Analytical analysis of stationary Li-Ion-battery storage-system efficiency on a large scale

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***Abstract*— In recent decades, Li-ion battery (LIB) technology has matured and is now the dominant battery technology for many mobile applications. Building on that success, LIBs are increasingly being adopted for stationary applications, as well. The Energy Information Administration (EIA) datasets show a huge increase in LIBs' use in the country, providing an opportunity to quantify their real-world performance. In this study, the reported efficiency of stationary LIBs units in storage plants in the USA is analyzed using the energy storage plants' data available in the EIA datasets. The plants are categorized according to the initial operating year; each group's efficiency is modeled as a function of the number of cycles/month. We found that 1) newer plants show higher efficiencies, 2) the efficiency typically increases with the LIBs' number of cycles/month, 3) the efficiencies are between 80-90 % for those that cycled more than five times in a month, 4) The combined efficiencies of battery and power electronics are observed to be 87-94%, and 5) the degradation of the efficiency is imperceptible from these data, even for the systems that have been operating for > 5 years. Finally, we discuss possible reasons for the lower reported efficiencies for those systems that cycle infrequently.**

I. 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 [1,2]. 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. 1 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 arbitrage, 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.

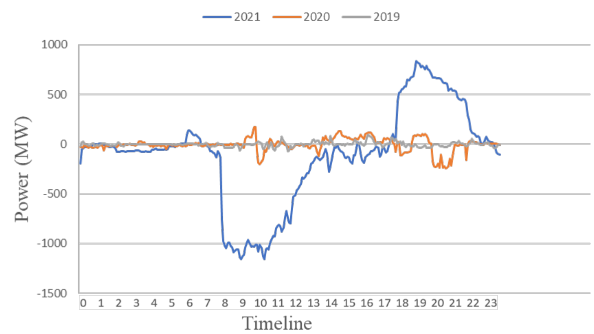


Figure 1. A significant increase in battery utilization in 2019, 2020, and 2021 using August 18th as a representative day, based on California Independent System Operator (CAISO) data [3,4]

A study by Choi et al [5] 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 1. These RTEs reflect the efficiency of the batteries rather than the efficiency of an entire system.

Table 1. RTEs measured for LIBs [5]

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. [6] identified 18 loss mechanisms in a stationary LIB container storage system. A summary of their categorization is shown in Fig. 2. This figure shows the three loss mechanisms associated with the batteries (as in Table 1). 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.

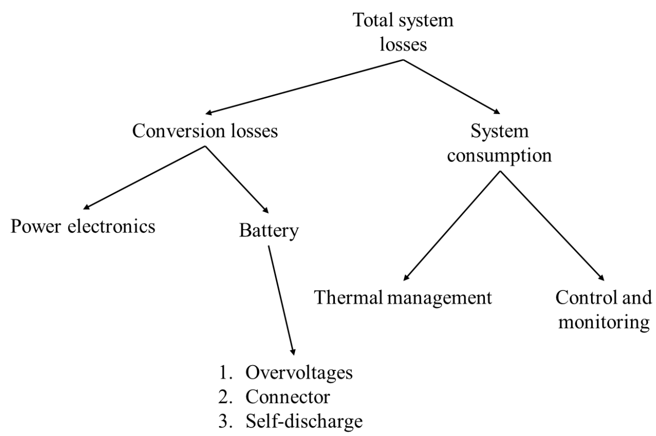


Figure 2. Loss mechanisms presented by Schimpe et al. [6] for a stationary LIB container storage system

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 [7], a typical LIB has a self-discharge of around 5% per month. In addition, according to the estimation provided by Battery University [8], 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 [9]. 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. [10] 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 [11].

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 [12]. That study did not explore the 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.

II. ANALYTICAL MODELING

In this study, the datasets EIA923 [13] and EIA860 [14] 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 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 [13]. 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 [12]. Specifically, eq. 1 relates the efficiency of the plants in terms of two empirical coefficients and the number of monthly cycles [12].

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

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

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

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.

III. RESULTS AND DISCUSSION

(a) Observed efficiencies and modeling

Fig. 3 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. 4. 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. 5 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. Fig. 5 shows the best curve fits and the corresponding coefficients, including the uncertainties.

The fit coefficients are summarized in Figs. 6 and 7. 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. 6, 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 [6], we predict that the system efficiencies would be lower than reported in Table 1. Specifically, considering the range of 91-96% for the LIBs' efficiencies reported by Schimpe et al [6], the range of power electronics efficiencies will be 95.5-98%. By multiplying the efficiencies, the maximum system efficiencies will be between 87% and 94%. This prediction is quite consistent with what we show in Fig. 6.

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. 8 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. 8, the small values of C_2 calculated from the self-discharge numbers provided in the literature, are much smaller than the observed fit values for C_2.

Both Fig. 7 and Fig.8 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. 2), and that might be the reason why we are getting more losses than the self-discharges reported in the literature.

(b) Degradation of the efficiency

Fig. 9 shows the efficiency of the plants with the initial operating years of 2017 to 2019 versus time. The 2020 and 2021 plants are not studied here to make sure we have at least one full year of data for each plant. The average rate of change of the efficiency for the 2016 plants in Fig. 9(a) is -0.0009 %/month. These rates of change for the 2017, 2018, and 2019 plants are +0.0032, -0.049, and +0.0063 %/month, respectively (Figs. 9(b), 9(c), and 9(d)). Fig. 10 shows the histogram of efficiency change per month for all these plants. The figure shows that most plants show less degradation in efficiency than the uncertainty of the measurement. The highest observed efficiency loss is about 0.2%/month for two plants.

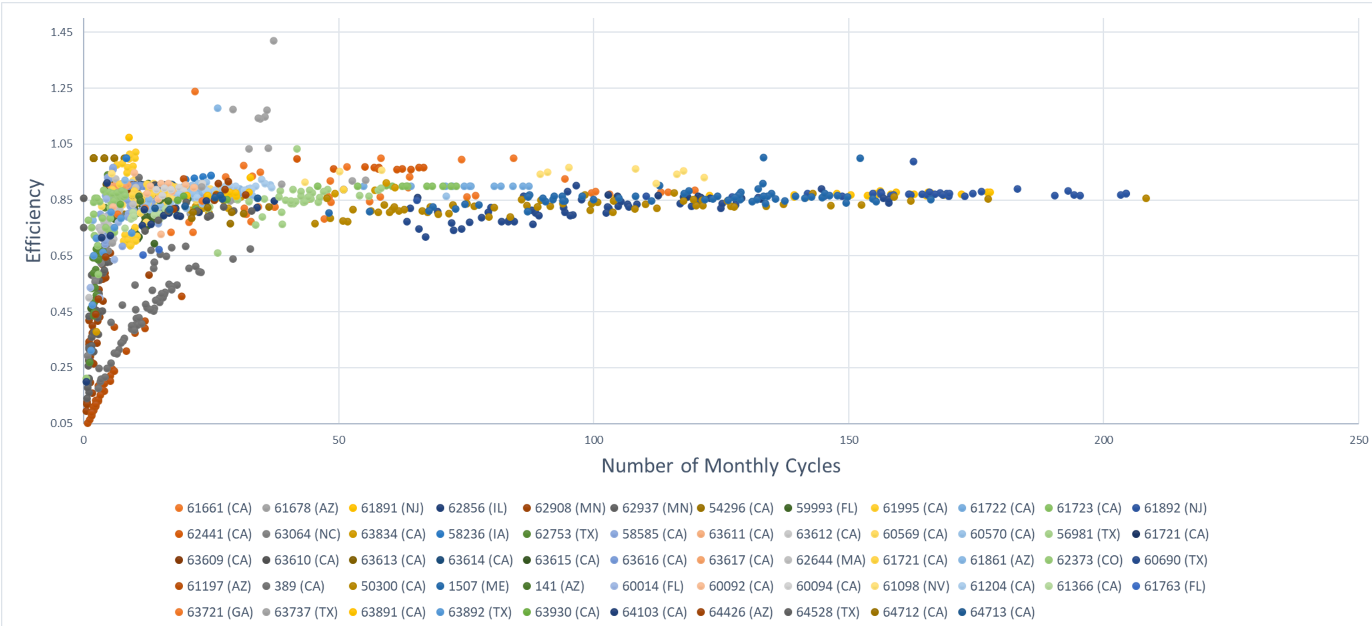


Figure 3. Efficiency versus number of monthly cycles for 58 plants based on the data from the EIA datasets; The state of each plant is indicated in the parentheses next to the plant IDs below the graph [12].

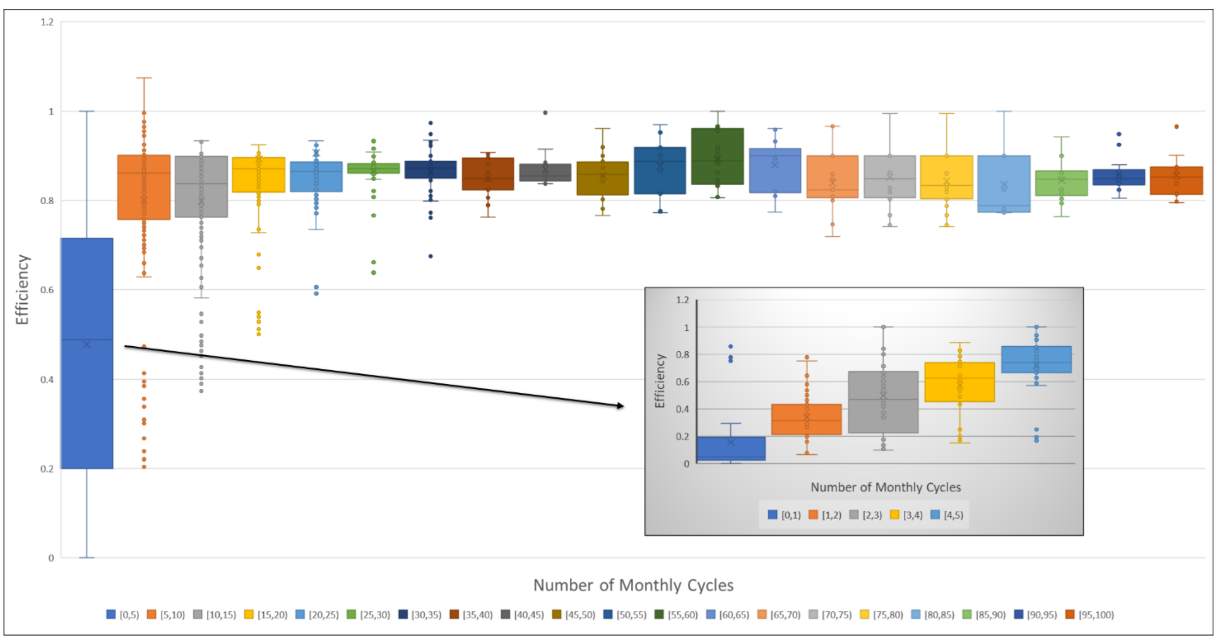


Figure 4. Box and Whisker plot of the data in Fig. 3 with 5 cycles intervals [12]

IV. 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.

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

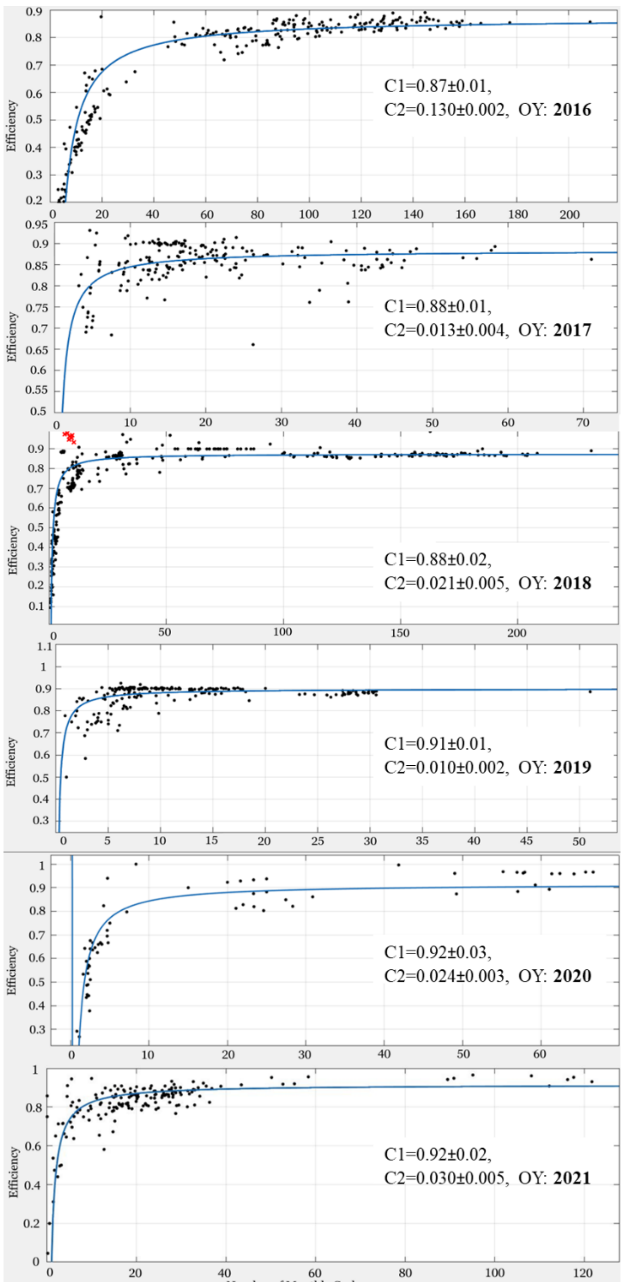


Figure 5. The best curve fits for plants with the installation years of 2016 to 2021, updated from reference 12.

cycled batteries. However, the data are clear that for modeling of stationary storage systems that are anticipated to be cycled about once per day, the combined efficiencies of the batteries and power electronics are observed to fall in the range of 87%-94%, providing a real-world data benchmark for modelers who wish a realistic value for the efficiency.

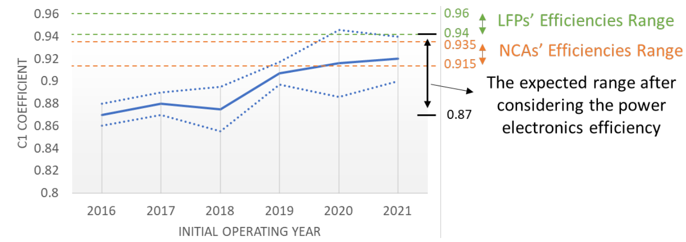


Figure 6. Calculated C_1 coefficients vs the initial operating year, compared with efficiencies measured for the batteries alone [5]

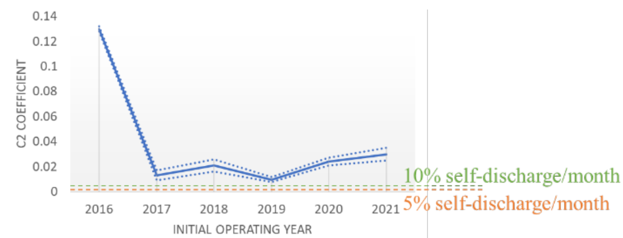


Figure 7. The calculated C_2 coefficients vs the initial operating year, compared with values we would expect for idle losses reported in the literature

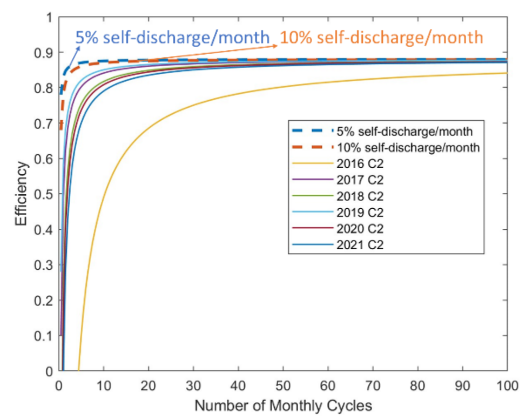
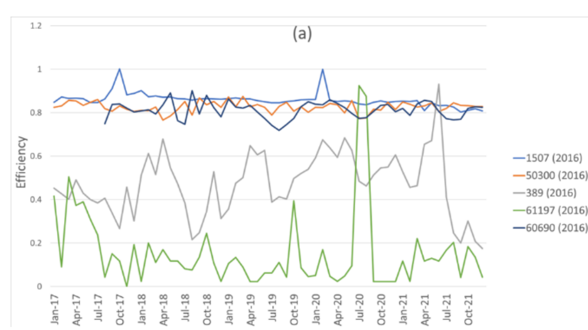


Figure 8. Efficiency predicted by the model for different values of C_2 and for the ones reported in the literature versus the number of cycles/month; C_1 is set to 0.88 for all of the cases



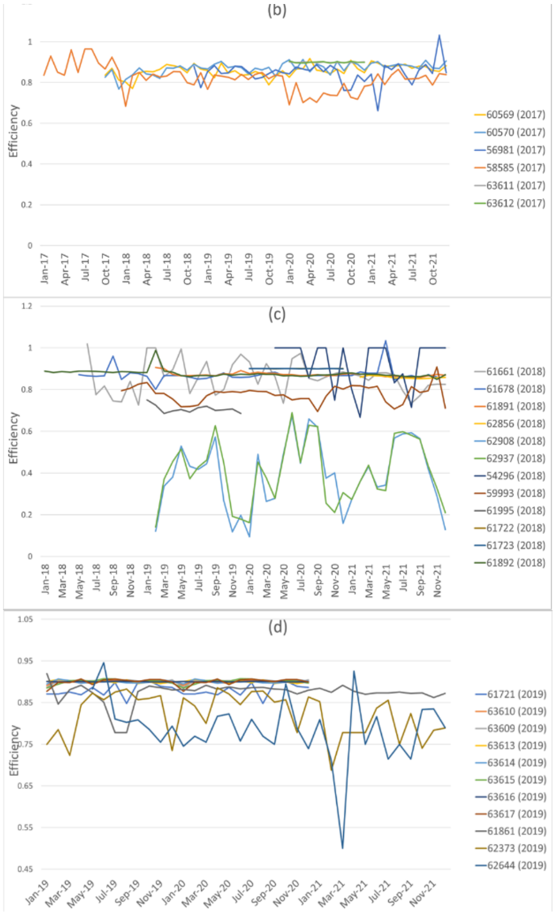


Figure 9. Efficiency versus month for the plants with the initial operating year of (a) 2016 (b) 2017 (c) 2018 (d) 2019

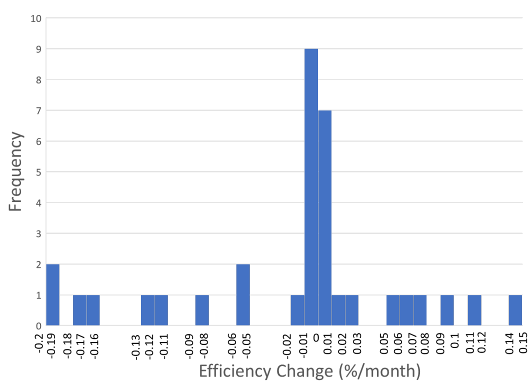


Figure 10. Histogram of the efficiency changes for the 2017 to 2019 plants

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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 [12].

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