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# Optimal Operation of Residential Battery Energy Storage Systems under COVID-19 Load Changes

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**Abstract:** Over the past few years as COVID-19 was declared a worldwide pandemic that resulted in load changes and an increase in residential loads, utilities have faced increasing challenges in maintaining load balance. Because out-of-home activities were limited, daily residential electricity consumption increased by about 12–30% with variable peak hours. In addition, battery energy storage systems (BESSs) became more affordable, and thus higher storage system adoption rates were witnessed. This variation created uncertainties for electric grid operators. The objective of this research is to study the optimal operation of residential battery storage systems to maximize utility benefits. This is accomplished by formulating an objective function to minimize distribution and generation losses, generation fuel prices, market fuel prices, generation at peak time, and battery operation cost and to maximize battery capacity. A mixed-integer linear programming (MILP) method has been developed and implemented for these purposes. A residential utility circuit has been selected for a case study. The circuit includes 315 buses and 100 battery energy storage systems without the connection of other distributed energy resources (DERs), e.g., photovoltaic and wind. Assuming that the batteries are charging overnight, the results show that energy costs can be reduced by 10% and losses can decrease by 17% by optimally operating batteries to support increased load demand.

**Keywords:** battery energy storage system; distributed energy resources; mixed-integer linear programming; wholesale energy market

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## 1. Introduction

The global COVID-19 pandemic has changed our societies in a dramatic way, including the way people work and learn, with many homes being transformed into offices and classrooms. This has caused increased obstacles to utilities when it comes to meeting their load demands [1]. Not only is reliability more important now in case of outages due to inclement weather and aging infrastructure [2], but residential power usage also has been witnessed to be climbing, with peak times shifting away from mornings and evenings to midday. In addition to the load changes, the climate crisis is deepening, and thus the urgency to reduce carbon emissions is rapidly increasing and utilities are obliged to significantly reduce their emissions to abide by legal standards and regulations [3–7]. For this reason, utilities are beginning to take significant measures to decrease their emissions. A utility in Detroit, Michigan has committed to a 50% reduction by 2028 and 80% by 2040. To achieve this ambitious target, they have developed strategies like retiring coal-fired power plants; adding more solar, wind, and solar under wind energy projects; investing significantly in large-scale storage infrastructure; and installing residential battery systems. Utility-owned and operated residential battery energy storage systems are one of the essential DERs, with a significant opportunity to provide value streams like peak shifting, where the BESS allows shifting electricity usage from peak hours to off-peak. This can lower the need for additional power generation, resulting in potential cost

saving [8–10]. The operation of the BESS considering peak load offers the utility the opportunity to reduce charges at peak prices by dispatching storage instead of buying from the wholesale market. Other benefits are backup power, grid stability, and market participation. Utilities are also challenged by recent Federal Energy Regulatory Commission (FERC) orders that have removed obstacles preventing DERs from having the same access as traditional resources to regulated wholesale markets. The integration of residential BESSs into the grid can present technical challenges for utilities and system operators. These new orders, on the other hand, provide a variety of benefits, including lower costs through enhanced competition, more grid flexibility and resilience, and more innovation within the electric power industry. With these orders, utilities can use owned residential energy storage systems to maximize their benefits. To ensure that BESSs are reaching their full potential, it is critical to optimize the operation strategy, which involves finding the optimal combination of generation, storage, and demand-side management to meet the energy needs of customers while minimizing the cost of energy production and distribution. Current mathematical models used for scheduling BESSs do not account for the load changes due to COVID-19 and focus on customers' benefits rather than the utilities'. This paper studies the optimal operation of residential battery energy storage systems to minimize losses, generation fuel prices, market prices, cost of generation at peak hours, and battery operation cost while also maximizing the batteries' state of charge.

The main contributions of this paper are as follows:

1. The consideration of loads during and after COVID-19.
2. Cost optimization from a utility perspective.
3. A study of a real-life model using supervisory control and data acquisition (SCADA) real-time data.
4. The use of a BESS without solar.

The rest of this paper is structured as follows: Section 2 provides an extensive literature review on load fluctuations induced by COVID-19 and the limitations of the current BESS optimization methods. The proposed approach for cost optimization is outlined in Section 3 along with stating the objective function, constraints, and anticipated output. In order to validate the efficacy of the proposed approach, a utility circuit is used as a case study, which is explained in Section 4. Finally, this paper is concluded in Section 5.

## 2. Literature Review

### *2.1. Load Changes*

Since the beginning of the COVID-19 pandemic, researchers have been studying the impact of quarantine restrictions on the energy sector and load profiles as the measures taken by the government to address this emergency have caused significant changes in people's habits and activities, resulting in a notable effect on loads [11]. Although commercial and industrial loads decreased as people were working from home, residential loads increased for the same reason [12]. Global demand experienced around a 3.8% decrease, while residential loads increased by an average of 20%. According to [13,14], the weekly residential energy demand in Europe increased by 9% under limited restrictions, 17% under partial lockdown, and 24% under complete lockdown. Load curves were also significantly impacted as peaks had shifted [15–17]. During weekdays, the morning peak was reduced, and another peak was observed around midday. Also, the weekday and weekend profiles looked very similar. Figure 1 below shows a residential load curve of a utility in Michigan. Because customers were spending more time at home, the average household daily consumption saw an increase from 19.7 kWh to 22.1 kWh. This forced people to invest in renewables (e.g., a solar roof) to reduce their utility bill [14]. Moreover, customers who already owned renewables were now selling less power back to utilities due to their higher consumption, requiring utilities to make up for the shortfall. In Germany, the low global energy demand during the pandemic and high renewable energy outputs set a record of negative wholesale power prices. For the mentioned reasons, it is essential for utilities to understand the new load curves and optimal operation of DERs.

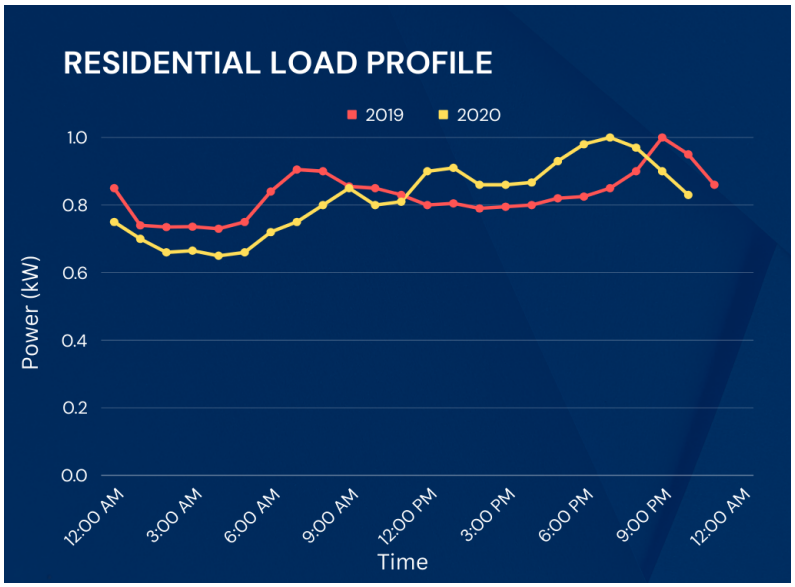



**Figure 1.** Residential load changes.

### *2.2. Cost Optimization*

In recent years, DERs have experienced widespread adoption due to a decrease in their prices [18–21], the urgency to reduce carbon emissions, and consumers' interest in improving reliability and decreasing energy costs [22–24]. On the other hand, with the increased outages due to natural disasters, utilities are also interested in installing residential DERs like energy storage systems to improve customers' satisfaction. DERs offer multiple benefits to the energy system by providing backup power, which increases grid resilience, minimizes interruptions [25,26], reduces transmission losses because they are installed closer to the point of consumption [2,27,28], supports peak loads by supplying additional generation to meet load demand [29,30], and maintains grid stability by regulating frequency and voltage [31,32]. Overall, DERs are essential to transform the traditional energy grid into a more flexible and reliable system benefiting both utilities and customers. Although DERs offer numerous benefits, they also have some disadvantages such as variability as they are mostly weather-dependent: if wind is not blowing, wind turbines are not generating. Another disadvantage is grid interruption: DERs could cause low voltage (e.g., if installed on the wrong bus) [28,33,34]. Therefore, it is crucial to study the optimal operation of DERs to maintain a stable electric grid. There have been several research studies on optimization and specifically on cost optimization. A number of research papers are summarized in Table 1. For example, the authors in [35] aimed to minimize the energy cost and environmental impact by considering electricity buyback, carbon tax, and fuel switching to biogas. A multi-objective linear programming (MOLP) approach was proposed to support grid operators in selecting the best generation source. However, the research did not account for BESS operation costs and focused only on customer benefits. In [36], mixed-integer linear programming was used to optimize the unit size and location while also minimizing investment and operation costs and emissions. However, the objective function constraints were very minimal, and the paper was not limited to a BESS but included multiple different DERs. A multi-objective linear programming method was formulated in [37,38] to minimize the total energy cost and primary exergy input. Nevertheless, it did not consider system losses in the weighted sum optimization. Similarly, in [39], multi-objective optimization aimed to determine the quantity and size of DERs to minimize the annual cost and improve the exergy efficiency. This study overlooked different DER constraints. In [40,41], the researchers studied the optimal operation of BESSs to minimize distribution losses and battery cycle loss by regulating the voltage, reducing losses and peak loads. However, the rates of charge and discharge of the BESS were not considered, which may pose a safety hazard. Also, [41,42] focused on minimizing customer bills and battery degradation costs

but did not consider BESS constraints as part of the study. In [43], the authors focused on reducing customers' energy bills by optimally dispatching residential storage. In both papers, BESS constraints were very minimal and losses were not considered. Additionally, in [29,44], the papers aimed to minimize energy bills, total system peak load demand, and emissions using MILP. In [44], the MILP was then converted into weighted sum optimization for more accurate results. However, system losses were not considered in either study. To address these research gaps, a MILP approach is proposed. MILP is widely adopted in optimization for its accuracy, flexibility, and efficiency when the objective function and constraints are linear. The goal of this optimization is to optimally schedule residential BESSs to find the cheapest generation source to meet the load demand considering load changes caused by COVID-19. These changes resulted in significant challenges for both the grid operators and the grid itself.

**Table 1.** Optimization literature review.

| Ref. | Year | Focused Topics | Research Gaps | Optimization Method | DER Composition |
|---|---|---|---|---|---|
| [35] | 2010 | To minimize energy cost and environmental impact, considering electricity buyback, carbon tax, and fuel-switching biogas. | Research is not specific to BESS specifically; it studies DERs in general. DER operation cost and pay back period were not considered. | multi-objective linear programming (MOLP) | PV, fuel cell |
| [36] | 2013 | Find the optimal unit size, location, and distribution network structure while minimizing annual investment and operating cost. In addition to analyzing the economic and environmental impacts of DERs compared to traditional generation. | Very minimal constraints were considered in the algorithm and the paper is focused on multiple DERs not limited to BESS. | MILP | solar thermal, PV, heat pumps, wind turbines (WTs) |
| [37] | 2015 | To minimize a weighted sum of the total energy cost and total primary exergy input. | Losses were not considered. | MILP with Pareto frontiers | biomass boiler, solar thermal plant, Combined Cooling Heating and Power (CCHP), reversible heat pump, thermal BESS |
| [39] | 2017 | To determine the types, numbers, and sizes of energy devices to reduce annual cost and increase the overall exergy efficiency combining heat and PV using MOLP. | Considered all DERs the same. This research did not consider different DERs' constraints. | MOLP | PV |
| [41] | 2015 | To minimize distribution system loss and battery cycle loss. BESS is investigated for three main services options: (1) voltage regulation; (2) loss reduction; and (3) peak reduction. | Rates of charge and discharge were not considered, which could cause a safety hazard. | MOLP | PV, BESS |

**Table 1.** *Cont.*

| Ref. | Year | Focused Topics | Research Gaps | Optimization Method | DER Composition |
|---|---|---|---|---|---|
| [42] | 2018 | To minimize customer bill and battery degradation cost. | BESS constraints were not included as part of the study and focused on customer's benefits. | not identified | thermal storage, compressed air, chemical batteries |
| [21] | 2018 | To minimize the customer's energy cost while reducing aggregated demand peaks by optimally scheduling residential storage units. | Losses were not taken into consideration. | MOLP | PV, BESS, Electric Vehicle (EV) |
| [43] | 2018 | To minimize the real-time energy gap and battery operation cost where power loss reduction is implied using particle swarm optimization. | For constraints, only BESS power and SOC were considered. | non-linear mixed-integer programming | WT, PV, BESS |
| [44] | 2019 | To minimize total energy bill and total system peak load demand using mixed-integer linear programming, which is then converted to a linear combination by weighted sum. | Losses were not considered as part of the objective function. | MOLP | BESS, time-shiftable residential appliances |
| [29] | 2016 | To minimize total energy cost by making sure that at each hour the cheapest available generation is dispatched to meet system load using linear programming. | System losses were not included in the study. | MILP | BESS, PV |
| [7] | 2020 | To minimize the total cost of DERs, reduce environmental emission, and increase penetration level using particle swarm optimization. | Multiple DERs were considered in the study. System losses were not included. | particle swarm optimization | WT, PV, BESS |
| [4] | 2020 | Reduce the $CO_2$ emission, increase the penetration of RES, and minimize the total cost of the MG. | Losses were not included as part of the study. | MOLP | BESS, PV |
| [40] | 2021 | A new formulation for optimal allocation and sizing of DERs and energy storage systems (ESSs) to improve voltage profile and minimize annual costs using a multi-objective multiverse optimization method (MOMVO). | Very limited ESS constraints also considering distributed generation in the study. | multi-objective multiverse optimization method | WT PV, BESS |
| [45] | 2021 | To minimize the cost and emissions and maximize the overall exergy efficiency of the system. | Minimal constraints were considered in the study. | MOLP | BESS, PV |
| [38] | 2021 | To provide a comprehensive review of BESS concerning optimal sizing, system constraints, and various optimization models and their advantages and weakness. | Research review included very basic BESS constraints, such as capacity and state of charge. | MOLP | PV, WT, BESS |

## 3. Methods and Algorithm

This section presents an overview, the objective function, the BESS management strategy, the objective constraints, and a summary of the proposed approach.

### *3.1. Method Overview*

The main objective of the algorithm is to balance demand and supply loads every 15 minutes and 1 h, as shown in block (A) of Figure 2, by dispatching the most cost-effective generation source while minimizing traditional generation costs, system losses, market prices, peak process, and battery operation cost. Due to most utilities being regulated, they cannot simply shut down their generation as they are participating in the wholesale market. Any unavailable generation may result in a fine being imposed on the utility by the regulatory authority. Thus, if additional generation is needed and BESSs are not dispatchable to meet demand and market prices are high, the only option will be to shed the load after the risk has been identified. If BESSs are evaluated to be the most cost-efficient resource to meet load demand, it is necessary to constantly reevaluate their constraints (i.e., power, energy, and SOC) as shown in (B), making sure they are not operating outside of limits that could impose safety hazards. If the BESS is not the cheapest source, then, as shown in (C), the BESS is in a standby state and other resources are evaluated. When the load demand is higher than the generation, batteries are charged if they meet their constraints or power is sold back to the wholesale market. The optimization is performed in all three blocks ((A), (B), and (C)).

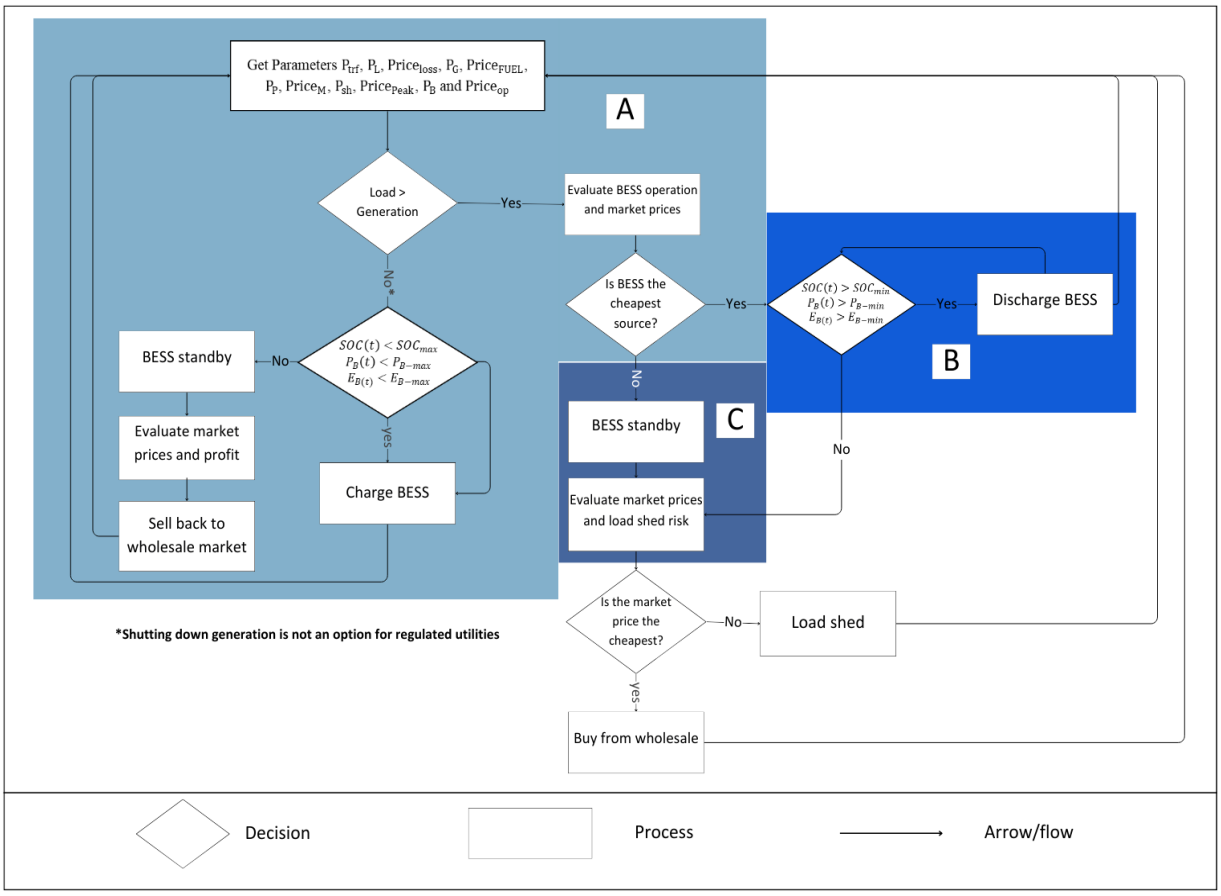



**Figure 2.** Optimization flow chart.

### *3.2. Objective Function*

The cost function in (1) is constructed to minimize the generation cost, which is considered to be the generation fuel price, market fuel price, and generation cost during

peak times; to minimize the distribution cost in terms of the cost incurred due to system losses; to minimize the battery operation cost; and to maximize the battery state of charge. This function was used to schedule one day of operation of the BESS with 15 min intervals.

$$f(x(t)) = \sum_{t=1}^{96}[\alpha(min(\mathrm{C}_{loss}^{DS}(t) + \mathrm{C}_{f}^{G}(t) + \mathrm{C}_{f}^{M}(t) + \mathrm{C}_{P}^{G}(t) + \mathrm{C}_{B}^{op}(t)) + \beta(max\mathrm{CP}_{B}^{SOC}(t))] \quad (1)$$

where

- $\mathrm{C}_{loss}^{DS}(t)$ is the cost of the distribution losses;
- $\mathrm{C}_{f}^{G}(t)$ is the cost of running utility-owned generation;
- $\mathrm{C}_{f}^{M}(t)$ is the cost of the power purchased from the wholesale energy market;
- $\mathrm{C}_{P}^{G}(t)$ is the cost of generation at peak times;
- $\mathrm{C}_{B}^{op}(t)$ is the battery operation cost;
- $\mathrm{CP}_{B}^{SOC}(t)$ is the battery capacity—state of charge;
- $\alpha$ and $\beta$ are the weights assigned based on their relative importance.

Because minimizing and maximizing in the same objective function can be challenging, maximizing the battery state of charge can be achieved by minimizing the battery's depth of discharge (DoD). Thus, (1) is converted to multi-objective minimizing optimization, shown in (2)–(8).

$$f(x(t)) = \sum_{t=1}^{96}[\alpha(min(\mathrm{C}_{loss}^{DS}(t) + \mathrm{C}_{f}^{G}(t) + \mathrm{C}_{f}^{M}(t) + \mathrm{C}_{P}^{G}(t) + \mathrm{C}_{B}^{op}(t))) + \beta\mathrm{CP}_{B}^{DoD}(t)] \quad (2)$$

where

$$\mathrm{C}_{f}^{M}(t) = \mathrm{P}_{p}(t) \cdot \mathrm{Price}_{M} \quad (3)$$

$$\mathrm{C}_{f}^{G}(t) = \sum_{N=1}^{N}(\mathrm{P}_{G}(t) \cdot \mathrm{Price}_{Fuel}) \quad (4)$$

$$\mathrm{C}_{P}^{G}(t) = \mathrm{P}_{Sh}(t) \cdot \mathrm{Price}_{Peak} \quad (5)$$

$$\mathrm{C}_{DS}^{loss}(t) = (\mathrm{P}_{trf}(t) + \mathrm{P}_{L}(t)) \cdot \mathrm{Price}_{loss} \quad (6)$$

$$\mathrm{C}_{B}^{op}(t) = \mathrm{P}_{B}(t) \cdot \mathrm{Price}_{op} \quad (7)$$

$$\mathrm{CP}_{B}^{DoD}(t) = DischargedPower(t)/FullCapacity \quad (8)$$

where DoD = 1-SOC such that

- $\mathrm{P}_{p}(t)$ is the power purchased from the wholesale market;
- $\mathrm{Price}_{M}$ is the market prices;
- $\mathrm{P}_{G}(t)$ is the generated power;
- $\mathrm{Price}_{Fuel}$ is the generation fuel prices;
- $\mathrm{P}_{Sh}(t)$ is the peak loads;
- $\mathrm{Price}_{Peak}$ is the peak prices;
- $\mathrm{P}_{trf}(t)$ is the transformer losses;
- $\mathrm{P}_{L}(t)$ is the line losses;
- $\mathrm{Price}_{loss}$ is the losses cost;
- $\mathrm{P}_{B}(t)$ is the BESS power;
- $\mathrm{Price}_{op}$ is the BESS operation cost;
- $\mathrm{CP}_{B}^{DoD}(t)$ is the BESS capacity—depth of discharge;
- $\alpha = \beta = 0.5$.

Below is a summary of the proposed approach to optimally manage the BESS.

1. As shown in Figure 3, the inputs to the optimization problem are time-variant transformer power losses, line losses, generation outputs, generation–fuel curves, power purchased from the wholesale market, power generated during the peak time, and new load profiles that reflect the COVID-19 load changes gathered from a SCADA real-time system, in addition to wholesale market prices and peak prices that are collected from the wholesale market. All the inputs are collected every 15 mins and every hour.
2. The outputs are the power purchased from the wholesale market, the power purchased during peak hours, and the battery output power. The optimization problem is a linear constrained problem that is solved using a MILP algorithm.
3. The electricity prices comprise four main components: (1) wholesale market cost $\text{Price}_M$, (2) generation fuel cost $\text{Price}_{Fuel}$, (3) losses cost $\text{Price}_{loss}$, and (4) BESS operation cost $\text{Price}_{op}$.
4. The cost function will not consider the cost of transmission losses because they are almost negligible compared with the distribution losses.

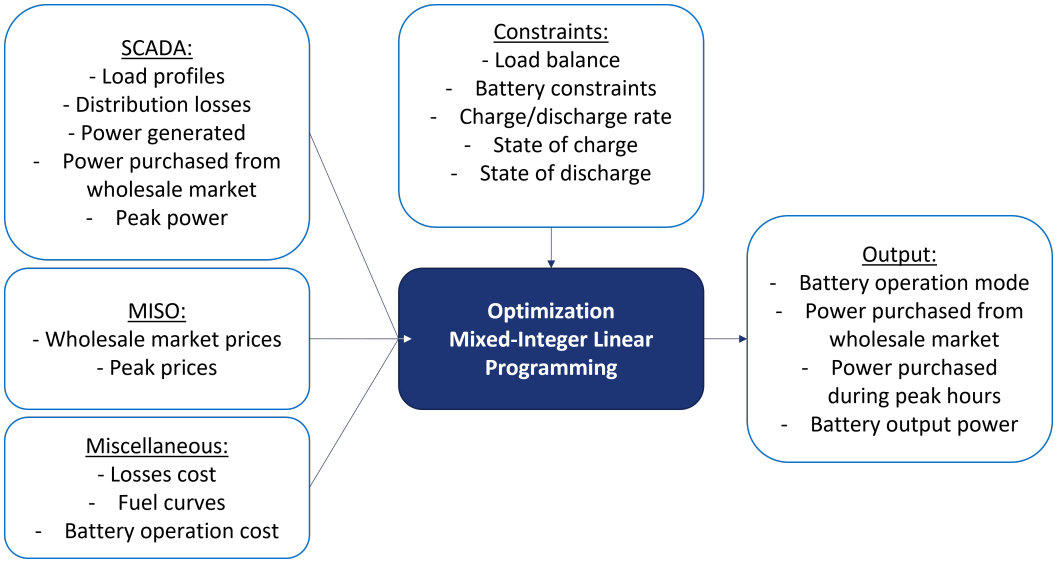



**Figure 3.** Optimization overview.

### *3.3. Objective Function Constraints*

1. Load balance: Maintaining the load balance is crucial to ensure the optimal performance and availability of a system.

$$\mathrm{P}_{demand}(t) + \mathrm{P}_{losses}(t) + \mathrm{P}_B(t) = \mathrm{P}_{generated}(t) \tag{9}$$

where

- $\mathrm{P}_{demand}(t)$ is the total load demand;
- $\mathrm{P}_{losses}(t)$ is the total system losses;
- $\mathrm{P}_{generated}(t)$ is the total system generation;
- $\mathrm{P}_B(t)$ is the total BESS power.

2. Battery constraints: Battery constraints are added to ensure that batteries operate within their normal limits.

$$\mathrm{P}_{B-min} \leqslant \mathrm{P}_B(t) \leqslant \mathrm{P}_{B-max} \tag{10}$$

$$\mathrm{E}_{B-min} \leqslant \mathrm{E}_B(t) \leqslant \mathrm{E}_{B-max} \tag{11}$$

where

- $\mathrm{P}_{B-min}$ is the minimum BESS output power;

- $P_{B-max}$ is the maximum BESS output power;
- $E_{B-min}$ is the minimum BESS capacity;
- $E_{B-max}$ is the maximum BESS capacity;
- $E_B(t)$ is the BESS capacity at time = $t$.

3. State of charge and depth of discharge: To extend the lifetime of the battery, it is essential that it not be fully charged or discharged at any time. For this reason, the SOC and DoD are considered to be between 20% and 80%.

$$SOC_{min} \leqslant SOC(t) \leqslant SOC_{max} \quad (12)$$

$$DoD_{min} \leqslant DoD(t) \leqslant DoD_{max} \quad (13)$$

where

- $SOC_{min}$ is the minimum state of charge;
- $SOC_{max}$ is the maximum state of charge;
- $SOC(t)$ is the state of charge at time = $t$;
- $DoD_{min}$ is the minimum depth of discharge;
- $DoD_{max}$ is the maximum depth of discharge;
- $DoD(t)$ is the depth of discharge at time = $t$.

4. Charging rate: To avoid any thermal safety hazards, batteries need to charge and discharge according to their charge rate.

$$R_{Discharged}(t) \leqslant R_{Discharged} \quad (14)$$

$$R_{charged}(t) \leqslant R_{charged} \quad (15)$$

where

- $R_{Discharged}(t)$ is the discharge rate;
- $R_{Discharged}$ is the BESS-rated discharge rate;
- $R_{charged}(t)$ is the charge rate;
- $R_{charged}$ is the BESS-rated charge rate.

### *3.4. Summary of Proposed Approach*

This paper proposes a cost optimization method using mixed-integer linear programming (MILP) in MATLAB R2021b. The optimization runs every 15 min and 1 h to find the optimal battery operation to minimize the distribution and generation cost, battery operation cost, and battery depth of discharge. The optimization will return the following:

1. The value of the power purchased from the wholesale market, $P_p(t)$.
2. The value of the power purchased during peak hours, $P_{Sh}(t)$.
3. The battery output power, $P_B(t)$.
4. The battery mode of operation (charge, discharge, or standby); it is based on the sign of the battery output power $P_B(t)$, a negative value being discharge while a positive value is charge and zero is standby.

## 4. Case Study

### *4.1. Case Study 1: DTE Energy 315-Bus System, 15 minutes Intervals*

A 13.2 kV 315-bus (mostly manufactured by EATON, Dublin, Ireland) distribution circuit was used to study the optimal BESS schedule to minimize the objective function. The batteries were randomly installed at different buses. Table 2 shows the circuit details. The batteries were simulated based on the real-time load and generation data that were obtained from DTE's SCADA system from 14 April 2022. The day-ahead and peak prices were taken from the MISO website [46] and are presented in Figures 4 and 5, respectively. The battery system specifications are based on those of a Sonen battery, as stated in Table 3. To show the effectiveness of the proposed MILP optimization method, we compared the

system performance with the BESS every 15 min, with the BESS every hour, and with and without the BESS over a 24 h period.

**Table 2.** Distribution circuit details.

| Device | Count |
|---|---|
| Circuit breaker | 1 |
| Cable | 40 |
| Fuse | 28 |
| Overhead by phase | 579 |
| Recloser | 1 |
| Regulator by phase | 5 |
| Capacitor | 2 |
| Load | 272 |
| Transformers | 273 |
| BESS | 100 |
| Bus | 315 |




**Figure 4.** Market prices.




**Figure 5.** Peak prices.

**Table 3.** Battery system specifications.

| Specification | Quality |
|---|---|
| Usable capacity | 27 kWh |
| Depth of discharge | 100% |
| Efficiency | 81.6% |
| Continuous power | 10 kW |
| Chemistry | Lithium iron phosphate |

The circuit-level load pre-COVID-19 and during COVID-19 is shown in Figure 6. Given the proprietary nature of this study involving a real-life utility circuit, we regretfully cannot disclose specific load details due to confidentiality agreements.

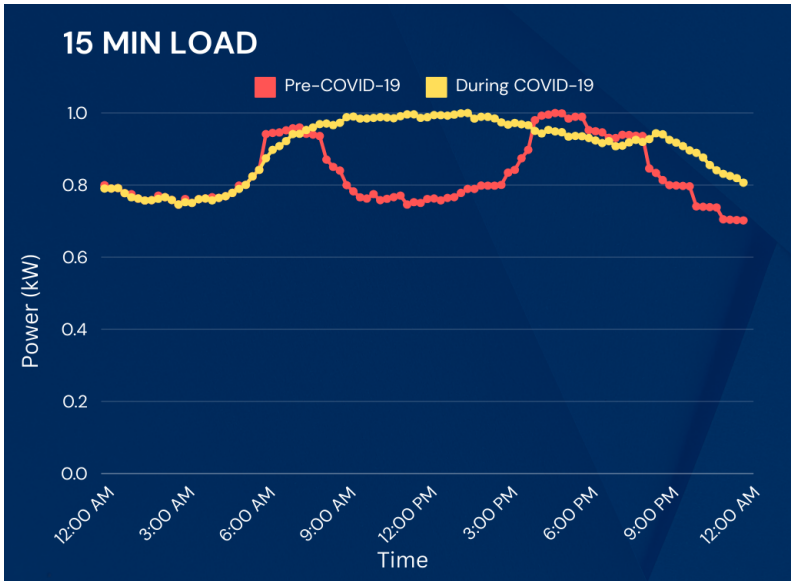



**Figure 6.** The 15 minutes load.

In contrast to pre-COVID-19 loads, where peak periods were in the morning from 6:00 to 8:00 am and in the evening from 4:00 to 6:00 pm with the highest peak at 5:15 pm, a notable shift is observed, with the current peak occurring at 1:30 pm. As shown in Figure 7, because the load overnight is low, we are assuming that the batteries are fully charging overnight and reach a full capacity of 800 kW by 6:00 am; through the day they undergo multiple discharge cycles, primarily between 11:45 am and 1:30 pm to support peak demand and generation deficiency. All batteries installed are operated and controlled collectively. Because our objective is to also minimize the depth of charge, the batteries charge to full capacity as soon as they discharge. At 2:30 pm, the batteries reach full charge and maintain that level throughout the remainder of the day.

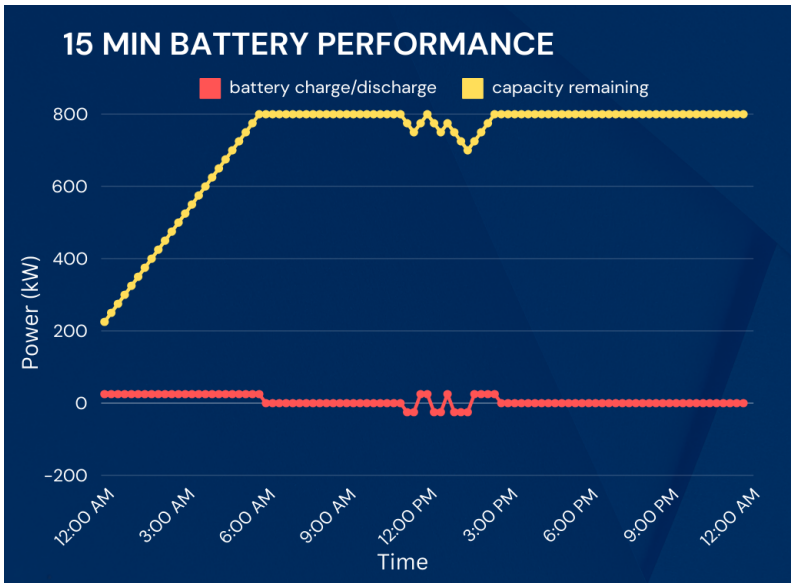



**Figure 7.** The 15 minutes interval battery performance.

*4.2. Case Study 2: DTE Energy 315-Bus System, 1 h Intervals*

To find the ideal run time, the optimization was performed hourly using the same system as in case study 1. Finding the best time is essential to making better operating decisions because system loads change regularly. The circuit load pre-COVID-19 and during COVID-19 is shown in Figure 8. The peak load is determined to be at 1:00 pm during COVID-19 and 5:00 pm before COVID-19.

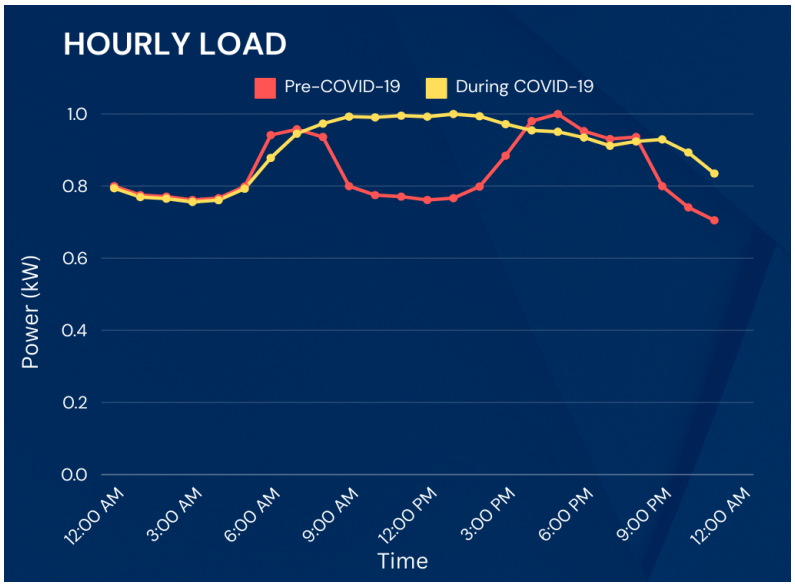



**Figure 8.** Hourly load.

The hourly battery performance is shown in Figure 9. Assuming the batteries are charging overnight, they reach full capacity at 3:00 am. To balance the load and avoid high peak prices, the batteries discharge at 1:00 pm and then start charging to reach full charge at 3:00 pm. Comparing the BESS data to case 1, it is noticed that although charging and discharging patterns are very similar, certain charging and discharging cycles are missing In both cases, the BESSs operate around midday. While in case 2 the BESSs operate only once at 1:00 pm, in case study 1 the BESSs discharge multiple times at different time frames between 11:15 am, 11:45 am, and 1:00 pm. Thus, we realize less detailed operations

in case 2. In addition, the proposed optimization algorithm finds the ideal solution in fewer iterations.

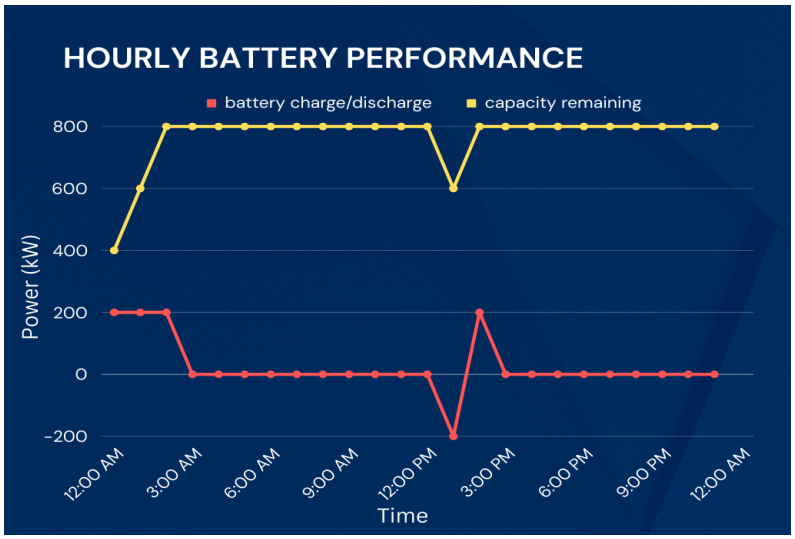



**Figure 9.** The 1 hour interval battery performance.

### *4.3. Case Study 3: DTE Energy 315-Bus System, without BESS*

Table 4 compares between the line and transformer losses percentage and cost on the distribution circuit with and without the BESS. The losses cost is calculated by multiplying the amount of losses by the average cost of generation. As shown, using a BESS can improve losses, thus causing significant savings over a period of 24 h.

**Table 4.** Circuit performance comparison with and without BESS.

| | **Without BESS** | **With BESS** |
|---|---|---|
| Losses | 21% | 8% |
| Total losses cost | USD767 | USD290 |

The main objective of this paper is to operate BESSs optimally to maximize utility benefits by considering load changes due to COVID-19 and using real-time SCADA data for accurate results. The results of both case studies reveal that the BESSs are being dispatched during peak hours to support load demand. Based on the optimization approach output, a 10% cost savings is observed considering that power is not purchased from the wholesale market. In addition, there is a 17% decrease in distribution losses. Moreover, BESSs recharge to maximum capacity right after discharging to satisfy the optimization objective of maximizing the BESS capacity for the longest time possible in case they are needed to be offered for bidding in the wholesale market, according to the recent FERC orders such as order 2222 that removes previous restrictions, enabling distributed generation to equally compete with traditional generation in the wholesale market. The optimal operation of the BESSs not only accommodated the new load patterns caused by COVID-19 but also resulted in a cost saving of approximately USD155,000 when considering the losses cost, battery operation cost, market prices, and generation prices.

## 5. Conclusions

When it comes to meeting their load demand, utilities are facing critical challenges due to multiple uncertainties such as new load fluctuations brought on by COVID-19. This paper proposes a cost optimization method for residential BESSs that takes new load variations into account. Contrary to most cost optimization techniques found in the literature, the approach proposed in this paper adopts a multi-objective optimization

function to maximize utility benefits, because additional costs to utility companies will probably result in an increase in the price of electricity to the customer. An analysis of a case study of a Detroit, Michigan distribution circuit is used to validate the suggested optimization model. According to the simulation data comparing the 15-minute-interval and 1-h-interval results, the results from the optimization are more precise the more often they are performed. Also, dispatching BESSs around noon avoids the need to make electricity purchases during peak hours. To completely comprehend the impact and propose best practices for scheduling BESSs to optimize utility advantages, more work has to be conducted. The system should be tested with different distribution voltage levels and load profiles from various seasons to consider seasonal changes. And to align with market bids, it would be beneficial to use 5 minutes load data. Also, forecasting load profiles and market prices instead of using historical data could improve the utilities experience. Additionally, it is important to consider system limitations; thus, combining the unit commitment with the optimal power flow can achieve more accurate results. This combination ensures that the grid is not put at risk due to voltage violations or load imbalances where the BESS output is adjusted to meet the load flow requirements as voltage limits. Another way to maximize cost savings could be by restricting BESSs from charging during peak periods by introducing a new constraint to identify peak hours and potentially initiate charging after 70% of the peak has passed. We believe that this could potentially result in additional savings. To ensure optimal results using the proposed optimization approach, it is critical to identify and test multiple values of $\alpha$ and $\beta$. Finding the optimal values results in the most favorable outcomes.

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