic loads. However, these seasonal variations might correlate with seasonal variations in the number of monthly cycles. Separating the two effects would be interesting but is beyond the scope of this study.

In the end, the main takeaways of this thesis can be concisely found in Table 3 below:

Table 3. The main takeaways of the thesis

Attribute	Findings of the thesis
Performance (efficiency)	85% for plants with >5 cycles/month
Performance variation with monthly cycles	For some plants with an infrequent number of monthly cycles, the observed loss is close to the idle loss values in the literature. For other plants, it is larger and could be related to parasitic losses.
Degradation in the efficiency	Less than 0.1%/year

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